Image Content-Based User Preference Elicitation for Personalised Mobile Recommendation of Shopping Items

By

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Declaration

I, Stanley Ade Oyewole, student number 21242711, hereby declare that this thesis was written by me and that the work contained herein is my novel contribution. In the instances, where other concepts, approaches, tools, and techniques are used, they have been properly referenced. To the best of my knowledge, the work proposed in this thesis has not been hitherto submitted for any other degree at any university, institution of higher learning, or professional qualification. I have not endorsed and will not allow anyone to copy my work to pass it off as his/her work.

_____ __________ 26/10/2021

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Dedication

This thesis is dedicated to God the Father, the Son, and the Holy Ghost whose provision for the successful completion of this programme is beyond my ability, understanding, and natural strength. To Him is all the glory forevermore.

I am also dedicating this thesis to my parents.

Who left me, to eternal glory, when I most need him?
My Father, Late Elder Oyewole, Akanni Julius

Who is a woman I always depend on?
My Mother, Late Abigeal Modupe Oyewole.

My awesome family, without their constant support and encouragement, the writing of this thesis would not have been possible:

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Who are full of witty ideas and inventions?
My sons, Solomon Ayobami Adekunle, and Emmanuel Oluwatobi Adebisi

Who always makes me laugh every day?
My daughter, God-Praise Esther Adebola Gold

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List of Abbreviations

ANN	Artificial Neural Network
CBF	Content-based filtering
CF	Collaborative-based filtering System
BP	Back propagation
HOG	Histogram of Oriented Gradients
HSI	Hue Saturation and Intensity
kNN	k-Nearest Neighbor
LBP	Linear Binary Pattern
L*A*B	Lightness, Green-red and Blue-yellow colour opponents
LaRBF	An MKL-SVM kernel that hybrids Linear and RBF kernels
MAE	Mean Absolute Error
GDP	Gross Domestic Products
PwC	PricewaterhouseCoopers
EIU	Economist Intelligence Unit
MLP	Multilayer Perceptron
MSE	Mean squared error
PICA	Pixel Intensity Clustering Algorithm
RBF	Radial Basis Function
RMSE	Root Mean Squared Error
SVM	Support Vector Machine
SVM-MKL	Support Vector Machine Multi-Kernel Learning
Top-N	Number of items to be recommended
ULBP	Uniform Linear Binary Pattern
YC_bC_r	Luma, Blue-different and Red-difference Chroma components

Symbols		Chapter
$e-I_{cb}C$	Enhanced image content-based classification model	Ch1
n	Total number of users in a recommender	Ch1
m	Total number of items in a recommender	Ch2
R_0	Non-negative integer rating value	Ch2
$\overline{R}_{u,i}$	Denotes the AVR rating score of user *u on* the rated item i	Ch2
$P_{u,i}$	The predicted rating, $\boldsymbol{R}_{u,i}$ for item	Ch2
IRS	Image retrieval similarity model	Ch2-5
u_i	Recommendation Users	Ch2, 3
u_a	Active user	Ch2, 3
$(i, j)th$	Stands for entry of the matrix for user u_i's rating on item j	Ch2
$Utility(u_a, i)$	In Content-based the prediction of an item i for user u_a	Ch2, 3
x_u	The profile of users u	Ch2, 3
$\lvert k \rvert$	Number of image attributes or criteria information	Ch3
$I_{cb}-UPE$	Image-content-based user preference elicitation framework	Ch3
$ItemCat_{1,2...N}$	Product item categories	Ch3
$Sh^t_{loc\_pt}$	Shop Sh in cluster *t* in spatial location point	Ch3
$Sim(c, j)$	The similarity between actives user and his neighbors	Ch3
μ_t	Set of t centroids of a cluster in a regional location	Ch3
μ	Minimum centroid out of all available in a cluster	Ch3

img	The image captured from camera-enabled mobile phone	Ch3, 4
$MSimItem$	Most similar item based on all the item aggregation scores	Ch4
$dist(i, j)$	Represent distance apart, given items i and item j	Ch4
T_c	The time user captures his initial preference item, I_c	Ch4
T_j *and* T_c,	Two algebraically calculable timestamps that records the time when active user captured i and purchased item j	Ch4
$\theta\lvert\nabla t\rvert$	The time lag between purchase dates T_c and T_j $\lvert \mathrm{T_j} - T_c \rvert$	Ch4
$d_{c,j}$	A minimum distance of the user preferred items j with their corresponding purchase dates T_c and T_j.	Ch4
$jRECENCY_c^T$	Recency scores or similarity score ($Sim(c, j)$) of item j,	Ch4
Ch.	Chapter	Ch1, 6

List of Publications

- **Oyewole, S.A.,** Olugbara, O.O., Adetiba, E. and Nepal, T., 2015, Classification of product images in different colour models with customized kernel for support vector machine. In *2015 third International Conference on Artificial Intelligence, Modelling and Simulation (AIMS)* (pp. 153-158). IEEE.

- Olugbara, O.O., Adetiba, E. and **Oyewole, S.A**., 2015. Pixel intensity clustering algorithm for multilevel image segmentation. *Mathematical Problems in Engineering*, *2015*.

- **Oyewole, S.A.** and Olugbara, O.O., 2018. Product image classification using Eigen Colour feature with ensemble machine learning. *Egyptian Informatics Journal*, *19*(2), pp.83-100.

Abstract

Personalised recommendation of product items has been recognised as an exciting snug suggestion for an individual customer. This is required to meet the preferences of an individual customer and improve the sales of merchants. Most current research works in content-based recommendation heavily relied on an orthodox 2-dimensional “user by item” data structure has been used extensively in different application areas for product items recommendation. However, this structure is limited in delivering personalised recommendations to mobile customers because of the inherent “problem of concept drift” that can result in degrading the performance of a recommendation system. This research work introduces an image content-based preference elicitation model based on the approach of supervised machine learning to deliver personalised product items recommendation to mobile customers. This model of product items recommendation leverages the extraction of multiple aspects of item dynamic features to characterise the preferences of mobile customers. This will help mobile customers and nomadic to pervasively discover product items that are most relevant to their interests and reduce barriers to purchase. To start with, a new image-based item classification framework that leverages a novel 4-dimensional colour image representation and Eigen-colour features is built to realise efficient item-class features. The framework is devised to realise a time-dependent item relevance score for selecting a set of product items of interest. These features were integrated with other features such as price, location, and incentive associated with a product item to improve the performance of a shopping recommendation system. This is to build the proposed design towards addressing the concept drift problem and large recommendation space problems often associated with the orthodox items recommendation systems. Experimental results of testing an implementation of the proposed item classification framework have shown a recommendation system to produce low-dimensional item features and an implicit short-term preference profile for a new system user with recommendation accuracy of 92.2% on popular PI100 e-commerce shopping items corpus. Moreover, another experiment on item-based multiple criteria decision-making techniques has revealed that multiple factors can adequately address the concept drift problem. The proposed technique spawns better top-5, top-10, and top-15 rank personalised recommendation accuracy results when compared to the orthodox content-based approach. Finally, as a proof of concept, an imaging interface that anchors the proposed framework in a client-server system was simulated on a mobile phone.

CHAPTER ONE

Introduction

1.1 Background Information

A recommendation system helps to overcome the information overloading problem by making personalised suggestions to the user. A personalised recommendation is a tailored-made suggestion that is required to meet the preferences of an individual or group of users (Capelleveen et al., 2019). This type of intuitive recommendation makes every customer feel that there is shop assistant personnel available to be of help in providing needed services. Personalised recommendations of product items are an integral part of any successful strategy for retailer eCommerce. The delivery of personalised recommendations of shopping items and services has become a recognised way of increasing sales and customer loyalty in retailed e-commerce (Grbovic and Cheng 2018; Mohammadsadegh et al., 2021). This is substantiated by some big companies like Amazon (shopping), Pandora (music), Shopify (shopping), Netflix (movies), Yahoo (News), Tripadvisor(travel), Yelp (restaurant), Facebook (people), TED (articles), and Moviefinder.com (Movie) that are now making extensive use of personalisation techniques to improve sales. For instance, statistics from studies carried out by McKinsey and Technology Emergence (McKinsey, 2013), revealed that personalised recommendation system has brought 23.7% growth to BestBuy as well as 35% growth to Amazon revenue. The same report also stated that up to 75% of video consumption on Netflix comes from personalised recommendations, in the same perspective, 60% increase of views on YouTube come because of personalised recommendation features. In the same vein, studies conducted in Amazon (Antavo, 2020) shows that 86% of consumers agree that personalisation plays a significant role in their purchasing decision. These significances have influenced positively on both users and merchants, and as well, serves as one of the motivating factors for delivering personalised recommendations.

The effectiveness of a personalised recommendation system heavily depends on the algorithm applied and the quality of contextual features annexed (Adomavicius and Tuzhilin 2005; Olugbara, Ojo and Mphahlele 2010; Polatidis et al, 2017; Pimenidis, Polatidis and Mouratidis 2019; Lalitha and Sreeja 2020). On the aspect of recommendation algorithms, these algorithms are usually classified into a collaborative approach, content-based approach, as well as their hybrid (Shu et al, 2018; Rabiu et al., 2020; Mohammadsadegh, et al, 2021). Collaborative filtering makes a recommendation based on past similar rating history of the active user (u_a) and his similarity with neighbours, which are rarely available in practice (Shi, et al., 2014). On the flip of the coin is another popular technique of a content-based recommendation system, that makes suggestions on an item that are akin to that stuff that an active user (u_a) had purchased sometime in the past. The content-based approach usually relies on keywords, text words, and most recently the use of item-image content information for describing the object in view. Conventionally, the content-based approach extracts knowledge information from all and compares it to others. These are usually regarded as relevancy scores.

In this work, a content-based approach is selected, and the rationale for selecting this approach is laid on two (2) premises first, it can amend its recommendations within a short time, and secondly, ensures user privacy (Bishop, 2006). However, one of the major issues in content filtering research is the cold start problem, which is popularly called *new user* cold-start problem purchases (Xu et al., 2005; Gantner *et al.,* 2010; Bernardi et al, 2015; Liu et al., 2014), wherein user that is having little receive non-personalised recommendation. The other issue is that content filtering is characterised by the recency effect wherein recent items tend to speak volumes about user preferences than past data. This concept, sometimes called the concept drift effect (Saha, et al, 2008; Li, Liu, and Huang, 2016; Iwashita, and Papa, 2018; Wu, Zhang, and Liu, 2019; Rabiu et al., 2020; Rabiu, and Salim, 2020) is absent in the traditional content filtering algorithm. In this research work, an attempt has been made to come up with a novel model that would try to resolve the cold start problem and would consider the user drifting effect by integrating relevant dynamic context information.

On the plight of integrating relevant context information in shopping recommendation, the work of Olugbara, Ojo, and Mphahlele (2010) stands tall among others. These researchers introduced additional item context variables such as item price, item-location, item-bait, and item-relevance in the design of their system tagged TellMe system (TMS). However, this work of Olugbara, Ojo, and Mphahlele in 2010 seems indifferent to item temporal features. Account from the literature shows that temporary context remains very important in the e-commerce domain, as similarity-relevance between two items is not only on their content similarity but also is a function of time and fashion. In addition, apart from the fact preferences of most users were class or brand-inclined. Inclusion of item-class improved accuracy and speed-up recommendation processing (Chen, Yang, and Yang (2017).

This becomes very important to a mobile user who is always in haste. Thus, negligence of these context variables can affect the level of personalisation deliver by the content-based recommendation approach. On this background, this thesis proposed an image content-based user preference elicitation model, which introduces multiple additional context variables. Time-based item similarity relevance and item-class stand as the two core components of the proposed model. This multiple criteria-based model also integrates multiple aspects of item dynamic feature variables (IDF) that are realisable from TMS item information (bait, location, and price). This item-based multi-criterion $\left(I_{cb}MC\right)$ information is used to learn the drift preferences of a user over time and deliver personalised recommendations to the mobile user.

The proposed method is unique as it relies wholly on item dynamic feature variables. Integration of item-class information and low dimensional item feature to build an implicit short-term profile for a new user is a unique ideal of improving content-based approach. The proposed method uniquely builds a new time-based similarity model that integrates temporal feature with others item dynamics feature to capture user periodic preference style on a particular item. Finally, prospective beneficiaries of these personalised services rendered by the proposed work, in the shopping domain include visitors (mobile users) such as tourists, transporter, and conference attendees. Others are field service workers such as journalists, long-distance vehicle drivers, business travelers, nomads, equipment maintenance operators, nomads, and individuals who want to receive personalised shopping recommendations ‘on-the-go.

1.2 Statement of the Problem

Delivering personalised mobile recommendations to new users (A user who is just joining recommendation systems) is a long-standing issue of recommendation systems. One of the major issues facing the content-based recommendation approach is that the interests of users of recommendation systems and item features may change over time especially in the eCommerce domain, where new mobile users incessantly interact with the environment (Žliobaitė, Pechenizkiy, and Gama 2016). In this situation, capturing the dynamic context variables of items over time to effectively deliver personalised mobile recommendation with the existing classical recommendation algorithms remain very challenging.

The approach of image content-based seems to be promising and dwell richly on the aesthetic information that turns out to be very important in the e-commerce domain because it tends to produce high-quality recommendations (Ben-Elazar and Koenig-stein, 2014; and Herlocker, *et al.,* 2017; Mohammadsadegh et al., 2021). However, to date, extracting this rich information from colour images in low dimensions remains an important challenge (Geng, et al., 2015; Iwana, *et al* 2016). Moreover, another very important problem in content-based recommendation is that in profiling, system users are usually faced with large dimensions of items. As such, filtering of relevant items from the large dimension often generates high computational problems (Pazzani and Billsus, 2007; Wasid, and Ali, 2018, Raghuwanshi and Patenaq, 2019) and high false-positive results (Dabrowski and Acton, 2010; Zhang and Sha, 2013).

1.3 Research Questions

The challenges and important issues discussed in the statement of the problem section directly led to the research questions raised in this study. These questions must be adequately answered in a bid to respond to the statement of the problem elucidated. These questions are defined as follows.

- How can the rich content information of colour-image be aptly extracted as a low-dimensional features space for recommendation generation?
- How can the problem of high computational filtering inherent in content-based profiling be addressed toward building a personalised recommendation system?
- How can a time-based relevance feature be realised using a decay function that provides the best approximation to address the inherent problem of high false-positive results that is often experienced in the content-based recommendation?

- ❖ How can the dynamic context features of user-preferred items be captured over time, and used to deliver effective personalised shopping recommendations to mobile users?
- ❖ How can an adaptive imaging interface that anchors on the model of image content be realised on a camera-enabled mobile device?

1.4 Study Aim and Objectives

The overarching aim of this study was to elicit the drift preferences of users of a personalised recommendation system based on multiple criteria image content towards improving the system performance. The specific objectives of this research are to:

i. Realise a low-dimensional content-based feature of all product images.

ii. Use the low dimensional features (Eigen color feature, ECF), generated in (i) above to realise a class-based discriminative filtering feature, that could reduce search space,

iii. Realise the best decay approximation function that generates time-based image relevant features

iv. Develop an image-content multi-criteria model, that integrates item feature information generated in (ii) and (iii) above with the TSM item-information (bait, location, and price) to deliver personalise recommendations to the user.

v. Implement the proposed model as a mobile app., and anchor it with an imaging interface.

1.5 Research Methodology

The user preference elicitation method of image content employed in this study has applied the fine-grained analysis of multiple criteria to characterise user preference. This proposed approach is in sharp opposition to the current classical recommendation methods that relied on coarse-grained analysis of a single criterion. In the architectural design of the proposed model, different methods and frameworks were built to extract, preprocess, and annex novel features for delivering personalised recommendations of e-commerce product items. The entire process of developing a model of e-commerce product item recommendation that is appropriate for mobile system users should provide the following essential components.

- A new 4-D colour image representation method that extracts low dimensional Eigen colour features.
- An enhanced image content-based classification ($e - I_{cb}C$) profiling method for search space reduction.
- An efficient time-based similarity framework built with a time-decay function.
- A multiple criteria image content-based user preference elicitation method based on the approach of multiple criteria to address the problem of concept drift for personalised mobile recommendation of product items.
- A dynamic imaging interface technique for practical realisation of an image-content-based recommendation system for mobile shoppers.

The effectiveness of the foregoing choice of system component was demonstrated by experimentation. Different experiments were successfully conducted to assess the performance of the proposed system that uses image-classification profiling and time-based preference elicitation against the current classical recommendation approaches. Top-N rank accuracy metric was used for average recommendation accuracy. The famous performance metrics of accuracy and mean absolute error (MAE) were used to measure the overall classification accuracy and classification error rate. The uniqueness of this study is first in the choice of solution approach that relies heavily on the solo image-content features. This approach does not follow the orthodox keyword-based approach of item representation that has been besieged with many intrinsic limitations. In addition, the integration of time social factor as an important parameter is unique to this study because it has improved the recommendation quality. The other uniqueness of this study is that the proposed approach seamlessly integrates the methods of machine learning, and decision theory with temporal components to build a novel user profile to resolve cold-start scenarios often associated with recommendation generation. The newly proposed four-dimensional (4-D) colour model for colour feature representation is particularly unique to this study. The model uses 12 image channels instead of the conventional 3 channels to represent features of an item as image colour features.

1.6 Contributions to Knowledge

The approach proposed in this work seemly relies on solo image content features representation, which is an important contribution in the content-based recommendation assistance technology. The image-based visual capturing approach is a *new user*-oriented approach that allows new users to explicitly specify items of choice by capturing the product image. Literature has recorded that this approach allows for both users derived hedonic motivation and better utilitarian values when indulging in recommendation (Holbrook 1998; Mikalef *et al.,* 2013; Salo *et al.,* 2013). A detailed evaluation of the newly proposed product item recommendation method has provided a rational performance assessment of the new architecture. The design and implementation of the new cross-platform imaging interface that elicits user context attribute that anchor on a recommendation architecture in the mobile shopping domain is an important artifact from this study. The unique contributions of this study to the existing knowledge of multiple criteria decision-making methods, machine learning, and recommendation applications in the e-commerce domain are succinctly summarised as follows.

(a) Creation of a new image-content based feature representation algorithm that uses four-dimensional (4-D) colour model representation and Kaiser criterion retention heuristic to generate item-class attribute with an accuracy of 92.2% on a popular e-commerce dataset PI 100 (Xie, *et al.,* 2008),

(b) Improvement on an existing multiple attribute content-based recommendation architecture by integrating the temporal component and an enhanced image content-based classification model. This model does not only reduces the search space and improves the scalability of the system but also improves accuracy. Specifically, this model could be incorporated into any other decision support application for recommendation application. This remains a huge contribution to dimensionality reduction and personalised recommendation technology.

(c) Demonstrates that effective integration of multiple aspects of item features is a promising method for resolving the problem of concept drift because it considers the multiple preferences of mobile users in depth.

1.7 Thesis Outline

This section outlines the chapters in this work and briefly summarises the contents of the thesis. The thesis consists of other seven chapters. The first chapter provides the background information, problem statements, research questions, study aim, and thesis outline following the standard norm for thesis writing. The remaining six chapters detailed the existing methods as theoretical foundations and methods that have been developed to support the proposed method and experiments to address the problem of personalised mobile recommendation in the e-commerce domain. Specifically,

- **Chapter 2:** *Literature review* – gives the overview of methods for improving elicitation of user preference and personalisation in the e-commerce domain. In addition, recommendation approaches for exploiting preference information in the user profile, issues around user preference modelling and mining are also discussed, personalisation steps, past related works, and gaps are described.

- **Chapter 3**: *Theoretical Foundation – the* efficacy of a recommendation algorithm rests on the accuracy of the elicitation algorithms that are used. This chapter discusses theoretical frameworks behind the proposed work such as colour image features representation, extraction of image high-level feature from a low-level feature, dimensionality reduction method, profile leaning method, time-base model, and other image-based techniques that have influenced the current study. There are numerous algorithms available in the literature for image feature extraction, representation, classification, and time-based preference elicitation. On this background to select or create or improve on any of these algorithms, this chapter reviewed image representation, image feature extraction/selection, description, classification, and time-based models that are suitable for the current study in the e-commerce domain. Performance evaluation techniques for comparing recommendation results are also reviewed in this chapter.

- **Chapter 4**: *Methodology-* discusses design issues for the realization of the proposed algorithms, model, and architecture. Additionally, a new colour image representation and dimensionality reduction technique using the Eigen colour feature and Kaiser Criterion retention method was developed and presented. This chapter also presents a new recommendation architecture based on those algorithms reviewed in Chapter 3.

- **Chapter 5**: *Experimentations, Results, and Discussion* -- focuses on the design of experiments conducted, results, and discussion of the analysis of the experimental results. Attention is on also focus the experimental evaluation of results on the image-based classification model, classical content-based model, and sensitivity analysis of decision algorithm on multi-criteria factors.

- **Chapter 6**: *Conclusion and Future Works* – this chapter summarises and concludes the research work by summarising the results of the experiments performed and the contributions of the study. The chapter also shows how the research questions of this study were perceptibly resolved and an analysis of future directions for this research is provided.

CHAPTER TWO

Literature Review

2.1 Preamble

In this part of this thesis, a critical review of related works with a specific focus on how to improve the accuracy of classical content-based recommendation systems and to make them fit to deliver personalised mobile recommendations in a shopping environment. Personalisation entails the application of decision support tools to acquire accurate knowledge information from user/item to deliver tailored-made suggestions for user satisfaction. User preference elicitation has been identified in the literature as a critical issue of interest toward personalised recommendation. This cut across different fields but is not limited to e-commerce, psychology, behavioral science, consumer research, intelligent (interactive) systems, as well as decision support systems (Silva et al., 2018; Fernandez et al., 2019). In delivering personalised recommendation in mobile recommendation scenarios, with a content-based recommendation, three (3) important concepts needed to be considered are, the recommendations method, user contextual variables, and user privacy (Gavalas et al., 2014; Rodriguez-Hernandez and Ilari, 2016; Polatidis et al., 2017; Pimenidis, Polatidis and Mouratidis 2019).

The last part of this chapter reviewed past works that applied to recommendation method, user contextual variables, and user privacy. First, challenges in the different recommendation approaches and their shortcoming were summarized. This is followed by different performance evaluation techniques that are related to the job at hand. Finally, gaps from the reviewed literature were highlighted followed by the proposed idea of integrating image-content feature and temporal context components to enhance the quality of recommendation systems at large. The subsequent section begins with different recommendation methods that can be applied to represent the preference of a mobile user.

2.2 User Preference Acquisition Methods

The task of acquiring user preference from items can be accomplished by either applying explicit-based, implicit-based, or Infer-based methods (Kuflik et al., 2007). These methods can also be combined or used singly (Gauch *et al.,* 2007). To know the right method to apply there is a need for effective study of user preference, and different methods that can be applied to discover what users like or dislike at a particular point in time (Knijnenbur and Willemsen, 2010).

The explicit method asks a user directly, his/her likes and possibly dislikes (Ardissono *et al.,* 2002; Olugbara, Ojo, and Mphahlele 2010; Mohammadsadegh et al., 2021). However, preferences learned based on this technique typically represent a subclass of the user's complete "needs and wants" (Ricci and Nguyen 2005). The explicit method could also be achieved by asking the user to assign a rating to a set of items; this is perhaps the most distinctive form that is ever used in the literature to obtain user preference information. The feedback response scale for ratings can be discrete, binary, or unary (“like”). One limitation of this method is that often time a substantial fraction of the people concerned is not keen to quantify their interest in any of the items at all. There is a situation where the designer makes the option to decide whether to ask people concerned to give their interest rate on a set of items, or whether the recommender should spontaneously pick items to rate for users (Nguyen et al., 2013). Even though the explicit collection of a user modelling data via rating, like/dislike, comments, and so on are considered more accurate, but there are considered an effort and time-consuming task.

Some researchers have proposed implicit techniques to address the issues associated with user effort and time spent in acquiring user preference. These techniques learn from current user purchases, actions, and contexts. The implicit method involves the application of different cognitive mechanisms that suggest the required preferences based on user observation behavior. The idea of using time-of-the-day, periodic change, or user navigation behavior to determine and acquire user preference is one good example of an implicit approach (Billsus *et al.,* 2000; Dunlop *et al.,* 2004). User, item, location, and current time of the day were all extracted implicitly from the mobile device content storage in this work. However, this method can easily misconstrue user behavior, as, in a real sense, both explicit method and implicit method are often combined (Kuflik et al., 2007).

The infer method is another way that can be used to extract information from an item. This method extracts features by conjecturing relationships between two entities. In a relationship between two items, take for instance, if one capture image is like images in the database, and image in the database has a correlation with learned item-images from the active user profile, then captured item has relation with the user preference and so any complementary items attached to it. If the captured item *x* is dissimilar to the items *y* in the database, and a captured item is preferred to that item that is dissimilar to the captured item, then the non-similar items cannot be preferred to the captured items. If mRn and nRm then mRn (transitivity). Explicit, implicit and infer methods were used in the different segments of this current research work. The dynamic nature of mobile users has necessitated the introduction of a dynamic user interface.

2.3 Review of User Preference Modelling Methods

The preference of a mobile user for a product item can be modelled using different methods and techniques. The scores of item features are also calculated and matched to determine which items are closer to the other or rather closer to a user profile. Generally, the matchmaking process borders on how to exploit user profile information to analyze filter, and deliver it to the user. This can be accomplished with different recommendation methods that exploit the user profile information for user preference modeling as shown in Fig. 2-1. The figure shows the classical-based recommendation systems and multi-dimensional recommendation systems (MCRS) approach and its subdivisions. All these approaches are further reviewed in the subsequent sub-sections.

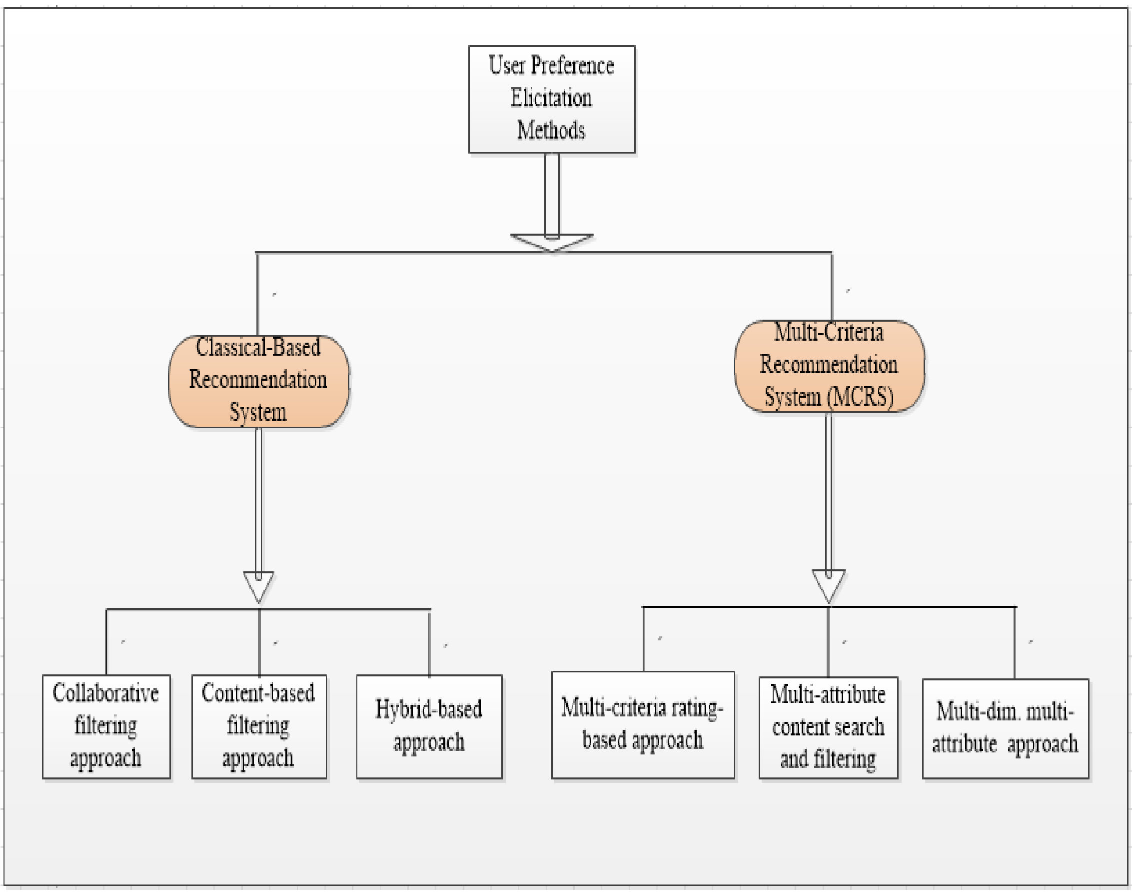


Figure 2-1: Taxonomy of Approaches for User Preference Modeling

2.4 Classical-Based Recommendation Systems

Structurally, all classical recommendation systems function in a bi-dimensional space of (u , i), where u and i represent users and the set of all possible items that can be suggested to each customer, respectively. In addition, in figure 2-1 one can observe a classical-based recommendation system and its subdivisions.

2.4.1 Collaborative-based filtering

A collaborative-based approach has been extensively utilised to filter relevant information from user profiles to deliver personalised recommendations. It has also been successfully deployed both in academia and in industry, such as Group Lens, Ringo, Amazon.com (Su and Khoshgoftaar 2009; Kulkarni *et al.,* 2016). Conventionally, this filtering algorithm has two main stages where:

(i). Match score between the u_a and the rest of the users (or ‘neighbors’) in the base is determined (Zhou, Liang, and Dong 2017).

(ii). the similarity scores found in (i) above are utilised to predict the preferences of an active user.

The main drive for this filtering method stems from the notion that people usually receive effective suggestions from their neighbours that have similar tastes. These similar users are also called neighbors (Adomavicius, Huang, and Tuzhilin, 2008; Anand and Mobasher, 2005). This approach implies that items are predominantly evaluated based on opinions of other users, differing from the use of natural characteristics of items or services that the recommendation system provides (Schafer *et al.,* 2007). The user-item rating Table 2-1 shows different item ratings from different users.

Table 2-1: User-Item rating

	i_1	i_2	i_3	$i_{\ldots}$	$i_{c\ldots}$	$i_{\ldots}$	i_n
u_1	$r_{1,1}$	$r_{1,2}$	$r_{1,3}$	$r_{1,\ldots}$	$r_{1,c}$	$r_{1,\ldots}$	$r_{1,n}$
u_2	$r_{2,1}$	$r_{2,2}$	$r_{2,3}$	$r_{2,\ldots}$	$r_{2,c}$	$r_{2,\ldots}$	$r_{2,n}$
u_3	$r_{3,1}$	$r_{3,2}$	$r_{3,3}$	$r_{3,\ldots}$	$r_{3,c}$	$r_{3,\ldots}$	$r_{3,n}$
$u_{\ldots}$	$r_{\ldots,1}$	$r_{\ldots,2}$	$r_{\ldots,3}$	$r_{\ldots,\ldots}$	$r_{\ldots,c}$	$r_{\ldots,\ldots}$	$r_{\ldots,n}$
u_d	$r_{d,1}$	$r_{d,2}$	$r_{d,3}$	$r_{d,\ldots}$	$r_{d,c}$	$r_{d,\ldots}$	$r_{d,n}$
$u_{\ldots}$	$r_{\ldots,1}$	$r_{\ldots,2}$	$r_{\ldots,3}$	$r_{\ldots,\ldots}$	$r_{\ldots,c}$	$r_{\ldots,\ldots}$	$r_{\ldots,n}$
u_m	$r_{m,1}$	$r_{m,2}$	$r_{m,3}$	$r_{m,\ldots}$	$r_{m,c}$	$r_{m,\ldots}$	$r_{m,n}$

There is a need to know the degree of similarity of active user (u_a) interest to his neighbourhood to provide an effective recommendation in collaborative-based filtering. This is often achieved by searching for other users that are like u_a. Numbers of similarity functions have been implemented to measure this, but among them all the two frequently used are for collaborative filtering are Pearson correlation and cosine rule function (Liu *et al.,* 2014).

Conversely, a recommendation system that is purely built on collaborative filtering suffers several problems. The sparsity problem is one of them. This problem occurs when the acquired input data on the user-item rating matrix are quite small (sparse) compared with what the recommenders need to make an accurate prediction (Burke, 2002). In other words, this limitation occurs if the existing user neighbour is smaller in comparison to the large volume of predicted item information (Balabanović and Shoham, 1997). In addition, conventional collaborative filtering has cold-start and scalability problems (Sarwar et al 2000a; Liu et al., 2014; Gupta and Gadge 2015). The cold-start issue covers what some researchers called a new-item problem while others refer to it as a *new user* problem. The latter occurs when the recommendation system has little or no information about user apriori. As such predicting user preference in that regard becomes very difficult (Liu et al., 2014; Gupta, and Gadge, 2015), while new item problem occurs possibly because a new item that is in the recommendation environment might not have been purchased by a sizeable number of users. As mentioned earlier to deliver personalised recommendations, algorithms and contextual information have been recognised as two important components (Pimenidis, Polatidis, and Mouratidis 2019). Subsequent sections review the literature on how personalisation can be delivered.

2.4.2 Content-based filtering method

Another popular recommendation approach that has gained attention in user preference filtering is the content-based filtering approach (Zhang and Koren, 2007; Rana and Jain 2012; Nzeko, Tchuente, and Latapy, 2017). The motivation for content-based filtering comes from the idea that people tend to like similar items to those they have liked in the past, as such, this approach suggests relevant items such as content, services, and products that are alike in features to either the items or user profile (Olugbara, Ojo and Mphahlele 2010; Shambour, Hourani and Fraihat, 2016). This approach believes in the persistency of user taste and each active user is assumed to operate independently. Content-based preferences modelling uses item characteristics, but most existing Content-based recommendation applications wholly rely on static text-based filtering representation and filtering. Text-based filtering is one of the most commonly used techniques in the recommendation technology cycle. However, text-based feature extraction techniques often produced redundant items feature that completely ignores aesthetic qualities and dynamic information that turn out to be necessary particularly in the e-commerce domain (Lops, De Gemmis and Semeraro 2011).

Content-based item recommendation approaches build a user profile based on information that was acquired from the description of items that is currently or hitherto rated by a user (Nanas, De Roeck and Vavalis 2009; Tewari, Singh and Barman 2018). In the content-based similarity process, those products that are like the items in the profile of the user or like the content of the items preferred by users are recommended (Van and Van 2000; Pazzani and Billsus 2007; Amini, Ibrahim and Othman 2011; Saveski and Mantrach 2014). The connotation of content-based recommendation emanated from the image retrieval technique (Lops, De Gemmis, and Semeraro 2011). The technique tries to match query features with the item features (Saveski and Mantrach 2014).

On the part of using keywords, formulating the right set of keywords for one preference can be frustrating in certain situations (Jansen *et al.,* 1998; Yeh, Tollmar and Darrell 2004). In this situation, only context and item information may not be sufficient as other information needs to be considered. Therefore, for any e-commerce application system to make fast, accurate, and personalised suggestions, such a system must perfectly consider image-content information within users' environments. These give rise to another class of recommendation systems architecture that considered integration of dynamic image multi-content features, such as preliminary features (colour, shape), abstract/social-context attributes (price, incentive), item-location, time of purchase, and image logical content feature, such as item-categories, item-taxonomy. These dynamic image features are further reviewed as follows.

Content-based filtering has the following strengths:

- ❖ **User independency:** Unlike collaborative-based filtering that needs other user ratings for determining "nearest neighbors" for active user and subsequent collaborative recommendations, content-based filtering only need only one profile for the recommendation, thus there is no dependency on other users and this approach still produce reliable results.

- **Transparency**: A recommended item can be described to a user if it is trustworthy and transparent. This can be achieved via explanation while a particular recommendation is suggested to an individual user. Content-based has the capability of providing recommendation results alongside succinct explanations information such as content similarity score, item location proximity score that tells how the recommender system works is arrived at. Amazon does this by saying something along the lines of: “This item is recommended to you because ….”. All the above-mentioned criteria are important criteria or indicators needed to be referred to in deciding whether to trust a recommendation system.

- **Invulnerable to item cold-start problem**: A situation when a recommendation system has little or no information about an item. This is possible because the item is new or has not been rated previously by a user, which is a problem called item cold-start state. This problem affects the performance of collaborative filtering, but the content-based approach is invulnerable to this problem (Bernardi et al., 2015). Conversely, preference elicitation method that is purely based on content filtering suffers limited content analysis, over-specialization, *new user* cold-start (Ricci, Rokach and Shapira 2011; Bobadilla, Ortega, and Hernando, 2012).

- **Limited content analysis**: Content-based filtering has been shown to produce high-quality recommendations, but one of the main challenges that often inhibit the delivery of personalised recommendations to users is the limited content analysis problem (Tintarev and Masthoff 2011; Desrosiers and Karypis, 2011; Lops, De Gemmis and Semeraro 2011). This has to do with those circumstances that can debar the system from obtaining or extracting enough information from the user. This is popularly referred to as a user-based limited content analysis problem or item that is widely referred to as an item-based limited content analysis problem to precisely discriminate the characteristics of entities. Some of the reasons that use limited content analysis do occur could be partially attributed to user privacy concerns which might refrain them from supplying peculiar information. The lack of information in content-based filtering could also trace to difficulty in obtaining precise content of some items such as music or e-commerce product items. Lastly, another reason could be the fact that only the content of an item seems inadequate to describe all characteristics of the item that seem essential for user preference elicitation (Desrosiers and Karypis 2011; Lops, De Gemmis and Semeraro 2011). Another reason is domain knowledge is often desirable, for example, in product recommendations content based contain scheme that necessitates all image-content information that recognise the product item primitives such as colour, product item logical information such as item-class, some other abstract information such as the location where the item can be found, and some other field ontologies are sometimes required. If any of the above occur the recommendation itself risks being imprecise.

- ***New user***: The new user scenario happens when it is little or no purchases (Bernardi, et al., 2015; Liu, et al., 2014). In that situation, recommendation systems can suggest poor recommendations because the collaborative information offered for the system to determine preferences or build a solid profile is scanty. The new user problem is widely called the cold-start problem.

- **Over-specialization, Non-serendipitous recommendation**: Serendipity refers to recommendation generations that a user will like but has no idea of their existence. The content-based approach has no fundamental method to find out the unique, serendipitous, or 'surprise' taste of a user (Tewari, Singh, and Barman 2018). Consequently, a typical active-user only receives suggestions on analogous items to those he has purchased before or ranked high before, when she/he started to use the service (Tejeda-Lorente, et al., 2014). For example, a shopper who has only ranked high shopping items – Milo from beverages category in the past, he/she will get recommendations only milo products. It has been observed that this non-serendipitous recommendation leads to low user satisfaction (Tejeda-Lorente, et al., 2014; Castel, Hurley, and Vargas 2015) and to address this more detail of each item are needed (Eirinaki, et al., 2018).

- **Recency effect:** Another issue is that the recency effect counts most in fashion, particularly in e-commerce wherein recent items tend to speak volumes about user preference than past data. This concept is sometimes called the drift effect is absent in the traditional content filtering algorithm (Saha, et al., 2008). For example, a shopper might like to buy a shop item only when its recency score has not extended beyond half of its expiring date, and not just buy the item like that. This problem which relates to how to make the utmost desirable recommendation at the right time is one of the least explored challenges in this field (Rabiu and Salim 2020).

2.4.3 Hybrid recommendation system

In addressing limitations of classical recommendation approaches to deliver personalised recommendations the idea of integrating both collaborative and content-based came to the limelight. The hybrid approaches focus on realising a perfect synergy between components. Both collaborative and content-based filtering, for instance, have their different merits and drawbacks. The inherent bottleneck of one method can be surmounted by the agglutination of multiple methods. It is on this background that most of the existing user preference elicitation frameworks have utilised the hybrid of both recommendation systems that combine the advantages of these methods (Burke, 2002; Kim et al., 2012; Heng-Ru, et al., 2015).

In 2002, Robin Burke classified different methods that can be used to achieve a hybrid recommendation system into seven categories, which are, feature combination, switching, weighted, feature augmentation, cascade, mixed, and metal-level (Burke, 2002; Heng-Ru, et al., 2015). Even though hybrid recommendation systems are based on the use of a single-criterion factor, the methods have been proposed in various areas to overcome some of the intrinsic problems highlighted.

The multiple criteria recommendation system-based approach is another useful form of a hybrid recommendation approach that integrates multiple criteria information with either content-based filtering or collaborative filtering. In general, the multiple criteria-based recommendation system (MCRS) can be classified into multiple criteria rating-based approach, multiple criteria content search and filtering, and multiple dimensional multiple criteria filtering approach.

2.5 Multi-Criteria Systems Dynamic Data Source and Acquisition

Data collection is one of the basic steps of building recommendation systems. Likewise, the type of data source where information is acquired sometimes determines analysis that can be performed on the data collected and the extent of their dynamism. A recommendation data source can be either dynamic or static, as discussed in Rabiu et al., 2020. Static data do not vary and do not take a long time before they change (Ricci, Rokach, and Shapira 2015). Examples of such data are item name, item class, user-id, gender, and so on. Classical recommendation systems, which usually rely on static data, are built on the supposition that the history of users can be used to completely represent user preference (Li, Liu, and Huang, 2016). On the contrary, dynamic data sources or dynamic recommendation systems (DRSs) are built on dynamic or periodic user preferences (Wu, Zhang, and Liu 2019). As such, dynamic scenarios relying only on a recommendation system that is built on the notion of static data, mostly end up generating non-personalised recommendations (Lo et al., 2017).

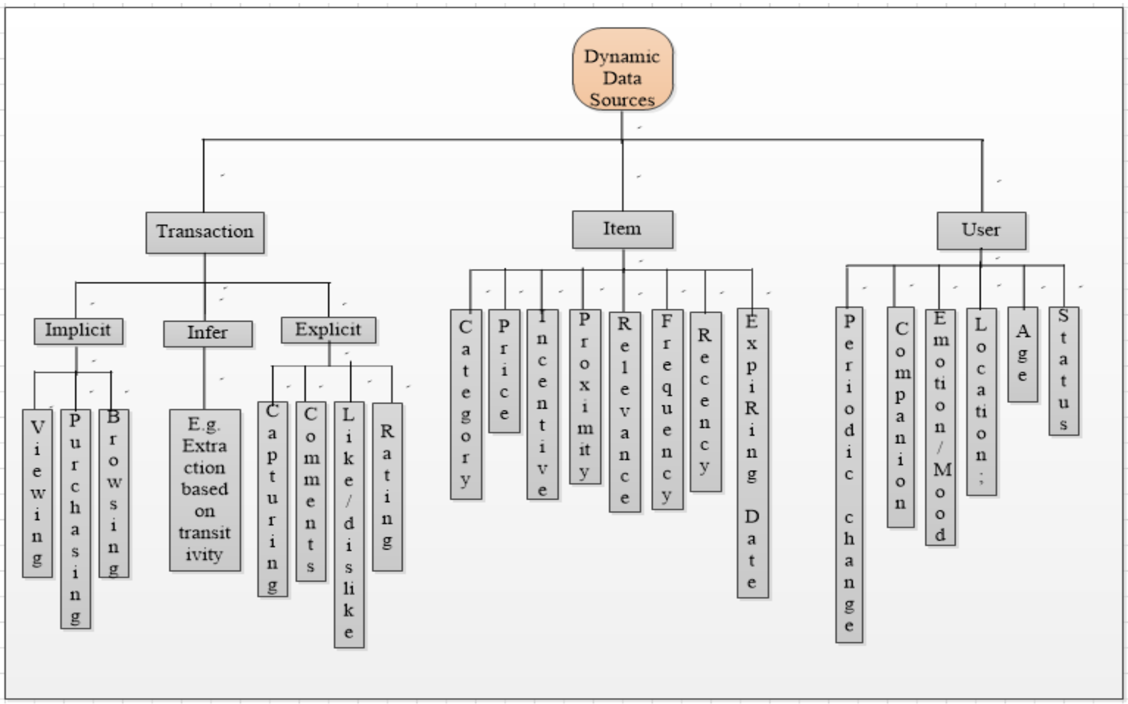


Figure 2-2: Taxonomy of dynamic data source for shopping systems

The research work reported in this thesis focuses on different dynamic data attributes and transaction methods that can be used to track different concept drifts in the life of a new user who is newly indoctrinated into the fold of a recommendation system. In addition, a taxonomy of dynamic data source as it concerns with a shopping recommendation is built as shown in Figure 2-2. In the same view, this dynamic information can further be grouped into the following three sub-headings, which are preliminary item-image content information, context-based information, and logical item-image content information. The subsequent section expatiates on these groups particularly those researchers that have rightly utilised them.

2.5.1 Preliminary Image Content Information

Some of the related research works on primitive image-content recommenders are reviewed as follows.

Shan *et al.,* (2008) proposed a multimedia-enhanced goal-oriented requirement elicitation method in which media measures are used to help capture user requirements and preferences more easily. Sáez, Luengo, and Herrera (2010) present a technique to improve content-based recommendation systems, using color-impression-based image retrieval. Likewise, Zhang *et al.,* (2012) proposed working toward realising visual search using a new model based on image contextual idea, where users are made to specify a salient area by depicting on an object interest a circle-based sign called the “o” gesture. Shen et al., (2012), suggested a product image-feature search framework in the mobile domain that extracts objects in a particular query image. Top-n images are generated based on how cleanness of an image background. A weighted mask approach is employed to mine the object feature in the query image as well as its background-cleaned level. Image search is finally achieved with the cleaned query image. These researchers reported that performing a query with the object-of-interest that is extracted from a clean background seems to work better.

Another image search architecture in a mobile environment is proposed by Guan et al., in 2014. A bag-of-features (BoF) feature extraction approach was employed. The authors applied an approximate nearest neighbor search to allow the use of bag-of-features descriptors with minimal memory usage. The search architecture exploits GPS data, emanating directly from the mobile device. Researchers, Zhou et al., (2014) propose a mobile-based image filtering framework that requires less memory because its design is void of codebook usage. The Zhou et al., the system applied SIFT descriptors and Principal Component Analysis (PCA) for dimensionality reduction. Similarly, TapTell (Zhang et al., 2015) is another mobile visual search architecture that is built on human-computer interaction. The users can take a snapshot of the image with TapTell, and then specify via drawing of patterns that segment objects of interest from the captured image. Digimarc Discover (DigiMarc, 2015), as well as Point and Find (Nokia, 2015), are two popular mobile search applications that allow mobile users to point a camera-enabled mobile device to an object and get instant information about it. In the same direction, Amazon Flow (A9.com, 2015) is another recent mobile search application that does the same operation.

Kooaba (2015) and PlinkArt (2016) are two domain-specific search systems. The former focus on e-commerce domain product such as game covers, books, and DVD. Conversely, the former targeted at artworks domain. With PlinkArt (2016) customer can point their camera-enabled mobile device to the artwork of their choice and get instance info about the artwork. Similarly, CamFind (2015) is one of the existing general-purpose object search systems in a mobile environment. It first applied segmentation and then filters. Take for instance, when an active user uses his camera-enabled mobile device to take a snapshot of a scene, salient objects within the scene are recognised and scenes that have similar salient objects are recommended to the user.

In Çalışır *et al.,* 2017 a multiple-view image-based search architecture is proposed. Multiple queries of the object image are obtained by taking various views of objects at different orientations and sizes. The researchers employed Bag of words to extract image features. The histogram of these Bag of words is then combined to build an image feature database. However, these above-reviewed works neglected some other pertinent user preference profile components.

The work by Prando, et al. (2017) is one of the prominent studies that focus on addressing the problem of new users using the content-based recommendation approach. In the work, the researchers propose to recommend product items to a user based on his/her favorite identified category. Furthermore, the authors applied a technique that associates e-commerce products with the basics of social networking. As such, in a situation where there are neither explicit nor implicit ratings, the extracted features from a social network stand in lieu and of course adequate to determine user preference. Examples of such data that the author proposed to use include data that signify the likes of a user from his/her direct posts on Twitter, those posted by another user that he/she likes, and lastly, those pages he/she likes on the Facebook page.

2.5.2 Context-based Image information

Some of the related works that have used social context information (abstract image content-based feature) to improve recommendation accuracy are detailed below. Context is the most common use information to improve rating, and content-based approach (Adomavicius, and Tuzhilin 2005; Sassi, Mellouli and Yahia 2017). Adomavicius and Tuzhilin (2005) suggested that next-generation recommendation systems should be able to adjust to user preference naturally and understand their heterogeneous context and criteria. Another application that considers user ratings in different contexts is an offer by Passemier *et al. (*2010). The researchers integrated user profile and feedback mechanism thereafter Bayesian classifier is applied to record context-dependent preferences of a user, such as a mood, time, and location. Also, bargain finder (Krulwich, 1996), the first well-known shot-bot provides comparison-shopping for music CD product items. It searches eight online music stores and displays all prices on a webpage. The approach is portable since it is independent of the system, but in all preferences of a user were not learned. In addition, apart from privacy issues, tracking mobile user preference with only contextual does not seem enough.

The account from the work of Baltrunas, *et al.,* (2012), reveals that users find mobile context-aware recommendation systems (CARS), more effective and satisfactory than a typical mobile recommendation system anchored by the same interface. In the same view, Adomavicius and Tuzhilin (2010) also attested to the fact that contextual information remains a vital tool for boosting the quality of a recommender in respect to some settings. Equally, the work of Gorgoglione, Panniello, and Tuzhili (2011) shows that CARS produces more quality results than classical recommendation systems when customer purchasing behavior and trust are engraved in suggesting recommendations.

In a mobile world, one way of delivering personalised recommendations is via acquiring contextual information around a user. In (Sambolec *et al.,* 2011) the description of their system called RecoMMobile system was highlighted. RecoMMobile is a real-time contextual-aware recommender system that enables recommendations of items from a retail store. The system does not account in any way for the user interest or any personalisation mechanism. Yang, Cheng, and Dia (2008) propose a recommendation architecture that suggests vendor webpage offers and promotions. The user preference information is acquired by web-log data recorded in the mobile device and accordingly recommendations are based on web-log data and the distance between a user and the recommended product. Levandoski *et al.* (2011) proposed a location-based system. This recommendation system that is called LARS, for short, deals with 3 types of location-based ratings for items oriented based recommendations. Literature affirmed that only contextual information would not produce effective recommendations.

2.5.3 Logical Image-content Information

Recommendation systems use artificial intelligence (AI) methods that can use image logical information such as taxonomy and item class to elicit user preferences. For example, an online e-commerce shop may use a machine learning (ML) algorithm to classify e-commerce products by genre and then recommend other products to a user buying a specific product. Several research studies have employed various machine learning approaches, in this direction particularly image semantic classification techniques (Zeng, 2011; Salo *et al.,* 2013) to implement multiple criteria recommendations. Zeng (2011) presents an intelligent recommendation system, which integrates semantic similarity computation and technique for order preference by similarity to ideal solution (TOPSIS). The author uses the ontology approach to compute the semantic similarity of customer profiles and product documents.

Image classification is regarded as a precursor to classical content-based image retrieval as it could facilitate efficient searching with lesser time. Most of the current classification algorithms use preliminary low-level features directly. This often results in an enormous semantic gap. Specifically, the classification process is very useful in predicting categorical class levels, which can restrict searching only within the class of interest instead of searching the whole database (Thepade *et al.,* 2013[a]; Thepade *et al.,* 2013[b]).

Xie *et al.,* (2008) presented a system design and challenges for a mobile multimodal search. In their design, they integrated product image categorization and ringtone search, which uses image-based queries and audio queries, respectively. They built a system for recognising the category of products based on image type. This module was based on the nearest neighbor categorization technique. In their work, each feature of the query image was treated separately, not as a unit.

In Paireekreng, (2012), a mobile content recommendation system for tackling the cold-start problem in a non-interactive platform is developed for personalisation. This content filtering concept is meant to predict items derived from other user preferences and use this prediction model to make recommendations to a user who has a profile close to a certain category of users.

Many of these multi-criteria-based filtering approaches are based on either collaborative or content-based integrated with other criteria. Effective integration of these components does not only generate quality image representation (Eirinaki, et al., 2018) and meet up with the heterogeneous nature of users but also serves as a means of acquiring information for mobile users. However, most existing image-based recommendation architecture relied solely on primitive image-content feature along with classical retrieval technique. Typically, this architecture does generate overwhelming results with a high false-positive rate. Recipients of such a recommendation could hardly make any useful decision with it, as it can be very frustrating and confusing. Since there is much existing literature as regards improving recommendation accuracy. Past-related works on these aforementioned areas are reviewed below.

Park, Park, and Cho (2008) proposed an algorithm that integrated item-based multiple criteria and collaborative approaches to tackling the cold start and sparsity problems associated with recommendation systems. Similarly, Shambour and Lu (2010) propose a multi-criteria trust approach to enhance the collaborative-based filtering method to address single criterion user-based collaborative-based filtering. Their integrated method has two main components, which are multi-criteria user-based collaborative-based filtering and multi-criteria user-trust filtering techniques. The authors' report shows that their proposed approach proves its importance over single criterion collaborative filtering techniques. Shao, Chen, and Huang (2010) proposed a recommendation system that relies on multi-agent technology. In their work, their criteria were combined into an overall ranking list of services using the multiple criteria and association rule mining approaches. Costa *et al.,* 2007 have a similar view as that of Shao, Chen, and Huang (2010). The previous authors incorporated contextual and ontology-based systems. The domain ontologies were used to supplement and enrich the description of contextual information.

Nilashi *et al.,* (2016), a proposed hybrid of expectation maximization (EM), and classification and regression tree (CART) based technique to improve the accuracy of multiple criteria recommendation system. In addition, they applied the principal component analysis (PCA) method to alleviate the multi-collinearity problem. In Bhattacharya and Das (2014), an improved image-content-based classification that boosts customer satisfaction in digital marketing platforms was proposed. The authors computed higher density feature and lower density feature vector from each pixel and used them to test the performances of three single classifiers as well as their ensemble. The authors reported that their experimental results on the Wang dataset show an increase in precision accuracy with their proposed algorithm. To resolve the cold-start problem, Bao, Zhen, and Mokbel (2012) model the preferences of users by first determining the hierarchy of his interesting category, and this is followed by assigning weight to each category. In Kim et al., (2012) hybrid technique and content-boosted recommender systems were used to improve recommendation output and to address cold-start problems with a reciprocal recommendation framework.

The work of Olugbara, Ojo, and Mphahlele (2010) proposes the integration of image content with a location-based multi-criteria recommendation system called the TellMe System (TMS). Their design relies heavily on the multidimensional rating of the item location, item price, and bait to support the extracted shape-based features. In the same vein, Zuva *et al.,* (2012) proposed how the shape visual content of an item can be used to realise effective recommendations of similar items.

Due to the user concept drift (user interest drift) problem which exists over time because of a change in user interest (Iwashita and Papa 2018), delivering personalised mobile recommendations over time with hybrid multi-criteria recommender systems remains a very challenging one. As such, all the above-reviewed hybrid multi-criteria recommender systems could not deliver personalised recommendations as they all face the challenge of new user interest drift.

Basically, from the literature there are three methods to address the concept drift problem in other to deliver user interest over time as highlighted in (Farid, et al, 2013): The first one is the window-based approach, ensemble of classifiers, and lastly the weight-based approach. The window-based methods rely on a set of prior preferences to train a classifier (Katakis, Tsoumakas, and Vlahavas 2010). The window-based method selects user preference instances out of a fixed or dynamic sliding window (Farid et al, 2013). This approach assumed that older user preferences are unsuited with the current preferences. Hence the recommendation system must overlook hoary instances that are considered not too relevant to handle concept drift (Katakis, Tsoumakas and Vlahavas 2010).

Ensemble of a classifier is another method that often incorporates many outputs from various classifiers in other to define a final classification output (Farid et al., 2013). In a situation where the final output decreases, a new classification is made to replace and poorly performance classifiers out of many others. Lastly, it is the outputs from all classifiers that are then combined to classify user preferences, commonly with a weighted-voting mechanism (Katakis, Tsoumakas, and Vlahavas, 2010).

The concept drift problem has been addressed using a weight-based approach that removes the outdated instance according to their scored weights (Farid et al., 2013). As time goes on, this method reflects old information gradually becoming irrelevant. However, even though all existing user preferences are considered, new instances have more relevance and can serve as a weight to other preference parameters (Katakis, Tsoumakas, and Vlahavas, 2010). The weight-based approach is employed in this current research work, as earlier mentioned. In the context of this work, the weight-based approach refers to methods that are applied as weight various dynamic item multi-criteria features to acquire score values to characterise user preference. Similarly, the hybrid multiple criteria method is a multi-dimensional (3D) preference modelling tool that exploits data sources of different types from both the item content feature, and similarities among users to better capture user preference (Nilashi, bin- Ibrahim and Ithnin, 2014; Ebadi and Krzyzak, 2016; Esteban, Zafra, and Romero, 2018).

Past related works on the weight-based approach that had been engaged to introduce temporary information are reviewed below. Lee and Park (2000) present an approach for building time-based collaborative filtering that is wholly rooted in implicit response. This approach relied on a pseudo-rating matrix where the time when such product was launched to the market, as well as the time when it was purchased, are used to improve the precision of a temporal-based recommendation. The work of Ding and Li (2005) proposes a temporal algorithm that works out time weights for various product items. The algorithm predicts the use of future purchased interest by assigning a declining weight to old data. Xia et al., 2010 propose a dynamic Top-N item-based collaborative approach that utilised the time decay function to realise a time-based recommendation model. The authors use a real e-commerce data set realised from Alibaba China (http://legendadealibaba-inc.com/intro-projectssp).

Rana and Jain (2012) present a paper that analyses the effect of time factor based on book category is content-based. The duo implement technique that stores counter for each item. This counter recognises no of time an item is purchased by a customer over time and this is updated about other items. Setting counter for every item in the system will not be computation effective, also a popularly based algorithm has not been found to generate a personal recommendation. Lindstrom (2013) proposes an approach to handle the concept drift problem. The approach sporadically selects a small number of cases that are of utmost suitable in a particular case for labelling. In turn, the recently labelled cases are then utilised to re-train a linear kernel (SVM) classification system to knob any adjustment in the concept that might ensue. This approach is referred to as decision value sampling (DVS).

Larrain et al., (2015) present a time-based collaboration filtering approach that focuses on understanding the effect of temporary information on recommendation systems as it relates to social tagging. The authors also study when to inject temporary information into a collaborative filtering algorithm, and as well as how to determine the similarity between users and their preferred items. In their research work, five (5) difficult decay functions were used to model the recency of user interactions.

Though there are many research works on product item recommendations, but none of them have investigated how time factor and image-class can help to realise personalised recommendations in the shopping domain. In addition, there seems to be a gap in the literature on how both item and user concept drift can be addressed at once. The major attention of this work is to propose an image content-based preference elicitation model that leverages the extraction of multiple aspects of item dynamic features to characterise mobile user preference. Different from the above-reviewed models and existing research works. This current work establishes a mathematical model for user preference, considering the interaction of image-content-based high-level semantic features and temporal factors. This feature is then used for the concept user preference model, using an item-based feature and categorical compositionality concept that is rooted in category theory:

This current work is set to enhance existing works in the following ways:

- ❖ Integration of an image-based classification framework will boost recommendation accuracy and will assist in realising accurate recommendations in less time.
- ❖ This work contributes a concept drift-aware multi-criteria approach, this approach relies on an image-content-based algorithm that learns user preference using weights of multiple image features.

- ❖ The introduction of a high-level image feature representation will enhance image representation and personalised recommendation results.
- ❖ Integration of time, dynamic item feature. This will boost classical content-based accuracy and address the problem of user drift.
- ❖ Thirdly, generating visual-based output as against text-based output. Visual-based interfaces constitute another important factor that often influences the usefulness of recommendations to users (Boutemedjet and Ziou, 2008). Visual appearance is one of the key components that made many e-commerce products such as jewelry or clothes to be more cherish or embraced by customers. This visual appearance defines the aesthetic, look-and-feel of many of these e-commerce products as regards their shape, colour, and texture (Fiore et al., 2004). Colour images often convey meaning that cannot easily be expressed by mere words, as such, colour images habitually serve as a proficient means of advertising particularly in marketing (Messaris, 1997; Creusen and Schoormans, 2005).
- ❖ Integration of temporal information to enhance the accuracy of content-based recommendations.

2.6 Stages of Personalised Recommendation

In general, every recommendation algorithm follows the three fundamental processing stages in delivering personalised recommendations:

(i) data accumulation,

(ii) adoption of personalised recommendation technique(s) and

(iii) determination of recommendation impact.

For instance, the UDM personalisation process suggests that at its first stage, preferences information should be acquired from the input data; this is followed by relevant computation and lastly at the presentation stage recommendation are suggested via user interfaces (Gauch *et al.,* 2007; Huang and Huang, 2009). In the same view, Chen *et al.,* 2011 also classified steps in achieving personalised recommendations into three main elements. The first step has to do with the application of different acquisition methods that extract necessary information. The second step analyses user preference and the algorithmic module results are generated, and lastly, the performance of the system is checked. In this work UDM approach, is employed.

Understand-deliver-measure (UDM) methodology asserts that personalisation in its broad form is an iterative process comprising of several phases, combined into one system. The methodological approach that is proposed by Adomavicius and Tuzhilin (2005) defines the personalisation process in terms of a cycle consisting of six (6) stages/phases as shown in Figure 4-1. Before given technical implementation or detail of UDM, this segment-first presents a general overview that constitutes an advanced theoretical description of personalisation process of UDM process as given below:

a) ***Understand users:*** at this stage, comprehensive information about users or items of their choice is collected and converted into actionable knowledge. This information is then stored in user profiles.
b) ***Deliver personalised recommendation:*** at this stage, UDM related recommendation algorithms are applied to the user information stored in the user profile for personalised recommendation and delivery.
c) ***Measure the impact of personalisation:*** this last segment measure or evaluate the impact of personalisation results based on user satisfaction level or accuracy of the result delivered. This stage delivers information that serves as feedback to users, to improve their understanding of the personalisation process components or the entire system. The feedback to a user forms one process for the system that gives room for another stage for the subsequent cycle.

This famous dynamic duo further defines personalisation process in form of a cycle consisting of six (6) stages. Figure 2-3 depicts a technical implementation of the UDM framework.

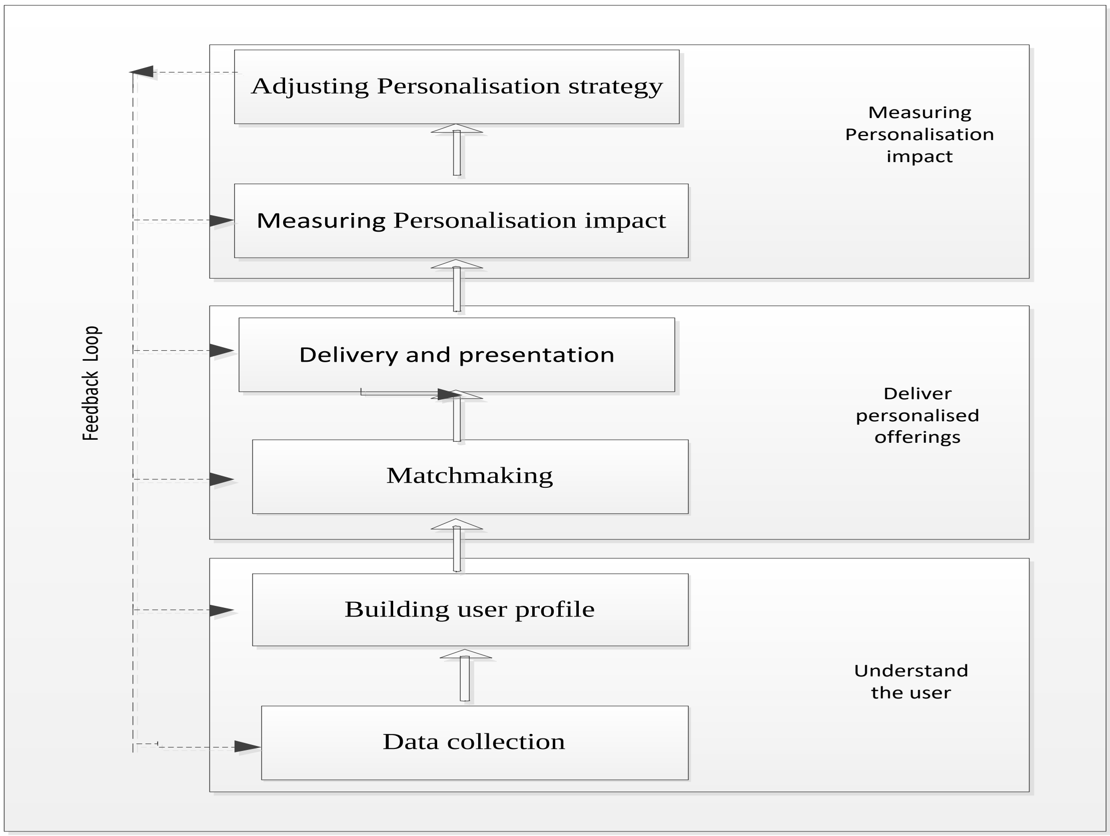


Figure 2-3: Personalisation Process (Source: Adomavicius, and Tuzhilin, 2005b)

Stage 1: Data Collection

The first stage of UDM process personalisation starts with the acquisition of pertinent and related information about items and users. This stage is one of the essential steps in building a personalised recommendation (Tao and Li, 2009). Some forms of “interactions” in data collection include browsing, searching, and purchasing data online, with a phone, using direct e-mail, and employing image capturing methods. This phase entails a design to extract fresh information about the user as regards his preferred objects in his/her environment (Gauch *et al.,* 2007), as shown in Figure 2-3. Data collection also entails an effective study of user preference and different methods that can be applied to acquire it. It also involves discovering what users like/dislike at a particular point in time (Knijnenbur and Willemsen, 2010). This task can be accomplished by either applying explicit-based method, implicit-based method, or their hybrid (Hanani, Shapira, Shoval, 2001; Kuflik, et al., 2007).

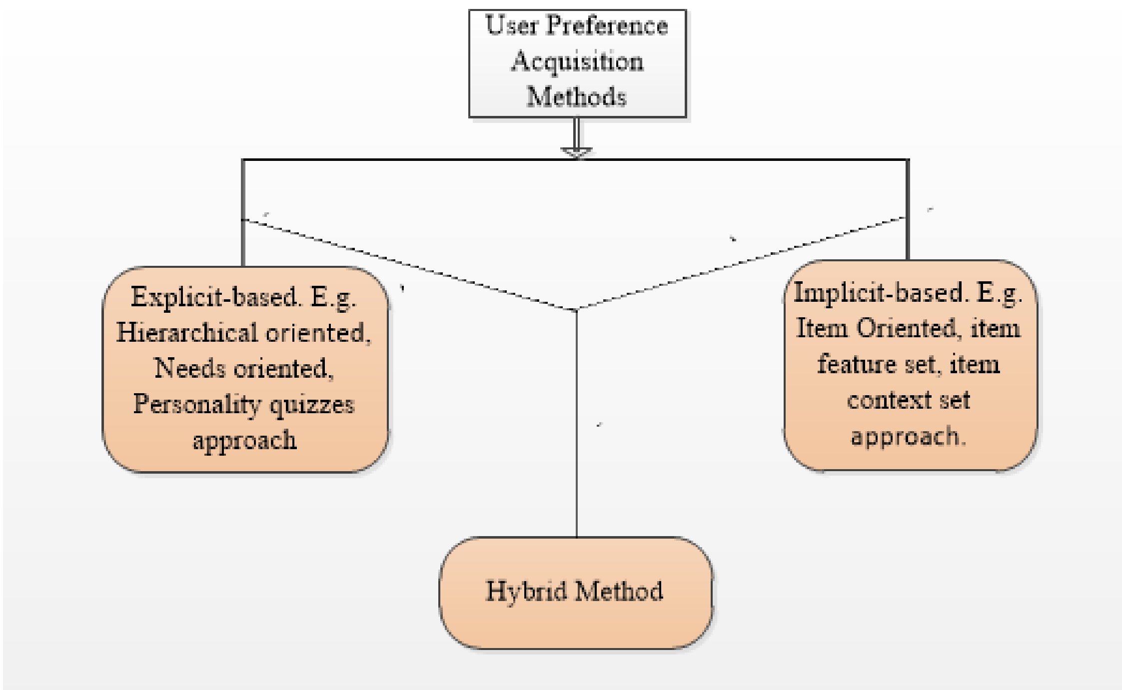


Figure 2-4: User Preference Elicitation Taxonomy

Explicit techniques ask customers directly, their likes and possibly dislikes (Ardissono *et al.,* 2002; Olugbara, Ojo and Mphahlele, 2010). In addition, this can be done by asking a user to assign ratings to a set of items. However, the preferences learned based on this technique typically represent a subclass of the user's complete "needs and wants" (Ricci and Nguyen, 2005). In addition, apart from the fact that this method is not applicable in most situations, the approach requires more user effort and time. Some other researchers have proposed implicit techniques to address the issues of effort and time that users spent in acquiring preferences. These techniques learn from current user purchases, actions, and contexts. These are used to determine user preference. The use of time-of-the-day or user navigation behavior to determine and acquire user preference is one good example of an implicit approach (Billsus *et al.,* 2000; Dunlop, *et al.,* 2004).

The explicit method of providing user ratings can be conceived as one of the best forms of user preference information that is often used in recommendation research. The rating feedback scale can be discrete, binary, or unary (“like”). One limitation of this method is that often time a substantial fraction of the users are usually reluctant to give their opinion on items. There is a situation where the designer makes the option to decide whether to push some set of items to the user and then request him/her to supply his rating to those items or allow the machine to spontaneously pick items to rate for users (Nguyen, et al 2013). Though an explicit collection of user modelling data is rated as more accurate compared to others, nonetheless it is a time and effort -consuming task. Alternatively, the implicit-based approach involves the application of several reasoning mechanisms that shows require information based on the user observation behaviour. This method can easily misinterpret user behaviour. On these notes, both methods are often combined (Kuflik, et al, 2007). Each of the three preferences acquisition methods can be implemented using either a hierarchical, feature-oriented, or needs-oriented based approach (Jugovac and Jannah, 2017).

The hierarchical-oriented approach acquires user preference based on item category (Thepade, *et al.,* 2013[a]; Hassanpour and Mashayekhi, 2017). The works of Bogers, 2010, Bao, Zheng, and Mokbel, 2012; Wang, Rosenblum, and Wang, 2012, and Mellouli and Yahia, 2017, to mention but a few, have also shown that users do have interest in a particular category based on their context. In addition, the work of Kerschberg, Kim, and Scime, 2002, can also be classified as a hierarchical approach, where users give their general preferences on the item by creating a hierarchical taxonomy tree and assigning relative weight to each component in the tree. The recommendation is finally made based on the most relevant items item taxonomy earlier specified. In this regard, different classifiers in marching learning can be used to estimate user preference. For instance, Netflix used a neural network to see what genre of movies you prefer to watch *(*Morgan, 2014). In a way, this type of approach restricts searching within only the class of interest compared to the classical retrieval approach that searches the entire database. However, identifying the appropriate taxonomy or category label that matches shopper needs and interest remains challenging.

The needs-oriented is another form of explicit approach, here instead of asking users about their desirers for item features, this approach elicits user needs based on what item feature constituents can be used for and its correlation with the user personality. This is often achieved via personality quizzes and critiquing, which take a variable length of time to complete. IBM's online store (http://commerce.www.ibm.com) utilises this approach to elicit user preference. Image visual-based capturing is a recent user needs an oriented approach that allows user to explicitly specify item of his choice via capturing of a product item. Literature has recorded that with this approach, users can derive both hedonic motivation and better utilitarian values when indulging in the image capturing approach (Mikalef, *et al.,* 2013; Salo, *et al.,* 2013).

Another method is feature-oriented, where users relied on the use of form to specify their preferences to the preferred feature of a product. Collations of their stated preferences are then used to build up a query that is used to probe the entire database of available products. This can be challenging if shoppers are not professionals in the product domain. Some recent feature-oriented approaches have made extra provisions to help users ascertain some vital feature-oriented requirements based on static criteria about the intended use of the product. The work of Olugbara, Ojo, and Mphahlele (2010) is in this category. The work proposes a design of a shopping framework that can exploit knowledge contained in 4-dimensional item features. In their design user need not have to know details about a product feature, neither is personal quizzing needed. Shambour, Hourani and Fraihat, (2016) propose an approach that creates the profiles for users using the item features that a user has provided satisfactory ratings. In this current research work hierarchical and feature-oriented user, preference approaches are combined, in a bid to share the merits of both approaches.

Stage 2: Building User profiles

After acquiring information from all the preference elicitation methods, the next line of action in developing personalisation recommendation is at stage two, where these facts about users or items are incorporated together to create and represent a user profile. Apart from image primitive features, other additional information often finds in the user profile are the user, item location, temporal information such as time, user demographics, user largest purchase within a certain duration of time.

The recommendation system creates user profiles based on their information collected either explicitly or implicitly. Different techniques of user profile representations are then applied. Generally, information about users can simply be kept informed of a relational database as a *record*. However, complicated information, such as information about interactions among users, may entail the use of ontologies, classifications theory, and graphs (Burke, 2002). In the same way, time fragments as it relates to weeks, days, hours, and minute's information can be implicitly acquired to populate a user profile.

Generally, either knowledge-based or behavior-based are the two widely used user profiling representation approaches. A knowledge-based approach generally can be represented using a rule-based technique in proposing items (Amini, Ibrahim, and Othman, 2007). Conversely, behavioural technique constructs a user profile by building the behaviour of the user to discover useful behavioural patterns (Middleton, Shadbolt and De Roure, 2004). The behavioural patterns such as frequency patterns and sequential patterns of a user are represented using the graph or machine learning models (Liang, et al., 2010). However, situations do arise in which this factual profile may not be sufficient to capture the most discriminating behavioural patterns of a user. This calls for additional information and the use of predictive data mining models such as SVM, ANN, and RBF for instance.

Stage 3: Matchmaking

The next process border on how to exploit user profile information to deliver an effective personalised recommendation. At this stage, a matchmaking model is built to realise user preference. This is achieved by matching user initial preferences with several other individuals in the base. This process finds the *utmost relevant preferences* to individual user preferences in a definite setting. Commonly used preference models are vector similarity models, probability models, and association rule-based preference models (Jung et al., 2005), others are feature-based item-frequency and strict partial order (SPO) preferences models, which are models further reviewed in subsection 2.3. How to match the elicited user preference will depend on the goal of personalisation and the number of criteria under consideration. One goal might be to the maximised utility of the offering while some are to make a prediction. Some goal is based on single criteria while some are based on multiple criteria.

Current personalisation techniques are inhibited by the use of preference models with limited expressiveness (Holland et al., 2003). Most of the traditional user preference modelling approaches either use scores to describe preferences or just enumerate liked and disliked values. Thus, in these models, real preferences in the form of "I like A more than B" cannot be expressed naturally. As such, a traditional method of exploiting user preference information lacks user expressiveness. Moreover, not only that these models are deficient in preference measures, which gives an intuitive explanation of a preference. These models majorly perform the function of information analysis and filtering.

Stage 4: Delivery and Presentation

This stage is concerned with how personalisation is delivered, the number of items to deliver, and the format of items like text, image, and voice. After matchmaking, one or several suggestions (Top-N) is selected for the active user. The Top-N preference items suggested need to be delivered and present to a user in the best possible ways. The best possible ways constitute the marketing output of the methodology process approaches, which deliver recommendations to a user as it serves to entice the user. At this stage, personalised recommendations are offered to users, using either push, passive, or pull methods (Schafer et al., 2001). In a situation where a recommendation system employs push methods of delivery, information could get to a user that is presently not relating to the system. A good example of a push method is E-mail messaging. Passive delivery displays information based on the previous activities that have been performed by the user in context. One popular passive method is in a situation where related items are added as a complimentary recommendation. One good example can be seen in the popular Amazon syndrome of “those who purchased this item also purchased these items”. On the other hand, the pull methods try to avoid intruding into the activities of a current user. Hence, it notifies a user that personalised information is obtainable, but it displays the information only when the active user explicitly asks for it.

Stage 5: Measuring Impact of Personalisation

It is quite important to assess the efficacy of delivering personalised recommendations. This could be achieved via several metrics scores, commonly used among them are, diversity, accuracy, and loyalty. The most commonly used metrics for determining the influence of personalisation on *performance evaluation-related* metrics that measure accuracy and relevancy of the recommendation results (Herlocker et al., 2004).

In UDM, personalised unit testing is carried out at each stage. Absolute reliance on only one metric will not allow a clear understanding of the performance of each of the units. It is a fact that the efficiency and efficacy of a designed personalised system can be appositely demonstrated through well-selected evaluation methods (Hevner *et al.,* 2004, Pimenidis, Polatidis, and Mouratidis, 2019).

Stage 6: Regulating Personalisation Policy

Lastly, after measuring the impact of personalisation, the next is stage is to regulate personalisation policy which can be used for possible perfections to other stages. This is where the importance of unit testing comes to play. If one is not satisfied with the measurement results, as a whole or as unit causes of such can easily be identified and adjusted based on the earlier discussed methods at each of the five stages. This results in the virtuous cycle of personalisation.

2.7 Literature Gaps

Despite the various classification of recommendation systems, and a huge number of researches that have been channeled toward delivering personalised recommendations, inaccurate user preference modelling particularly due to user interest drift problem remain challenging (Gong and Tarasewich, 2004; Mandyam and Boyns, 2008; Ricci, *et al.,* 2010; Xie, *et al.,* 2014; Neidhardt, *et al.,* 2014; Sun, Li and Zhang, 2018).

It is worth noting that the research idea presented in this thesis is related to the work presented by Olugbara, Ojo, and Mphahlele (2010), Zuva et al. (2012), and Sáez, Luengo, and Herrera (2010). However, apart from the fact that the impact of temporal concept and image categories not considered, these existing research works also relied on classical image filtering approach that is susceptible to the problem of *user-drift* and large space search experience in a pure content-based recommendation system.

At this junction, one could observe from the highlighted literature that much research has been carried out on the use of item features to model user preference and to improve the performance of recommendation systems, but none of them considered the seamless integration of multiple items dynamic features. Most of them entirely relied on classical retrieval techniques to filter similar images from generic or non-class specific measures (Olugbara, Ojo and Mphahlele, 2010; Wang, *et al.,* 2011; Datta, *et al.,* 2008; Rahman, *et al.,* 2011) to build user preference profile where applicable. However, in a mobile domain where mobile users are impatient, the use of a classical image-based retrieval system seems not to be effective because it often generates a huge number of irrelevant results. In addition, the processing time of the request-product-buy chain in the retrieval system increases with the increased volume of process images (Jansen, *et al.,* 1998; Tollmar, *et al.,* 2004). This has an adverse influence on the persistence level of customer loyalty and his purchase decision-making as established in the marketing philosophy (Bhattacharya and Das, 2014).

Similarly, Wasid and Ali (2007) made a giant step in improving recommendation quality by addressing the multi-dimensionality problem in recommendation systems. These researchers achieve this by integrating multi-criteria ratings and K-means clustering, with a collaborative recommender system. While generating neighbourhood these authors utilised K-mean to condense search space. The clustering technique has been used by some other researchers to reduce search space and improve accuracy (Bilge and Polat, 2013; Xiaojun, 2017). Xiaojun (2017) suggested an enriched clustering-based recommendation algorithm. This researcher employed the K-means type of clustering to group customers, there after an enhanced similarity method is establish0ed to produce utmost akin neighbors in the cluster to the active-user. Similarly, K-means clustering has also been integrated with collaborative filtering recommender to address scalability and accuracy problems (Bilge and Polat, 2013).

In the same way, there are three approaches to acquiring temporal information (Wang and Tang, 2015). These approaches are based on the time decay-based approach, which allocates more weight to more recent items. The second one is the time slots method, which rifts the time serial into numerous slits, applies related algorithms to each slit, then pools the results together. Lastly, the time cost approach treats time as a kind of cost and incorporates it into the recommendation algorithms. Time decay is often used in the literature because of its popularity.

On this background, the current work is inspired by the limited attention on personalised content-based recommendations when compared to the volume of research carried out in the last few years on personalised recommendations. As such, motivated by the need for better research work in image content-based recommendation systems to realise accurate user preference elicitation and personalisation in the shopping domain. It is on this background that this work proposes to integrate image processing and machine learning to extract and integrate multiple dynamic information (6-D image features). None of the reviewed studies in the extant literature has considered in-depth these image content components.

This current research is tailor-made to explore how multiple dynamic image content-based information can be acquired and effectively combined to address the open problem of concept drift. One of the major image high-level semantic information added as additional information is the image-class feature. This ideal is depicted in an image-content-based user preference elicitation ($I_{cb} - UPE$) framework that is anchored by an imaging interface. Literarily, one can observe that integration of image-category information tends to achieve better personalisation as it can act as an antecedent to content-based, which reduces the generation of irrelevant results, by confining the search within the category of interest. In addition, the classification approach aids in realising an implicit short profile that can assist dynamic user preference acquisition in the recommendation process with reduced search space. Effective realisation of this recommendation system relied on accurate extraction of colour image features, which to date remains a very challenging problem. Another additional information is temporal. This has been found to improve the accuracy of classical recommendation systems.

2.8 Chapter Summary

Existing works that are related to the proposed approach of integrating additional information to improve recommendation systems were reviewed in this section. The key to extracting and integrating additional features is to acquire information about the hidden preferences and drifting interests of the mobile *user* to build a rich user profile implicitly. As indicated by the reviewed literature this processing happened at the acquisition stage of the recommendation process. Chapter 3 and chapter 4 respectively present a theoretical foundation regarding image feature extraction and detail of the proposed recommendation system framework.

CHAPTER THREE

Theoretical Foundation

3.1 Preamble

In this thesis, due to the usefulness and peculiarity of image-content-based information, in realising image-class features. It becomes imperative to have an efficient understanding of some related image-based algorithms and techniques. It is on this note this chapter is set to investigate the theoretical foundation of related algorithms and techniques which are considered for the realisation of stated objectives in chapter one. These algorithms can be found in related fields under image processing, image pre-processing, feature extraction, feature selection, image representation, image-based classification, content-based recommendation, and machine learning, etc. Deep understanding of the way these algorithms work will guide us to know whether to select, create or improve on any of the existing algorithms in these areas, that are suitable for current work in e-commerce domains. On this background, this chapter first examines two generic content-based recommendation systems architectures earlier developed to handle pertinent issues in a content-based recommendation that this current thesis is set to address.

Secondly, algorithms and approaches currently used in addressing the problems like the one treated in this thesis are summarised. This is supported by a clear demonstration of their differences are confronted. In addition, since the efficacy of a recommendation algorithm rest on the accuracy of the algorithms and techniques that are used; limitations of these algorithms and techniques to the novelties introduced in this thesis are highlighted based on their accuracy. In this chapter, performance evaluation techniques used to assess personalisation in the recommendation are discussed.

In this current chapter relevant references were drawn from academic research knowledge databases such as Web of Science, Scopus, IEE explore, Google Scholar, Springer Ling, Science Direct, and Association for Computing Machinery (ACM) to describe the development of existing personalised preference elicitation approach from the perspective of content-based recommendation systems paradigms.

3.2 Image-Content-Based Generic Architectures

In the literature, many architectures have been designed toward utilizing the rich content information in an image for personalised recommendation (Gauch et al 2007; Huang and Huang 2009; Olugbara, Ojo and Mphahlele 2010; Chen *et al.,* 2011; *and* Lops, De Gemmis and Semeraro 2011). Literarily, these researchers have classified the steps in achieving personalised recommendations into 3 main phases. The first phase, which is the acquisition phase has to do with a collection of relevant information and representation. The second phase/stage is the profile construction and representation stage, which focuses on how to use information collected to build and represent user profile; and the third stage is the matchmaking stage, which has to do with exploiting info for personalised recommendations. Of importance is the work of Olugbara, Ojo, and Mphahlele (2010), and that of Lops, De Gemmis, and Semeraro (2011). The first provides a foundation for using item-class to create an implicit profile, while the second provides a basis for this work in the multi-criteria aspect of recommendation. So, both motivate the new recommendation method proposed in this thesis. On this background, these two architectures were reviewed in this section to lay a foundation for the proposed method in Chapter 5 of this study.

3.2.1 High-level content-based (*HLCB*) architecture

Figure 3-1 below shows a flow process of a semantic architecture of a High-Level Content-based (*HLCB*) recommendation system by Lops, De Gemmis, and Semeraro. This process flow tells us, how utility function in a typical content-based recommendation engine matches the information source from item profiles with that of user-profiles, to generate recommendation outputs.

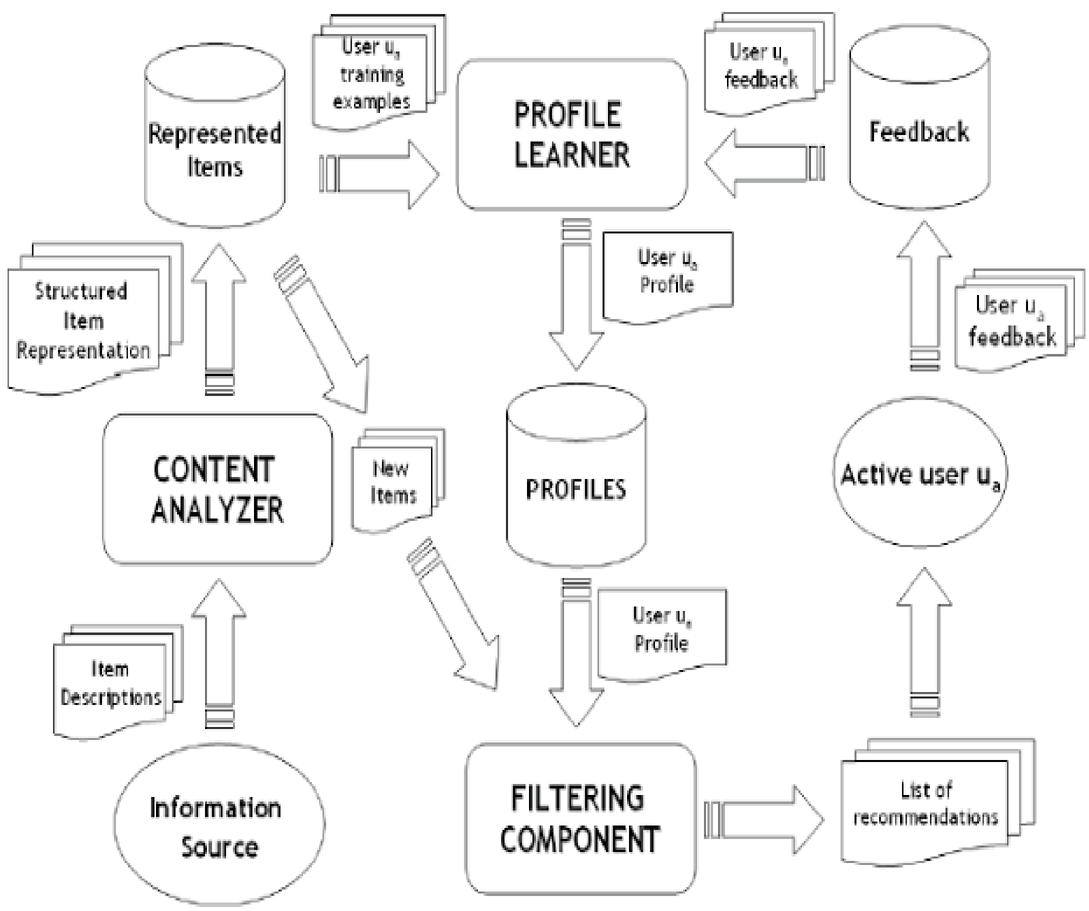


Figure 3-1: A Semantic Framework of a High-Level Content-based Recommendation. *Sources: (*Lops, De Gemmis and Semeraro 2011).

In a broad sense apart from the content profile and user profile that was earlier mentioned. In Figure 3-1, there are three other processing steps of a classical content-based recommendation system, viz., content analyzer, profile learner, and filtering component.

3.2.1.1 Content analyzer

This step is to acquire or analyze the content of an item and represents it in a numeric vector format. It does this by extracting only the non-redundant information (structured or unstructured) from an item, using item description algorithms. Several works have been done at the content analyzer level (Olugbara, Ojo and Mphahlele 2010; Sáez, Luengo, and Herrera 2010; Binucci et al, 2017). To build up a multi-attribute image description, Tang and Acton (2003) suggest a new approach that extracts and combine diverse features from diverse images. These features are utilised to build up image feature representation for the final query image. Recent advancement in mobile device technology regarding both hardware and software has made access to image-content information via image visual content feature possible.

3.2.1.2 Profile learner

This module collects user preference as representative data. Thereafter machine learning operations are performed on this data to construct a generalised user profile of preferences. This differs from one application area to another. For example, a profile learner of a product recommender can be used to implement a categorical method (Nadee, *et al.,* 2013; Bagher, Hassanpour, and Mashayekhi, 2017) in which the learning technique integrates all the image content feature vectors. Machine learning algorithms such as the SVM, ANN, and RBF can be applied to accomplish the learning process.

3.2.1.3 Filtering component

This processing step tries to build either a new or an existing utility function. Generally, a utility function performs a specific task related to the management of computer functions or resources. In the same vein, the utility function matches the extracted features of an item against a series of item features in a user profile. Finally, the system will recommend items that are fit for a user. Some popular existing utility functions are cosine, Euclidean, matchmaking, decision theory-based algorithms, the nearest neighbour is a set of algorithms that can be applied to achieve this filtering process.

3.2.2 TellMe System (TMS)

TellMe System (TMS) by Olugbara, Ojo, and Mphahlele (2010), is a scientific apparatus created to facilitate the study of user preference elicitation in a mobile shopping recommendation environment. Figure 3-2 TMS architecture (Olugbara, Ojo and Mphahlele, 2010), displays how recommendation systems that fully rely on image content can be used to actualize shopping recommendations which can aid mobile users in realising the right decision. TMS utilises Generic Fourier Descriptors (Zhang and Lu (2002) to exploit knowledge information confined in items. TMS considered user context.

The architecture of TMS is designed to take an image of a shopping item as the primary input and picture outputs in text format. As shown in Figure 4-2, the TMS encompasses mobile user, fixed user, and location-based shopping recommendation systems for item registration and recommendation processes. TMS has the unique advantage of building four-dimensional features from shopping items and providing shopping services based on these multiple criteria components. On the TMS architecture, the component extract item features, serve the same purpose as the content analyzer on *HLCB* architecture. This component acquires or analyses the content of an item and represents it in a numeric vector format. Likewise, the user profile serves the same purpose as the profile learner in *HLCB* architecture. In the same vein, the rank recommendation in TMS serves the same purpose as the filtering component in *HLCB* architecture.

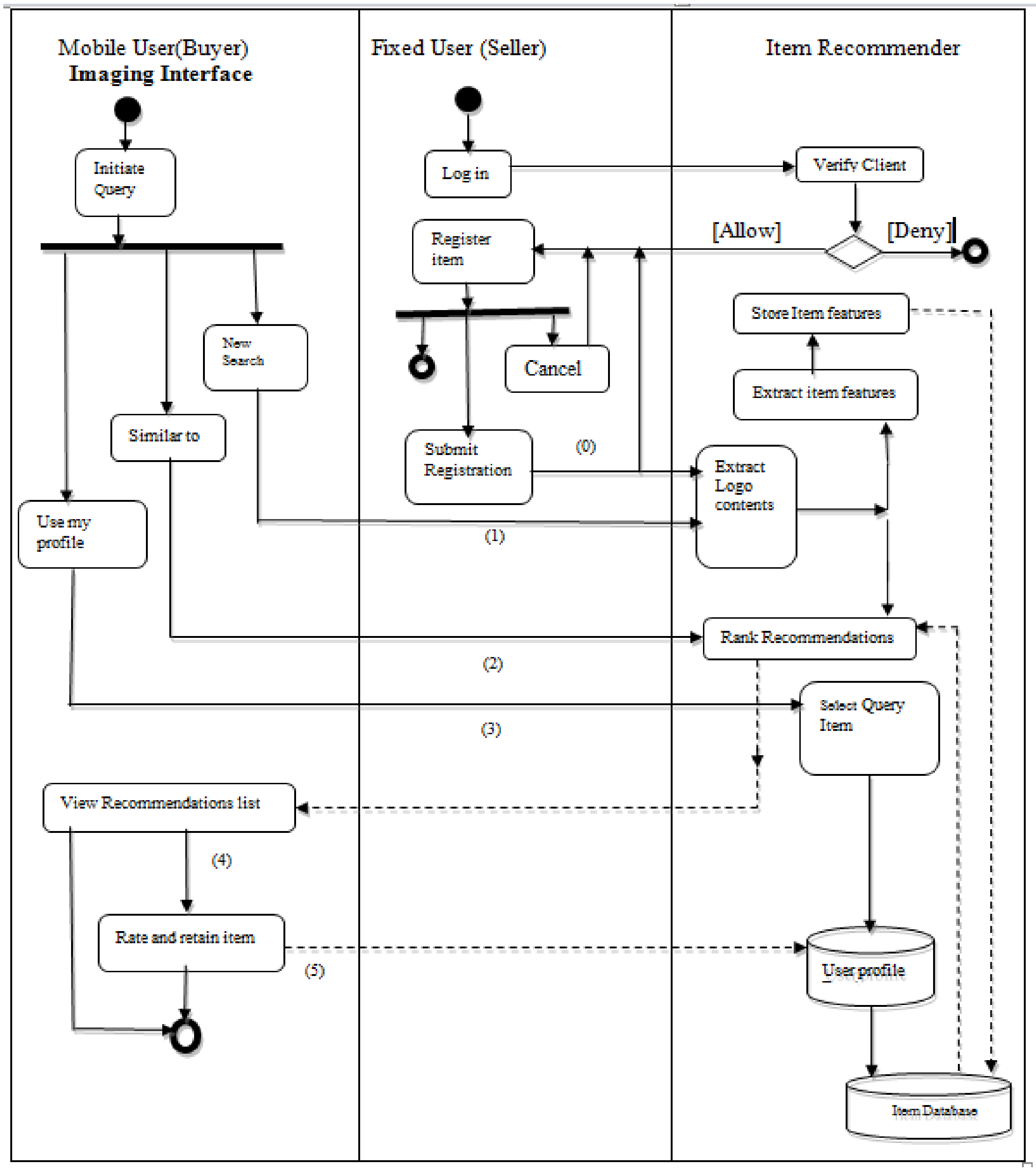


Figure 3-2: The TellMe System Architecture (Source: Olugbara, Ojo and Mphahlele, 2010)

However, most of the existing mobile recommendation systems architectures including the TMS are equipped with classical image retrieval-based filtering functionality which may impose some accuracy challenges, such as large search space problems. Image-based classification would be capable to handle huge search space problems.

The main work of a recommender is not just to recommend products, but in addition, user satisfaction is very paramount. The commonly used text-based interface in many e-commerce applications is very limited and produces a low level of user satisfaction (Boutemedjet and Ziou, 2008). Literature records that the rich information mined from images may lead to an improved image similarity and as well improve the discriminative among image categories (Lowe et al 1998). In the same view, Olugbara, Ojo, and Mphahlele, 2010 also highlighted that an improved image-content extraction algorithm will enhance the effectiveness of TMS architecture. The Generic Fourier Descriptors (GFD) applied by TMS calculates radial frequency that is defined by size and angular frequency. GFD is translation, scale, and rotation invariant.

Different techniques and approaches that are used to implement the three (3) major components 'Extract item feature'/ 'content analyzer', 'user profile'/' profile learner', and lastly 'rank recommendation'/ 'filtering component' in the TMS architecture will be further discussed.

3.3 Extracting High-Level Features from Image Primitive

The following section discusses methods and some research efforts towards extracting a high-level image feature from image primitive features (low level). Image representation and description are critical for a successful content-based recommendation approach. In a codicil, choice of colour model and curse of dimensionality, are also issues confronting effective image feature representation. At large, these have a ripple effect on image classification accuracy.

Keyword and text-word have been the conventional input data used for filtering in content-based recommendation systems. Since these traditional methods can hardly satisfy the demanding preferences from customers. A shift from keyword to preliminary image features information for recommendation emerged. However, it was reported in an extensive experiment, carried out by Kuan, Bock, and Vathanopha (2008) that direct usage of this low-level feature (image preliminary features) has generated a high semantic gap problem. This problem made low-level features to be less efficient compared to high-level features. It was also reported that low-level features-based images matching is often too crude in that too many unrelated images are retrieved. Consequently, their performances are unsatisfactory. Therefore, it is required to apply further image processing operations to acquire high-level features information. It was in this regard that the architecture in Figure 3-3 presented in Oyewole and Olugbara 2018, will be followed to extract image high-level features from image low-level features.

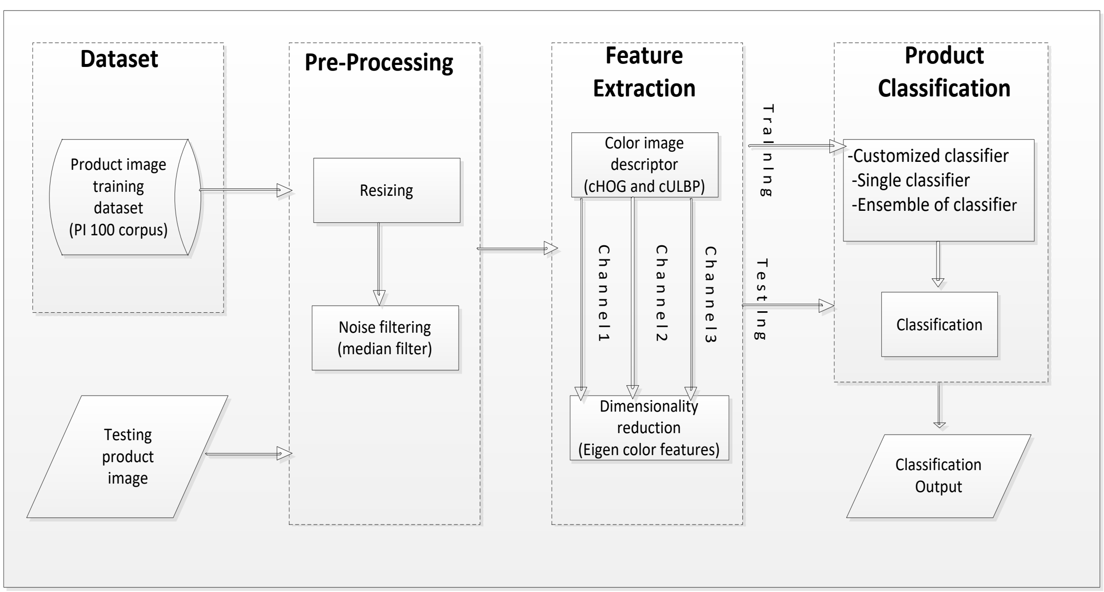


Figure 3-3: Enhanced Image-based Product Classification Architecture

(Source: Oyewole and Olugbara 2017)

The author utilised different algorithms to realise an enhanced image representation; these algorithms are grouped under image preprocessing and dimensionality reduction. These are further discussed in the subsequent section:

3.3.1 Image Pre-processing

Extracting image low-level features often requires pre-processing to realise efficient and effective image features. Image (Jassim and Altaani, 2013). Pre-processing operations may include resizing, to realise a meaningful size of say N X M pixels. Noise removal is another pre-processing operation. Inability to take cognizant of how to address noise often results in poor output and subsequently low performance (Brodley, and Friedl, 1999; Sáez, Luengo, and Herrera, 2010). Pre-processing may also include image enhancement, which manipulates images so that the results will be more suitable for specific applications. Other prominent ones are masking, image feature normalization, and segmentation.

There exists a wealth of algorithms in the literature that has been applied in various disciplines to pre-process images some of these are image segmentation, clustering, particle swarm optimisation, and evolutionary metaheuristics-based approach.

3.3.1.1 Image segmentation

Images need to be broken down into their structural components before any high-level reasoning can be applied to them. The image segmentation-based approach separates image objects from their background. Segmentation filters only those image regions, which are important (Ma, and Sheng, 2007). Image segmentation plays important role in human visual perception. This operation is still one of the toughest traits of handling images. Image saliency detection has been applied to implement image segmentation. It has proved to have a great impact on subsequent image processing stages in terms of accuracy and speed since the salient images are preferentially taken as inputs instead of the whole image (Han and Choi, 2010). Application of image saliency will allow the recommendation engine to identify the salient and semantically meaningful image regions, and then region-based matching can be effectively achieved. Uniquely, image saliency detection processes image without any prior knowledge and additional assumptions. Segmentation can also be achieved via thresholding and clustering techniques.

Thresholding is the simplest technique of pixel-based image segmentation. It is one of the most prevalent image segmentation techniques where colour regions are determined by thresholding the peaks in the image histogram. The popularity of image thresholding can be traced to its core benefits such as high execution speed, simple computational cost, compact storage space, simplicity, and real-time applicability that it offers (Osuna-Enciso, *et al.,* 2013; Dong, *et al.,* 2008). Segmentation based on thresholding such as Otsu and even multilevel thresholding still suffers the inherent problem surrounding the choice of selecting the best threshold value.

Clustering is another image segmentation-based technique. In the literature, Clustering is reputed to be very popular (Vartak and Mankar, 2013). This technique is described by Zhang (Zhang, 2006) as multidimensional extensions of thresholding concepts. It has proved to be a very effective segmentation technique (Jyoti and Gupta, 2014). Clustering is commonly applied in science and engineering disciplines with many and varied application domains. (Boutsidis *et al.,* 2009). In this research work, an idea of the image clustering approach called Pixel Intensity Clustering Algorithm (PICA) is one of the techniques explored to extract image features. This is further discussed in subsection 3.4.1.5.

3.3.1.2 Colour model model

Colour models have been developed as a pre-processing step for image analysis to make image representation more robust. Colour features are relatively robust to background complications and are independent of image size and orientation.

Different colour models have been used to represent pixels of colour images with each pixel having unique properties, strengths, limitations, and areas of application (El-Bendary, et al 2011). A typical 3D colour model has three component channels and the performance of any image-processing algorithms largely depends on the choice of a colour model (Jurio *et al.,* 2010; Khattab *et al.,* 2014). This section briefly reviews some popular 3-dimensional colour models.

The RGB colour model is the most frequently used 3-dimensional colour model. Image capturing devices such as digital cameras were designed to deliver colour images using the RGB colour model that provides three primary colours, which are R, G, and B. In some situations, the RGB colour model has superior performance over other colour models as reported in (Shih, and Cheng, 2005; Mohanty, et al., 2013; Oyewole, Olugbara, Adetiba, 2015). However, RGB images are subtle to luminance condition, surface-oriented condition as well as other photographic conditions. Other related colour models are typically formed from the RGB model either by linear or nonlinear transformation techniques. The r', g', b' colour model for instance is realised from the RGB image by normalising the corresponding red, green and blue channels as in Eqn. (3.1).

$$\left.\begin{aligned} r' &= \frac{R}{R+G+B} \\ g' &= \frac{G}{R+G+B} \\ b' &= \frac{B}{R+G+B} \end{aligned}\right\} \qquad (3.1)$$

The normalization effect on the RGB model made r', g', and b' colour channels is illumination invariant to light intensity change, shading, and shadow (Gevers, et al 2006).

Furthermore, to carry out image processing with ease and to obtain good image representation results, another colour model based on hue, saturation, and intensity (HSI) colour model, was developed (Ohyama *et al.,* 1985). HSI is commonly applied in various areas, for example in luminance scaling, colour shifting, and image segmentation because the processing images in the model requires low computational efforts. The mathematical transformation from the Red, Green, Blue (RGB) colour model back to the HSI colour model is given by (Chien and Tseng 2011; Khattab *et al.,* 2014):

$$\left.\begin{array}{l} I = \dfrac{R+G+B}{3} \\[2ex] H = \begin{cases} \cos^{-1}\left(\dfrac{0.5[(R+G)+(R-B)]}{\sqrt{(R-G)^2+(R-G)(G-B)}}\right), & if\ \ B \le G \\[3ex] 360-\cos^{-1}\left(\dfrac{0.5[(R+G)+(R-B)]}{\sqrt{(R-G)^2+(R-G)(G-B)}}\right), & if\ \ B > G \end{cases} \\[3ex] S = 1-\dfrac{\min(R,G,B)}{I} \end{array}\right\} \qquad (3.2)$$

where the parameters S and I, are in the range of [0, 1] and the H parameter is in the range of [0, 360^0]. Nonetheless, from Eqn. 3.3, three cases of the ranges on the Hue (H) channel are considered to compute the inverse transform as follows (Chien and Tseng 2011).

$$\left.\begin{array}{l} R = I(1-S),\ G = I\left[1+\dfrac{S\cos H}{\cos(60^0 - H)}\right],\ B = 3I - R - G;\ if\ \ 120^0 \le H < 240^0,\ with\ H = H - 120^0 \\[2ex] G = I(1-S),\ B = I\left[1+\dfrac{S\cos H}{\cos(60^0 - H)}\right],\ R = 3I - (G+B);\ if\ \ 240^0 \le H < 360^0,\ with\ H = H - 240^0 \\[2ex] B = I(1-S),\ R = I\left[1+\dfrac{S\cos H}{\cos(60^0 - H)}\right],\ G = 3I - R - B;\ if\ \ 0^0 \le H < 120^0 \end{array}\right\} \quad (3.3)$$

The HSI colour model is old and widely used in many practical colour applications.

$$\left.\begin{array}{l} H = \tan\left[\dfrac{3(G-B)}{(R-G)+(R-B)}\right] \\[2ex] S = 1 - \dfrac{\min(R,G,B)}{V} \\[2ex] V = \dfrac{R,G,B}{3} \end{array}\right\} \quad (3.4)$$

However, the hue (H) becomes undefined whenever the value of saturation S=0. The most popular form of HSV transformation is realised by colour channel normalization as earlier shown in Eqn. 3.1. Thus, the H, S, and V values are computed as shown in Eqn. (3.5).

$$
\left.\begin{aligned}
&V = \max(r, g, b) \\
&S = \begin{cases} 0 & if\ V = 0 \\ V - \dfrac{\min(r,g,b)}{V} & if\ V > 0 \end{cases} \\
&H = \begin{cases} 0 & if\ S = 0 \\ \dfrac{60 * (g-b)}{S+V} & if\ V = r \\ 60 * \left(4 + \dfrac{(r-g)}{S+V}\right), & if\ V = b \\ \dfrac{60 * (g-b)}{S+V} & If\ V = r \end{cases}
\end{aligned}\right\} \quad (3.5)
$$

The need for an independent device and a perceptually linear colour model has led to the development of the CIE L*a*b* colour model (Wang *et al.,* 2014). This colour model defines all colours that are detectable to the human eye. The international commission on illumination described L*a*b* as the most complete out of all existing colour models (Baldevbhai and Anand, 2012). Structurally, the L* component represents the lightness of colour going from zero (dark) to 100 (white), while the two chromatic components (a* and b* channels) represents the position of the colour between red/magenta (+a) and green (-a) and the last component indicates its position between yellow (+b) and blue (-b) respectively. In practice, their range goes from 128 to 127 with 256 levels. The L*a*b* colour model is given by Eqn. 3.6 (Chen, 2003).

$$
\left.\begin{aligned}
L^* &= 116\left[f\left(\frac{y}{Y_n}\right) - 16\right] \\
a^* &= 500\left[f\left(\frac{x}{X_n}\right) - f\left(\frac{y}{Y_n}\right)\right] \\
b^* &= 200\left[f\left(\frac{y}{Y_n}\right) - f\left(\frac{z}{Z_n}\right)\right]
\end{aligned}\right\} \quad (3.6)
$$

where X_n, Y_n and Z_n are the CIE XYZ tri-stimulus values of the reference white point while parameter f (t) is expressed in Eqn. 3.7.

$$f(t) = \begin{cases} t^{\frac{1}{3}} & if \quad t > \left(\frac{6}{29}\right)^3 \\ \frac{1}{3}\left(\frac{29}{6}\right)^2 t \quad + \frac{4}{29} & if\ otherwise \end{cases} \tag{3.7}$$

Likewise, the conversion of RGB images to XYZ colour images is given by Eqn. 3.8 (Chen, 2003).

$$\begin{bmatrix} X \\ Y \\ Z \end{bmatrix} = \begin{bmatrix} 0.608 & 0.174 & 0.201 \\ 0.299 & 0.587 & 0.114 \\ 0.000 & 0.066 & 0.117 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} \tag{3.8}$$

The oRGB is a colour model that is built on opponent colour theory (Bratkova, *et al.,* 2009). Comparatively, in several image processing tasks, account from the literature shows that oRGB gives better performance (Sande, Govers and Snoek, 2008; Banerji, Verma, and Liu, 2011; Wang *et al.,* 2014[b]). oRGB is like HSV and it is an invertible transform from RGB. Likewise, this colour model has an affinity to add a non-linear perceptual brightness to HSV. Mainly this colour model is centered on LC_1C_2.

$$\begin{bmatrix} L \\ C_1 \\ C_2 \end{bmatrix} = \begin{bmatrix} 0.2990 & 0.5870 & 0.1140 \\ 0.5000 & 0.5000 & -1.0000 \\ 0.8660 & -0.8660 & 0.0000 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} \tag{3.9}$$

The extensive review of the HSV, YUV, and XYZ colour models and conversion of these colour models to other colour models have been described

(Gonzalez, and Woods, 2002; Nishad and Chezian, 2013; Stokman and Gevers,2007). The huge number of colour products in the e-commerce domain has made product classes discrimination between products much harder and less accurate. In compliance with this philosophy, most of the existing feature extraction methods operate on a grayscale image, or better still, they quantized colour image into grayscale to extract a set of compact features. Quantisation of colour images can lead to loss of essential information because colour images are said to convey more useful information than greyscale. In addition, a large amount of noise is often seen in the reconstructed images when quantisation technology is used (Javaid, and Rao, 2014). This type of problem often presents the segmentation, image extraction, and selection of important features as indispensable processing steps in the pipeline of any feature-based classification system. These steps are not only meant to minimize computational intricacy but then to enhance performance by reducing the amount of redundant and inapt information in the image logo.

3.3.1.3 Four-dimensional colour model

Colour images are rich in quality information and colour model such as RGB, HSV, and YUV are good examples of 3D colour models that are used to represent colour images. Some of these conventional 3D colour models have been found very limited, due to their failure to capture detail luminance features, as such, it conveys less information. Exceptionally, the above-named colour model except for RGB along with HSL all have value, lightness, and luma as their colour components. These components measure the preciseness intensity of light. Thanks to advancements in the image processing field, a new set of research works have incorporated lightness components to build a 4-Dimensional colour model (Romero, Lado, and Mendez, 2018; Yang et al, 2013). The other 4D colour models are CMYK (cyan, magenta, yellow, and key (typically for black)), and ARGB (Alpha, Red, Green Blue).

Among all the 4-D colour models highlighted above, the recent work of Romero, Lado, and Mendez (2018) and that of Yang et al (2013) are of note. In this research work, Romero, Lado, and Mendez (2018) presented a colour channel algorithm. The algorithm, which relies on statistical method uses a new scaling coefficient for image representation and it is defined by a new colour called Lightness-Red-Green-Blue (LRGB). The algorithm can be used to address the problem of matching an image with another image, based on illumination changes. The colour difference components in each of the above colour channels are deduced by deducting the lightness component from the corresponding primary colour components. The function to transform, RGB components $(C_i, C_2, C_3)^T$ to LRGB components $(L, T_i, T_2, T_3)^T$ are given by:

$$T_i = C_i - L \quad i = 1,2,3 \tag{3.10}$$

While the inverse functions are given by:

$$C_i = T_i + L \tag{3.11}$$

$$L = 0.299 \times C_1 + 0.587 \times C_2 + 0.114 \times C_3 \text{, and} \tag{3.12}$$

Likewise, Yang et al (2013) presented a 4D colour model saliency-based colour image segmentation technique that detects alien fiber objects in a substance using either colours, brightness saliencies, or a combination of both. The author uses an empirical thresholding approach to ascertain whether a pixel at a point is a colour object pixel or not. Likewise, the same operation is repeated in the brightness-saliency map detection with a different threshold. The author then used the bitwise “OR” operator as a binarisation method to fuse salient objects detected from both colour and brightness.

The authors extract each colour features component by subtracting the average of the other two colour channels. Similarly, in Yang et al, 2013 the function to transform the RGB components $(C_i, C_2, C_3)^T$ to LRGB components $(L, T_i, T_2, T_3)^T$ can be expressed as in Eqn. 3.13.

$$T_1 = c_1 - \left(\frac{c_2 + c_3}{2}\right)$$
$$T_2 = c_2 - \left(\frac{c_1 + c_3}{2}\right) \qquad (3.13)$$
$$T_3 = c_3 - \left(\frac{c_1 + c_2}{2}\right)$$

In addition, the author represents the brightness component (L) as follows.

$$L = 0.299 \times C_1 + 0.587 \times C_2 + 0.114 \times C_3 \qquad (3.14)$$

The thresholding approach employed by Yang et al (2013) is simple and fast to implement, but it does not guarantee coherency of extraneous object pixels in an image, since it fails to capture varying intensity contrasts at different image interfaces. Hence, the need for another effective 4-D colour model.

3.4 Dimensionality Reduction of Image Feature Vectors

The colour image is rich in quality information. However, colour images produced a high number of dimensions with both relevant and irrelevant numbers of features for instance RGB colour images features. Consequently, it comes with high dimensional features compared to grayscale images. Likewise, a hybrid of colour models comes with high dimensional features. The vast features that are often used to represent e-commerce product image data create a sort of obstacle that make patterns discrimination between product much harder and less accurate, with increase processing time (Ponti, Nazaré and Thumé, 2016). The aftermath of these constraints is felt in image feature-based systems such as classification and recommendation systems, where the accuracy of image features is paramount.

Feature selection and feature extraction are two approaches often used for image dimensionality reduction. One benefit of this dimension reduction is feature reduction that prevents training samples from growing exponentially as the number of features increase, a phenomenon that is popularly known as the curse of dimensionality. Another benefit of dimension reduction is the decreased computational complexity of the pattern matching models in the user preference learning systems. The other benefits include transmission of fewer features over a client-server network is useful as it results in a concomitant reduction of image features file traffic to the server, which further reduces processing/response time on a mobile network. The Principal Component Analysis (PCA) is one popular example of dimension reduction methods in image processing. The models of feature extractions include colour Histogram, LBP, ULBP, and the Histogram of Oriented Gradient (HOG).

3.4.1 Image Feature Extraction

The extraction of image features has to do with the mining of image characteristics using various measures of colour, texture, edge information, and boundary information (Guyon, et al 2008). These characteristics provide valuable information for different computational tasks with images. It is an axiomatic fact that the correctness of the image classification result relies essentially on the strength of the extracted features. In addition, it is a function of how a robust feature extraction method can extract meaningful low dimensional patterns from high dimensional data (Nilashi, Ibrahim, and Bagherrifard, 2018). Feature extraction is a dimensionality reduction method that builds a set of discriminating features based on a transformation of the original features. This process lessens the problem of resources management, including the utilisation of less memory and the requirement of less computational complexity. The method creates a subclass of the features using a mixture of the existing features. PCA is a popular method for performing dimensionality reduction in image indexing and retrieval systems (Liu and Wechsler 2000; Nilashi, Ibrahim, and Bagherrifard, 2018). Section 4.4 discusses how this method has been applied in the proposed Eigen colour feature representation in this study.

The problem of extracting image features can be formulated as follows. Given a feature space $X_i \in R^N$ with M < N, (where N is the size of the feature space and M is the dimension of the extracted image features) find a mapping of the form $y = f(X): R^N \rightarrow R^M$ such that the transformed feature vector $y_i \in R^M$ conserves most of the information in R^N . An optimal mapping $y = f(X)$ will be a result in a reduction in the error probability.

$$\begin{bmatrix} X_1 \\ X_2 \\ \cdot \\ \cdot \\ X_N \end{bmatrix} \textit{feature extraction} \rightarrow \begin{bmatrix} Y_1 \\ Y_2 \\ \cdot \\ \cdot \\ Y_M \end{bmatrix} = f\left(\begin{bmatrix} X_1 \\ X_2 \\ \cdot \\ \cdot \\ X_N \end{bmatrix}\right) \tag{3.15}$$

The task of image feature extraction and representation is an important phase of image processing. Commonly use image features extraction algorithms in the e-commerce domain are local binary pattern (LBP) (Ojala et *al.* 1996; Ojala *et al.,* 2002), Histogram of oriented gradient (HOG) (Dalal and Triggs, 2005), scale-invariant feature transform (SIFT) (Lowe, 2004), binarized statistical image features (BSIF) (Kannala, and Rahtu, 2012), speeded-up robust features (SURF) (Bay *et al.,* 2008), Gabor filter (Manjunathi, and Ma 1996) and PCA (Turk, and Pentland, 1991). However, the LBP and HOG have established their successes in many areas such as classification (Lorenzo-Navarro, *et al.,* 2014), human behavior recognition (Ming, Wang and Fan 2015), face recognition (Ahonen, Hadid, and Pietikainen, 2006), pedestrian recognition (Gan, and Cheng, 2011) and Bioinformatics (Adetiba and Olugbara, 2014). These algorithms are further reviewed in the subsequent section.

3.4.1.1 Histogram of` oriented gradient (HOG)

HOG (Dalal and Triggs in 2005) was originally developed for human detection. HOG remains a global descriptor that is invariance to illumination and strong for identifying the shape of objects, edge orientations within a region, appearance, and texture information from various regions in an image (Shapiro, and Stockman, 2001; Ojala *et al.,* 1996; Dalal and Triggs, 2005; Dipankar, 2014). It has proven effective in several object classification tasks (Lorennzo-Navarro, *et al.,* 2014) texture analysis, face recognition, and medical (Adetiba and Olugbara, 2014) E-commerce (Oyewole and Olugbara, 2018), and so on.

The whole connotation of HOG summarizes that, in a typical image window, the descriptor considers each pixel one after the other. The descriptor determines in values the extent of image gradient at different directions, then, in turn, forms histogram count representation for an image. In this research work, HOG is one of the main descriptors that is employed to mine colour feature characteristics from product images. Four main steps involved in realising these features are highlighted below:

- **Pre-processing and Gradient Computation:** At the pre-processing stage normalised colour feature and descriptor normalization are realised. There after the colour data of the image are filtered by either applying a finite difference approximation on the pixel intensity. Let $I_{i,j}$ be the i, j pixel value of each sub-region of an image I. In colour images, three different pixel values can be distinguished, with each corresponding to the component. The gradient at pixel value i, j in the x-direction ($dx_{i,j}$) and y-direction $dy_{i,j}$ can respectively be given as:

$$d_{x_{i,j}} = I_{i,j} - I_{i+1,j}$$
$$d_{y_{i,j}} = I_{i,j} - I_{i,j+1} \tag{3.16}$$

Alternatively, image gradient can be achieved by applying any of the convolution masks such as Sobel, Prewitt, and Canny on the input image. This is achieved by finding the derivative of x and y components of a grayscale image using the following convolution operation:

$$d_{x_{i,j}} = I * D_x$$
$$d_{y_{i,j}} = I * D_y \tag{3.17}$$

The upper leftward corner of a suitable mask is superimposed over each image pixel in turn. A simple value is realised for $d_{x_{i,j}}$ or $d_{y_{i,j}}$ using mask coefficients in a weighted sum of the value of pixel (*i*, *j*) with its neighbors.

$$d_{x_{i,j}} = I_{i-1,j-1} * D_x(1,1) + I_{i-1,j} * D_x(1,2) + I_{i-1,j+1} * D_x(1,3) \tag{3.18}$$

The magnitude of an image *I* is determined thus:

$$M_{i,j} = \sqrt{dx^2_{,j_i} + dy^2_{,j_i}} \tag{3.19}$$

HOG is the grayscale-based extractor. To extend HOG to colour image, after the gradient magnitude has been determined separately for each channel such as *red* θ $dM_{i,j}$, *green*$M_{i,j}$ *and blue*$M_{i,j}$ the one with the maximum magnitude is used for further operation. The corresponding gradient direction, $\theta_{i,j}$ at pixel i, j for *max* ($redM_{i,j}$, $greenM_{i,j}$ *and* $blueM_{i,j}$)

is $\theta(k) = \arctan\frac{dy_{i,j}}{dx_{i,j}} \quad 0 <= \theta(k) <= 360$. In this thesis, the value of k that is used ranges from 20° to 180°.

- **Orientation Binning:** At this stage, both gradient orientation and gradient magnitude are used to create an orientation-based cell histogram channel. Histogram means a count of occurrence of an event. Each pixel in a cell cast a weight based on the number of occurrences of gradient orientation in that cell. The weight can be either the gradient magnitude itself, the square root, or the square of the gradient magnitude (Dalal and Triggs, 2005). The authors found that unsigned gradients were obtained by Eqn. 3.20 in combination with nine histogram channels gave the finest result in their experiments performed on human detection.

$$H(k) = \sum_{d_{i,j \in \theta_k}} M_{i,j} \tag{3.20}$$

- **Blocks for Descriptor:** to interpret changes in illumination and contract, the gradient strength must be normalised. This requires the combination of cells into more spatially connected blocks. In the experiment by Dalal and Triggs, the best parameters were found to be three-by-three cell blocks of six-by-six-pixel cells with 9 histogram channels, that is 3 x 3 x 9 = 81 features which this study adopted.
- **Block normalization:** HOG descriptor concatenates normalised cells histogram from all the block regions. This normalization becomes necessary since votes from each block vary widely; for example, in using SVMs to calculate the remoteness between two support vectors by the distance. If one of the votes in one block has a broad range of values, the distance will be governed by that block. Therefore, the range of all votes

from each block should be normalised so that each vote contributes proportionately to the final target descriptor. Normalization will also speed up HOG processing operation. Feature normalization can be done using either rescaling, standardization, or scaling to unit length. Dallas and Triggs used the scaling to unit length feature scaling method in their experiment. Generally, normalization factor can be done using L2-norm, L1-norm, L2-hys, or L1-sqrt.

Dalal and Triggs carried out experiments on the L2-hys, L2-norm, and L1-sqrt and L1-norm structures. The authors reported that all the four normalised methods showed very substantial improvement over the non-normalised data. However, the authors added that Li-norm showed a less reliable performance. L1-sqrt is used in this work.

3.4.1.2 Histogram features

Given an image, its colour histogram *can be defined as a* graph showing grey-level intensity values of a colour channel against the number of pixels at that value. A colour histogram *H* of an image *I* in each colour model C, is defined below as:

$$H_c(I) = \{N(I, C_i) | i \in [1, \dots \dots n]\} \quad (3.21)$$

In this definition, the variable *I* is an input image, $\boldsymbol{C_i}$ represents a cell, *i* is the colour level in a colour model C, and $\boldsymbol{N}(\boldsymbol{I}, \boldsymbol{C_i})$ denotes the number of pixels in *i* that assign into a cell $\boldsymbol{C_i}$ while $i \in [1 \dots n]$. In another form, H can be seen as a vector (h_1, $h_{2\dots}$ $h_{i\dots}h_n$) in which each h_i contains the number of pixels of colour *i* in the image. The euclidean similarity distance measure is usually used.

This research work realised a new histogram feature called Histogram of Eigen Colour features (*HECF*) descriptor. Here, a histogram is used as a model of probability distributions of the Eigen colour feature. The main advantage of using the *HECF method* is swift generation and comparison of the feature vectors.

3.4.1.3 Uniform Linear Binary Pattern (ULBP)

The ULBP extends the original LBP feature descriptor that was developed by Ojala *et al. (2002).* The LBP operator takes an image and forms a set of binary labels for the pixel blocks using each pixel with the center value to build thresholding within a 3x3 neighborhood. The texture descriptor used is the histogram of the 2^8 (256) different labels because the neighborhood has eight pixels. The ULBP was proposed to reduce the complexity of high dimensionality of the resulting LBP feature vector (Maenpaa, *et al.,* 2000). Their research has stretched the LBP operator to a more generic form to enable the use of neighborhoods of differing sizes, including a circular neighborhood. Hence, given a pixel (x, y) belonging to a greyscale image I, and g_p represents the grey value of a sampling point in an evenly spaced circular neighborhood of *P* points with a radius of *r* around the pixel (x, y). Furthermore, assuming that $g_c = I(x, y)$ is the grey value of the pixel. The local image texture I (x, y) is assumed to be branded by the joint dispersal of grey pixels given as:

$$T = t(g_c, g_0, g_1, ..., g_{P-1}) \tag{3.22}$$

The midpoint pixel gray value is then deducted from the pixels in the same region, pixel grey value as:

$$T = t(g_c, g_0 - g_c, g_1 - g_c, ..., g_{P-1} - g_c) \tag{3.23}$$

It is presumed for easier factorization that the midpoint pixel g_c is statistically independent of the difference contained in equation (3.24) which is approximated as follows:

$$T \approx t(g_c)t(g_0 - g_c, g_1 - g_c, ..., g_{P-1} - g_c) \quad (3.24)$$

t (g_c), being the gray value of a center pixel contains no useful information and could therefore be discarded following the analysis of local texture patterns to obtain equation (3.24) that is used to model the local image texture.

$$T \approx t(g_0 - g_c, g_1 - g_c, ..., g_{P-1} - g_c) \quad (3.25)$$

Nevertheless, obtaining a consistent approximation of this multidimensional dispersal from image data poses a great challenge, which is addressed by applying learning vector quantisation (Schclar, *et al.,* 2009). The learning vector quantisation-based method has characteristics that are faced with usage difficulties arising from the g_p - g_c differences values. This challenge can be managed by considering the signs of the differences:

$$t(s(g_0 - g_c), s(g_1 - g_c), ..., s(g_{P-1} - g_c)) \quad (3.26)$$

The thresholding function denoted by s (z), is given as:

$$s(z) = \begin{cases} 1 & z \geq 0 \\ 0 & z < 0 \end{cases} \quad (3.27)$$

A joint distribution used to obtain the generic local binary pattern operator by summing the threshold differences as follows:

$$LBP_{P,R}(I) = \sum_{p=0}^{P-1} s(g_p - g_c)2^p \quad (3.28)$$

where *P* is the total number of neighboring pixels and *p* is the counter.

The principle of uLBP originated from the idea that certain binary patterns exist more frequently in images than others, particularly in texture. These most recurrent 'uniform' binary patterns agree to local texture primitive features. These primitive local textures are characterised by the binary patterns having at most two bitwise transitions from either 1 to 0 or 0 to 1 following a circular traversing of the bit pattern. Examples of such uniform binary patterns include 00100000 (2 transitions), 11111111 (0 transitions), 11110111 (2 transitions), and 01111111 (1 transition) while patterns such 01010101(7 transitions) and 11001001 (4 transitions) are not uniform. Different uniform outputs for mapping patterns of bits are calculated as $P*(P-1)+3$. This entails the computation of separate labels for each uniform pattern while grouping them under a single label of all other non-uniform patterns such that for (8, R) neighborhoods indicating 8 sampling points. A uniform mapping produces 59 different output labels and 243 labels for (16, R) neighborhoods.

Uniform patterns are strongly considered in uLBP while relegating the non-uniform patterns as shown in experiments on texture images (Ojala, Pietik¨ainen, and M¨aenp¨a¨a, 2002; Ahonen, Hadid, and Pietikainen, 2006; Shan and Gritti, 2008; Pietikainen, *et al.,* 2011). However, this feature extraction technique has not been widely applied in the e-commerce domain, which has influenced the decision to experiment with uLBP in this work.

3.4.1.4 Local Binary Patterns (LBP)

In general, features are extracted from grayscale images in LBP applications (Ojala *et al.,* 2002). The feature descriptor works by thresholding a specified window of pixels using a center pixel value and interpreting the result as a binary pattern of numbers, which are then used to label the image pixels. A histogram of such a pattern of numbers can be constructed to represent a feature descriptor. Pixel neighborhood of 16 x 16 kernel was used in this study to obtain interesting results. This non-parametric kernel descriptor tags the pixels of a greyscale image by thresholding n × n neighborhood pixels surrounding an active pixel $(\mathrm{e}_C, \mathrm{f}_C)$ with the intensity value of the middle pixel. This has resulted in a consequent pattern of 2^n bits of binary numbers. Then these binary numbers are used to encode the pixel and the resulting codes are used to represent the texture appearance of a region. The size of the neighborhood will determine the length of the encoded string. For instance, $LBP(8,1)$ will produce a histogram of size $2^{8,}$

and $LBP(16{,}2)$ will produce a histogram of size 2^{16}. Formally, the expression to compute the generalized LBP takes the following form:

$$LBP(\mathrm{e}_C, \mathrm{f}_C) = \sum_{N=0}^{7} S(i_n - i_c)2^n \tag{3.29}$$

where i_c matches the grey value of the center pixel (e_C, f_C), in the grey values of the eight neighboring pixels. The functional representation Q of this scheme is defined as.

$$Q(\mathrm{e}) = \begin{cases} 1 & if \quad e \geq 0 \\ 0 & if \quad e < 0 \end{cases} \tag{3.30}$$

The LBP operator applies different values between pixels. This operational structure made the LBP operator be invariance (less sensitivity) against illumination and exhibit notorious robustness to monotonic grey-scale transformations (greyscales changes). Apart from its tolerance against illumination variations, LBP is computationally simple and preserves pixel intensity order in a local neighborhood. The structural properties of LBP will be very helpful in the extraction process of both indoor and outdoor shopping products, where its features often vary due to variations in illumination, scaling, blurring. Recently, due to the LBP texture discriminative property, it is now being used in a real-time environment particularly in pattern recognition.

LBP descriptor has been applied for image retrieval (Talaka *et al.,* 2005), cell phenotype image classification (Nanni and Lumini, 2008b), face localization (Huang, *et al.,* 2004), health (Zhao and Pietikäinen, 2007; Adetiba and Olugbara, 2015), face recognition (Zhao *et al.,* 2005; Nanni and Lumini, 2007) and biometrics (Nanni and Lumini, 2008a).

3.4.1.5 Pixel intensity clustering algorithm (PICA)

PICA (Olugbara, Adetiba, and Oyewole, 2015) is a multilevel image segmentation method that utilises the forgy technique to perform the initialisation of cluster centroids. PICA is employed for saliency map binarization as discussed in chapter four of this work. PICA performs preprocessing operations on images by applying the segmentation technique. This algorithm fulfills the crucial stuff of clustering by partitioning a given $M \times N$ input image into K clusters as given in Eqn. 3.31.

$$C = (c_0, c_1, c_3, ...c_k): \tag{3.31}$$

The resemblance of the pixel intensity values in the same cluster c_j, j = 0, 1, …, K-1 is high, but the pixel intensity values from the dissimilar clusters have proved to be extremely unrelated. The resulting clusters fulfill the following necessary conditions (Das, Abraham, and Konar, 2006).

$$C_j \neq \{\}, \forall j = 0,1,........K-1; \quad and \quad C_i \cap C_j \quad \neq \{\}, \forall i, \quad j = 0,1,.........K-1) \tag{3.32}$$

The cluster initialization scheme of PICA is forgy, stable and it eliminates the occurrence of ‘dead centers’. This scenario is one of the most common issues in traditional image-based clustering and segmentation algorithms such as k-means and Fuzzy c-means (Siddiqui and Isa, 2012). Moreover, the total number of pixel intensity values that are processed is less in size when compared to the dimension of the input image. The important property of PICA serves as a firsthand strategy for reducing both computational cost and image dimensionality. The PICA algorithm uses the Otsu between cluster variance criterion function (Otsu, 1979). This function is often utilised in multi-level thresholding to categorise image pixel intensities into appropriate clusters. In addition, it satisfies the principles of survivability and recoverability because PICA can work for any number of clusters from 2 up to the maximum number of pixel intensities in the input image without breaking down. This algorithm can be used at the preprocessing stage to segment an image into k number of clusters. Algorithm 1 neatly defines PICA (Olugbara, Adetiba, and Oyewole 2015).

Input: $M \times N$ grayscale image, K number of clusters.

Output: $M \times N$ grayscale image.

Let $S = (e_0, e_1, \dots, e_{Q-1}), Q \leq L,$ represents the set of image pixel intensities and assuming BCV is the between cluster variance.

(1) **for all** $j = 0, 1, \dots, K-1$ do
(2) t=(int) $((j * Q)/K)$
(3) estimate the jth cluster centroid using the pixel intensity e_t
(4) assign cluster label j to the pixel intensity e_t
(5) swap the pixel intensity e_t with the pixel intensity e_j
(6) **end for**
(7) **for all** $i = K, K+1, \dots, Q-1$ **do**
(8) **for all** $j = 0, 1, \dots, K-1$ **do**
(9) tentatively allocate pixel intensity e_i to the jth cluster
(10) BCV = w_j * (variance of the jth cluster centroid)
(11) **for all** $k = 0, 1, \dots, K-1$ and j not equal to k do
(12) BCV = BCV + w_k * (variance of the kth cluster centroid)
(13) **end for**
(14) **end for**
(15) permanently allocate e_i to the cluster that gives maximum BCV
(16) assign cluster label to the allocated pixel intensity e_i
(17) update cluster centroid
(18) **end for**
(19) compute output image
(20) **stop**

Algorithm 1: PICA Algorithm

3.4.1.6 Colour moments

Colour moments are very effective for colour-based image analysis and representation. Image colour moment is determined by calculating separately for each RGB the statistical moments of pixels counted into each colour component. The first four-colour moments calculated over the image information available in each cluster can be defined as follows.

Mean of an image:

The mean value of an image is the sum-total of values of the colour value in an image divided by the total number of pixels in the image. It provides information on the distribution of pixels in an image.

$$MeanC_j^i = \frac{1}{N}\sum_{t=1}^{N} t_{i,j} \tag{3.33}$$

where $t_{i,j}$ is defined as the ith image pixel in jth colour channel, C_j^i as the quantized class gray levels in ith 4D colour channel, while the total number of pixels in the image is represented by N.

The standard deviation of an image:

In determining the standard deviation of an image, one needs to first determine the image variance. The average of the square root of image variance is determined to obtain the standard deviation. It provides information on the dispersion of the distribution of pixels in an image.

$$StdDevC_j^i = \frac{1}{N}\sqrt{\sum_{i=1}^{N}\left(t_{i,j} - MeanC_j^i\right)^2} \tag{3.34}$$

Image Skewness:

The connotation of image skewness can be understood as a measure of the degree of asymmetry in the distribution of pixels in an image as follows.

$$SkewnessC_j^i = \frac{1}{N}\sqrt{\sum_{i=1}^{N}\left|t_{i,j} - MeanC_j^i\right|^3} \tag{3.35}$$

Kurtosis:

Image kurtosis provides a piece of information about the shape of the pixel distribution in an image and is defined as follows.

$$KurtosisC_j^i = \frac{1}{N}\sqrt{\sum_{i=1}^{N}\left|t_{i,j} - MeanC_j^i\right|^4} \tag{3.36}$$

Many researchers have investigated the inherent spatial information problem in colour histograms by integrating these measures.

3.4.2 Image Feature Selection

Features describing the image dataset usually contain both relevant and redundant features (Cao and Li, 2007). In the classification setting, relevant features are the features that contain discern information about the classes. On the flip of the coin, non-relevant features are redundant and noisy features that cannot distinguish images from dissimilar classes. Moreover, eliminating such useless features lessens computational cost, decreases processing time, and enhances performance. This process of lowering feature space to a lower dimension by finding a set of the most compact and informative features is what is referred to as feature selection (Barrag´ans-Mart´ınez et al, 2010).

On the contrary, feature selection methods aim at realising an adequate subset of features, still preserving the actual features, and maintaining the physical meanings of the features. Both methods have the advantage of improving the quality of the resultant image feature, classification performance, and increasing computational efficiency. Feature selection is rapidly gaining more attention in the disciplines of machine learning, image processing, and computer vision (Li, Zhang, and Ogihara, 2004; Yang, Wang, and Yang, 2008; Megchelenbrik, 2010), and computer vision, such as information retrieval. This work focuses on the application of the feature selection method based on the histogram of the Eigen colour feature (HECF) in the framework of image content-based shopping recommendation. The Kaiser criterion (Kaiser, 1990) is a factor retention method that was utilised to achieve feature selection. The other factor retention methods in the literature are parallel analysis, cumulative percentile of variance, scree test, and minimum average partial. The Kaiser criterion technique has been applied in this study for feature selection because of its popularity.

3.5 Extracting Image-Class from Image Low-Level Features

The following section discusses the methods for extracting image category, a high-level image feature from image primitive features. In addition, this set of techniques can be used in mining user preference from the session image feature.

3.5.1 Data Mining

Different data mining techniques have been applied in the disciplines of machine learning, pattern recognition, statistics, and computer vision. Many data mining techniques have been developed over the years, some of which are discussed in the following subsections. This part of the work gives a brief overview of association rule mining, clustering, and classification technique. Much more emphasis will be put on the classification task, which is the only classical technique applied in this study.

3.5.2 Association Rule Mining

The association rule mining is one of the most applied data mining techniques for local pattern discovery in unsupervised learning systems (Kantardzic, 2003). Given a massive collection of items, association rules define how likely various combinations of items are to occur concomitantly in a set of items. The association rule mining can be used in some indirect preference models but cannot be used easily to automatically mine for intuitive user preference.

3.5.3 Clustering

Data clustering is one of the most widely used data mining techniques for identifying interesting distributions and hidden patterns in the underlying large dataset. The fundamental problem of the clustering problem is to partition a given set of data into clusters where the samples in each cluster are most similar. Clustering algorithms effectively handle heterogeneous data types, attributes, or traits. The other unique characteristics of clustering algorithms are scalability to data dimension, capability to discover clusters with arbitrary shapes, minimal requirements for domain knowledge to determine input parameters, ability to deal with noise and outliers in data, insensitivity to the order of input records, resilient to high dimensionality, interoperability, and usability. However, not all clustering algorithms pose all the above-mentioned characteristics. Quite many challenges exist in clustering algorithms. Generally, these algorithms can be classified based on how they perform their clustering process, into hierarchical clustering, partitioned clustering, and incremental clustering.

3.5.4 Classification

Classification can simply be regarded as a process of assigning unlabeled samples to discrete labelled classes. On this note, the expected information component from the classification is the image label that signifies its class. Classification can be used to realise image high-level features**.** The image-class feature is achieved by training a function that maps a sample into one of the several predefined classes. Similarly, this also doubled as mining of user preference. Once feature extraction has been extracted, it will be followed by allocating class labels to test images. The classification method is one of the utmost processing tasks of content-based recommendation systems (Zhou, *et al.,* 2013), that has been found useful for user profiling (Ma and Sheng, 2007; Han, and Choi, 2010). The user profiling process entails the collection of structured items that serve as user preferences (Aggarwal, 2016)**.**

This method has also been used in various recommendation applications namely, product retrieval (Vailaya, *et al.,* 2001; Vikas, 2011), product taxonomy browsing Pohs (2013), to increase scalability (Jain, and Wadekar, 2011), and improved overall recommendation accuracy. It has also been found useful in shopping recommendation assistant systems (Hu, *et al.,* 2014). Classification methods require an efficient feature extractor and classifier to mine image-class attributes. Many classifiers exist in the literature. Classifiers such as ANN_MLP, SVM, Radial Basis Function Network (RBFN) and Bayesian, are good examples of classification methods that can be used as profile learners. ANN_MLP and RBF neural networks are two nature-inspired computation models that have been applied successfully in similar application areas for classification tasks (Witschel, and Schmidt, 2006; Silla, and Freitas, 2011; Shen, Ruvini, and Sarwar, 2012). Both networks are feed-forward networks and universal approximators.

3.5.4.1 The Radial basis function (RBF) classifier

The RBF is a multilayer feedforward network that uses the radial basis activation functions. The architecture of RBF as shown in Figure 3-3 has three layers, which are input, hidden, and output layers (Hyontai, 2009). The input layer transmits input data, and the output layer yields the response of the network that is built by linearly combining the radial basis functions of the inputs and hidden neuron parameters, which can be represented with:

$$f(X): R^n \to R$$

X depends on the Euclidean distance between its centroid and the input.

In contrast to sigmoidal functions, radial basis functions have radial symmetry about a center in n-space and the connections between the input and the hidden layer neurons are not weighted. This implies that the inputs reached the hidden layer nodes unchanged. For an input X^i, the j^{th} hidden node produces a response h_j given by, where $\|X^i - \mu_j\|$ is the distance between the points representing the input X^i and the centre of the jth hidden node as measured by some norms.

The map f is then generated by taking a weighted linear combination of these radial basis functions:

$$f(X) = \sum_{i=1}^{q} w_i \phi(X - c_i) \tag{3.37}$$

Where the parameter q connotes the number of radial basis functions, w_i and c_i are the weight and centroid of the RBF ϕ_i respectively. The widely used RBF is typically a Gaussian function of the form:

$$\phi(\|X - c_i\|) = \exp\left(\frac{\|X - c_i\|^2}{\delta_i^2}\right) \tag{3.38}$$

Where the parameter δ_i^2 is the width factor of the i^{th} unit in the hidden layer.

Parameters such as widths, weights, and centroids are some of the constraints that a RBFN learns. The RBF network has been extensively used for time series prediction, function approximation, control system, and classification (Haykin, 1999). The Euclidean norm RBFN has been used in this work to construct a product classification model that treats the extracted feature vectors as inputs and their classes as output. A typical RBF network has 1 hidden layer, and the activation functions of neurons are Gaussian functions with centre and spread as illustrated in Figure 3-4.

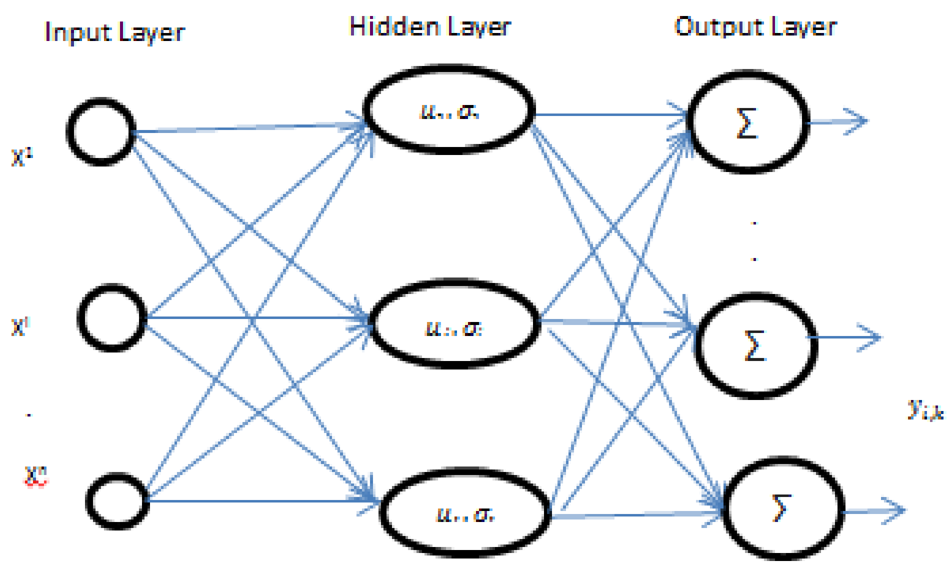


Figure 3-4: RBF Network Structure

These hidden layer neurons do not operate on the same weight summation as it is done in MLP; instead, it computes a respective field from individual function overlaps. In RBF, spread and centre values are the model parameters, which are estimated by inducing the suitable weight values (Kasiviswanathan, and Agarwal, 2012).

3.5.4.2 The Artificial neural network (ANN) classifier

The ANN classifier is a unified set of neurons that relies heavily on a computational model that mimics the structuring and role of the biological nervous system (Huang, 2009; Rahbari, 2014). The design of the interconnections amid the input neurons and transmission of data is called the network topology in ANN. MLP neural network is a nature-inspired computation model that has been applied successfully in similar application areas for classification tasks (Silla, and Freitas, 2011; Witschel and Schmidt, 2006; Shen, *et al.,* 2012). In addition, this network is a feedforward network and universal approximator. A brief overview of this model is given in this section while detailed information about the network has been provided (Shafi *et al.,* 2006). MLP is a network that is comprised of many neurons, divided into layers, and interconnected by weights. Figure 3-5 shows a MLP neural network structure with three types of layers, which are the input layer, hidden layers, and lastly the output layer.

The two major kinds of ANN topologies are recurrent and feedforward networks. Many research works carried out using feedforward ANN have pointed out that the feedforward topology of ANN could estimate multifaceted non-linear mappings. The feedforward topology of ANN contained a highly parallel structure that can handle noisy data and still offers an apt model for problems, which classic parametric techniques are unable to handle (Cheng, *et al.,* 2015). Furthermore, the feedforward topology of ANN has the inherent generality capacity that assisted them to detect and retort to image feature patterns that are related to each other but not the same as the ones that have earlier been trained (Vosniakos and Berardos, 2007; Zama and Hirose, 2010).

The neurons in the input layer of a network act as buffers for distributing the input signals, X_i^n to neurons in hidden layers. Each neuron, i in a hidden layer sums up its input signals, X_i^n after weighting them with strengths of respective connections weight $w_{i,j}^n$ as the input value of ith layer. The output value, Y_i^n of each neuron is computed as a function f of the sum (Russel and Novig, 2002):

$$Y_i^n = f\left(\sum_{i=1}^{m} w_{i,j}^n * X_{i,}^n\right) \tag{3.39}$$

Where the value m is the number of neurons in the nth layer and f is the activation function that can be a sigmoidal, hyperbolic tangent, or radial basis function.

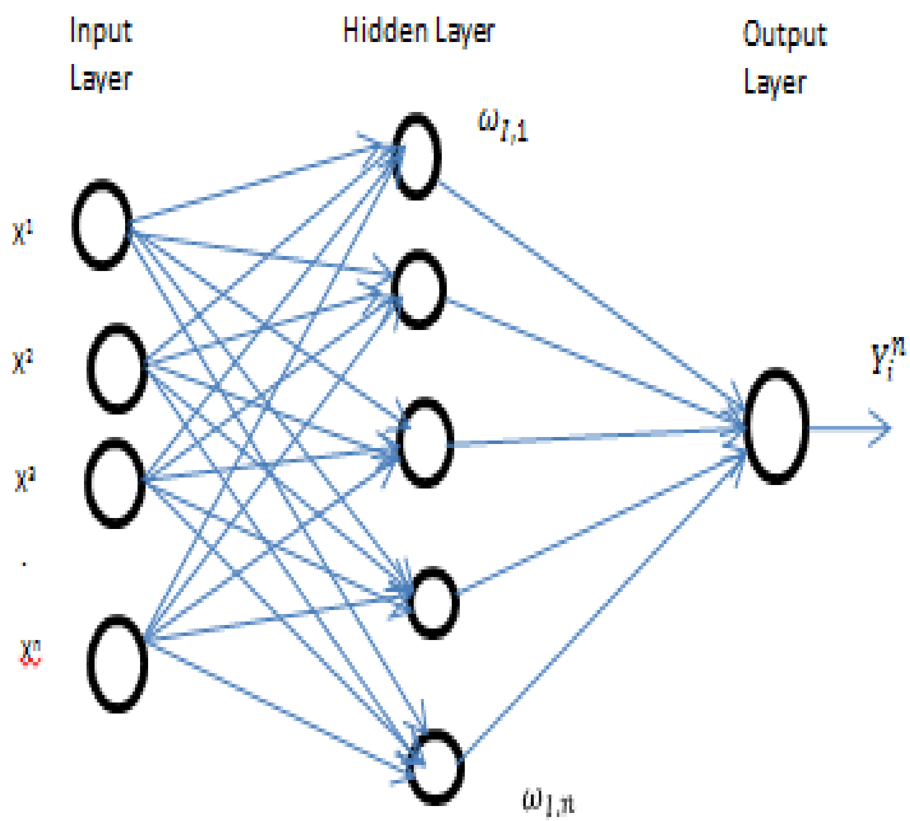


Figure 3-5: Schematic Diagram of a MLP Neural Network Structure

The common activation function used for Backpropagation (BP) training algorithm is the sigmoid function. Therefore, with the sigmoid function the output value of each neuron can be calculated as:

$$Y_i^n = \frac{1}{1 + \exp\left(- \sum_{i=1}^{m} w_{i,j}^n * X_{i,}^n \right)} \tag{3.40}$$

Similarly, the output generated by the neurons in the output layer is calculated, where the previous output of neurons in each layer can serve as input to the succeeding layer neurons. The learning process during training is done in three fundamental steps at the hidden layers. These steps are forward pass, backward pass, and computation entrance pass. The training process often takes a long time because the backpropagation (BP) systems rely heavily on a greedy search algorithm like gradient descent. Even though this later algorithm works well in most cases, but local optima is sometimes considered as global optima (Howlett and Jain, 2001; Stastny and Skorpil, 2007; Russel and Novig, 2002). This algorithm computes $\Delta w_{i,j}^n$, the change in the connection-weight between the two neurons i and j is in the form stated in Eqn.3.41.

$$\Delta w_{i,j}^n = \gamma \, \sigma_j \; X_{i,}^n \tag{3.41}$$

Where γ denotes the learning rate and σ_j is a factor that depends on the neuron j, which is an output or a hidden neuron in the network. The number of hidden layers n is one important factor while configuring the architecture of ANNs (Shafi *et al.,* 2006).

In furtherance to detailing feedforward network topologies, Multilayer Perceptron (MLP) is one the most popular form of ANN feedforward network topologies. MLP has all the good properties of a feedforward ANN (Svozil *et al.,* 1997) and on this background, MLP is a classifier used in this study.

3.5.4.3 Support vector machine (SVM)

The SVM is one of the most used machine learning classifiers in the e-commerce domain and it has been extensively applied for image classification (Bergamaschi, Guerra, and Vincini, 2002; Banerji, Verma, and Liu 2011; Zanaty, *et al.,* 2009; Jia, *et al.,* 2010). In addition, SVM has successfully been applied in several other application areas. Some of these areas are bioinformatics (Adetiba and Olugbara, 2015), product image tagging (Tomasik, *et al.,* 2009), pattern classification, and density estimation (Liu and Zheng, 2005), environmental sound classification (Choi and Jiang, 2010), speech recognition, (Lin and Wei, 2005), product image classification (Meskaldji, *et al.,* 2009; Oyewole *et al.,* 2015), and Soccer Video Summarization System (Zawbaa, *et al.,* 2011).

The SVM algorithm discriminates image samples of dissimilar categories by determining a hyperplane that separates with maximum verge in the input space. In a two-class-based classification task, the training dataset is given as $(x_1, x_1), (x_2, x_2) \ldots (x_i, x_i)$ where x_i $(x_i \in \Re^n)$, is recognised as an image sample of n-dimensional vector space and each image sample is assigned a class label y_i (Bonnett, 2016). The hyperplane f for resolving this type of binary classification is defined as follows.

$$f(x) = (w^T.x + b) \tag{3.42}$$

SVM is a constrained optimisation problem that has been formulated as follows.

$$\min_w \frac{1}{2} \| w \|^2 \tag{3.43}$$

$$\text{Subject to } y_i(w^T.x_i + b) \geq 1 \tag{3.44}$$

The optimisation problem can be solved using the technique of Lagrange multipliers (Hsu, *et al.,* 2007). However, in general Equation (3.43) has no solution because data points are often non-linearly separable. The modified SVM has been introduced with a slack variable c>=0 to circumvent this problem. This parameter regularises the penalty for misclassification. The modified optimisation problem can be written as follows:

$$\min_{w,\xi} \frac{1}{2} \| w \|^2 + C \sum_i \xi_i \tag{3.45}$$

Subject to $y_i (w^T . x_i + b) \geq 1 - \xi_i , \xi_i \geq 0$ (3.46)

The primal equation stated above can be solved by applying the optimisation technique of Lagrange multipliers as in Equation 3.47.

$$W(x) = \left\{ \sum_{i=1}^{l} \alpha_i - \frac{1}{2} \sum_{i,j=1}^{l} \alpha_i \ \alpha_l \ y_i \ y_l \ x_i \ x_l \right\} \tag{3.47}$$

Subject to $0 \leq \alpha_i \leq C$

In resolving the above quadratic optimisation task, many of this α_i must have tended to zero to satisfy the constraint $\sum_{i=1}^{l} a_i y_i = 0$. The vectors x_i corresponding to $x_i > 0$ are called “support vectors” as shown in Figure 3-6.

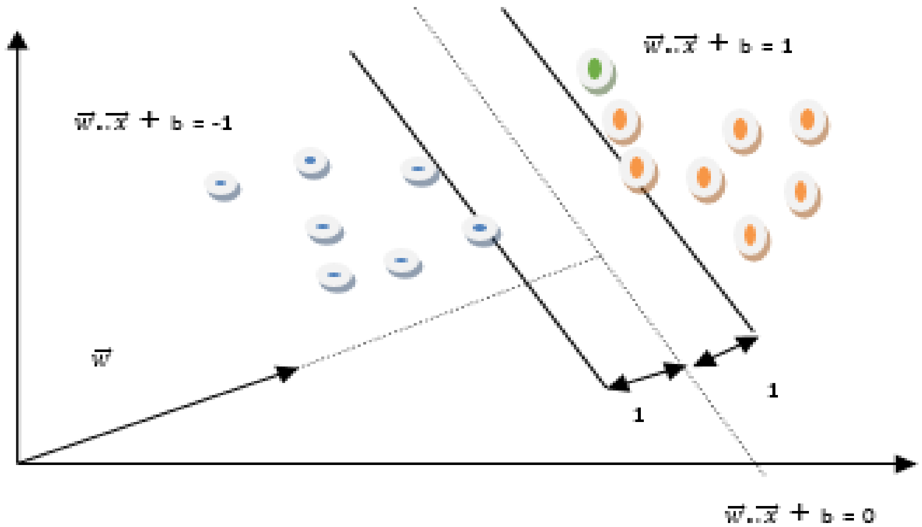


Figure 3-6: Support Vector Machine (SVM) and margin

Since some data point has been removed, it means $i = 1,2,3...n$ where $l < n$. Therefore, w, which is the separating plane is computed as:

$$w = \sum_{i=1}^{n} \alpha_i y_i x_i \tag{3.48}$$

It is noteworthy that w exists only in feature space and cannot be computed directly; it needs to be mapped to a new space **Φ**(x) that usually has a higher dimension. To decrease the computational cost of a higher-dimensional space a technique called the kernel method, which allows effective computation of dot product $((x_i).(x))$ between transformed image data points. Therefore, the classification of a new image query ρ can be determined by figuring out a kernel function ρ along with all the support vectors using:

$$f(p) = sign(\sum_{i=1}^{l} a_i y_i K(p, x_j) + b) \tag{3.49}$$

Where $K(p, x_j)$ the kernel function and b the bias are determined during SVM training.

A kernel is a continuous real value function $k(x, y)$ of two arguments x and y real numbers, functions, or vectors and maps them to a real value such as $k(x, y) = k(y, x) \in \Re$. A kernel function ideally is expected to satisfy the condition of Mercer (Kecman, 2001). The kernel function $k(x, y)$ is said to satisfy the condiction of Mercer if for all square integral functions g(x) the following inequality holds.

$$\iint g(x)k(x, y)g(y)dxdy \geq 0 \tag{3.50}$$

A square integral or quadratic integral function can be a real or a complex-valued measurable function for which the integral of the square of the absolute value is finite. Hence, the function *f* is quadratic integral on the real line (∞, -∞) if the following inequality is satisfied.

$$\int_{-\infty}^{\infty} |f(x)|^2 dx < \infty \tag{3.51}$$

A full explanation of SVM can be found in the previous studies (Burges, 1998; Scho, *et al.,* 2002; Bishop, 2007). Selecting a set of appropriate kernel functions for SVM classifiers is an important decision in machine learning applications. Table 3-1 shows a list of common kernel functions used in conjunction with SVM applications.

Table 3-1: Common Kernel Functions

Single Kernel	Formula
Linear	$K(x, y) = x.y + \mathrm{c}$
Polynomial	$K(x, y) = (1 + x.y)^d \quad d = 3$
RBF	$K(x, y) = \exp\left(-\frac{\lVert x - y \rVert^2}{2\sigma^2}\right)$
Quadratic	$K(x, y) = (1 + x.y)^2$
Cauchy	$K(x, y) = \frac{1}{1 + \frac{\lvert x - y \rvert^2}{\sigma^2}}$

3.5.4.4 Ensemble of machine learning algorithms

Many researchers have explored the applications of ensemble machine learning algorithms to solve practical problems. These algorithms agglutinate several machine learning techniques into a single model of prediction to decrease variance (bagging), decrease biases (boosting) or improve machine learning results (stacking) (Dong et al., 2020). Presently, an ensemble of machine learning is considered a preeminent way to unravel machine learning problems (Sagi and Rokach, 2018).

The success of this ensemble (meta-algorithm) has been demonstrated in numerous application domains such as social engineering (Modupe, Olugbara, and Ojo, 2011), classification of hyperspectral images (Abe, Olugbara, and Marwala, 2012; Abe, Olugbara, and Marwala, 2014), object detection (Romero, et al., 2014), lung cancer prediction (Adetiba, and Olugbara, 2015), product image classification (Oyewole and Olugbara, 2018), gender voice recognition (Zvarevashe, and Olugbara, 2018), and speech emotion recognition (Zvarevashe, and Olugbara, 2020a; Zvarevashe, and Olugbara, 2020b). Bagging **(**Breiman, 1996), boosting (Schapire, 1990; Freund and Schapire, 1996), and stacking generalisation (Wolpert, 1992) are three categories of ensemble learning algorithms in existence (Ribeiro and Dos, 2020) that will be explicated subsequently. Generally, ensemble models are generated with the paradigms of sequential ensemble methods (Boosting), parallel ensemble methods (Bagging), and combination ensemble methods (stacked).

a. Bagging ensemble

Bagging ensemble learning algorithms fall under the parallel sequential ensemble approach. In the bagging ensemble process, multiple learning algorithms are trained on a set of *n* training samples that are randomly drawn with replacement from the original training set of *m* items. This process is iterated *N* times, after which the classification for each sample in the overall dataset is decided. Such sampling approach is called **B**ootstrap **agg**regat**ing** (Efron, and Tibshirani, 1993), from where Bagging was derived. The algorithm relied on bootstrapping sampling technique (Efron, and Tibshirani, 1993) to build and train multiple classification models. The results of each weak classification algorithm are pooled by an algorithm called majority voting for classification and averaging for regression problems. The generic design of a typical Bagging ensemble learning algorithm is displayed in Figure 3 – 7.

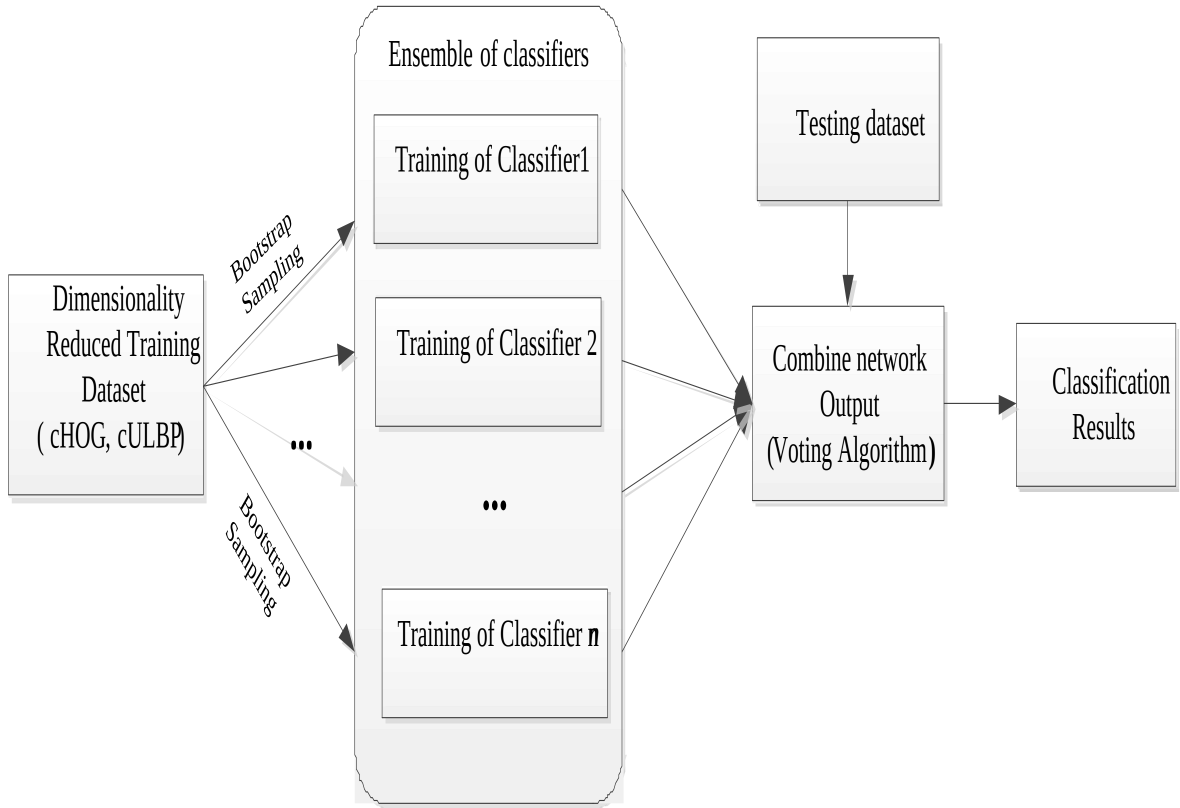


Figure 3-7: Bagging ensemble architecture (Oyewole and Olugbara, 2018)

Machine learning literature has shown that bagging ensemble learning methods have proved effective in many application areas. Moreover, experimental results have revealed that this learning approach generates superior performance when compared with any single learning algorithm used in isolation (Dong et al., 2020). For instance, the music recommendation system of Tiemann, and Pauws, 2007, is a good example where ensemble-learning methods were utilised. A combination of stacking and bagging has also been investigated (Ting and Witten 1997b). Similarly, Oyewole and Olugbara (2018) have applied bagging ensemble product image classification with high accuracy.

b. Boosting ensemble

Boosting ensemble algorithms belong to the category of a sequential ensemble method. They refer to a family of algorithms that can convert weak learners into strong learners as introduced by Kearns and Valiant (1989). They were introduced to respond to the problem of whether weakly learnable and strongly learnable problems are equal, which has been investigated by previous researchers, including Schapire (1990). This implies that it is possible to boost a weak learner into a strong one using boosting ensemble. The basic tenet of the boosting ensemble is to exploit the independent predictive capability of a base learner because classification error can be reduced by combining multiple independent learners.

Most boosting algorithms even though are not algorithmically constrained, consist of iteratively learning weak classifiers to distribution and adding them to a final strong classifier. The addition of a weak learner to a classification model will require the readjustment of data weights in a process of "re-weighting". The mechanism of weighting and reweighting of samples will change over time to allow the classification system to optimise its decision by considering results from samples in proportion to their impact on the system performance. The recently introduced boosting algorithms include LPBoost, TotalBoost, BrownBoos, xgbboost, MadaBoost, LogitBoost, and RALOG. In particular, the RALOG is an ensemble learning algorithm that agglutinates random decision forest, AdaBoost, logistic regression, and gradient boosting machine for speech emotion recognition (Zvarevashe, and Olugbara, 2020b). Freund *et al.,* 2003, have offered RankBoost boosting ensemble learning algorithm for hybrid user preference that integrates collaborative-based filtering in an e-commerce recommendation system.

c. Stacking ensemble

Stacking ensemble is an important machine learning technique that is widely used in many applications. Stacked generalization is a fused ensemble learning method where a learner usually called a meta-learner that is trained to efficiently combine the computational results of individual learners. The output of a learner serves as input for the meta-learner. The learners are often made up of diverse learning algorithms, but it is possible to create a stacked ensemble from the same learning algorithms.

The training data in the process of stack generation are usually used to generate new data for the meta-learner. Consequently, it is generally recommended that new instances be created from the training features for the new data. This, in turn, will make it possible to consider not only the predictions but the confidence of the first-level learners. Wolpert (1992) has shown that it is important to consider the types of features for the new training data, and the types of learning algorithms for the meta-learner, particularly when considering a classification problem.

d. Multiple kernel transformation (MLT)

Multiple kernel transformation (MLT) is another form of an ensemble of machine learning algorithms that combine kernels (Breiman, 1996; Romero, et al., 2014; Oyewole, et al., 2015). Due to some intrinsic limitations of a single SVM kernel for recent developments in classification, researchers have stressed the necessity to explore the use of MLT. The MLT delivers high performance with better flexibility even with a high dimensional dataset (Zanaty, Aljahdali, Cripps, 2009; Nguyen and Ho, 2007; Zanaty, 2012; Romero, Iglesias, and Borrajo, 2015).

The other important step in MLT, especially the one with SVM based classification problem is how to choose a suitable kernel. The choice of a kernel influences the performance of the entire classification model. It has been widely reported that a combination of two effective kernels can produce a stable classification result. The analytical expression for a combination of several kernels is as follow:

$$K(x, y) = \sum_{i=0}^{n} a_i K_i(x, y) \quad (3.52)$$

where n stands for the sum-total of sub-kernels and a_i is weighted value $a_i \geq 0$.

Different approaches do exist for combining SVM kernels, but generally, the combination of SVM kernels can be pertinently classified into linear, data-dependent, and non-linearly (G¨onen, and Alpayd, 2011). The first type of a modest combination mechanism can be subdivided into weighted and unweighted sums. The unweight sum approach is used often in building LaRBF (Oyewole *et al.,* 2015) because it has a very low computational cost (G¨onen and Alpayd, 2011).

Many combinations of kernels have been designed in recent times based on MLT methods (Romero, Iglesias, and Borrajo, 2015; Nguyen and Ho, 2007). Many of them combine radial basis kernel and polynomial kernel to explore their strengths concomitantly. Zhang and Sha (2013) have proposed a SVM-kernel ensemble called PRBF kernel in consonance with ideas of previous authors (Zanaty, *et al.,* 2012). The kernel integrates polynomial function with RBF to take advantage of the strengths of both. Moreover, the authors have improved on PRBF to create a new SVM kernel that is popularly referred to as Gaussian Radial Basis Polynomial Function (GRPF) (Zhang and Sha, 2013) improve the classification accuracy for both linear and non-linear datasets. Phienthrakul and Kisirikul (2005) have proposed a new combination of kernels for SVM recognition tasks. They have used both additive and multiplicative operations to combine polynomial and RBF kernels. Romero, Iglesias, and Borrajo (2015) have introduced a novel text classification using multi-kernel Linear-RBF based on SVM.

In the same vein, a new approach that relies on MKL for image classification has been proposed by Oyewole *et al.,* (2015). It is a customised LaRBF kernel that exploits the technique of unweighting the sum of linear hybrid of linear and RBF kernels. LaRBF kernel enjoys the inherent advantages of both linear and RBF kernels as PRBF and GRPF (Zhang and Sha, 2013). For instance, RBF is usually characterised by an apt classification accuracy and inherent high-speed act in the linear kernel (Romero, Iglesias, and Borrajo, 2015). LaRBF kernel is used to inevitably categorised e-commerce images in 5 colour models into hundred classes. The architecture relies on 243-dimensional vector space for the histogram of an oriented gradient. The theory behind LaRBF-SVM can be expressed as follows.

$$LaRBF = a_1 K_{Linear}(x, y) + a_2 K_{RBF}(x, y) \text{ where } a_1 = a_2 = 1 \qquad (3.53)$$

The linear combination of these kernels follows the Mercer theorem because both Linear and RBF kernels are admissible Mercer kernels. The new kernel has been applied to product image classification and experimentally compared with five other kernels in the e-commerce domain (Oyewole, et al 2015). It was reported that the MKL-LaRBF classifier consistently outperformed other traditional SVM kernels by an average of 83.5% classification accuracy (Oyewole, et al 2015).

3.6 Mining Spatiotemporal Information from Image

Time and location are two important spatiotemporal image contextual information for generating effective personalised recommendations. The reason is that the preferences of individual users do change over time (temporal) and can depend heavily on user location (Yehuda, 2010). The fundamental notion about temporal information is that user preference is periodic (Baltrunas, et al., 2011; Lee et al., 2008). Personalised recommendation exploits these dimensions to enhance more distinct product recommendations.

3.6.1 Time Weighting Schemes

Time-dependent user preferences are applied in this research work to weigh user interest decaying over time. Decay functions measures how quickly user preference for a product diminishes with time. Decay functions are used to model data values that is decreasing over time. The examples of decay functions are exponential, logistic, power, linear, concave, convex, quadratic, rational, and radical decay. The first four decay functions mentioned were used in succession to model the recency of user preference after user perceptions of an item over a period.

a. Exponential decay function

The exponential decay function is used frequently to quantify the process of reducing an amount by a consistent percentage rate over a period t. Examples of exponential decay functions are radioactive, user interest decay, and population decrease, which has been utilised in several studies (Ding and Li, 2005; Li, et al 2013). The function value lies in the range of 0 to 1 and the more recent an item is purchased over a period, the higher is the value of the time function as follows.

$$\theta(t) = e^{-\lambda * \Delta t} \tag{3.54}$$

Δt, denotes the date difference of a preferred item j with the corresponding purchasing dates t_j and current date $t_{current}$.

$$\Delta t = \Delta t_{current,j} = \left| \mathrm{T_j} - T_{current} \right| \tag{3.55}$$

b. Power decay function

The power decay function was earlier utilised by Wu et al (2012) for the computerisation of digital libraries, specifically for social tagging. In their work, user-based collaborative filtering was adopted utilising the power decay function.

$$\theta(t) = \Delta t^{-\lambda} \tag{3.56}$$

c. Linear decay function

Lee and Park (2006) used a linear decay function in a recommendation system. The time variable in a collaborative recommendation filtering before calculating the user similarity is as follows.

$$\theta(x) = 1 - \frac{x}{\Delta t} * r \tag{3.57}$$

Where x denotes the time that is used as the basic time interval unit, and r, denotes the rate of decay that could be referred to as linear decay constant $, r \in [0,1]$.

d. Logistic decay function

The logistic decay function has been suggested as an alternative to the exponential decay function to represent user preference (Ding and Li, 2005). The decay function is written as follows.

$$\theta(t) = \frac{2}{1 + e^{\lambda * \Delta t}} \tag{3.58}$$

3.6.2 Location Contextual Variable

The geographical location of a user relative to the location of a product item plays an important role in shopping recommendation because it tells a shopper the distance of the nearest shops to find an item within his/her vicinity. The knowledge of using the physical location of a shopper to have access to information about an item is rapidly involved (Colombo-Mendoza et al., 2015; Gavalas et al., 2014). Consequently, location information is usually exploited by preference locality that is spatially close to the item that a shopper prefers. The location features can be grouped typically into three categories:

- Location history - this has to do with the use of user location check-in history or online rating history of different locations (Canny, 20002; Tzvetan, Nitya, and Venu, 2006; Mao, et al 2011).
- Location tag - this has to do with the use of the information such as location information in social media (Zhijun, et al 2011; Jia-Wei, Jian, and Xi-Feng, 2004; Qiang, et al 2010).
- User trajectories - this has to do with the use of information such as the visiting sequence, travel path, GPS trajectory, and so on (Vincent, et al 2010; Yu and Xing, 2110; Olugbara, Ojo and Mphahlele 2010). This category is very popular in the literature, because of its simplicity.

In this work, the user trajectory category is applied to determine user proximity to the shops where a particular item to procure can be found.

3.7 User preference Mining with Decision Theory

Decision theory is about how human beings make choices and judgments in day-to-day activities. The theory has to do with taking goal-directed actions in the incidence of heterogeneous and confusing options and can be espoused to compute recommendation utility. The theory serves as a rich tool for building interesting recommendation systems (Lakiotaki, Matsatsinis, and Tsoukias, 2011). Almost everything that a mortal being does requires quality decisions making (Hansson, 2005). Therefore, any system that intent to mimic human activities is not only trying to theorize about human activities and their relationship with the environmental context of a user but also try to strictly theorize about human decisions making.

Generally, in any decision-based system, three essential components that do exist are (i) alternatives (the available choices), (ii) the states of nature, which are not under the control of the decision-maker, and (iii) the outcome. Given the background, that the user is multi-dimensional, multi-criteria ranking becomes another inevitable hurdle to cross, to deliver personalised recommendations to users. A classical similarity-based approach such as cosine, correlation coefficient, and the like could not efficiently in a multi-faceted-based decision system due to the complexity of the decision that is required. In this study, the decision theory technique is adopted in mining user preference. This technique combines all the social factors and determines the best user preference alternative.

Common Multi-Criteria Decision-Making (MCDM) techniques that can be explored for generating ranked item recommendations (Shao, Chen, and Huang 2010) are the following. The Analytical Hierarchical Process (AHP), Simple Additive Weighted (SAW), Weighted Product Method (WPM), Analytical Network Process (ANP), Cooperative Game Theory (CGT), Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), and Simple Multi-Attribute Rating Technique (SMART). First, adapting the heuristic technique from decision theory to synthesis are all vital criteria to provide an effective ranking. In this work, a mathematical decision theory that is based on an image multi-attribute information processing model is proposed.

3.7.1 Simple additive weighting (SAW)

The SAW is one of the most frequently used multi-attribute decision techniques because of its simplicity and elegance. The SAW technique is based on the weighted average according to the following equation.

$$S_i = \sum_{j=1,\ i=1,2.....N}^{m} w_j r_{i,j} \tag{3.59}$$

Where S_i is the overall is a score of the i^{th} alternative product $r_{i,j}$, is the normalised rating of the i^{th} alternative product for the j^{th} criterion and is computed as follows:

$$r_{i,j} = \frac{X_{i,j}}{Max_i(X_{i,j})} \text{, for the benefit criteria} \qquad (3.60)$$

$$r_{i,j} = \frac{\frac{1}{X_{i,j}}}{\left[Max_i\left(\frac{1}{X_{i,j}}\right)\right]} \text{, for the cost criteria} \qquad (3.61)$$

Where $X_{i,j}$ represents the original value of the j^{th} criterion of the i^{th} alternative product.

3.7.2 Technique for order preference by similarity to ideal solution (TOPSIS)

TOPSIS is one of the most widely used Multiple Criteria Decision Making (MCDM) techniques. It has been applied successfully in different application areas to assist humans in decision making, including product recommendation decisions (Tewari, Youll, and Maes, 2002; Plantie, Montmain, and Dray, 2005; Nguyen, and Haddawy, 2011; Zeng, 2011). It deals with the optimum selection of a set of alternative products against multiple criteria that can be conflicting. The benefits of this technique include (a) its intuitively appealing logic, (b) its simplicity and directness, (c) its computational efficiency, and (d) its ability to measure the relative performance of the alternatives to individual criteria in a simple mathematical format. In this work, TOPSIS is applied as an aggregate function to mimic human multi-dimensional preference ranking. The MCDM problem can be succinctly conveyed in matrix format as follows.

Table 3-2: Decision Table Format

	C_1	C_2	$\dots$	C_n
A_1	$X_{1,1}$	$X_{1,2}$	$\dots$	$X_{1,n}$
A_2	$X_{2,1}$	$X_{2,2}$	$\dots$	$X_{2,n}$
$\dots$	$\dots$	$\dots$	$\dots$	$\dots$
A_m	$X_{m,1}$		$\dots$	$X_{m,n}$
W =	$[w_1$	w_2	$\dots$	$w_n]$

Where $A_1, A_2, \dots A_m$, are possible alternative products among which decision-makers have to choose, $C_1, C_2, \dots C_n$, are criteria with which alternative performance are measured, $A_{i,j}$, is the rating of alternative A_i with respect to criterion C_j w_i, is the weight of criterion C_j.

3.8 Image-Based Performance Evaluation Metrics

In determining the performance of an image-based recommendation system, the accuracy of results generated is essential. The most popular measures of accuracy where items are categorised as either relevant or not relevant are precision and recall. The F-score measure (F1) amalgamates precision and recall into a compact metric of weighted average measure. Similarly, normalised recall and normalised precision are two measures, which further extend precision and recall. Furthermore, error rate metrics such as Mean Absolute Error (MAE) and Root Mean Error (RME), are used frequently to evaluate recommendation accuracy. The appropriation of these metrics in a recommendation system implies viewing the system as an information retrieval task. Simply put, retrieve all product items, which are predicted to be "relevant". As formulated in equations 3.64 to 3.65 respectively (Herlocker, *et al.*, 2004; Melville and Sindhwani, 2010).

3.8.1 Recall and Precision

Recall (R) means a measure of completeness, which defines the subset of relevant items recommended from all relevant product items. That is the proportion of all relevant product items recommended. Precision is the likelihood that a suggested product item meet-up with the user's interests and preferences. Four ways of being relevant are right or wrong: True Negative (TN), False Negative (FN), and False Positive (FP), True Positive (TP):

$$R = \frac{TP}{TP + FN} \tag{3.62}$$

Where

- TN refers to a situation where the predicted relevant recommended item was not correctly predicted.
- TP refers to a situation where the predicted relevant item is correctly recommended.
- FN refers to a situation where the predicted relevant item is wrongly predicted irrelevant.
- FP refers to a situation where the predicted relevant item is irrelevant is wrongly predicted to be relevant.

Precision (P) in the context of recommendation system means a measure of correctness, which defines the segment of relevant items retrieved out of all retrieved items, for example, the proportion of recommended product items that are truly relevant to the query item is given in Eqn. (3.63). Accuracy of the suggested recommendation is given in Eqn. (3.64).

$$P = \frac{TP}{TP + FP} \tag{3.63}$$

$$A = \frac{TP}{TP + TN + FP + FN} \tag{3.64}$$

The general performance of a recommendation algorithm can be evaluated using both precisions and recall together (Lu*, et al.,* 2012). Previous studies have shown that precision and recall are inversely related and dependent on the length of the result list returned to the user (Shani and Gunawardana, 2011; Lu*, et al.,* 2012). One approach is the $F1$ metric, which uses a harmonic function to amalgamate the performance measures of precision and recall into a single performance metric.

$$F1 = \frac{2 * (P * R)}{P + R} \tag{3.65}$$

In addition, this metric assures the evaluation of the performance of recommendation systems (Shani and Gunawardana, 2011).

3.8.2 Precision/Recall Top-N Rank Accuracy Metric

Precision and recall can be used further to evaluate the ranking of product items. The Precision-Recall @ rank N, which is sometimes referred to as Precision-Recall Top-N rank accuracy is important to this current research because it literarily correlates with the assumption of the behavior of mobile users. The assumption is that mobile users are usually interested in examining the output ranking of Top-N results from top to bottom until they are satisfied or when they reach saturation point and give up. Precision@N is the proportion of the number of the recommended product items that are relevant at N to a number of the recommended product items at N. In addition, recall is the proportion of the number of recommended product items that are relevant at N to the total number of relevant product items. The goal of the Top-N recommendation is to recommend a small set of N items from a large collection of items to a user (Cremonesi, Koren, and Turrin, 2010). The research reported in this thesis has employed this metric to evaluate the output of a recommendation system. The metric will be further described in the next chapter where further details of the metric will be provided.

3.8.3 Normalised Recall and Normalised Precision

Another similar performance evaluation method that can also use image-based evaluation is called normalised recall and normalised precision. Two measures proposed by Rocchio in 1964, take average recall and precision obtained for all possible cut-off points as input. Normalised recall is strictly linked to other measures such as the CRE measure and the likely search length. Apart from the recall-precision and the recall-precision-graph, the normalised recall is one of the useful evaluation measures for information retrieval systems (Zeng, *et al.,* 2014). Its attractiveness stems from the point that it yields one single number in contrast to recall-precision and recall-precision-graph. This always permits the comparison of ranked retrieval outputs. This method takes the ranking into concern and hence has a more comprehensive measurement of retrieval results.

3.8.4 Mean absolute error (MAE) and root mean error (RME)

The MAE computes the deviation between the predicted recommendation rating and the actual rating of recommendations like RME. However, the RME places more emphasis on large deviation as formulated in equations (3.66) and (3.67) (Melville and Sindhwani, 2010).

$$MAE = \frac{1}{n}\sum_{i=1}^{n} | P_{u,i} - R_{u,i} | \qquad (3.66)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (P_{u,i} - R_{u,i})^2} \qquad (3.67)$$

Where $P_{u,i}$ is the predicted recommendation rating for an item, $R_{iu,i}$ is the actual recommendation rating, and N is the total number of recommendation ratings in the dataset.

3.8.5 Line plot graph for image feature visualization

As we all know, a picture is better than 1,000 words. Picture vectors are the feature vector of a picture image, created using some image-feature extraction techniques. In this study colour Histogram, HOG, LBP, etc. image vectors having 132 features dimensional for each image are realised for one image with 11 principal components. The difficulty with a visually distributed representation of this type of image feature vectors is that they are multidimensional for which are quite higher than the visual 2- or 3-dimensional vector plots that a human can see and interpret. Since there are no direct ways to project these data points on the plot that is easy for a human to understand, there is a need for some powerful method to map these high dimensional data into 2 or 3-dimensional space. Here Line plot graph played the trick.

3.9 Chapter Summary

In this chapter, the useful algorithms for image feature extraction, description and classification have been comprehensively revised for product item recommendation computation. The introduction of machine learning approaches suitable for product item recommendation has been conducted and reported. Image content-based recommendation system requires an efficient feature extraction technique to improve system performance. The reviewed feature extraction algorithms showed that low dimensional feature requires less space and run faster. In any Top-N recommendation tasks, an exact rating is not needed, items are ranked according to their appeal to a user. The highlighted approaches have been utilized in building MLT kernel systems for product items classification in the e-commerce domain (Zanaty, Afifi, and Khateeb, 2009[b]; Jia, Gu, and Zou, 2010; Romero, Iglesias, and Borrajo, 2015). However, most of these existing studies have used an inadequate number of product classes that are far from the practical reality in the e-commerce domain with thousands of different kinds of products.

CHAPTER FOUR

Research Methods

4.1 Preamble

Based on those algorithms reviewed in the previous chapters, this current chapter presents the proposed image content-based preference elicitation approach in a client-server architecture. This approach takes leverage of the multiple attributes of item temporal features. The new architecture follows the understand-deliver-measure (UDM) methodology (Adomavicius and Tuzhilin, 2005). To lay a foundation for the rest sections of the chapter, the chapter first introduced the concept behind UDM and the six (6) stages of UDM, that offer a methodological model in realising the aim and objectives stated in chapter one of this thesis are discussed. Finally, the proposed architecture will be presented.

In the proposed architecture, high-level image representation which captures richer semantic content of an image and perceptual feature is used along with other image contextual features such as item proximity, time, image class, item price, item-incentive, and item-relevant are used in building user profile. Likewise, this work pushes forward the idea of categorical compositionality from a category theory perspective to represent user preference based on the relationships between one category to others categories and item to item. In the current research work, a decision-theory application tool is utilised. Likewise, the visual-based output is used against generating text-based output, used in most existing works. Visual-based interfaces constitute another key factor that induces the worth of product recommendations (Boutemedjet and Ziou, 2008). Some of the e-commerce product items like clothes or pieces of jewelry are cherished by many users because of their visual appearances that define the look and feel based on primitive features such as shape, texture, and colour characteristics (Fiore et al 2004).

4.2 Image Content-Based Preference Elicitation Model

The design of an image-content-based user preference elicitation *(I_{cb}-UPE)* framework is shown in Figure 4-1. During the process of item registration, sales item information or what can be tagged 'image social-context information' in this thesis must have been posted using an imaging interface by the fixed-users. This contextual information includes the item price, shop location, item expiration date, and attached incentive to be captured by the fixed users who are registered merchants. This mechanism makes the filtering results of recommendations more reliable. The item database is manually indexed into classes on a unique identifier, *ItemID* that is automatically generated for each item during this item registration process.

The major input to the *I_{cb}-UPE* system shown in Figure 4-1 is the image, img_k of the preferred item. This image is captured by an active user u_a . Similar to other items in the item profile this image has criteria information $|k|$ such as location attributes (this context information which signified where the image is captured is available in the EXIF-header of the captured query image in the form of GPS coordinates), product categories ($ItemCat_{1,2...N}$), and item feature vectors remain unknown.

The recommendation framework proposed in this study consists of six important components. They are user interface, user/item profile database, location descriptor, image-based classification, image similarity, and recommendation ranking. The UDM approach borders mostly with an understanding of user preference to enable accurate acquisition of information concerning user preference and building of user profile that acquires $|k|$

information about this user preference-item, img . At the next stage personalised recommendation is delivered, this entails matchmaking and recommendation computation, where acquired information is used to perform item neighbourhood formation and item-based recommendation, and lastly measure of personalisation impact, like what is highlighted by Huang and Huang (2009) and Lops, De Gemmis and Semeraro (2011). Subsequent sections discussed processes involve in delivering personalised recommendations, as presented in Figure 4-1.

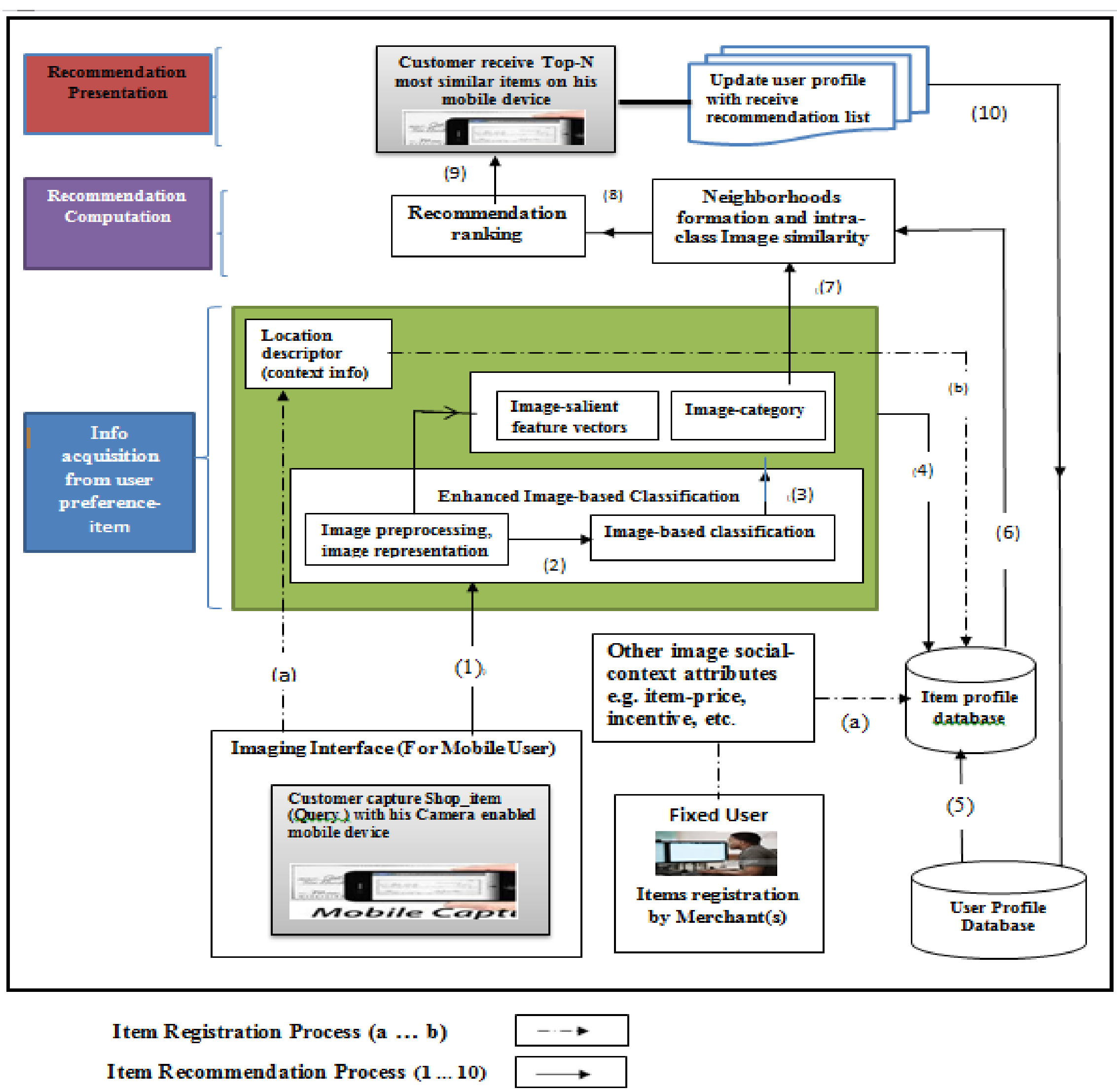


Figure 4-1: Image-Content-based User Preference Elicitation Framework

Algorithm-2: Image-Content-based User Preference Elicitation $(I_{cb} - UPE)$ Algorithm

Input: MxNx3 is a camera captured-item or (item Prefer Product) Q.
which is used for initial filtering to generate P, with relevant weights of criteria

Output: Top-k Product list

P_i = $\{e_i, \quad e_2, \quad e_j, e_{j+1}..........e_m\}$ where e_j stands for j^{th} criterion/weight value(score) of item P in category I

$$w = \sum_{j=1}^{m} e_j \quad \text{and } w=1$$

Let Cat = $\{P_1, P_2, P_3 ... P_{n-1}\}$, represents the set of product items in the same category of items preferred by a user.

(1) Pre-process(Q)

(2) ImageRepFeatureExtraction(Q)

(3) DetermineCat(Cat)

(4) Begin

(5) For each P_i do

(6) If(log(e_j)) < 0 Then Do //logarithm of each criterion and since each e_j are < 0, then log(e_j) <0

(7) Load(e_j)

(8) GetImgSocialContextAttribute( )

(9) ComputeSimilarityScore (e_j ,Q)

(10) InsertTo(M-1)

(11) GetProductRec(P_i)

(12) InsertTo(ProductList)

(13) Endfor

(14) Output(ProductList, Top-k)

(15) End

4.3 Data Set

E-commerce product images from PI100 (Xie, *et al.,* 2008), is collected and used for the experiment conducted in this section. The PI100 corpus contains 10,000 colour images. These images are alienated into one-hundred categories. Figure 4-2 presents a sample of randomly selected images of eighty items from 10 classes in the above-mentioned dataset. A close look at each of the items classified in the same class shows that there are analogous in shape and look, but with a slight difference in the colour content. On the contrary, one can observe that a wide dissimilarity exists among product images across the different classes in terms of the shapes and sizes of their semantic features. An image sample of 20 per class is considered for each of the 100 classes in the corpus and this sum-up to 2,000 colour images.

Figure 4-2: Selected Product image from PI 100 dataset

The image chosen from the PI 100 dataset is used as a query image. In a codicil, to query the database, the image captured by a mobile phone is used as a query example in other to filter out similar product images from the above-mentioned databases. To extract quality features from images, there is a need for effective representation.

4.4 Proposed Four-Dimensional Colour Image Representation

Literature records that in some situations, the RGB colour model has superior performance over other colour models (Shih, and Cheng, 2005**;** Mohanty, *et al.,* 2013). However, the RGB colour model may not be generally suited for image analysis in some cases because slight variations of the illumination can influence all colour channels (Schikora and Schikora 2014). RGB images are subtle to luminance condition, surface orientation condition as well as other photographic conditions.

This work proposes a new L r\`g\`b\` colour model to reduce RGB sensitivity. The proposed image representation model rest on r', g', and b' constituents. Correspondingly, each of these components is defined by normalizing corresponding components of primary colour as shown in Eqn. 3.1. The normalization effect made r', g', and b' components be illumination invariant to light intensity change, shadow, and shading (Gevers, Van Stokman, 2006). Similarly, in Yang et al, 2013, the function to transform the RGB components $(C_i, C_2, C_3)^T$ to LRGB components $(L, T_i, T_2, T_3)^T$ can be expressed as in Eqn. 4.1 below.

$$\left.\begin{aligned} T_1 &= \left(\frac{c_1}{c_1 + c_2 + c_3}\right) \\ T_2 &= \left(\frac{c_2}{c_1 + c_2 + c_3}\right) \\ T_3 &= \left(\frac{c_3}{c_1 + c_2 + c_3}\right) \end{aligned}\right\} \tag{4.1}$$

The lightness component L is computed using the definition of Luma generally represented similar to what was done by Romero, Lado, and Mendez (2018) and Yang et al (2013) as given below in Eqn. 4.2.

$$L = 0.299 \times C_1 + 0.587 \times C_2 + 0.114 \times C_3\,, \tag{4.2}$$

The colour component in the RGB can be enhanced using the following transformation.

$$H_i = w * T_i + L \quad , \quad \text{and}$$

$$L = \alpha_1 c_1 + \alpha_2 c_2 + \alpha_3 c_3 \tag{4.3}$$

where w is a constant (Romero, Lado and Mendez, 2018).

The transformation matrix for the proposed 4D-colour models is derived thus:

$$H_1 = (1 + w)\alpha_1 c_1 + \left\{\alpha_2 + w\left(\alpha_2 - \frac{1}{2}\right)\right\}c_2 + \left\{\alpha_3 + w\left(\alpha_3 + \frac{1}{2}\right)\right\}c \tag{4.4}$$

$$H_2 = \left\{\alpha_1 + w\left(\propto_1 - \frac{1}{2}\right)\right\}c_1 + (1 + w)\alpha_2 c_2 + \left\{\alpha_3 + w\left(\alpha_3 + \frac{1}{2}\right)\right\}c_3 \tag{4.5}$$

$$H_3 = \left\{\alpha_1 + w\left(\alpha_1 - \frac{1}{2}\right)\right\}c_1 + \left\{\alpha_2 + w\left(\alpha_3 + \frac{1}{2}\right)\right\}c_2 + (1 + w)\alpha_3 c_3 \tag{4.6}$$

The transformation matric is given as

$$\begin{pmatrix} H_0 \\ \\ H_1 \\ \\ H_2 \\ \\ H_3 \end{pmatrix} = \begin{pmatrix} \alpha_1 & \alpha_2 & \alpha_3 \\ \\ (1+w)\alpha_1 & \alpha_2 + w(\alpha_2 - 0.5) & \alpha_3 + w(\alpha_3 - 0.5) \\ \\ \alpha_1 + w(\propto_1 - 0.5) & (1+w)\alpha_2 & \alpha_3 + w(\alpha_3 - 0.5) \\ \\ \alpha_1 + w(\alpha_1 - 0.5) & \alpha_2 + w(\alpha_2 - 0.5) & (1+w)\alpha_3 \end{pmatrix} \begin{pmatrix} c_1 \\ \\ c_2 \\ \\ c_3 \end{pmatrix} \tag{4.7}$$

The condition for a solution to enhance an image is $w = 0.5$ and $(2 \propto_i \geq 0.5)$

$$\begin{pmatrix} H_0 \\ \\ H_1 \\ \\ H_2 \\ \\ H_3 \end{pmatrix} = \begin{pmatrix} \alpha_1 & \alpha_2 & \alpha_3 \\ \\ 2\alpha_1 & 2\alpha_2 - 0.5 & 2\alpha_3 - 0.5 \\ \\ 2\alpha_1 - 0.5 & 2\alpha_2 & 2\alpha_3 - 0.5 \\ \\ 2\alpha_1 - 0.5 & 2\alpha_2 - 0.5 & 2\alpha_3 \end{pmatrix} \begin{pmatrix} c_1 \\ \\ c_2 \\ \\ c_3 \end{pmatrix} \tag{4.8}$$

Hence $\alpha_1 = \alpha_2 = \alpha_3 = 0.3333$

$$\begin{pmatrix} H_0 \\ H_1 \\ H_2 \\ H_3 \end{pmatrix} = \begin{pmatrix} 0.3333 & 0.3333 & 0.3333 \\ 0.6666 & 0.1666 & 0.1666 \\ 0.1666 & 0.6666 & 0.1666 \\ 0.1666 & 0.6666 & 0.6666 \end{pmatrix} \begin{pmatrix} c_1 \\ c_2 \\ c_3 \end{pmatrix} \tag{4.9}$$

This new model allows changes between the existing product image and the final background to be detected. In addition, the lightness, as well as the colour constituents, can be separately scaled and each of these components can be further enhanced by multiplying either the colour or the lightness components by a constant.

The segment also derived new transformation matric for the system proposed by Romero, Lado, and Mendez (2018) reviewed in chapter three. The authors have proposed a 4-dimensional model LRGB, lightness component, Luma L that is calculated using the definition from the YUV colour model, components $(c_i, c_2, c_3)^T$ (c_i, c_2, c_3) to LRGB components $(L, T_i, T_2, T_3)^T$ are given by:

$$H_i = wT_i + L \tag{4.10}$$

$$L = \alpha_1 c_i + \alpha_2 c_2 + \alpha_3 c_3 \tag{4.11}$$

$$H_1 = \{w(1-\alpha_1) + \alpha_1\}c_1 + (1-w)\alpha_2 c_2 + (1-w)\alpha_3 c_3$$

$$H_2 = (1-w)\alpha_1 c_1 + \{w(1-\alpha_2) + \alpha_1\}c_2 + (1-w)\alpha_3 c_3$$

$$H_3 = (1-w)\alpha_1 c_1 + (1-w)\alpha_2 c_2 + \{w(1-\alpha_3) + \alpha_3\}c_3 \tag{4.12}$$

$$\begin{pmatrix} H_0 \\ H_1 \\ H_2 \\ H_3 \end{pmatrix} = \begin{pmatrix} \propto_1 & \propto_2 & \propto_3 \\ w(1-\alpha_1)+\alpha_1 & w(1-\alpha_1)+\alpha_1 & w(1-\alpha_1)+\alpha_1 \\ w(1-\alpha_1)+\alpha_1 & w(1-\alpha_1)+\alpha_1 & w(1-\alpha_1)+\alpha_1 \\ w(1-_1)+\alpha_1 & w(1-\alpha_1)+\alpha_1 & w(1-\alpha_1)+\alpha_1 \end{pmatrix} \begin{pmatrix} c_1 \\ c_2 \\ c_3 \end{pmatrix} \tag{4.13}$$

where $H_0 = \alpha_1 c_i + \alpha_2 c_2 + \alpha_3 c_3$

$(w, \alpha) \in (0,1]$ Select $w = 0.5$

$$\begin{pmatrix} H_0 \\ H_1 \\ H_2 \\ H_3 \end{pmatrix} = \begin{pmatrix} \alpha_1 & \alpha_2 & \alpha_3 \\ \frac{1+\alpha_2}{2} & \frac{\alpha_2}{2} & \frac{\alpha_3}{2} \\ \frac{\alpha_2}{2} & \frac{1+\alpha_2}{2} & \frac{\alpha_3}{2} \\ \frac{\alpha_1}{2} & \frac{\alpha_2}{2} & \frac{1+\alpha_3}{2} \end{pmatrix} \begin{pmatrix} c_0 \\ c_2 \\ c_3 \end{pmatrix} \tag{4.14}$$

$\alpha_1 = 0.299, \quad \alpha_2 = 0.587, \quad \alpha_3 = 0.114$

$$\begin{pmatrix} H_0 \\ H_1 \\ H_2 \\ H_3 \end{pmatrix} = \begin{pmatrix} 0.299 & 0.587 & 0.114 \\ 0.6495 & 0.2935 & 0.057 \\ 0.1495 & 0.7935 & 0.057 \\ 0.1495 & 0.2935 & 0.557 \end{pmatrix} \begin{pmatrix} c_1 \\ c_2 \\ c_3 \end{pmatrix} \tag{4.15}$$

In this last segment, new transformation matric is also derived for the system proposed in Yang et al (2013) model, reviewed in chapter three. The authors proposed a 4-dimensional model LRGB, lightness component, Luma, L that is computed using components $(c_i, c_2, c_3)^T$ (c_i, c_2, c_3) to LRGB components $(L, T_i, T_2, T_3)^T$ are given by:

$$H_i = wT_i + L \tag{4.16}$$

Where $L = \alpha_1 c_i + \alpha_2 c_2 + \alpha_3 c_3$, the following colour transformation is realised:

$$\begin{aligned} T_1 &= c_1 - \left(\frac{c_2 + c_3}{2}\right) \\ T_2 &= c_2 - \left(\frac{c_1 + c_3}{2}\right) \\ T_3 &= c_3 - \left(\frac{c_1 + c_2}{2}\right) \end{aligned} \tag{4.17}$$

$$\begin{aligned} H_1 &= (w + \alpha_1)c_1 + \left(\alpha_2 - \frac{w}{2}\right)c_2 + \left(\alpha_3 - \frac{w}{2}\right)c_3 \\ H_2 &= \left(\alpha_1 - \frac{w}{2}\right)c_1 + (w + \alpha_2)c_2 + \left(\alpha_3 - \frac{w}{2}\right)c_3 \\ H_3 &= \left(\alpha_1 - \frac{w}{2}\right)c_1 + \left(\alpha_2 - \frac{w}{2}\right)c_2 + (w + \alpha_3)c_3 \end{aligned} \tag{4.18}$$

From Eqn. (4.16) to (4.18), we deduce a new matrix as in Eqn. (4.19)

$$\begin{pmatrix} H_0 \\ H_1 \\ H_2 \\ H_3 \end{pmatrix} = \begin{pmatrix} \alpha_1 & \alpha_2 & \alpha_3 \\ w+\alpha_1 & \alpha_2 - \frac{w}{2} & \alpha_3 - \frac{w}{2} \\ \alpha_1 - \frac{w}{2} & w+\alpha_2 & \alpha_3 - \frac{w}{2} \\ \alpha_1 - \frac{w}{2} & \alpha_2 - \frac{w}{2} & w+\alpha_3 \end{pmatrix} \begin{pmatrix} c_1 \\ c_2 \\ c_3 \end{pmatrix} \tag{4.19}$$

The condition to enhance the image is $\alpha_i - \frac{w}{2} \geq 0; \quad i = 1,2,3$ and $w \leq 2\min(\alpha_i)$

Take Hence $(\alpha_1, \alpha_2, \alpha_3) = (0.2126, 0.7152, 0.0722)$ with $w = 2 * 0.05 \leq 2\min(\alpha_i), \rightarrow w = 0.1$

$$\begin{pmatrix} H_0 \\ H_1 \\ H_2 \\ H_3 \end{pmatrix} = \begin{pmatrix} \alpha_1 & \alpha_2 & \alpha_3 \\ \alpha_1 + 0.1 & \alpha_2 - 0.05 & \alpha_3 - 0.05 \\ 2\alpha_1 - 0.05 & \alpha_2 + 0.10 & \alpha_3 - 0.05 \\ 2\alpha_1 - 0.05 & \alpha_2 - 0.05 & \alpha_3 + 0.10 \end{pmatrix} \begin{pmatrix} c_1 \\ c_2 \\ c_3 \end{pmatrix} \tag{4.20}$$

$$\begin{pmatrix} H_0 \\ H_1 \\ H_2 \\ H_3 \end{pmatrix} = \begin{pmatrix} 0.2126 & 0.7152 & 0.0722 \\ 0.3126 & 0.6652 & 0.0222 \\ 0.1626 & 0.8152 & 0.0222 \\ 0.1626 & 0.6652 & 0.1722 \end{pmatrix} \begin{pmatrix} c_1 \\ c_2 \\ c_3 \end{pmatrix} \tag{4.21}$$

Each of the above 4D colour models had its strengths and limitations, which can be tested via experimentation. One major aspect of the colour model that poses challenges is selecting the best out of these models. Thus, to afford this challenge and as well to take advantage of all the colour information contained in the product image, a hybrid of these colour channels seems viable. To achieve this in this thesis Eqns. 4.9, 4.15, and 4.21 are combined to build unified image features of the 4D colour model Eqn. 4.22.

$$\begin{pmatrix} H_1 \\ H_2 \\ H_2 \\ H_4 \\ H_5 \\ H_6 \\ H_7 \\ H_8 \\ H_9 \\ H_{10} \\ H_{11} \\ H_{12} \end{pmatrix} = \begin{pmatrix} 0.3333 & 0.3333 & 0.3333 \\ 0.6666 & 0.1666 & 0.1666 \\ 0.1666 & 0.6666 & 0.1666 \\ 0.1666 & 0.6666 & 0.1666 \\ 0.299 & 0.587 & 0.114 \\ 0.6495 & 0.2935 & 0.057 \\ 0.1495 & 0.7935 & 0.057 \\ 0.1495 & 0.2935 & 0.557 \\ 0.2126 & 0.7152 & 0.0722 \\ 0.3126 & 0.6652 & 0.0222 \\ 0.1626 & 0.8152 & 0.0222 \\ 0.1626 & 0.6652 & 0.1722 \end{pmatrix} \begin{pmatrix} c_1 \\ c_2 \\ c_3 \end{pmatrix} \tag{4.22}$$

The proposed 4D-colour image-content representation (4D-*CIR or* simply put as *CIR*) algorithm described above extracts low-level from colour image features. Generally, colour image generates high dimensional feature vectors, which tends to heighten the complexity in the computational rate with little no improvement in performance. On this note, the Nx3 colour image map is a further process bypassing this feature through the colour histogram feature descriptor, Eigenvector colour decomposition algorithm, and selection of important features using the Kaiser Criterion retention approach. The procedures below were followed to determine Eigen Colour Features (ECF) of the Nx3 feature matrix that was extracted from a colour product image. This attribute is realised through the colour *image representation (CIR)* algorithm described in the procedure below:

Step 1: Extract 12 raw colour channels using the proposed four-dimensional (4D) colour models.

Step 2: Apply classical descriptor on each feature channel and combine to have colour image feature map X.

Step 3: Compute the covariance of the colour image feature-map matrix, to have an N x N square matrix A as shown in equation (4.23):

$$A(i,j) = \frac{X(i,j)X(i,j)^T}{N-1} \quad for\ i = 1,2,...,N,\ j = 1,2,3 \tag{4.23}$$

This is to accurately compute the variance and linear correlation of the Nx3 colour feature matrix.

Step 4: At this step, eigenvalues and corresponding Eigenvectors of the covariance feature map are determined.

$$\begin{aligned} \boldsymbol{AY} &= \lambda \boldsymbol{Y} \\ (\boldsymbol{A} - \lambda \boldsymbol{I}_N)\boldsymbol{Y} &= \boldsymbol{0}_N \end{aligned} \tag{4.24}$$

Where λ represents the eigenvalues that are traditionally placed at the diagonal of the matrix and *Y* is the eigenvectors associated with the corresponding eigenvalues. These equations captured the relationships among the square matrix, eigenvalues, and the corresponding eigenvectors. The homogenous equation has a non-trivial solution if and only if $|A - \lambda I_N| = 0$. Therefore, the non-zero vector Y that satisfies equation (4.24) can be deduced as follows.

$$\begin{vmatrix} a_{1,1} - \lambda & a_{1,2} & \cdots & a_{1,N} \\ a_{2,1} & a_{2,2} - \lambda & \cdots & a_{2,N} \\ \cdots & \cdots & \cdots & \cdots \\ a_{N,1} & a_{N,2} & \cdots & a_{N,N} - \lambda \end{vmatrix} = 0 \tag{4.25}$$

The eigenvalues λ are computed as the roots of the characteristics polynomial function of order N in Equation (4.25) in a similar way to the previous study (Gaidhane, Hote, and Singh, 2014). The values $\lambda_1, \lambda_2, ..., \lambda_N$ sorted in descending order give the components in order of significance alongside its corresponding eigenvector Y (Kalita and Das, 2013; Gaidhane, Hote, and Singh, 2014). The eigenvector that is associated with the smallest eigenvalue represents the least variance and the eigenvector with the highest eigenvalue represents the greatest variance of the extracted feature data (Tsymbal *et al.,* 2002). This process expresses the most significant relationship between the data dimensions and presents the most dominant principal component of a product image dataset. The Eigenvector decomposition extracts the positive definite symmetric characteristic of the image feature map, while Kaiser Criterion is employed to select the significant features from the extracted feature, which is referred to in this thesis as the Eigen Colour Features (ECF).

The essence of this procedure is to eliminate the curse of dimensionality (Pechenizkiy, Puuronen, and Tsymbal, 2003; Xu, 2012), which consequently reduces the computational complexity of images (Ponti, Nazaré and Thumé, 2016). Not only that, but this further processing maps the entire image low-level features to a high-level concept, and this improves the descriptive power of colour image feature. This is like what is done in (Jiang, Chan, and Zhang, 2005) where a token is extracted from a low-level feature in a region-based image. Finally, the image feature vectors, called Eigen colour features (ECF) are used to train a machine learning classifier to generate another high-level feature, image-class.

4.5 Enhanced image content-based classification model WITH ECF

The image-class attribute is realisable using machine learning classifiers. Item-class attribute is one of the targetted features this research work intends to use to realise user preference elicitation. In this work, an item-class attribute is realised via ANN-RBF, ANN-MLP classifiers, and as well as the newly proposed MKL-SVM *LaRBF* classifier. The operation of each of them on unified image features extracted from the 4D colour model is described.

4.5.1 Realising Item-Class Attribute with Unified Image Features and ANN-MLP

The training dataset for multilayer perceptron normally lies on a set of features that says x_k and t_k, where k denotes the total number of features in the vector; x_k stands for the input feature vector whereas t_k represents target vector.

In this study, symbol t_k for each of the hundred classes was preset using one-per-class coding method (Dietterich, and Bakiri, 1995; Aly, 2005) as shown in Table 4-1. Each class target vector holds a hundred elements with '1' in the spot of the class number and '0' in the rest positions. Since each output neuron is labeled as the task of recognising a given class, hundred neurons are needed in the output layer of the multilayer perceptron.

Table 4-1: One-per-class coding for MLP-ANN

Class/Index	***1***	***2***	***3***	***4***	***5***	***6***	***7***	***8***	***9***	***10***	***11***	***12***	***13***	***…***	***98***	***99***	***100***
Class1	1	0	0	0	0	0	0	0	0	0	0	0	0	**…**	0	0	0
Class2	0	1	0	0	0	0	0	0	0	0	0	0	0	**…**	0	0	0
Class3	0	0	1	0	0	0	0	0	0	0	0	0	0	**…**	0	0	0
…						…								…		…	
…						…								…		…	
Class 98	0	0	0	0	0	0	0	0	0	0	0	0	0	**…**	1	0	0
Class 99	0	0	0	0	0	0	0	0	0	0	0	0	0	**…**	0	1	0
Class 100	0	0	0	0	0	0	0	0	0	0	0	0	0	**…**	0	0	1

The need to have a more accurate model that will classify product images in the e-commerce domain spring-up an ideal to develop a salient framework shown in Figure 4-3. This formed one of the major components part of the proposed recommendation systems. With the help of the above algorithm, an *image-class feature* has been generated.

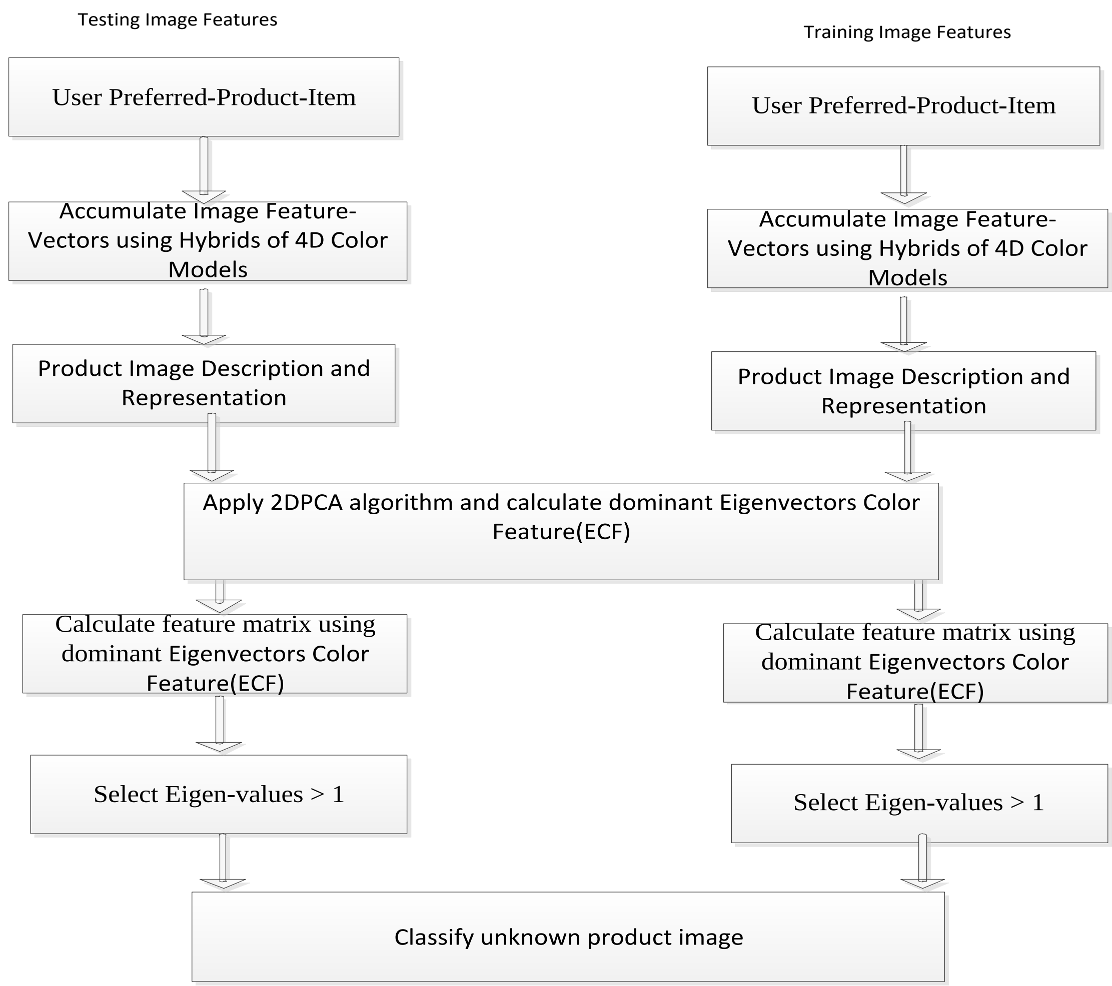


Figure 4-3: Proposed Four-dimensional (4D) Colour Image Representation Flow

Testing Mode: user prefers shopping item, probably an unknown shopping item, is mapped to the accumulated shopping items in the item profile to be converted to the testing matrix I_t of size $m \times n$. The image is projected on the dominated eigenvectors according to Eqn. (4.33). Thereafter the Euclidean distance di between Ft and Fi is measured as follows.

$$d_i = \sum \|F_i - F_t\|_2 \tag{4.33}$$

The proposed product item recommendation algorithm in this study makes its final decision to classify the unknown shopping item according to the minimum Euclidean distance. Furthermore, using a classifier with linear interpolation, the ANN-RBF (Q_0) that weights an input vector based on its distance to a neuron's reference vector are given as follows.

$$Q_0(D) = D^{-1} \tag{4.34}$$

Training Mode: With the training samples $(I_Q : Q = 1,2...\ Q_0)$ and the new input I_i , the algorithm finds output O for the networks:

$$O\ \alpha\ \frac{1}{Q_0}\sum_{Q} d_Q\ Q_0\ (\|F_i - F_t\|)\text{, where } d_Q = f(I_Q) \tag{4.35}$$

Simply put this algorithm assumes that the network has only one output neuron. However, any number of output neurons could be implemented to realise image-class attributes.

4.5.2 Encoding of Unified Image Features Vectors with ANN-RBF Classifier

Similar to the multilayer perceptron setting, the training dataset for RBF also lies on a set of features that says x_k and t_k, where k denotes the total number of elements in the feature vector whereas x_k and t_k stand for input feature and it equivalent target vector respectively.

The t_k for each of the hundred classes was preset with a 1-per-class coding method (Dietterich, and Bakiri, 1995; Aly, 2005) as shown in Table 4-2. As one could be observed from this table, each class target vector holds N elements with class index standing for the class label (1s for class1, 2s for class2). Since each output neuron is labelled as the task of recognising a given class, hundred of neurons are needed in the output layer of the RBF-ANN.

Table 4-2: One-per-class coding for RBF-ANN

Class/Label	***1***	***2***	***3***	***4***	***5***	***6***	***7***	***8***	***9***	***10***	***11***	***12***	***13***	***14***	***15***	***16***	***17***	***18***	***19***	***20***	***...***	***N***
Class1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	...	*1*
Class2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	...	*2*
Class3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	...	*3*
...							...								...					...		
Class 98	98	98	98	98	98	98	98													...		*98*
Class 99	99	99	99	99	99	99	99													...		*99*
Class 100	100	100	100	100	100														...			*100*

4.6 Item-Class Attribute and User preference Description

The idea of using a classification method to describe the elicitation of user preference is rooted in the category theory. The most familiar example of this structure is set-theoretic. The decision to use category theory to model user preference has stimulated the need for the application of recommendation systems. This section provides the fundamental explanation of the mathematical theory of category. The category theory uses morphism to show a connection amid two objects, for example, the connection amid the captured items and other items in the database.

4.6.1 Category Theory and Image-Class Similarity

Several approaches as introduced in Chapter-2, have been suggested on how user preference can be modelled from item characteristics and to mine user preference from user session data. In this section, user preferences are built based on category theory that is rooted in the categorical compositionality concept and implemented by an image feature-based classification approach.

Domain experts are often requested to provide item classification that is designed to assist users in locating their preferred product items quickly and effectively (Hung, 2005; Liang, *et al.,* 2010). One of the core advantages of product classification is that it shows item correlations within categories, which visually represent the structural relationship between categories. Moreover, in the e-commerce application domain, the classification or hierarchical structure of product items reflects the user preference from a category at the core nodes to a specific name of products that the user is interested in at leaf nodes (Kim and Chan, 2008). An intra-class similarity measure relevant to this research work is given as follows.

Definition 1 (Image Intra-Class Similarity Measurement)

Cosine similarity is the image similarity measurement adopted in this study as a similarity metric. It relies on the vector space model measure of similarity between a query image and the rest images in the base product item database (HUO, 2005). Now, given a preferred image q and a set of images in the base $I = \{i_1, i_1, ...i_n\}$. Suppose the query vectors $q = \langle w_1, 0, w_2, 0......w_n, 0\rangle$ and $I_j = \langle w_1, k, w_2, k......w_m, m\rangle$, *m* is the index numbers, w_j weight with index j to q, $\langle w_1, k\rangle$ the weight of the index in image *k*. So, the similarity $S_{i,j}$, between image I and image *J* can be determined using cosine measure of I_i and I_j.

$$S_{i,j} = \cos\theta = \frac{I_i \bullet I_j}{|I_i| \times |I_j|} = \frac{\sum_{k=1}^{m} w_{k,i} \bullet w_{k,j}}{\sqrt{\sum_{k=1}^{m} w^2{}_{k,i}} \sqrt{\sum_{k=1}^{m} w^2{}_{k,j}}} \tag{4.36}$$

4.7 User location Trajectories for Proximity Computation

The approach of user trajectories has been used in describing user location and applied to determine user proximity to shops where he/she can buy a particular item of choice. A location descriptor is a pre-filtering module that defines the user's geographical area and makes the nearest 8 shops visible to the user (Fang, *et al.,* 2012). The design of a location descriptor in the proposed recommendation system is based on the primary field tests (Fang, *et al.,* 2012). The authors reported that a mobile phone can detect signals from about eight nearby based stations. The similarity between the current user location and eight shops within the proximity of a customer is determined by the Haversine distance (Sinnott, 1984) and k-mean clustering algorithm in the design of the proposed shopping recommendation system.

Formally, the research work employed a k-mean algorithm to partition registered shops $Sh^t_{loc\_pt}$ (where $t = 1, 2, \ldots K$, and $pt = 1, 2, \ldots n$) in regional locations divided into $K - clusters$ $C_1, C_2, \ldots C_K$ $C_t = \{Sh^t_{loc\_1}, Sh^t_{loc\_2}, \ldots Sh^t_{loc\_m}, \ldots Sh^t_{loc\_n}\}$, loc_n may vary within each cluster, with spatial location and unknown" centroids" (μs). Each shop is represented and stored as $loc\_pt:t$ where $loc\_pt:t$ refers to the longitudes and latitudes of shop location. *K* number of clusters will have K-centroids $\mu_1, \mu_2, \ldots \mu_m \ldots \mu_k \in \Re^d$.

$$\mu_{t\_lat} = \frac{1}{n}\sum_{pt=1}^{n} Sh^{t}_{loc\_lat}$$

$$\mu_{t\_lon} = \frac{1}{n}\sum_{pt=1}^{n} Sh^{t}_{loc\_lon}$$

$$\mu_t = \mu_{lat} + \mu_{lon} \tag{4.37}$$

8-least most centroids are selected as visible clusters to u_a .

$$\mu = Min[\mu_t] \tag{4.38}$$

This implied that the appropriate cluster for u_a a cluster is μ.

In addition, the location descriptor module determines the proximity of u_a each shop, $Sh^t_{loc\_pt}$ within the cluster μ. This is done by computing differences between current user location u_{loc} and available clusters $Sh^t_{loc\_pt}$ within cluster μ (Adair and Turnbul, 1974). The difference between user location and other shops within that cluster is determined using:

$$d_i(U, Shop) = \{u_{loc} - Sh^t_{loc\_pt}\}$$

$$d_1 = \{u_{loc} - Sh^1_{loc\_1}\}$$

$$d_2 = \{u_{loc} - Sh^2_{loc\_2}\}$$

$$\dots$$

$$d_n = \{u_{loc} - Sh^n_{loc\_n}\} \tag{4.39}$$

Explicitly, d_1 is determined using the Haversine formula (Sinnott, 1984) given as

$$d_1 = \frac{2 * a\sin(sqrt(\sin((loc\_lat - loc\_lat1))^2}{2} + \cos(loc\_lat) * \cos(loc\_lat1) * \frac{((\sin(\sin((loc\_lon - loc\_lon1)))^2}{2} \tag{4.40}$$

For implementation purposes, all components of d_i were normalised thus:

$$d_1 = \frac{d_1}{\sum_{i=0}^{n} d_i}, d_2 = \frac{d_2}{\sum_{i=0}^{n} d_i} \dots d_m = \frac{d_m}{\sum_{i=0}^{n} d_m}, \dots d_n = \frac{d_n}{\sum_{i=0}^{n} d_i} \tag{4.41}$$

4.8 User temporal Preference Model

User preference change over time and item recency deteriorate slowly over time (Yehuda, 2010). This temporal information can be extracted from many entities such as item life cycle, expiring date, click history, news item publish time, periodic shopping styles, and use as a weight.

The proposed user temporal preferences model is meant to determine the recency weight of an item, to realise user preference drift over time. The main clue of this time-weighted algorithm rests on how to determine apt weights for all items, in such a way that items purchase recently contribute more to the subsequent recommend and as such, recent items are usually assigned higher weight value than those that have been purchased earlier. The theoretical components of this model consist of similarity function, time-decay function, and item-timestamp, will be discussed below:

4.8.1 Content-based item similarity algorithm

The item similarity is one of the major operations that are often performed in content-based recommendation systems. Item similarity problem can be represented as follows: Given a database D as a tuple < AU_i ; I_j ; $Fv_{i,j}$; $T_{i,j}$ >, where AU_i identifies the i^th^ active mobile user of the system. I_j identifies the j^th^ items of the system, $Fv_{i,j}$ represents the i^th^ feature vector of the j^th^ item, and $T_{i,j}$ represents timestamps that record the time when an active user i purchased item j. Find a list of k recently invoke items that will suit the preference of Active User (u_a) for each user U. To start with, the first step is to determine the similarity between I_a (the input/ or capture item by the user) and I_b (others items in the database).

There are three main approaches to determine the matching similarity score between two product items in the context of content-based recommendation as follows.

Cosine similarity: Fundamentally, an item is seen as a vector in the N-dimensional user space. The similarity score between different items is determined on this background using the cosine similarity as in Eqn. 4.36.

Pearson correlation coefficient: The similarity between two product items is measured with this metric as follows.

$$sim(I_a, I_b) = \frac{\sum_i^m \left(F_{ia} - \overline{F}_i\right) \times \left(F_{ib} - \overline{F}_i\right)}{\sqrt{\sum_i^m \left(F_{ia} - \overline{F}_i\right)^2} \sqrt{\sum_i^m \left(F_{ib} - \overline{F}_i\right)^2}}, \quad (4.42)$$

where $\overline{F}_i$, represents the average of the i^{th} feature vector of item a.

Conditional Probability-Based Similarity: It is an alternate way of calculating the similarity of two product items. That is,

$$P(i/j) = sim(i,j) = \frac{Pur(i,j)}{Pur(j)} \quad (4.43)$$

$$Sim(i,j) = \frac{1}{diist(i,j)} \quad (4.44)$$

$$Sim(i,j) = \frac{Pur(i,j)}{Pur(j)} = \frac{Num(i,j)}{Num(j)} \quad (4.45)$$

$$Sim(i,j) = \frac{Pur(i,j)}{Pur(j)} = \frac{Num(i \cap j)}{Num(i) \times (Num(j))^{\lambda}} \quad (4.46)$$

where $Pur(i)$, is the number of i^{th} items that have been purchased and λ is a parameter that takes values from 0 to 1. $Num(i,j)$, stands for the total number of times both item I, and j have been purchased together. $dist(i,j)$, represent the distance between items i and item j, when $\lambda = 0$ Eqn. 4.46 turn back to becomes

Eqn. 4.45. Similarly, when $\lambda = 1$, Eqn. 4.46 becomes symmetry. $P(i/j)$, the probability that an active user has purchased an item i under the condition that he had purchased item j before. All the above-mentioned similarity functions ignored the time factor. In this work time, the decay function is integrated with the similarity function and item recency timestamps are taken as an argument to conventional similarity function.

4.8.2 Time-decay algorithm

In an attempt toward injecting temporal components, time decay is integrated. Time decay is selected as part of this proposed model as it relatively models the ideal of decreasing preferences of a user as time increases. Fundamental theories of decay functions such as the exponential, power, linear, and logarithms have been covered in chapter four of this thesis. A comparative analysis is performed on the four most popular time decay functions in section 6.5 to determine the best one for product item recommendation.

4.8.3 Item timestamps

Item recency timestamps serve as an argument to the time decay function that is attached to the conventional similarity function. T_j *and* T_c, are two algebraically calculable timestamps that record the time when an active user captured i and purchased item j find within time range interval units t. $\left|\mathrm{T_j} - T_c\right|$, denotes the time lag between the two components. The number of basic time interval units between T_j *and* T_c is 7 days used by default as a periodic shopping pattern.

4.8.4 Building dynamic image content-based similarity

The purchase interest of a user is sensitive to time, therefore in eliciting the user preference and building personalised recommendations, a time-based function needs to be integrated. On this note, this work proposes a dynamic image content-based similarity, (that is simply referred to in this work as the item-recency model). This model is designed to allocate a higher level of significance to the latest purchase item in the recommendation process. The proposed model can be described with equation 4.47 as follows:

$$jRECENCY_c^t = Sim(c, j) = \frac{1}{d_{c,j} * \theta|\nabla t|} \tag{4.47}$$

Item-Timestamps, $\theta|\nabla t| = \theta|T_i - T_j|$

Where

$jRECENCY_c^T$, represents the recency scores or similarity score ($Sim(c, j)$) of item j, relative to the active user has captured item I_c, within the time lag $\theta|\nabla t|$. T_c, represents the time a user captured the initial preference item I_c. I_i Identifies other items in the same class with the capture item. Furthermore, the proposed time lag function presumes that the $\theta|\nabla t|$ is a monotonic decreasing function. This function reduces the uniformly within time T and the value of the time weight lies in the range (0, 1). That is, all the information extracted from all product items contribute to the recommendation of product items with the most recent information contributing the most. The old information, which reflects the previous user preferences, should have small weights in the recommendation results. The $d_{c,j}$ is a minimum distance of the item preferred by a user and j with the corresponding purchase dates T_c and T_j.

The intuition behind the proposed similarity approach is that two items are like each other when their purchasing dates T_c and T_j were close. The distance between when a user requests for purchase and former periodic requests because of the recent purchases are deemed to be more relevant.

4.9 Building Item and User profiles

The process of personalised recommendation of product items starts by building a profile for the user. A user profile often contains a set of features of interest and different types of information. The two types of information that often exist in the user profile are the following.

1. The history of the previous interactions of a user with the recommendation system. The profile information may include storing product items that a user has viewed with other information about the interaction.
2. The preference model such as the description of the types of product items that interest the user.

The current work deals with the second type of information, where the process commences by extracting the essential item information. The extracted information is derived from image representation and modelling of image features that are jointly shared by item classes. This makes the proposed system in this research work fit as an e-commerce application. At the onset image, the histogram of the Eigen colour feature (HECF) acquirable from each item is used to deduce the image category. These two features, in turn, are combined with other vital item information such as distinctive identifier, incentive, price, shop-location, recency, and image (logo) to build an item profile. In addition, unique salient image feature vectors are extracted and kept in the item database.

Generally, a recommender could efficiently be represented as a vector of *m* values $I = i_{1,} i_{2,} i_{3,} i_{4,} .....i_m$, where the value i_j may be nominal or numeric. An instance of the item feature vector is:

> i = (22315*,* “Face *Helmet*”*,* “Helmet”*, {. . .}* Mandyam, and Boyns, 2008*,* 1099.0*,* “Game”*, {*−29.73*,* 30.53*},* recently “2” i_8= 2 (i.e. recently purchased within 20 days period of time), “15 inch by size”, “1-year warranty”*,* 45), with : a distinctive identifier i_1 = 22315, and product name i_2 = “Face *Helmet*”, that is, regarded as the category i_3 = “*Helmet*”, with logo denoted by feature vector i_4 = *{. . .}* is sold at an average price of i_5 = 1099.0 Rand, at retail shop i_6 = “Shoprite” located at positioning coordinates (latitude and longitude) i_7 = *{*-29.73*,* 30.53*},* i_8= 2, that is recently purchased within 20 days period of time with specific features i_9 = “15 inch by size, “1 year warranty”, and incentive score, i_{10} = 45%.

In addition, the user profile can be represented as a vector of k values $u = u_{1,} u_{2,} u_{3,} u_{4,} .....u_k$. A typical instance of such a user profile is:

> u = (838990413290*,* 8560804202777*, {. . .},* 5*,* 6*,* 7*,* and 8), *with*:
> a key identifier u_1 = 838990413290 and u_2 = “Face *Helmet*”, that has logo denoted by the vector u_3 = *{. . .}* proximity, price-range, bait criteria-range, and size-range, recency.

where the unique identifier is the phone international mobile equipment identity (*IMEI*). Proximity is the user's closeness to the item location determined by GPS coordinates. The *logo* is the product item image that generates the salient image features representation of an item. Price range is what can be regarded as the range of prices for a particular item varying in size. In the same view, size range refers to various sizes that are available for an item. The user profile is modelled in a similar way to the item profile as a feature vector of m feature values.

4.10 Recommendation Computation Stage

The recommendation computation stage is like the filtering component in generic architecture discussed in chapter two. At this stage, all criteria information must have been accumulated and worked on by both similarity and ranking algorithms. The image category generated from the preference elicitation stage and image-salient feature is used to achieve intra-class similarity based on the initial preferences of a user. At this step, the acquired information is accumulated, and recommendation scores are computed using related algorithms.

The majorly existing recommendation algorithms can be classified specifically based on the type of input data used in the recommendation process (Liu, Mehandjiev, and Xu 2011). In this classification, two metrics are used in the classification namely: the total of criteria considered and that of context dimensions considered when recommending. These algorithms can be traditional recommendation systems such as collaborative, content-based, and hybrid, single criterion multi-dimensional system, multi-criteria 2-dimensional system, and multi-criteria system. *Criteria* stand for the different features of an item that satisfy the preferences of users. The ratings over the criteria reflect the user satisfaction of the item in meeting those needs or objectives. This gaps the c*ontext* dimensions, which signify diverse types of context parameters pertinent to the selection of the preference item.

In general, user preference can be acquired explicitly or implicitly. The former usually comes in the form of a rating where a user needs to express how much he/she likes an item. On the contrary, the implicit approach of user preference is automatically acquired from each user interaction with the environment. This type of approach is usually denoted by a set of 0's or 1's. In principle, this approach assumed that if an active user captures or clicks on an item, it means such a user has an interest in it, even if in the end, he did not purchase it. Recommendation systems that integrate both explicit and explicit approaches stand to gain the merits of both (Adomavicius and Tuzhilin 2005; Olugbara, Ojo and Mphahlele 2010). The use of a mobile-enabled device to capture an item preferred by a user is a typical example of an explicit approach. The auto-classification of product items can be referred to as implicit.

Product image categories normally build a hierarchy with many levels of abstraction based on semantic information. This semantic information can be used to label product items in a tree-like structure, from coarse-grained to fine-grained classes. In broad terms, product categories can be logically designed such that the root category of this tree-like structure is the most general and the classes become more exact towards the leaves. In this regard, one can rightly opine that the similarity of a user's interest to one item is concomitant with the semantic information generated in a classification-based system.

Against this background, this thesis proposes a framework based on a semantic image-based classification model to elicit the interest that an active user u_a has in a product item i_j, given product classification categories and the set of product items contained in each category. The image-based classification technique is used to achieve semantic similarities based on the class of product items preferred by a user and the rest of the items in other classes. The following needs to be observed to achieve such semantic similarities in a particular application domain such as e-commerce.

(1) The total number of product item categories ought to be well known.

(2) Build product item categories.

(3) Individual product items sought to be apportioned to the appropriate category.

More strictly, product image classification can be expressed thus: assume a database has N images $i_j \in [1, N]$ and the resolution of each image is $W \times H$ and the corresponding labels classes are Cat_j. The target of learning a more efficient representation $R(.)$ of i_j is to minimize the loss function $\sum_{j=1}^{N} \| C(R(i_j - Cat_j)) \|$, where $C(.)$ denotes a classifier. Every product item is characterised as a local feature vector *i,* which has values between 0 and 1, where

$$C\,(i_{j,\ Cat}) = \begin{cases} 1\, indicates\, that\ product\ j\, is\, assigned\ to\ a\ category\ Cat \\ \\ 0\, indicates\, that\ product\ j\, is\, not\ assigned\ to\, the\, rest\ (N-1)\, categories \end{cases} \quad (4.48)$$

$CatSize$, is the number of the classes of product items under consideration. The rationale for using the classification framework is that a user may have interest in a particular product, say beverages category, even though the user has not rated or purchased any product item in this category. The proposed framework provides a training method that can help recommendation systems realise this same role as human beings do. The proposed framework can allow a recommendation system to infer and extrapolate user preference from the limited information. This shows that user preference can be learned from the description of multiple component image information of a product item (Olugbara, Ojo, and Mphahlele 2010).

The relevant research works in the area of hierarchical classification that centers on applying the product hierarchies for enhancing efficiency are at this point mentioned. Albaradei and Wang (2014) have offered a new object classification that is based on a semantic hierarchy approach. This approach has relied on binary SVM classifiers and concept pairs for mid-level representation of the binary SVM classifiers. Gao *et al. (*2011) proposed a method that allows the overlying of object classes at every dissimilar child node. Deng, Berg, and Fei-Fei (2011) used object hierarchy to improve image retrieval and provide tradeoffs between accuracy and specificity in a large-scale recognition system (Deng *et al.,* 2012).

In Fan *et al.,* 2008 SVM-based classifier and mean shift method were used, to achieve image classification and automatic object image segmentation respectively. This method is utilised to extract semantic information of salient objects. Nadee, *et al.,* 2013 in their own opinion -- terms used to describe items can be formed as a concept hierarchy, as such concepts vectors are used to describe user profiles. The researcher also develops a concept hierarchy along with a new ranking function to address *new user* problems.

The proposed image-based classification strategy of this thesis is, therefore, to assign a label of one of the existing product categories Y_j, corresponding to leaf nodes in a category of items where the most specific semantics score or distinctiveness score is 1. Figure 4-4 illustrates an example of a classification tree realisable from the classification algorithm and kNN nearest neighbors. For a given image, extract perceptual information of salient objects by automatic image segmentation based on a salient region of a saliency detection model and image classification by using the ensemble of classifiers. Thereafter, intra-class similarity filtering is performed amid two items *i,* and the rest of items *j* which are computed with the standard vector-based kNN similarity algorithm. All e-commerce websites practically store items in this hierarchical order (Shambour, Hourani, and Faihat, 2016).

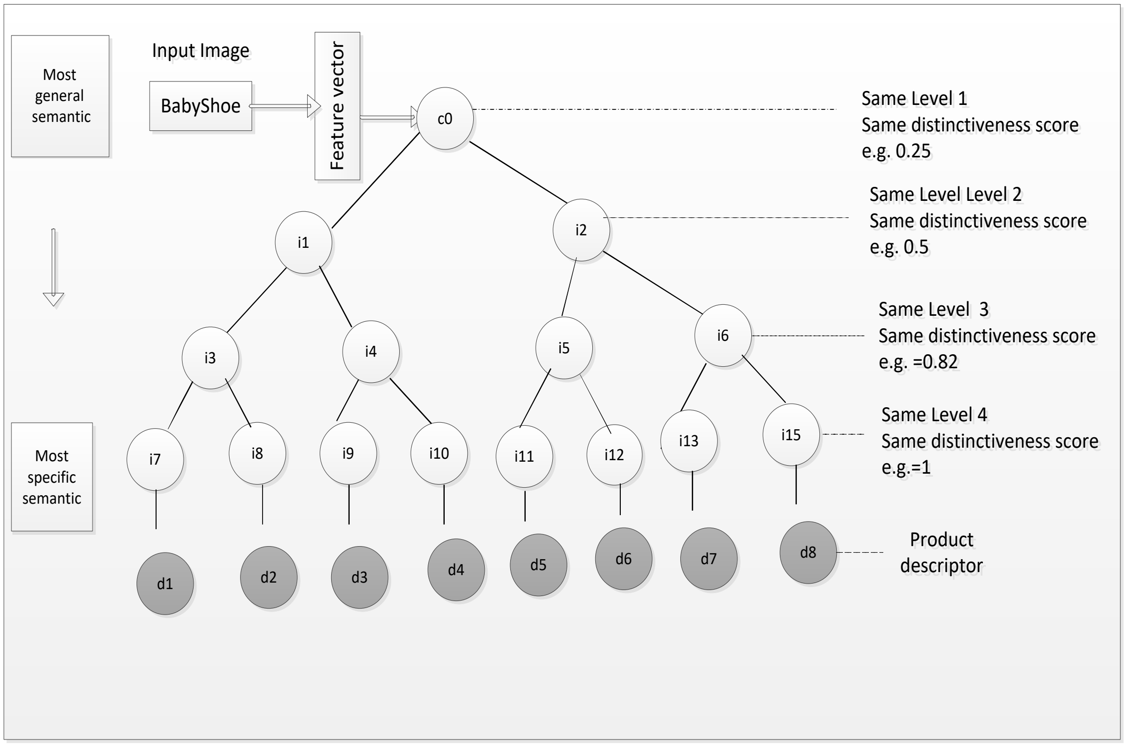


Figure 4-4: Tree-structured hierarchy of a semantic image-based classification

Inspired by the approach of Olugbara, Ojo and Mphahlele, (2010) this thesis provides an effective way to use semantic image-based classification attribute with image social context to generate user preference. The rationale is that instead of characterizing user preference with only item social-context attributes, the system can be made to learn these preferences (or interests) through other image-based attributes in particular classification-based semantic information of product items. The simple idea behind the semantic classification model is the axiom that a user has preferences that could be linked with notions of hierarchy. This in a way also reflects the fact that user preference is categorical and multi-criteria in nature rather than single items (Adomavicius and Tuzhilin 2005; Olugbara, Ojo and Mphahlele 2010). Subsequent sections reviewed popular classifiers often used in the e-commerce domain.

4.10.1 Neighborhood Formation and Intra-Class Similarity

Since the introduction of the first automated personalised recommendation systems by the GoupLens system (Resnick *et al.,* 1994), recommendation ratings for everyone have been used to identify the neighborhood of similar users or items. The image information has been used for neighbourhood-based classification (Desrosiers and Karypis, 2011) and is followed by the interclass image. Given as an image class for img the transitional implicit short-term profile can be created as a set of items $i = \{i_1, i_2, i_3, i_4, \ldots\ldots i_m\}$ that are in the same category as img. This process can be represented formally as follows.

$$img \xrightarrow{matched} ItemCat_{1,2,\ldots.N} = \{i_{1,} \; i_{2,} \; .i_{3,} \; \ldots i_{m,}\} \tag{4.49}$$

The user preference can be represented by a feature vector and each entry of the vector denotes the user interest in a product category. Likewise, in a user-item space, an item i_k is considered as a vector of dimension $|k|$ in which each entry serves as the link between the product item and a set of class elements in a 2-D space.

Generally, neighbourhood formation creates a subclass of most similar items $i_q \in I$ for an active user a_u. The neighbourhood formation process is one of the most vital processing steps in the process of generating recommendations. The notion of neighbourhood formation is meant to shrink the dimension of the neighbourhood that is built for the initial preference item in a large database. In the e-commerce application domain, if every product item is considered as a neighbourhood in a large database, this will adversely affect the performance of the system by slowing down its computation time and quality of its predictions (Jannach, *et al.,* 2010).

Classification methods have been found useful in increasing scalability (Jain and Wadekar, 2011) and improving overall recommendation accuracy. In this thesis, Neighbourhood-based classification and k-Nearest-Neighbours algorithms are utilised to find product item neighbourhoods. The image classification-based semantic process starts by determining the appropriate class Y_j, for the captured product item corresponding to leaf nodes in a category, where the most specific semantics score or distinctiveness score is 1. Thereafter, the neighbourhood for an active user u_a, the preferred item is determined by finding the similarities between the preferred and other items in the leave nodes. Similarity scores can be determined using functions such as the Jaccard coefficient, Pearson coefficient, and cosine similarity (Desrosiers and Karypis, 2011). However, the inadequacy of rating data often results to an incorrect neighbourhood formation. The ripple effect of this often lowers recommendation quality.

In this thesis, neighbourhood formation is formed by first determining k-neighbour items that are most similar to u_a preference items. The kNN and image-content-based matching methods are used rather than using item rating methods. The kNN selects the Top-N neighbourhood items that have the closest distance to the preference of the active user u_a. This is determined by computing the distances between the items the active user-preferred, and other items i_q at the nodes of the category tree.

4.10.2 Image feature matchmaking and similarity measurement

The advancement in the development of various techniques for digital images has encouraged the corresponding progress in realising that efficient techniques can be applied for image storage, filtering, retrieval, and indexing. In the same view, it is quite certain that the efficiency and effectiveness of any retrieval technique will depend on the similarity algorithm that is used in performing matchmaking. If an appropriate algorithm is chosen, this will enhance the final retrieval result. In this section, research work of image similarity measurement functions based on primitive features such as shape, colour, and texture is discussed.

- **Semantic image matching with similarity measure:** The concept of similarity has been successfully applied in many areas of artificial intelligence. In general terms, similarity expresses the degree of coexistence as it relates to extracted features of two image objects. In other words, it is a numerical measurement that tells the strength of closeness between two objects. Similarly, dissimilarity is a related measure of similarity that echoes the level of divergence between two objects of a reference set. The similarity between a preferred item i_k by a user and other images i_q in the database of N product images $i_j \in [1, N,]$ can be assessed through the extracted salient features of the images. The Euclidean distance function or any other similarity measure can then be used to decide whether two feature descriptors match each other or not. The value of item-based semantic similarity among a preferred item i_k and other items i_q can be denoted as the distance between two entities as follows.

$$d_{i,iq}^2 = (i_1 - i_q)^2 + (i_1 - i_q)^2 \qquad (4.50)$$

This implies that $d_{i,iq}$ is the square root function as follows.

$$d_{i,iq} = \sqrt{(i_1 - i_q)^2 + (i_1 - i_q)^2} \qquad (4.51)$$

The above is called the squared length of **x** that can be denoted by $d_{i,0}$ and the zero vector is called the *origin* of the space. In this research work, a definition of (dis)similarity is provided.

$$d_{i,0} = \sqrt{i_1^2 + i_q^2} \tag{4.52}$$

- **Definition 1:** A similarity measure is an upper bounded, exhaustive, and total function $s: X \times X \rightarrow I_s \subset \Re, \quad where\ \Re\ is\ the\ set\ of\ real\ numbers \left|I_s\right| > 1$. Therefore I_s is upper bounded and $\sup I_s$ exists.
- **Definition 2:** A dissimilarity measure is lower bounded and extensive exhaustive, as well as total function, $s: Y \times Y \rightarrow I_d \subset \Re, \quad where\ \Re\ is\ the\ set\ of\ real\ numbers \left|I_d\right| > 1$ (therefore I_d is lower bounded and $Inf\ I_d$ exists.

The connection that exists between similarity and dissimilarity gives room for the derivation of similarity constant values from dissimilarity values. The bond is given as follows.

$$s_{ij} = 1 - d_{ij} \tag{4.53}$$

where d_{ij} *is a normalised dissimilarity value between product image objects i and j such that* $s_{ij} \in [0,1]$ can be written as follows.

$$s_{ij} = 1 - 2d_{i,j} \tag{4.54}$$

Where d_{ij} *a normalised dissimilarity value between objects i and j* $s_{ij} \in [-1,1]$. Likewise, the equivalent relationship amid dissimilarity and similarity measurements can be determined as follows.

$$s_{ij} \geq s_{iz} \Leftrightarrow d_{ij} \; d_{iz}, \forall i, j, z \in x \tag{4.55}$$

4.10.3 Multi-Criteria Based Recommendation and Ranking

Multiple criteria-based recommendation system aggregates all criteria scores, ranks, and infers user interest according to his/her desired preferences. This system contains a user profile that stores all the extracted scores on each of the attributes. The problem can be formulated formally as follows.

$$MSimItem = SELECT \; FROM \; \{i_1, i_2, \ldots i_n\} \leftarrow CRITERIA \; \{CusReQScore_j, q_1, q_2 \ldots q_r\} \tag{4.56}$$

The focus of this multi-criteria ranking is to discover a set of product items that maximises the preferences of a user at a particular time. The multi-criteria rating system has more information about the items preferred by a user more than a single rating system. This information can be effectively used in the recommendation process to generate product items that meet user preferences. The multi-attributes scores are aggregated as the optimization problem of minimising and maximising the cost and benefit criteria to have an ideal preference ranking recommendation. The ideal preference ranking can be seen as being determined by a function that considered all the possibly conflicting criteria concomitantly. In past works, the averaging technique is a simple approach that is always used. An advanced and more promising approach based on the application of machine learning techniques to discover any existing veiled relationship among product items in user profiles. In this thesis, a technique for order performance by similarity to ideal solution (TOPSIS) has been adopted, but with a new modified weight, the model incorporated to assemble all the extracted image attributes.

TOPSIS is a famous method suitable for resolving a multi-criteria decision problem (Hwang, and Yoon, 1981). The main idea is that out of several competing alternatives, the best alternative should have a shorter distance from the positive ideal solution and farthest from the negative ideal solution concomitantly. Relating this to the work at hand, this is tantamount to finding an optimal shopping item, which satisfies the interest of a shopper. The virtue of the TOPSIS method rests on the fact that it can successfully handle both quantitative and qualitative data when its process evaluation is based on little computation load. The proposed multiple criteria decisions making (MCDM) based method evaluates various shopping items in the database against the given shopper requirement information and criteria and generates a list of most similar items (*MSItem*) that could satisfy user interest. This treats a set of items that are made available to users at a particular location as the alternatives and a set of qualifying item attributes as the criteria to be used by an MCDM-based method. The first thing to do in this regard is to build a rating table of the extracted criteria and a standardised decision matrix r using the following formula.

$$r_{i,j} = \frac{X_{i,j}}{\sqrt{\sum_{i=1\ldots n} X_{i,j}^{2}}} \tag{4.57}$$

A decision matrix r is a i,j matrix in which an element $x_{i,j}$, indicates the preference utility on an item i when j a criterion is considered. In the determination of the weighting process, the entropy method is adopted in combination with the analytical hierarchical process (AHP), to get a more reasonable and personalised weights model. The eigenvalue method in AHP was used in this study to estimate the subjective weights and the information entropy method to determine the objective weights of decision criteria. On this basis, a new modified weight function is obtained for TOPSIS as follows. The amount of information contained in *Eqn*. 4.57 that is associated with each criterion can be measured by the entropy value e_j as follows.

$$e_j = -k\sum_{j=1}^{n} r_{i,j} \ln r_{i,j} \tag{4.58}$$

Where the value $k = (\ln(n))^{-1}$ is a constant that guarantees $0 \le e_j \le 1.$ and n is the number of decision alternatives that were considered. The degree of divergence d_j of the average information contained by each attribute/criterion $C_j \quad j = (1 \ldots n)$ can be calculated as follows.

$$d_j = 1 - e_j \tag{4.59}$$

The value d_j represents the inherent quality possess by criterion C_j. The more divergent the performance rating $r_{i,j}$ for the criterion C_j, the greater is the resultant d_j. This is also the weightier the criterion C_j is for the decision-making problem under concern (Hwang and Yoon, 1981). The objective weight for each criterion can be obtained using Eqn. 4.65.

$$d_j : \lambda_j = \frac{d_j}{\sum_{i=1}^{n} d_j} \tag{4.60}$$

Let the subjective weights obtained using AHP in the consideration of the preferences of a user be ω_j. The overall preference weight used in this thesis is calculated as follows.

$$W_j = \frac{\lambda_j \omega_j}{\sum_{i=1}^{n} \lambda_j \omega_j}. \quad (4.61)$$

Where ω_j is the weight of the criterion j and $W_j = (\omega_1 \ldots \omega_n)$ is a normalised weight matrix in such a way that $\sum \omega_j = 1$.

Finally, the weight function is determined by a hybrid of entropy method and AHP to obtain a more reasonable and personalised weight function. The core eigenvalue method in AHP was used to estimate the subjective weights of decision elements while the entropy method was used to determine objective weights from a user profile. On this basis, a new modified weight was obtained and used to construct the standardised weighted decision matrix of Eqn. 4.62.

$$V_{i,j} = \omega_j * r_{i,j} \quad (4.62)$$

Let benefit criteria be denoted by J = distinctiveness, incentive, and recency while cost criteria are denoted by J' = Price and distance. Against this background, the positive ideal solution (PIS) is given by Eqn. 4.63.

$$A^{Ideal} = \left\{ \; V_1^{Ideal} \ldots\ldots \; V_j^{Ideal} \ldots\ldots \; V_n^{Ideal} \right\} \quad (4.63)$$

Where $V_j^{Ideal} = \left\{ Max_j (V_{i,j}) \mid j \in J; \quad \left\{ Min_j (V_{i,j}) \mid j \in J' \right\} \right.$

While negative ideal solution (NIS) is given by the following equation.

$$A^{Nideal} = \left\{ \; V_1^{NIdeal} \ldots\ldots \; V_j^{NIdeal} \ldots\ldots \; V_n^{NiIdeal} \right\} \quad (4.64)$$

Where $V_j^{NIdeal} = \left\{ Min_j (V_{i,j}) \mid j \in J; \quad \left\{ Max_j (V_{i,j}) \mid j \in J' \right\} \right.$

The next step is to determine separation from an ideal solution. This is done by taking the square root of the square of deviation, V [i, j] from the ideal solution:

$$S^{Ideal} = \left[\sum_{j} \left(V_{j}^{Ideal} - V_{i,j} \right)^{2} \right]^{\frac{1}{2}} \quad i = 1.......m \tag{4.65}$$

The same is done to a non-ideal solution.

$$S^{NIdeal} = \left[\sum_{j} \left(V_{j}^{NIdeal} - V_{i,j} \right)^{2} \right]^{\frac{1}{2}} \quad i = 1.......m' \tag{4.66}$$

Finally, the following equation was used to calculate relative closeness to the ideal solution. The result $C^{Ideal}(i)$, which is the closest to 1 is selected as the most preferred product item.

$$C^{Ideal}(i) \quad = \quad \frac{S^{NIdeal}(i)}{S^{Ideal}(i) + S^{NIdeal}(i)} \tag{4.67}$$

4.11 Recommendation Presentation Stage

The recommendation presentation stage is the third fundamental processing step of recommendation systems. At this stage, recommendation output is displayed on the interface to a user to either accept or amend. The output can either be in the form of text, image, or a combination of them. In addition, rich contextual information about a user can effectively be elicited to characterise the shopping interests of a user.

As shown in Figure 4-1, the imaging interface represents the central access point to a recommendation process. This interface takes advantage of mobile devices to propose an interface in a 3-tier client and server recommendation architecture for shopping items. The imaging interface aspect is envisioned to offer users native experiences. On this note, the design and implementation of the proposed imaging interface are based on a recently emerging trend of mobile application development, which has to do with the application of cross-platform application development frameworks. This approach allows system developers to take advantage of the hardware capabilities of emerging mobile devices without caring about the multiple underlying operating systems (Mesfin, *et al.,* 2016). The proposed recommendation architecture of this study is anchored with an imaging interface that is implemented using the PhoneGap3.0 technology unlike most of the research works in the literature on mobile recommendation systems.

PhoneGap is one important facility that is often used, because of its popularity (Isabelle, *et al.,* 2013; Manuel, Singh, and Cicchett, 2012). PhoneGap is a free and open-source framework for creating native software applications for different mobile operating systems, including iOS, Android, Blackberry, WebOS, Windows Phone, and Symbian devices. It acts like a “wrapper” that gives ample chances for developers to encode applications written in a known language into a native application. It did allow a mixture of both native and web-based codes (Manuel, Singh, and Cicchett, 2012). Smartphone applications can be appositely classified into the categories of native and cross-platform. The native smartphone applications are operating systems specific. The various smartphones in this category have unhindered access to device hardware, user interface, and all possible interactions in that mobile operating environment (William, 2013). On the other hand, cross-platform applications can conceptually be dedicated mobile web applications, generic mobile web applications, and hybrid applications (William, 2013). However, cross-platform refers to those dedicated mobile web applications designed to imitate native applications of the host operating systems but can execute on a web browser. Such applications are implemented based on a web browser, using fundamental web technologies like hypertext markup language (HTML5), JavaScript application development interface (API), and cascading style sheets (CSS). The application can be deployed into another platform through a wrapper.

4.12 Imaging User-Interface

The user interface is another important component that is often considered in eliciting user preference and delivery of personalised recommendations (Li and Murata, 2011; Pommeranz, et al, 2012). Generally, a user interface can be image-based, map-based, or text-based. Most of the existing content-based recommendation algorithms relied on text-based (Olugbara, Ojo, and Mphahlele, 2010). One major task that is germane to accurate elicitation of mobile user preference is consideration of the mobility nature of mobile users, and the system interface that can adapt to changes in the environment as well as user preference (Neammanee and Maneeroj, 2018). Recommendation accuracy is extremely important in the e-commerce environment, and this is often affected by the limited display sizes of current mobile devices. The recommender system is constricted ideally to provide a small set of highly relevant items that fit in the display. This task remains a challenging one in mobile recommendation technology. In response to this, a new mobile user interface that is evolving now is structured in such a way that mobile users can dynamically interact with their environment via any mobile device, irrespective of the system operating system is one of the apt solutions.

The current research work uses image capturing, a dynamic explicit transaction approach to acquire a shopping-item image. This user interface approach anchors the proposed recommendation architecture. Capturing product images by using a camera-enabled mobile phone affords users stress-free, quicker, and potentially more accurate results than using keywords (Kim, *et al.,* 2010). In addition, customers derive hedonic, utilitarian, self-oriented values by interacting directly with real-world images (Salo, *et al.,* 2013). Thus, in this thesis, the built-in camera in mobile phones is utilised as a tool for data collection. This user interface, which utilises the idea of Phone-Gap technology to design and implement dynamic user-interface on a mobile device, serves as a proof of concept. Dynamic user-interface safes a mobile user from the trouble of using a static explicit rating approach that is highly deficient in coping with the dynamic nature of mobile users (McCarthy, et al, 2005).

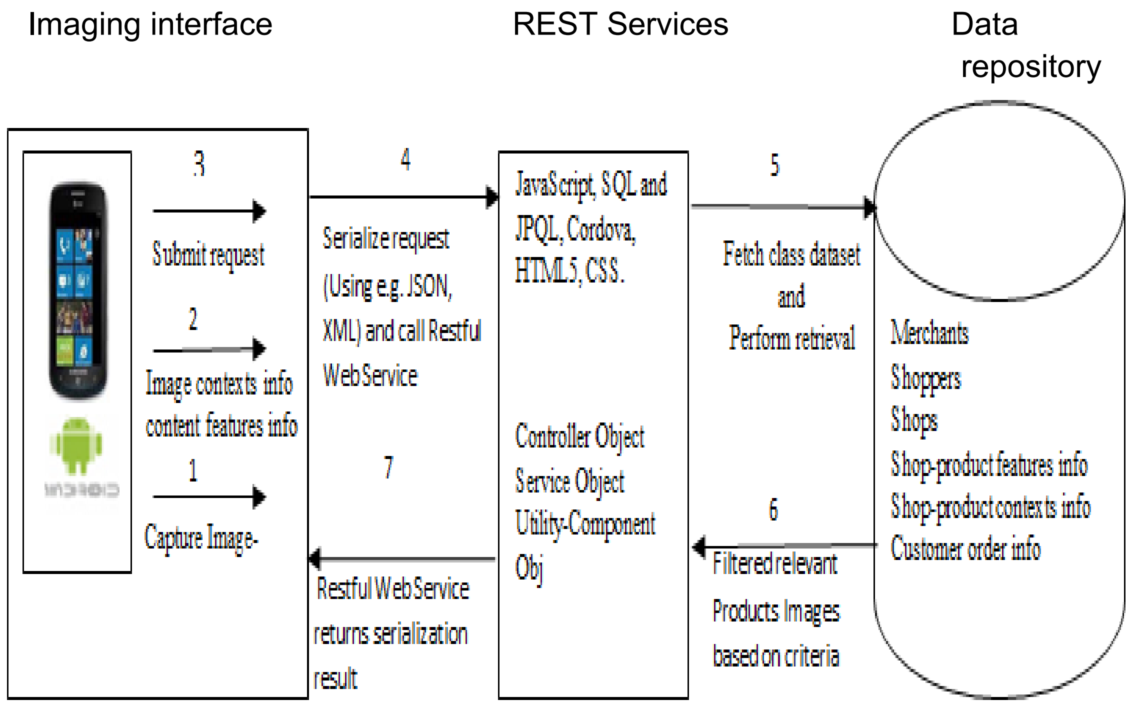


Figure 4-5: Image-based Recommendation in a Conceptual Client-Server Framework

The framework has at its core, a GPS receiver and wireless LANs e.g. Wi-Fi. The client and server communication flow between a mobile user interface and the image-based recommendation engine in a Restful-service is shown in Figure 4-5. As shown in the Figure, an image of a preferred item by a user is captured and information about this image and other contexts information is serialized using JSON and passed through RESTful services operations. The resultant output is used to build up image categorical information and filtering. Relevant products images are sent to the user interface for the response of a mobile user, who will either buy or restart the process.

4.13 Design Considerations for Personalised Mobile Interface

Mobile recommendation system offers potential opportunities for shoppers in the e-commerce domain. On this note, it becomes essential to have an operational understanding as well as the fundamental context in evolving a dynamic imaging user interface that is handy in meeting the nature of mobile users in the e-commerce domain. Quite a several interactions and interfaces exist between a mobile user and his/her environment. The characteristics of mobile handheld devices present challenges for good user interfaces (Preece *et al.,* 1994; Zhang, 2007; Zhou, Duh, and Billinghurst, 2008). The interfaces of these handheld devices typically have very small visual displays, limited input techniques, and poor audio interaction facilities. An important feature of mobile device technology is its context-awareness capability. This proficiency is experienced in a mobile shopping environment where the current situation and device functionality are adjusted to up with the user situation (Preece et al 1994). However, the design process of context-aware mobile devices usually comes with two major challenges. The first one is in terms of defining user context and the second is developing the appropriate concepts that are relevant to the scheme of contextual information on mobile interfaces.

Context is a component that plays an important role in the development and understanding of recommendation systems (Adomavicious and Thuzuling 2005). It is an area in a recommendation system that is concerned with the design, evaluation, and implementation of interactive computing systems for human use (Preece et al 1994). This means that user actions may not be useful nor completely comprehend without thoughtful consideration of the user environmental context (Xiao, and Benbasat, 2007). The understanding of mobile user context and all the necessary contextual information, including location in is of paramount importance in realising personalised recommendations. This requires a good user interface, which is the core of this part of the thesis. As such a generic design consideration for the personalised mobile user interface is derived and applied in building imaging interface.

- ❖ Easy and fast collection of user preference acquisition: The first stage in the personalisation of user preference is the acquisition process. One desirable characteristic of the user interface is that preference acquisition should be fast and done at ease. Capturing product images by using a camera-enabled mobile phone affords users stress-free, quicker, and potentially more accurate results than using keywords (Kim, *et al.,* 2010). In addition, customers derive hedonic, utilitarian, self-oriented values by interacting directly with real-world images (Salo, *et al.,* 2013). Thus, in this study, the built-in camera in mobile phones was utilised as a tool for data collection.
- ❖ Privacy cover: User ID, his preferences, and additional private data such as location should be kept back as private. As such, user location on the mobile device should be made inaccessible to other mobile users for security purposes.
- ❖ Minimum user interaction: Personalisation entails determining customer heterogeneous needs and interests with less user effort and time. Typing product names and using keywords for filtering can be time-consuming and requires user interaction with the mobile device. Since our target/subject is diverse in both language, ethnicity, age, and educational background, the use of keywords is not suitable in this situation. Therefore, one major desirable characteristic of a mobile user interface is that it should be easy to use, and the number of interactions needed to capture user-preference product items should be minimal.
- ❖ Feedback support: Provision for capturing user praises for an item should also be catered for. This can be used for strategic market planning and future recommendation to new mobile users.

- ❖ Support user multi-dimensional nature: The entire system interface should support the multi-dimensional nature of shoppers. This is achievable by making the entire architecture flexible enough to accommodate in real life, various user shopping patterns and criteria collected and managed in the system.

Apart from the fact that image-based interface addresses keyword ambiguity, user-derived hedonic and better utilitarian motivational values from using image-based shopping interface (Holbrook 1996, 1999; Mikalef, Giannakos and Pateli 2013; Salo *et al.,* 2013). In addition, an image-based interface retains physical image-based features such as colour image aesthetic patterns. These features have a strong impact on consumer attention. Moreover, not only that these features have been found to kindle the buying intention of consumers. Many of the popular approaches of searching have been emphasised upon in the content of the searched object rather than its name as a keyword (Bhattacharya and Das 2014). Many content-based recommendation approaches have been developed, for image-based filtering within the past few years. The interest in this area remains high. This is due to the giving demand on practical application as it can provide personalised recommendations and meet up with the dynamic nature of users.

4.14 Top-N Performance Evaluation Metric

The relevance of the recommended image products to active users is measured using information retrieval metrics such as the Top-N recommendation rate, Recall at N, and precision at N. Top-N evaluation measure how relevance recommendation or quality has been provided to satisfy users (Polatidis and Mouratidis, 2019). Top-N recommendation rates the impact of personalisation by determining whether the correct product image is among the Top-N returned images. The notion of the approach is that a mobile user u_a is mainly interested in a relatively few product items (Top-N recommendation) that are considered most relevant. In the case of the proposed work interest is only on calculating precision-recall and F measure at Top-N. The performance of a recommendation system can be evaluated using metrics such as precision, recall, and accuracy. Thus, all that is needed is to translate similarity scores usually from 0 to 1 into a binary problem of relevant and not relevant items. To achieve this, similarity scores have been preprocessed leveraging on the same translation of Tewari, Singh, and Barman (2018). That is any shopping item with a similarity score above 0.7 and in the same category with the query image corresponding to a relevant item, otherwise, it is regarded as irrelevant to query operation. A relevant item for a specific pair of user-item means that this item meets the interest of an active user. In this research work, the recommendation architecture was evaluated using Top-N rank precision and recall performance metrics, like what was done by Bellogín, Cantador, and Castells, 2010; Sassi, Mellouli, and Yahia (2017), and Tewari, Singh, and Barman (2018).

The Top-N precision is the proportion of recommended items in the top-n set that is relevant. The Top-N precision score of 1 indicates the best recommendation and 0 indicates the worst recommendation. The higher the value, the higher the quality of the recommendation. The Top-N precision, which is sometimes written as precision@n is defined with the Eqn. (4.68) as:

$$Top - N \text{ Pr}ecision = \frac{R_N}{NR_N} \tag{4.68}$$

Where

- R_N the number of recommended items that are relevant at N.
- NR_N the total number of recommended items at N.

The Top-N recall, which is sometimes written as recall@n is defined with the Eqn. (4.73) as:

$$Top - N\ \mathrm{Re}call = \frac{R_N}{TR} \quad (4.69)$$

Where

- R_N the number of recommended items that are relevant at N.
- TR the total number of relevant items.

The recommendation methods generate different outputs given a particular experimental dataset (Polatidis and Mouratidis, 2019).

4.14.1 An Illustrative Example

The example considered is meant to illustrative how precision@k and recall@k can be computed. All the classification-based retrieval scores for all the suggested items need to be known and sorted in descending order. For instance, the results will be as follows:

Table 4-3: Top-N Evaluation Table

Item	Item1	Item2	Item3	Item4	Item5	Item6	Item7	Item8	Item9	Item10
Similarity Score	1.0	0.84	0.65	0.88	0.68	0.8	0.59	0.76	0.87	0.81

Relevant items: The number of relevant items is the items with scores greater or equal to 0.8. It can be seen from the table that relevant items are item1, item4, item9, item2, item10, and item6. Hence the total number of relevant items is 6.

Recommended items: The recommended items @ 10 are item4, item6, item2, item10, item3, item5, item7, item8, item1, and item11, hence the total number of recommended items at 10 is 10.

Compute recommended and relevant items @ 10: is the intersection between Recommended@10 and Relevant@10, which are item4, item6, item2, item10, and item1. Therefore, the number of the recommended items that are relevant @10 is 5.

Precision @ 10:

Precision@10 is 50%. The interpretation is that at the top-10 only 50% of the recommendations are relevant to the user.

Recall @ 10:

Recall@10 is 83.3%. The 83.3% denotes the percent of the relevant items that were recommended in the top-10 items.

4.15 Chapter Summary

In summary, this chapter has carried out an overview of methods and techniques that have been used to address the open problems of concept drift and a new user that are usually faced by the classical content-based recommendation systems in the context of product items recommendation. In addition, the chapter has discussed some of the theoretical foundations of eliciting user preference as it applies to item-based recommendations. Some of the theoretical concepts discussed include Eigen-based colour image feature extraction, saliency detection using quaternion algebra, HOG, ANN bagging ensemble, MKL, LaRBF, and ANN. These theoretical foundations have been utilised for the experimental models in the subsequent chapters of this thesis. Apart from the theoretical background, their popularity in the literature was mentioned. Moreover, each method of the proposed framework was evaluated separately from the others and as an integrated whole at the end of Chapter fourth.

CHAPTER FIVE

Experimentations, Results and Discussion

5.1 Experimental Models

The works of Deshpande and Karypis (2004), and that of Papagelis and Plexousakis (2005) affirmed that there is a need for experimental testing and parameterisation, before a recommendation system can be deployed in a real-world setting. As such, this chapter five focuses on the set of experiments and evaluations that were conducted during the building up of the proposed recommendation system. Experiments were carried out with shopping items in the e-commerce domain for delivering accurate and personalised recommendations to a *new user* in the e-commerce domain. The chapter also conveys and discusses the outcomes of the experiments. The main target for conducting the experiments is to know how accurate one could deliver a personalised recommendation to *new user*s from his initial preferred shopping item.

Generally, one major focus of all the experiments is to realise an accurate and personalised recommendation system using high-level features extracted from an image. This will entail making sure that all the stages, such as feature segmentation, extraction, and selections of an image-based classification system, are optimally performing. This means that the workability of modules such as segmentation, extractor, and descriptor time-based recency modules needed to be confirmed in generating accurate and acceptable results. There is the need therefore for appropriate databases that suit the e-commerce domain. On this account, a popular e-commerce database of PI 100 (Xie, *et al.,* 2008) was employed in all the experiments conducted in this study. Samples of this database are shown in Figure 5-2. Eight different experiments were conducted in this study. The e-commerce database was made ready by preprocessing to make it suitable for the following operations.

- Evaluate and visually compare image features realised from the proposed representation algorithm in different colour models with colour histogram, HOG, and uLBP descriptors.
- Evaluate and compare the classification accuracy of the proposed representation algorithm with the selected image descriptors when use in RBFN classifier.
- Evaluate the accuracy of the image feature extraction method employed based on ensemble learning of RGB Eigen colour features.
- Comparison of the effectiveness of four-time decay functions (TDF).
- Evaluate the accuracy of the proposed image feature extraction method built on the newly proposed 4D colour model with Kaiser criterion retention heuristic.
- Compare the accuracy of the two above Eigen colour feature representation methods in the ensemble of ANN, multi-SVM kernel, and RBFN classifier. This is meant to select the best classification model that generates an effective image class.
- Integrate the image Eigen colour feature and classification model criteria with other image-based social criteria for simulation of a shopping recommendation architecture and measure the personalisation level with Top-1 rank metrics.
- Implement a cross-platform imaging interface on a mobile device to anchor the image-content-based mobile shopping recommendation architecture.

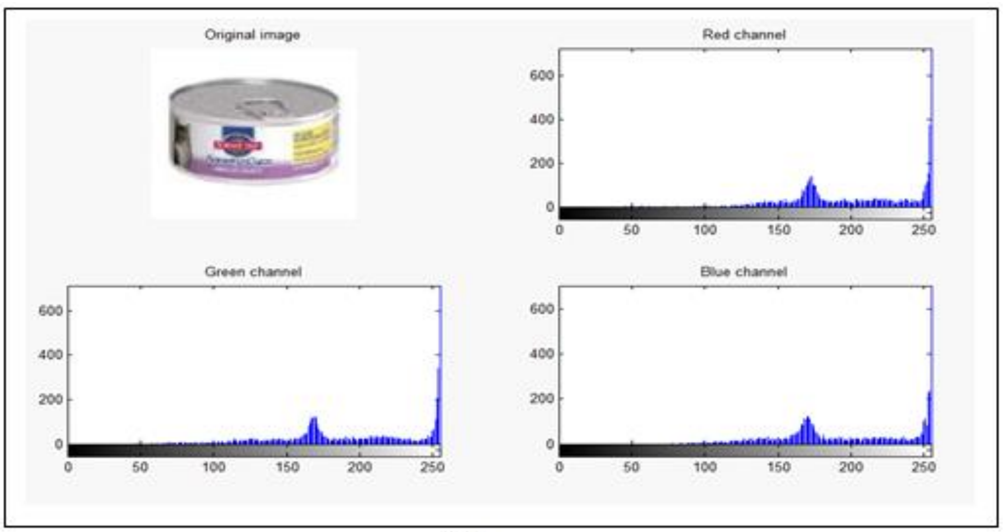
The first seven experimental models of this study were designed to preprocess images and determine the appropriate image representation and classification algorithms for the proposed recommendation system. All the major experiments were performed on a PC with Intel Core i5-2540MCPU @2.60GHz speed with 4.00GB RAM running a 64-bit Windows-10 operating system. The implementation programming language is the MATLAB R2015a. This study has relied on the 1AA strategy to extend the conventional SVM to the case of the multiple class classification task.

The eighth experiment conducted in this work has to do with the implementation of a mobile user interface system to anchor the proposed architecture. The design was meant to find out whether extracting and matching image-based information 'on the move' in a prototype recommendation system is practically realisable. The prototype has been built on a Galaxy S4 android smartphone taking advantage of its built-in camera with 1080 x 1920 resolution, 16:9 ratio, GPS receiver for position detection, and the support for multimedia messaging service (MMS). The captured image is sent to the server through the MMS. The mobile user interface was implemented using PhoneGap 3.0 to deliver to users with native experiences that support a wide range of the mobile operating system.

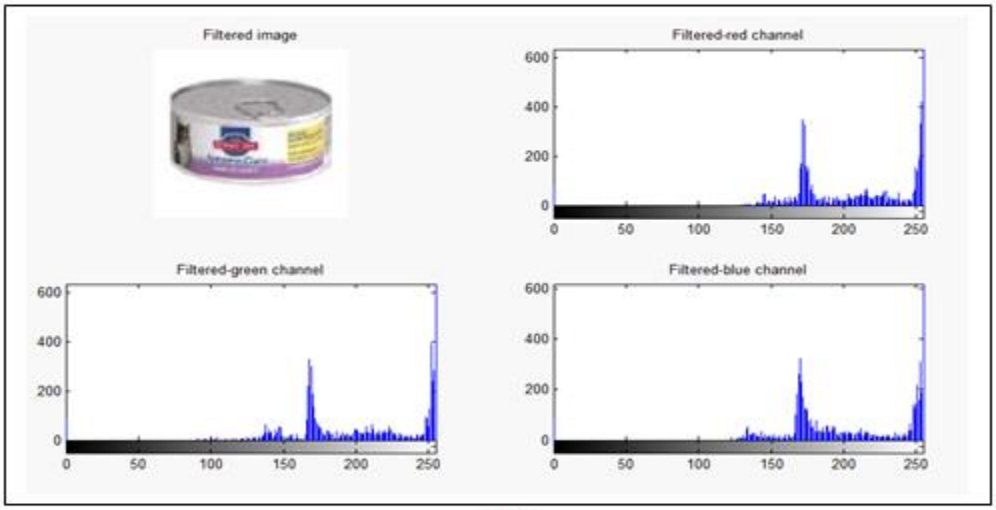
Also, the results and discussion of the analysis of experiments performed in this study are the main targets of this chapter. In the same view, attention is focused on the experimental evaluation of results on the image-based classification model, classical content-based model, and sensitivity analysis of decision algorithm on multi-criteria factors. The purpose of this chapter is to experimentally demonstrate how the research questions have been solved to achieve the study aim.

5.2 Experiment on Pre-Processing of Product Images

Figures 5-1a and 5-2a have the original images of items in the "Can" class and another item from the "Baby-Shoe" class, respectively. These same figures contained histograms of their RGB channels. Likewise, Figures 5-1b and 5-2b respectively show the final outputs of the preprocessed images after the median filter has been applied and their respective histograms of the RGB image channels. The qualitative comparison of Figures 5-1a and 5-2a that contain the raw images and that of Figures 5-1b, and 5-2b that contain the filtered images have shown the distributions of pixels in all image channels. For example, is the pixel per inch (PPI) for red components particularly within the 150- and 200-pixel intensities in Figure 5-1a is more than the pixel per inch distribution within 150- and 200-pixel intensities in the equivalent red channel of the cleaned image in Figure 5-1b. This result vividly explains the smoothening effect of the median filtering, which has improved the extraction of more discerning colour characteristics from the input images. Moreover, this result is in consonant with the stand of other researchers in the literature that have worked on the vital effect of first applying noise prefiltering on images before feature extraction (Jassim and Altaani, 2013; Sáez, Luengo, and Herrera, 2010). The settings are clear for all the images that were used in experiment 2.

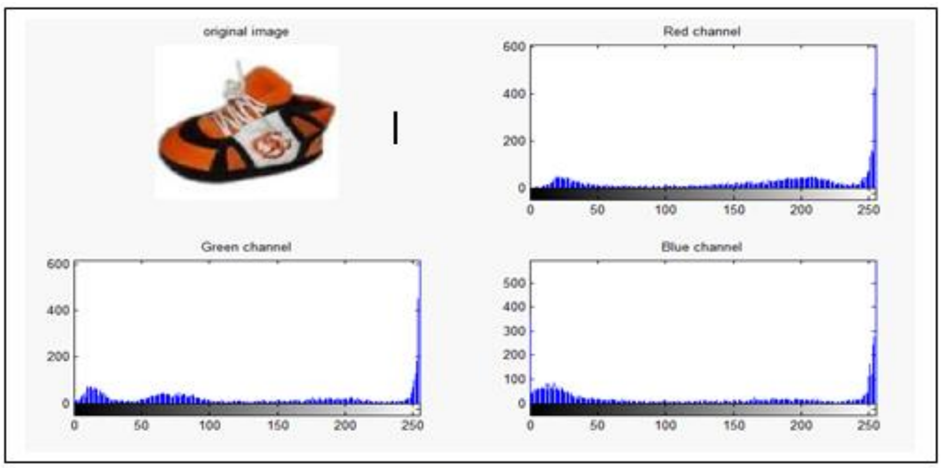


(a)

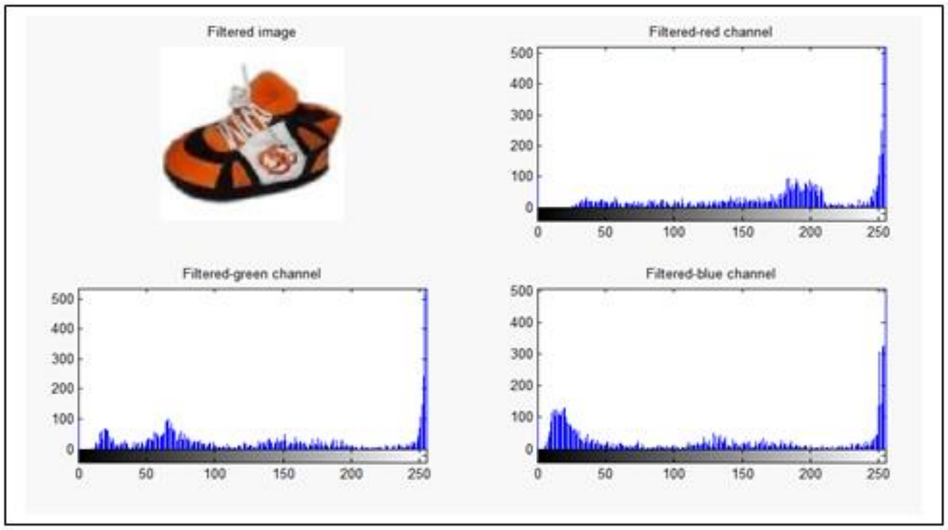


(b)

Figure 5-1: Output for (a) original (b) filtered image in Can category.



(a)



(b)

Figure 5-2: Output for (a) original (b) filtered image in Baby Shoe category.

5.3 Experiments on Image Feature Representation

In this experiment, the performance of two image feature representations algorithms ECF and ECF_GT1 were carried to determine their efficacy.

5.3.1 Experiment on ECF Image Representation

Experiment on visualization of image feature with ECF that retains the corresponding Eigen vector feature that has largest Eigen values (**ECF)** is first carried out as displayed in Figure 5-3- and 5-4-line plots. Figure 5-3 indicates the dot plots of HOG-ECF vectors for items that are picked randomly from each of the ten classes as earlier shown in Figure 4-2. In this Figure, each class is displayed as a dot plot with a separate colour, showing vivid difference amid the HOG-ECF mined features.

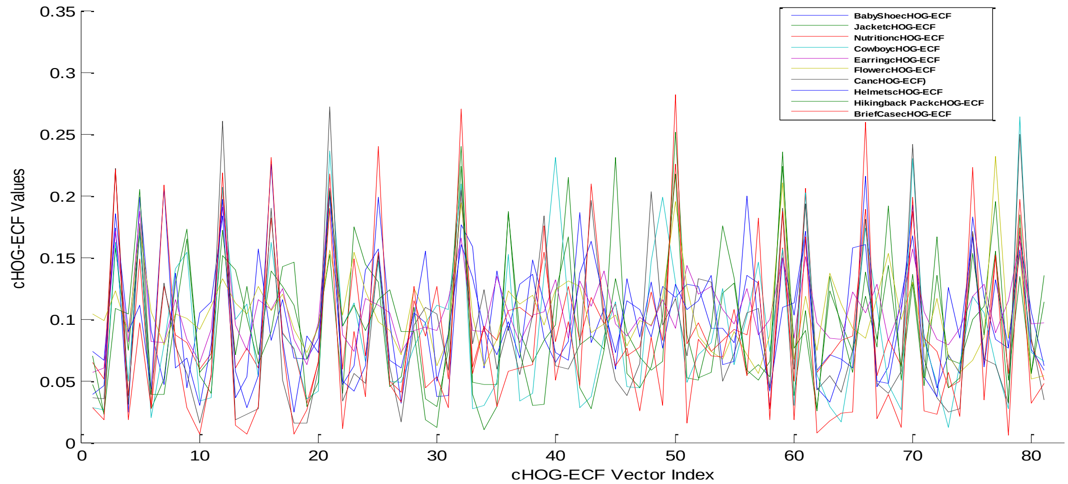


Figure 5-3: Dot plots of HOG-EC feature of images from ten dissimilar classes

Like what is done with HOG-ECF, Figure 5-4 below displays plots for ULBP-ECF vectors for each of the ten-item classes shown in Figure 4-2. Comparatively, the result in Figure 5-4 is unlike that of Figure 5-3. One can observe that there exist fewer overlaps of peak values and fewer discriminating values across different item classes.

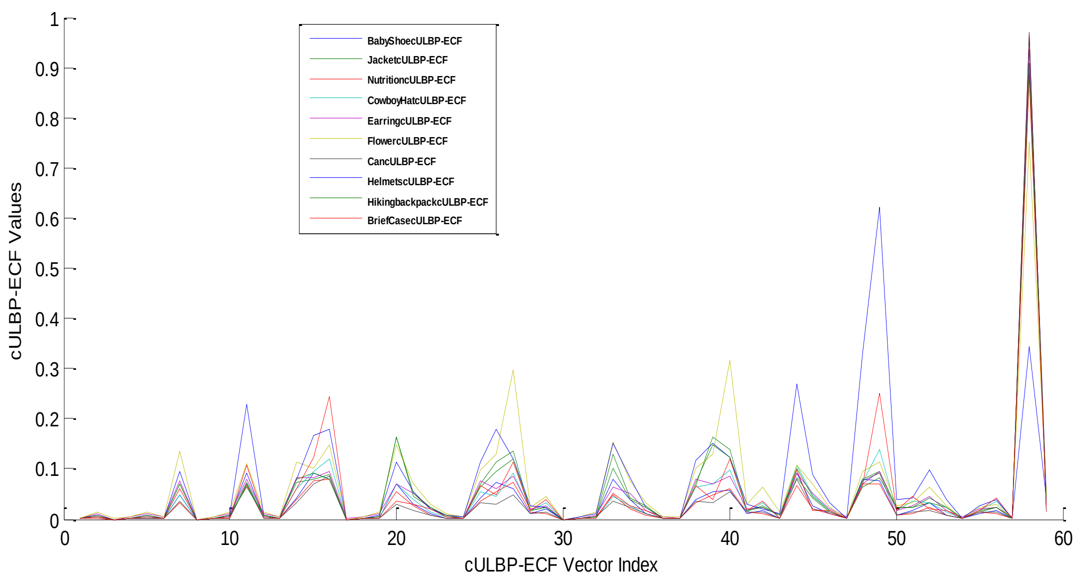


Figure 5-4: Dot plots of ULBP-EC feature of images from ten dissimilar classes

Equally, the HOG Eigen colour feature vector of briefcase items selected as samples from steadily has the top values from the 1st to the last item elements that have the peak value starting from 28 x 10^{-1} to the lowest value of 6.3 x10^{-3}. Figures 5-5 and 5-6 have to a large extent shown that each image that exists in the briefcase class bear a high level of similarity in term of their outline and colour characteristic. Furthermore, a systematic pictorial assessment on Figure 5-5 established that from 0.05 and above of many vectors of HOG Eigen colour feature overlapped, telling viewers the level to which image components of this class are like each other, while very slight variation occurs at the bases.

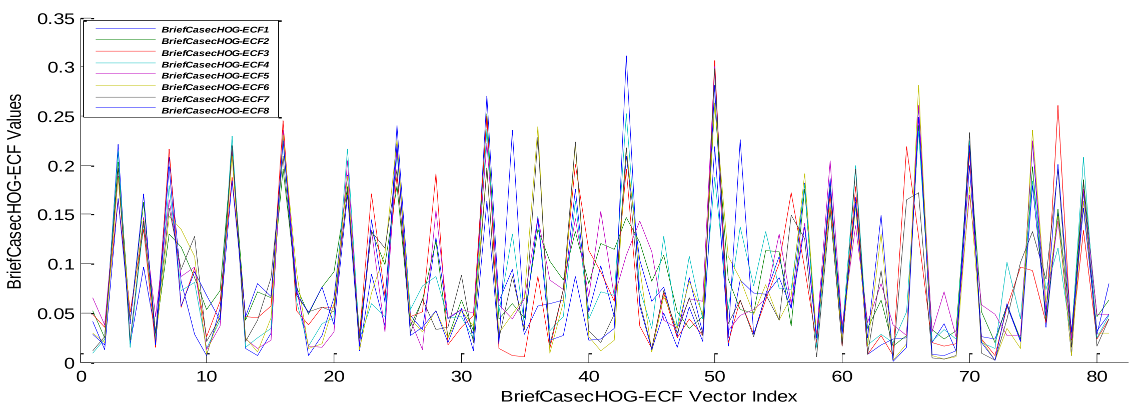


Figure 5-5: Dot plots of HOG-EC feature of images picked from Briefcase class

Figure 5-6 delivers a similar result to Figure 5-5 when viewed from image peak values and sizes. Nevertheless, detailed the number of overlap recorded in the colour descriptor of the uniform linear binary pattern is fewer when compared with the Eigen colour features the value of histogram of the oriented gradient. The odd gush of peaks that obtruded at the tail-end of ULBP-ECF vectors is another conspicuous peculiarity that one can see in Figures 5-5 and 5-6.

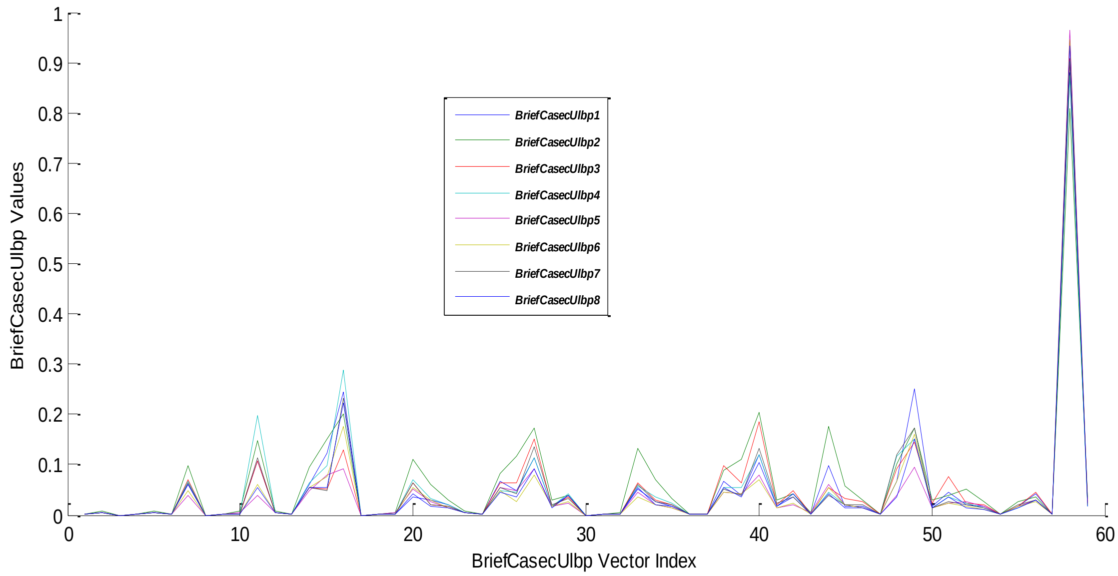


Figure 5-6: Figure 5-5: Dot plots of ULBP-EC feature of images picked from Briefcase class

The visualization of image feature viewing from a qualitative perspective shows that the value of ECF determines the corresponding values that are retained. Hence, the corresponding Eigen vector feature that has the largest Eigen colour values (**ECF),** shows it discriminatory forte. On this note, one can rightly say that HOG-ECF is consistently better than that of ULBP-ECF in the RGB colour model.

The quantitative experiment is carried out with a designated image feature (HOG-ECF) with single MLP-ANN to further evaluate the performance of the **ECF** image feature. The number of neurons with the utmost accuracy was taken and used as the initial result to start with the bagging. Similarly, the HOG-ECF feature from the above experiment is replaced with ULBP-ECF**,** the same procedures were afterward repeated. Figure 5-7 shows the results of all the experiments performed in this section.

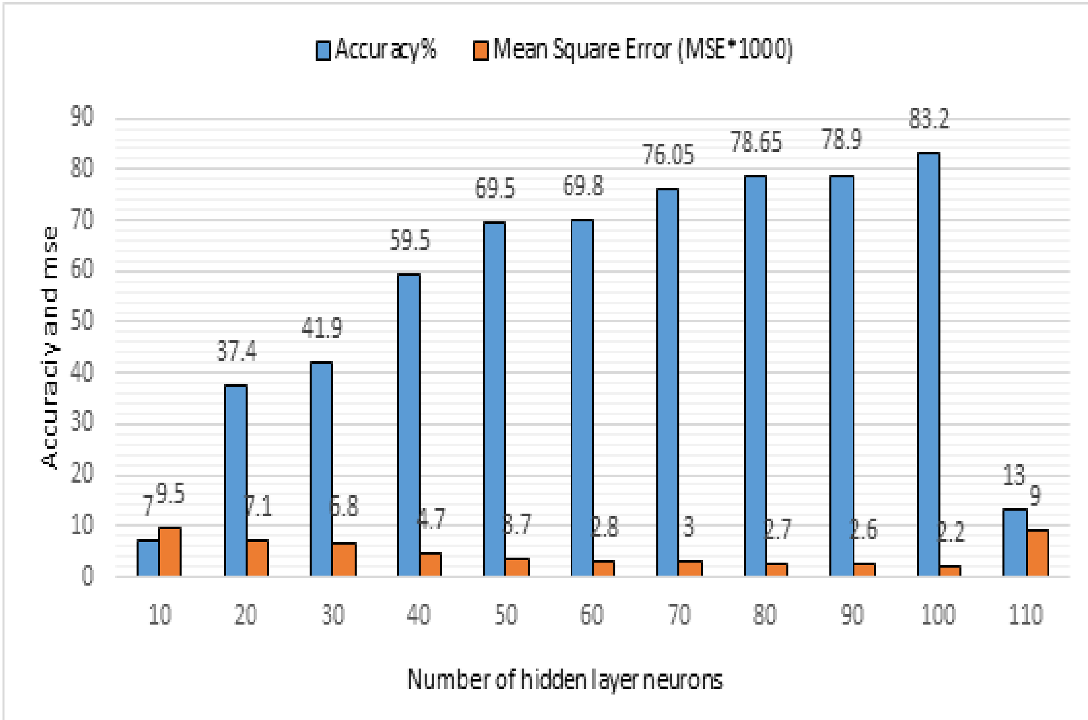


Figure 5-7: Results of HOG-ECF in single MLP-ANN classifier

Furthermore, in this section, an ensemble method called bagging was employed to resample the HOG-based Eigen colour features (HOG-ECF) and train the voted single multi-layer perceptron artificial neural network. The operation generates 20 dissimilar base multi-layer perceptron artificial neural network classifiers. The top 10 base classifiers were picked from all the 20 classifiers, like what was undertaken by Thakur *et al. (*2015)**.** Table 5-1 displays the results obtained from the assembling MLP-ANN with HOG-ECF.

Table 5-1: Results of using HOG-ECF in Ensemble MLP-ANN classifier

Base MLP ANN.	1	2	3	4	5	6	7	8	9	10	Total AVR.
Accuracy	87,50	87.35	87.60	87.30	86.15	87.05	86.60	87.70	87.60	87.20	87.20%
MSE	0.0015	0.0015	0.0013	0.0015	0.0017	0.0015	0.0016	0.0016	0.0015	0.0015	0.00152

Even though the classification accuracy of 87.20% is good, but one cannot just accept it as the final now, since other experiments have not been performed. As shown in Figure 5-8, the number of hidden neurons is varied by 10 up to 110 while a single MLP-ANN classifier is trained with the uniform linear binary pattern Eigen colour features (ULBP-ECF). For instance, in this work, MLP-ANN with 20 neurons in the hidden layers generated 32.45% accuracy with 8.1×10^{-3} error (MSE). Similarly, when 100 neurons were used in MLP-ANN, the highest accuracy of 67.10% is generated with the lowermost error of 4.2×10^{-3}. Figure 5-8 shows the other configurations.

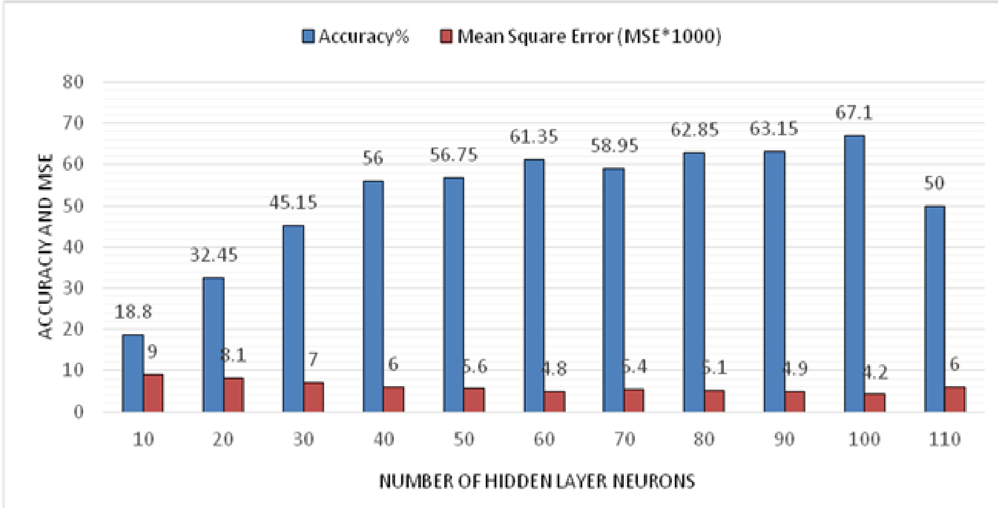


Figure 5-8: Results of ULBP-ECF in single MLP-ANN classifier

The 20-base multilayer perceptron artificial neural networks were integrated to build the bagging algorithm that is used in this experiment. Table 5-2 displays the results for base classifiers. In addition, 76.14% and 2.81 x 10^{-3} are the average classification accuracy and MSE realised respectively from the experiment.

Table 5-2: Results of using ULBP-ECF in Ensemble MLP-ANN classifier

Base MLP ANN.	1	2	3	4	5	6	7	8	9	10	Total AVR.
Accuracy	67.75	78.50	75.00	76.65	76.45	77.30	74.40	77.90	77.80	79.60	76.14%
MSE	0.0037	0.0027	0.0029	0.0027	0.0028	0.0027	0.0029	0.0026	0.0026	0.0025	0.00281

One can observe that the configuration used in the above two experiments with results shown in Table 5-1 and Table 5-2 are similar. Therefore, one can rightly infer that ECF image representation gave a better performance with ANN-ensemble classifier in HOG descriptor than with ULBP descriptor. In this regard, further experiments, and exploration of alternative classifiers such as LaRBF, quadratic, polynomial, RBF vis-à-vis the HOG-ECF and ULBP-ECF descriptors, were conducted as reported by Oyewole and Olugbara (2018).

5.3.2 Experiments on ECFGT1 Image Feature Representation

In this section, the evaluations of image features were performed using novel colour channels that are more than three. This is to establish and visually access the performance of the proposed new colour model with three other multi-dimensional colour models as proposed by Romero, Lado, and Mendez (2018), Yang et al (2013), and Lr’g’b’ colour models. Equally, the visualisation of ECF for product images proposed by Oyewole and Olugbara (2018) is presented.

Experiment on visualization of image Eigen colour feature, **ECF** that retains corresponding Eigen vector feature with (Kaiser-Based) Eigen values greater than one (**ECF_GT1)** is first carried out as shown in figure 5-9 through 5–16-line plots. For instance, Figures 5-9 through 5-12 respectively showed a plot of cHist-ECF_GT1 features in the three-Colour models under investigation and the proposed hybrid Colour model, for e-commerce product images that are randomly selected from 10 different classes. The number of channel features considered in the first three-Colour model is there (3), with 4 principal components selected for each Colour channel, which cumulate to a total of 12 features points for one image. In Figure 5-9, one should observe that image feature discrimination is more pronounced between data feature points 0 and 4, while variation reduces significantly between image data feature points 5 and 9.

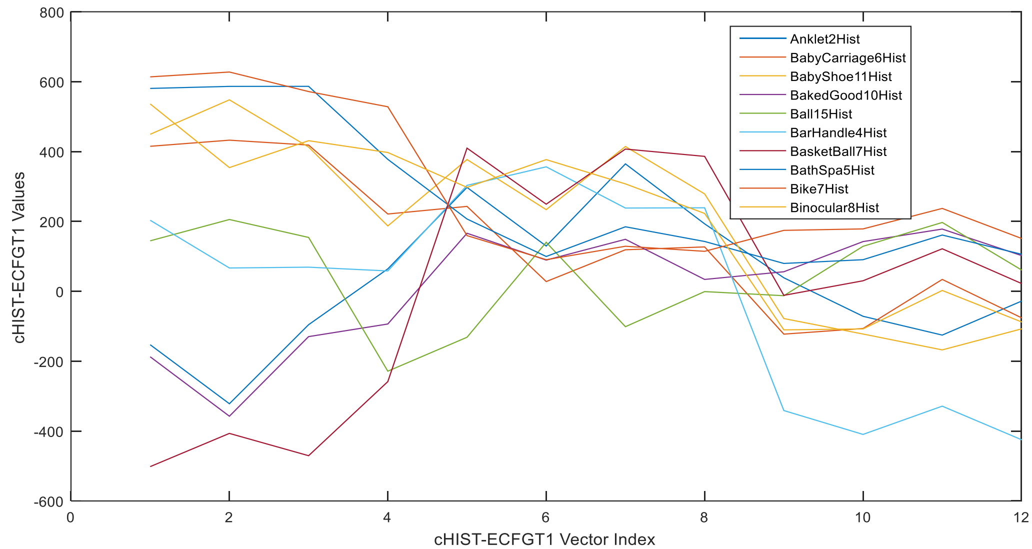


Figure 5-9: Dot plots of cHist-ECF_GT1 features for product images picked from ten dissimilar classes in Romero, Lado, and Mendez (2018) Colour model

Similarly, it will be observed in Figure 5-10 below that image feature discrimination is also more pronounced between data feature points 0 and 4, while variation reduces significantly between images.

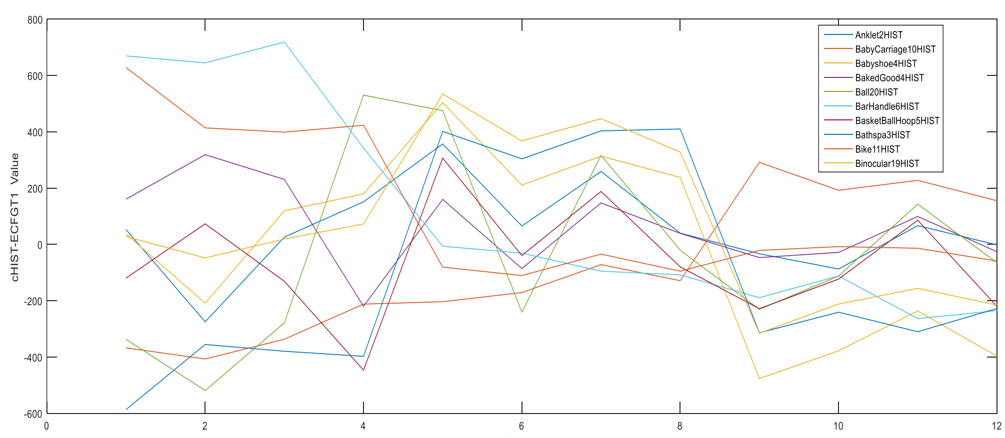


Figure 5-10: Dot plots of cHist-ECF_GT1 features for product images picked from ten dissimilar classes in Yang et al (2013) Colour model.

Likewise, Figure 5-11 of the Yang et al. (2013) colour model followed the same shape pattern that is like the two earlier described models. However, the image feature discrimination is much pronounced with Yang et al. (2013) colour model. This can lucidly be observed between data feature points 0 and 4, while variation reduces significantly between images data feature points index of 5 and 9.

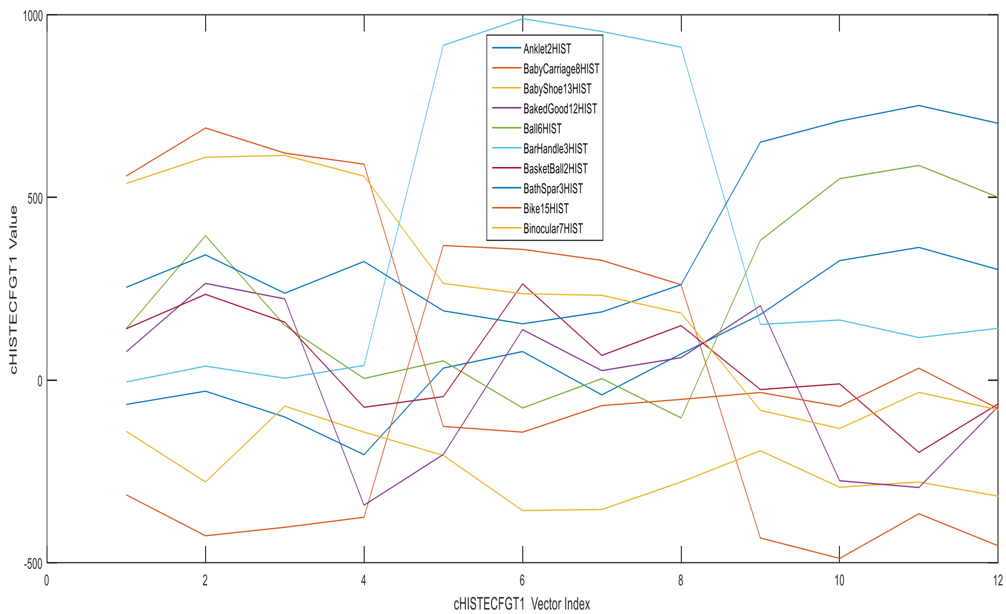


Figure 5-11: Dot plots of cHist-ECF_GT1 features for product images picked from ten dissimilar classes in Yang et al, (2013) Colour model.

On the contrary to the above three experiments on colour models, 12 different colour channels are used in the proposed colour model, with 11 principal components selected from each colour channel, which cumulates to a total of 132 features points for one image. This becomes more cumbersome compare with the 12 features points that exist in the previous colour model figured in 5-9, 5-10, and 5-11. For each product item, the extracted cHIST features in this colour model is distinctive in the different classes, likewise, Figure 5-12 display each class as a dotted line with a unique colour with strong variations between the cHIST-ECF_GT1 features.

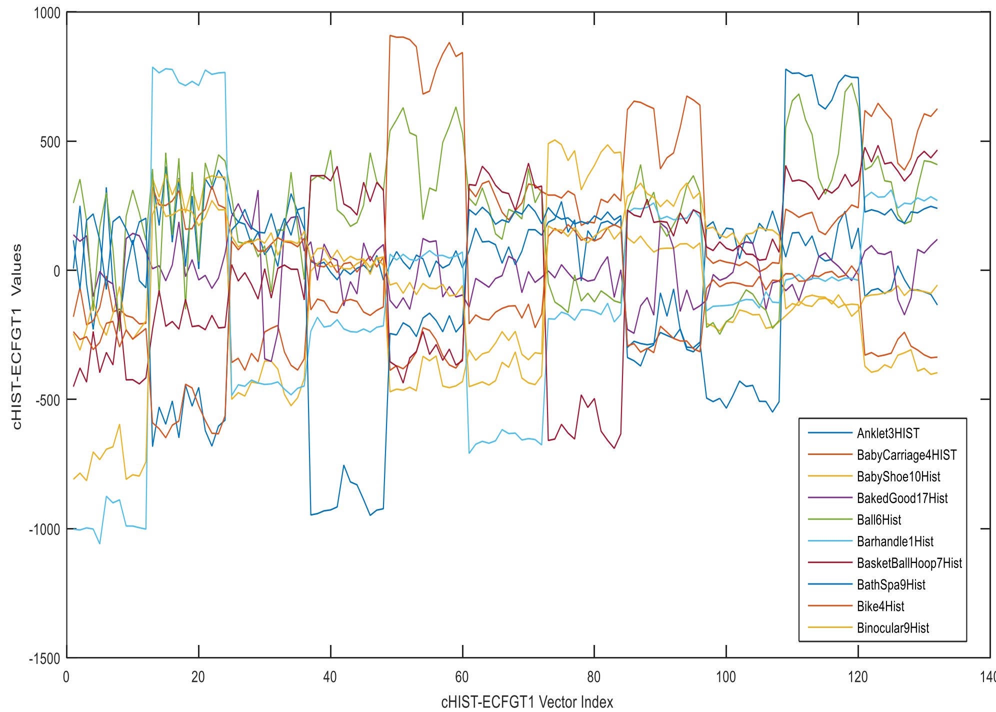


Figure 5-12: Dot plots of cHist-ECF_GT1 features for product images picked from ten dissimilar classes in the proposed colour model.

Summarily, from the Figures above the cHist-ECF_GT1 features of product images from 10 different classes show that each of the classes has unique features shapes. This visual discrimination between products in different categories is more pronounced in the proposed colour model closely followed by colour model suggested by Yang et al. (2013), Romero, Lado, and Mendez (2018), and finally, Lr'g'b' colour model. Furthermore, the cHIST-ECF_GT1 in the proposed colour model consistently has the highest set of similar values. This is in consonant with the highest accuracy of 92.20% with an MSE of 0.0061 realised with this colour model. In comparison with Yang et al. (2013), Romero, Lado, and Mendez (2018), and finally, Lr'g'b' colour models respectively have the accuracy of 86.15%, 67.60%, 80.70% with MSE of 1.05×10^{-1}, 1.90×10^{-2}, and 3.72×10^{-2} in the experiment conducted.

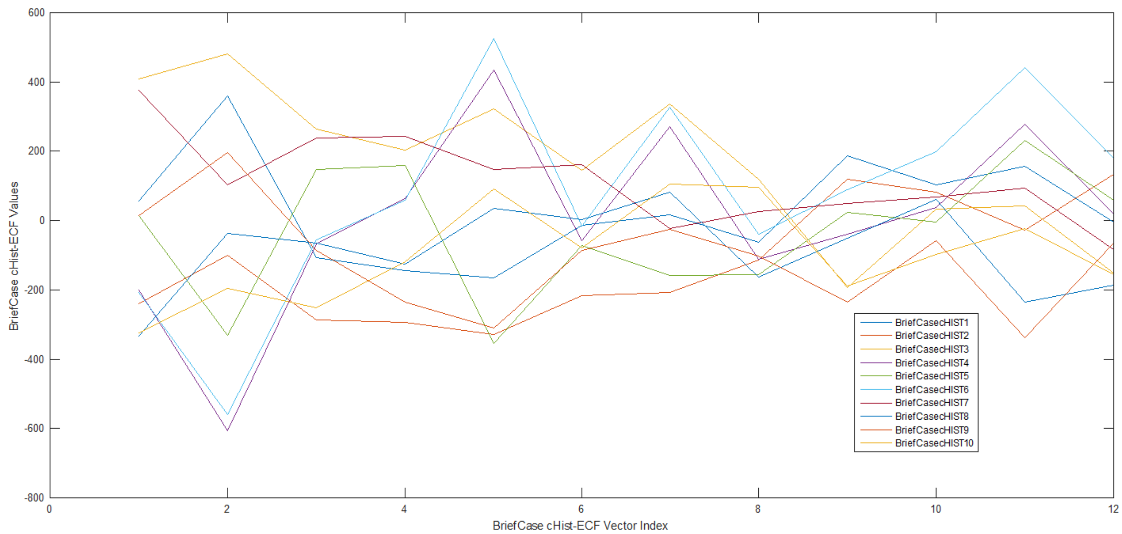


Figure 5-13: Dot plots of cHist-ECF_GT1 features for selected product items from Briefcases class in Romero, Lado, and Mendez (2018) colour model.

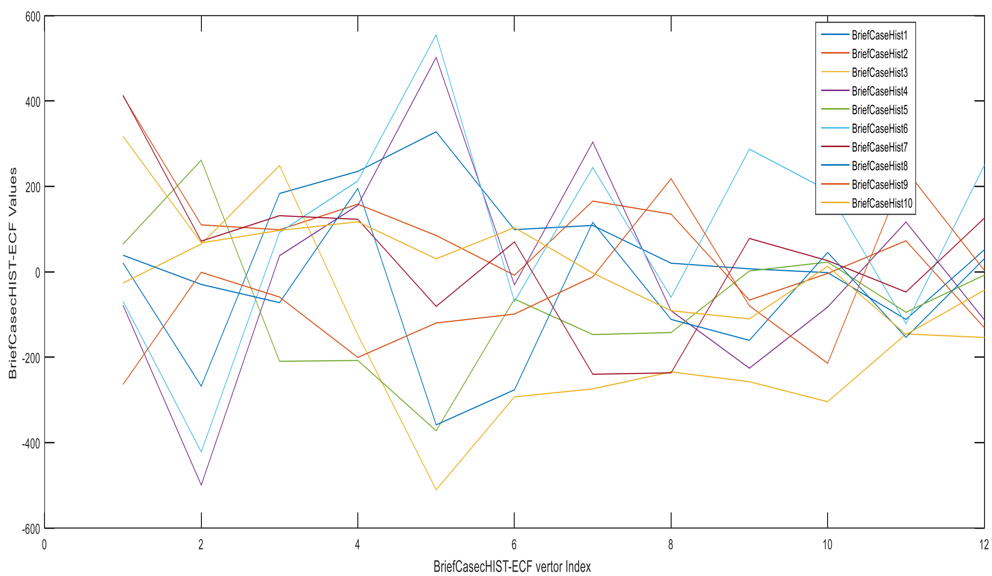


Figure 5-14: Dot plots of cHist-ECF_GT1 features for selected product items from Briefcases class in Lr'g'b' colour model

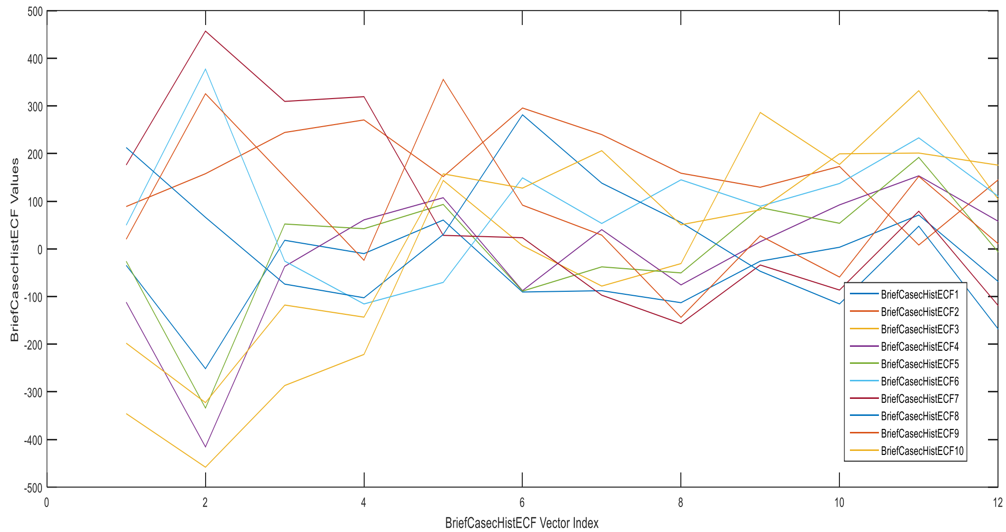


Figure 5-15: Dot plots of cHist-ECF_GT1 features for selected product items from Briefcases class in Yang et al (2013) colour model

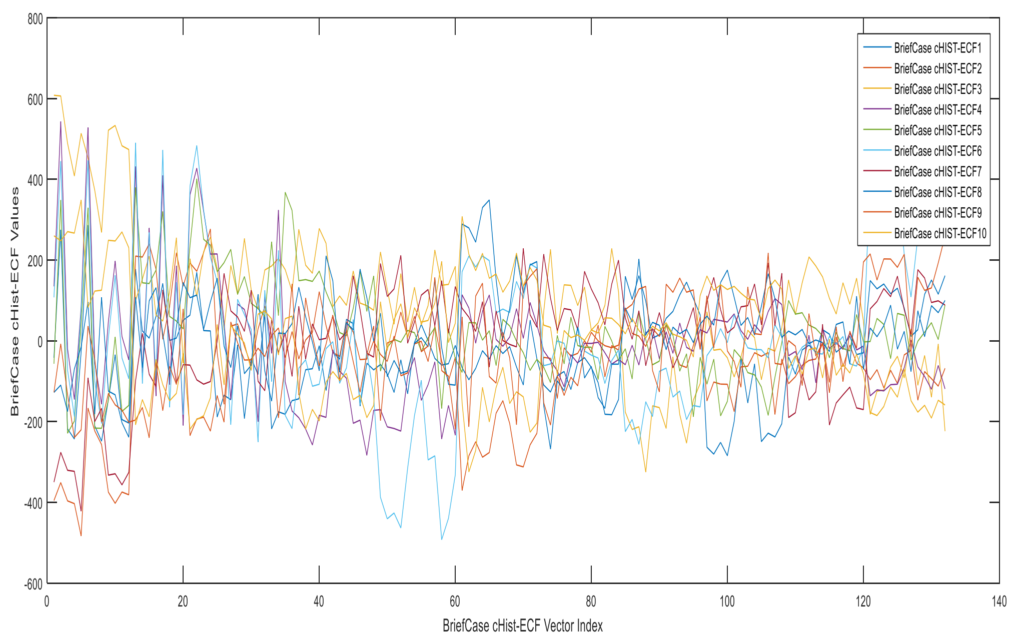


Figure 5-16: Dot plots of cHist-ECF_GT1 features for selected product items from Briefcases class in the proposed colour model.

It can be observed that Figure 5-16 which shows dot plots of cHist-ECF_GT1 features for selected product items from Briefcases class in the proposed colour model, is quite different from other results shown in Figures 5-13, 14, and 15. In Figure 5-16 there are more overlaps to the peak values of the line plot for cHist-ECF_GT1 features and less discrimination in values that were acquired from product items in different classes. These results have equally shown the discriminatory power of the cHist-ECF_GT1 in the proposed hybrid colour model when compared to the other colour models. In addition, the cHIST-ECF_GT1 vector of items from the briefcase class regularly has low values from the first to the last element with diverse peak levels as presented in the dot plots. From the above, it is apparent that the proposed colour model produces superior results when compared with other colour models.

5.4 Experiments on Realisation of $e-I_{cb}C$ Model and Performance of ECF_GT1 Image Feature Representation

An enhanced image content-based classification $e-I_{cb}C$ model has been developed to realise categorical information. This model is realised by using image cHist-ECF_GT1 train RBF-ANN with varying number of centers selected per category from 1 to 10. Equally, this segment introduces another technique that can also be used to assess the performance of the proposed image representation, ECF_GT1. The process starts by first testing the performance of the proposed image feature, ECF_GT1 in three-colour image descriptors: Histogram (cHist), HOG (cHOG), and uLBP (cuLBP), with RBFN classifier.

In this section, 3 different experiments were set to find out the best image descriptor that the proposed image representation model will best work with. One experiment is performed for each descriptor, both classification accuracy and MSE are used as metrics. In addition, the average classification accuracy of ten different experimental trials was reported along with their MSE. The results show that cHist-ECF_GT1 in RBF-ANN with 1-data point per category generate classification accuracy of 30.00% with 4.89 x 10^{-1} MSE. Likewise, the RBF-ANN with 8 data points per category offered the top classification accuracy of 92.20% and MSE of 6.1 x 10^{-3}. Thereafter, accuracies realised declined consistently. Table 5-3 through 5-5 show all the results.

Table 5-3: Results of using cHist-ECF-GT1 in RBF-ANN Classifier

Data-Point Per Categ.	1	2	3	4	5	6	7	8	9	10	Total AVR.
Accuracy	30.00	48.40	64.40	78.20	86.10	88.75	91.35	92.20	91.95	91.94	76.37%
MSE	0.4890	0.2510	0.1060	0.0270	0.0193	0.0125	0.0074	**0.0061**	0.0064	0.0065	0.0931

Table 5-3 shows the performance of HOG-ECF_GT1 in the RBF-ANN Classifier. It can be observed that the highest classification accuracy is realised data-point 6, with an accuracy of 91.60% and MSE of 0.0071. The accuracy declined progressively to 88.10% and data-point 10.

Table 5-4: Results of using HOG-ECF-GT1 in RBF-ANN Classifier

Data-Point Per Categ.	1	2	3	4	5	6	7	8	9	10	Total AVR.
Accuracy	27.45	49.85	67.50	80.00	87.00	**91.60**	89.50	89.02	88.20	88.10	75.82%
MSE	0.5256	0.2510	0.1056	0.0398	0.0169	**0.0071**	0.0081	0.0081	0.0088	0.0090	0.0971

Table 5-5 shows the performance of ULBP-ECF_GT1 in the RBF-ANN classifier. Conversely, it can be observed that the highest classification accuracy is realised at data-point 10, with an accuracy of 87.90% and MSE of 0.00145. The average classification accuracy realised with uLBP is 70.80% with MSE 0.123.

Table 5-5: Results of using ULBP-ECF-GT1 in RBF-ANN Classifier

Data-Point Per Categ.	1	2	3	4	5	6	7	8	9	10	Total AVR.
Accuracy	25.90	44.85	60.20	71.50	79.30	83.40	81.15	87.30	86.50	**87.90**	70.80%
MSE	0.5480	0.3091	0.1584	0.0809	0.0426	0.0276	0.0221	0.0161	0.0182	**0.0145**	0.123

The results of this study show that the highest accuracy is realised with the proposed 4D-colour model and colour histogram descriptor. The proposed colour model equally performance-exceeding good in HOG but relatively low with the uLBP descriptor.

The first research question of this study has been solved through experimentation. The research question pertains to how rich content information can be aptly extracted from colour images as a low-dimensional features space for recommendation generation. This work has realised an appropriate new colour image representation model for an effective feature descriptor. The final classification model, usually called the net model realised from using the proposed image representation, ECF_GT1 to train RBFN that has generated an improved classification accuracy of 92.2% on standard e-commerce product items. It can be integrated into any image-based recommendation system to reduce search space and invariably high computational filtering. This additional information can be used to characterise user preferences based on category theory. The second research question of this study has been equally solved based on this background. The problem of high computational filtering inherent in content-based profiling has been faithfully addressed by building a new image content-based preference elicitation model toward building a personalised recommendation system.

5.4.1 Comparison of ECF_GT1 with novel image representation

This section is meant to place the proposed image representation model in the literature. The proposed image representation model ECF_GT1 (cHIST Kaiser-Based ECF), gave 92.20% accuracy in the present study. One can observe that this results in an improvement over the other existing ones reported in the literature (Jia, Kong, Man, 2011; Jia, Kong, and Hong, 2012; Zhang and Sha, 2013; Oyewole and Olugbara, 2018). For instance, using the same dataset, Jia, Kong, Man (2011), achieved a classification accuracy of 86.9%. In the same manner, image feature representation with the largest ECF feature in ANN-Ensemble (Table 5-1) reported 87.20% with the ensemble method on the same dataset. Although the results of Jia, Kong, Man (2011), and Oyewole and Olugbara (2018) have been designated at different times as state-of-the-art to their classification accuracies, it is not as high as the 92.20% accuracy achieved in this present study as shown in Table 5-6.

Table 5-6: Classification accuracy on PI 100 dataset

Author	**Accuracy on PI 100 dataset**
Jia, Kong, Man (2011)	86.90%
Oyewole and Olugbara (2018)	87.20%
Proposed Work	92.20%

The satisfactory result realised from ECF_GT1 image representation shows that it can be incorporated as a component into any image-based shopping recommender system for mobile users. The overarching objective of these experiments, which is to generate quality image feature representation and in turn use it to realise an enhanced product image classification model has been achieved.

5.5 Experiment on Comparison of Time Decay Functions (TDF)

The time-based data are implicitly acquired at the time of purchase. Figure 5-17 shows the graph of the performance evaluation of four decay functions. One can observe that the graph of exponential time decay function decreases with a constant percentage over a period. The gradient of the curve at a data point that is close to zero is steeper than that of a data point that is farther from the zero point. The current data are represented when x is zero. The higher the value of x is, the older is the item. It can be observed from Figure 5-17 that the exponential decay function changes at a range of 0.5290.

Likewise, the performance of the logistic time decay function is like exponential decay, but its gradient at the middle of the data point is steepest. The range of decay values is 0.511 within 7 days and 28 days considered in this work. The power decay is another function that is considered in this work. One can observe from Figure 5-17, that the preferences of a typical user decrease uniformly at a very slow rate over the period. On the 7th and 28th days, the user preference values change minimally at the rate of 0.08. The linear decay function weakly represents a straight line with a little or no decay of user preference over the period considered in this work. The value of 0.01 stands as the range value with the starting day to the last 28 days in Figure 5-17.

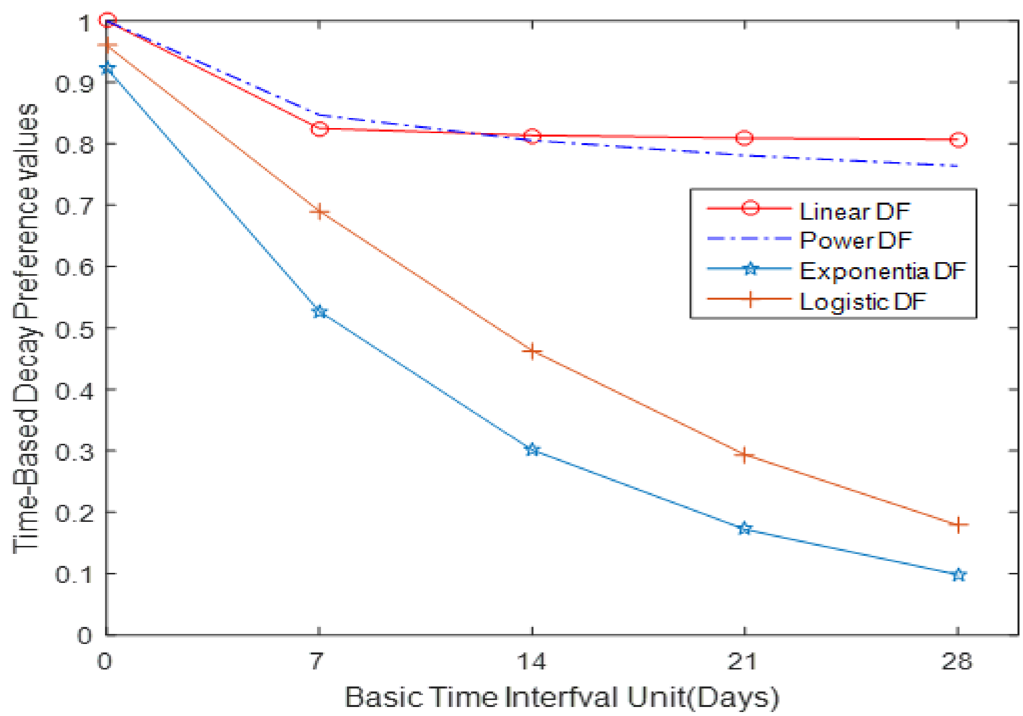


Figure 5-17: Performance evaluation of four Decay functions

The logistic, linear, and power functions are perceptible, less representative of user-item recent preferences because this work has stressed a recent purchase interest of a user. The exponential function has been found in this study to be more suitable because it has achieved the best approximation and less false-positive results that accurately match the aim of this research work. Consequently, the third research question of this study has been resolved. This question sought to answer how a time-based relevance feature be realised using a decay function to provide the best approximation to address the inherent problem of high false-positive results often experienced in a content-based recommendation.

5.6 Experiment on User Multiple Tastes and Preferences

Different image-content-based criteria, which are referred to in this thesis as 5-D social factors are considered in depth in this section to characterise the user multiple tastes toward addressing the problem of concept drift, and to deliver a personalised recommendation to new users. Apart from ECF_GT1 and item-category high-level features, other social factors such as item-relevance (item-distinctiveness), location-based context information, item price, item incentive, and item recency were all integrated into realising recommendations in this research work. The combination of the item relevance feature along with the concept of hierarchy similarities of item-class made up of the categorical user preference elicitation approach.

This section of the thesis will evaluate the overall performance of the proposed recommendation system in the application domain of e-commerce. The performance of the proposed recommendation system is experimental analysed and evaluated based on the results generated, and this is ultimately compared with the standard classical content-based (Classical-CB) recommendation methods where the classification model is not used. The approach of this study took into cognizance the suggestion of Tewari, Singh, and Barman (2018) that users in the e-commerce domain generally prefer to see less than 20-25 item recommendations on their interface at a time. Based on the research evidence, and couple with the inherent input and output limitations of current mobile devices, the number of outputs generated at once is fixed at 15, that is N=15.

Furthermore, the above two models were evaluated using Top-N precision and recall rank accuracy metrics (Bellogín, Cantador, and Castells, 2010; Sassi, Mellouli, and Yahia, 2017; Tewari, Singh and Barman, 2018). Multiple query images that were randomly selected from the PI100 e-commerce shopping database were used to assess the proposed model and the average recommendation accuracy for top-5 rank, top-10 rank, and top-15 rank were computed accordingly. The results in Figure 6-18 show ninety-eight percent for Top-5 using $e - I_{cb} C$ the model and seventy-four percent for with *Classical-CB* model. Similarly, on the same figure, top-15 results showed an average recommendation accuracy of ninety-one percent $e - I_{cb} C$ as compared to 49% with *Classical-CB* model-based recommendation systems. The interpretation of this is that at top-15 only 91% and 49% out of all recommendations offered to mobile users are relevant using $e - I_{cb} C$ and *Classical-CB* models, respectively.

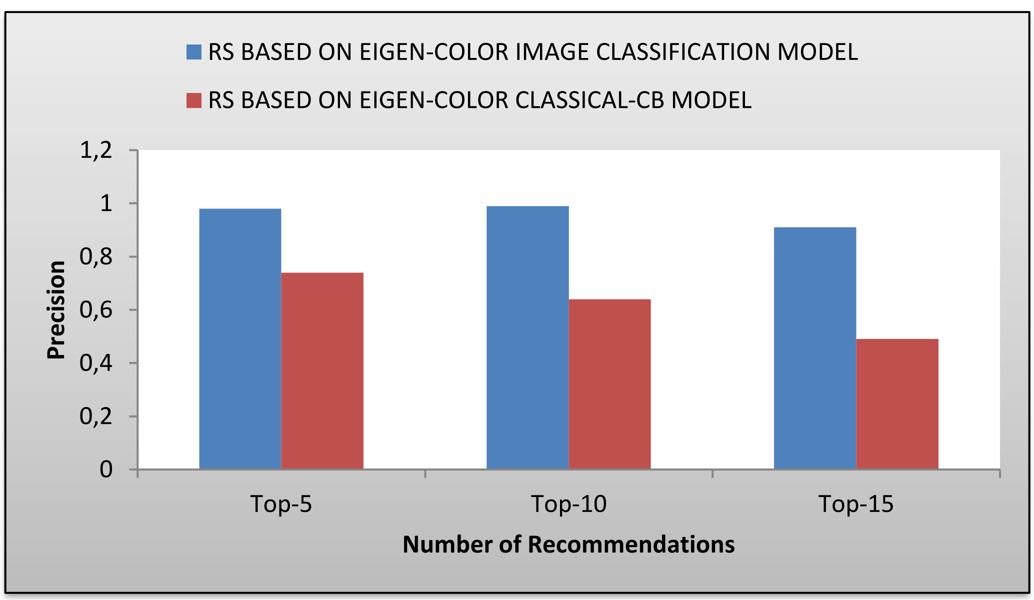


Figure 5-18: Top-N Precision recommendation accuracy for two recom models

Furthermore, the proposed method achieves thirty-eight percent, recall accuracy at top-5, while *Classical-CB* models had twenty-nine percent accuracy (Figure 6-19). The 38% recall accuracy can be interpreted that, 38% of the relevant items are recommended in the top-10 with the proposed classification-based recommendation system. In addition, recall accuracy at top-15 is ninety-seven percent by the proposed method as against fifty-nine percent of the Classical-CB model.

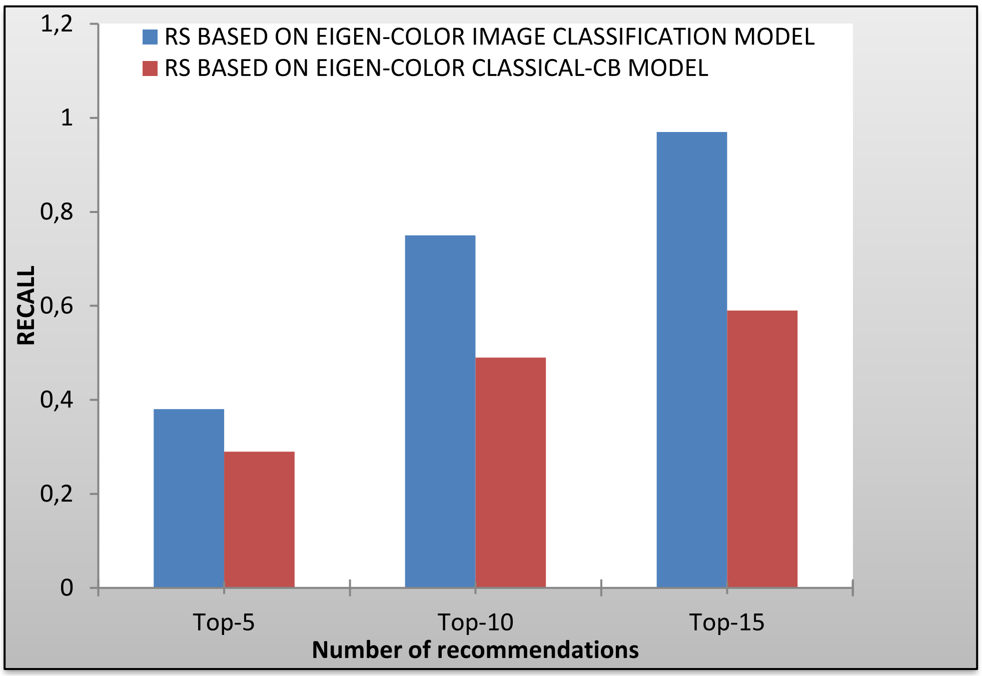


Figure 5-19: Recall comparison graph of two recommendation models

The result computed by F-measure shows the extent of the robustness of a classifier or similarity metric. A classifier is extremely accurate with high precision but low recall, but it misses a significant number of instances that are difficult to classify. An algorithm that has higher precision with lower recall is quite ok. However, in their situation one may not have such a strong goal, in that case, there will be a need to blend metrics. That is where F-measure deems very appropriate. With this, one is sure that with the F measure metric you are comparing some of the precision and some of the recall. Figure 5-20 shows F score at Top-5, Top-10, and Top-15. From Figure 5-20 an average recommendation accuracy of fifty-five percent is realise with $e - I_{cb} C$ the model as compared to 42% with *Classical-CB* model-based recommendation systems. The highest accuracy of nighty-four percent is realised at Top-15 rank recommendation while fourth two percent realised with *Classical-CB* at Top-5 is the lowest F-measure accuracy. This shows the robustness and effective balancing of the proposed model among precision, recall, and accuracy measures.

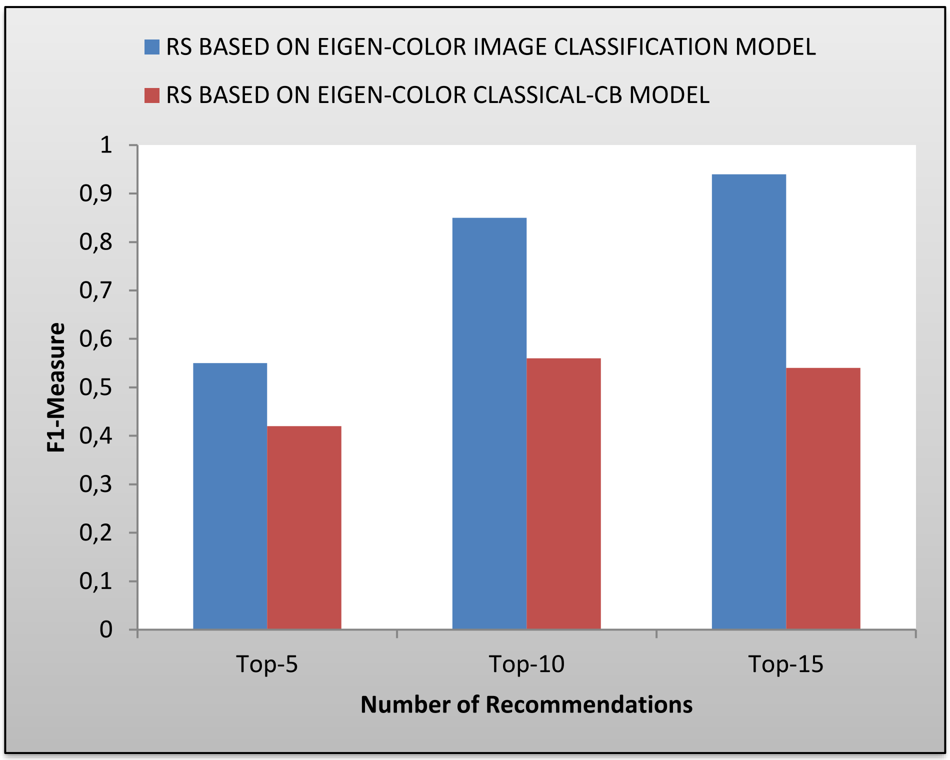


Figure 5-20: F-measure comparison graphs of two recommendation methods

The integration of $e - I_{cb}C$ the model based on all the results of the experiments conducted in this work has achieved high accurate recommendations. The integration of this model has acted as an antecedent to the classical content-based because it has reduced the irrelevant result generation by restricting the searching within the class of interest, instead of searching through the entire database. The good performance achieved by the proposed recommendation framework of this thesis is particularly of interest in the presence of new users. The accuracy of precision, recall, and F score @15 for the *Classical-CB* model are 49%, 59.0%, and 54%. These accuracies are low for effective delivery of recommendations that will interest a user. These types of poor recommendation accuracies hurt the persistence level of customer loyalty and their purchase decision-making, as established in the marketing philosophy (De Campos *et al.,* 2010; Bhattacharya and Das 2014).

The accuracy of precision, recall, and F1 score @15 for the proposed approach are 91%, 97%, and 94%. These accurate scores show that the solution provided by the $e - I_{cb}C$ model is interesting, particularly in addressing the multi-dimensional problem. The fourth research question of this study has been solved. It has been demonstrated in this study how the dynamic context features of user-preferred items can be captured over time and used to deliver effective personalised shopping recommendations to mobile users. The 5D social factors of the image should be integrated in a framework and simulated on PC. This prompted the selection of ECF-GT1/HOG and $e - I_{cb}C$ model with other image social factors for investigation. In addition, for experimentation purposes and clear distinction between experiments the $e - I_{cb}C$ model is one of the components integrated into building an effective recommendation framework.

Sample of results generated are shown in Figures 5-21 to 5-23 wherein one can observe visually that all items generated by the proposed recommendation method are from the same category with the query image. This result shows that $e - I_{cb}C$ the model beams its searching for the respective query image categories, instead of searching the entire database. This is in line with the assertion that classification restricts its searching only within the class of interest, instead of searching the entire database (Thepade, *et al.,* 2013a; Thepade, *et al.,* 2013b). The number of irrelevant product items has significantly reduced. The user requested for BabyShoe, BriefCase, and CowBoyHat for instance, and all recommendations are of different types of query images. So generally, this result will be interesting to a mobile user. Conversely, based on the subjective evaluation from Figures 5-21b, 5-22b, and 5-23b, one can visually observe that BabyShoe, BriefCase, and CowBoyHat are respectively used as the query images. In Figures 5-21b and 5-22b, more than half of the outputs generated bear no resemblance with the category of the query image.

a b

Figure 5-21: Results of ECF_GT1 Feature Extractor on BabyShoe Product Category using: (a) Classification (b) Classical retrieval system.

a b

Figure 5-22: Results of ECF_GT1 feature extractor on CowBoyHat product category using: (a) Classification (b) Classical retrieval system.

The query image is from the Nutrition category as one can observe from Figure 5-22b. The proposed recommendation model recommends similar items while the alternative model recommends all varieties of items from different categories ranging from the calculator, computer-monitor, baby-cage, toy-bear, to stopwatch category. Results like this imply that the proposed model of this study can understand the product item better. However, overall, the results generated by this approach are much diversified, but this type of result will not be interesting to mobile users because it requires frantic effort to filter and re-filter repeatedly before a user can find his/her preferred items.

a b

Figure 5-23: Results of ECF_GT1 feature extractor on Nutrition Product Category using: (a) Classification (b) Classical retrieval system

This section of the experimentation has helped in evaluating the performance of the proposed system in the domain of interest. The performance of the new system is experimental analysed and evaluated based on results generated and this is ultimately compared with the standard classical content-based (Classical-CB) recommendation approach (do not use without classification model). Tewari, Singh, and Barman (2018) reported that users in e-commerce generally prefer to see less than 20-25 recommendations at a time. Based on the research evidence coupled with the mobile devices I/O limitation the number of outputs generated at once is fixed at 15 that is N=15. On this background, a $I_b - MADA$ recommendation framework that incorporates product item category (realisable from $e - I_{cb}C$ the model), item distinctness feature obtained from ECF_GT1 feature representation, with others contextual information, price incentive as well as product recency factor is utilised in this work to generate the personalised recommendation.

5.6.1 Results of integrating $e - I_{Cb}C$ model with other multi-criteria factors

The assessment process of multi-criteria factors involves confronting tradeoffs between the alternatives under consideration. Each shopper will need to prioritize what matters to them most. Apart from recommendation accuracy, delivery of personalised recommendations is also paramount. In the proposed work, recommendations are suggested based on the image multi-criteria social-context information extracted from preference-item (cold-start user) or stored in the user profile. As a recap, for instance, in this work relevance, proximity, time, price, and incentive are the 5 image-based social-context attributes used to fully determine user preference. Most mobile users prefer to see only small size recommendation list with their items of interest in it. As a recap, one major purpose of the Top-N experiment is to determine the relative accuracy that a recommender can offer to a user, for a small value of n. Since the proposed system can realise top rank accuracy of Ninety-eight percent at Precision@5. This accuracy is good, as such in this work; Top-5 is selected as the maximum size recommendation list to be delivered to mobile users via the imaging interface.

One of the social-context factors considered in this study is item relevance. This social factor is obtained by matching item representation against the user profile. Item relevance is one of the three (3) major components of serendipity in recommendation systems (Kotkov, Wank, Veijalainen, 2016), and in this work, it can be referred to as the foundation, on which others 5D social factors relies. Therefore, it is important to know which weight this criterion will perform to the optimum by giving the best relevant image to the query image. This research work first carried out a sensitivity analysis by varying weight values assigned to relevance. The best result was realised when a lump weight of 0.6 out of 1 is assigned to relevance while 0.1 is assign to other criteria (i.e., Price = 0.1%, Proximity =0.1%, Recency =0.1%, Incentive =0.1% and Relevance =0.6). Figure 6-24 shows the results of recommendations. Furthermore, the weight sensitivity of each of the factors is investigated on Top-5 by repeating the same experiment for other social factors. Figures 5-25a to 5-25e show the results of recommendations. One can see that incentive, relevance and proximity offered a 100% precision score at Top-1 rank accuracy, with 0.6% weight. Subjectively, these factors gave the same image as the query image.

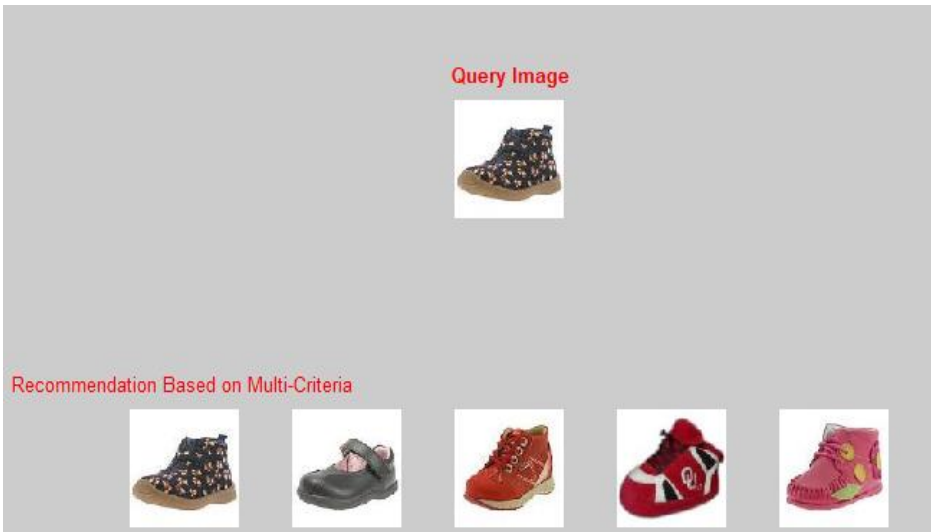


Figure 5-24: Sensitivity test for Image 5-D social factor weights with relevance weight =0.6%

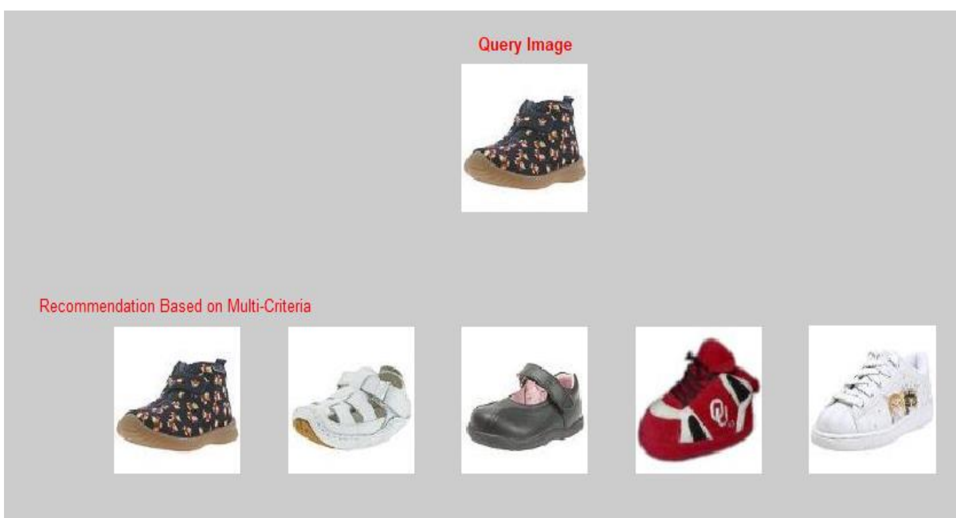


Figure 5-25: Sensitivity test for Image 5-D social factor weights with incentive weight =0.6%

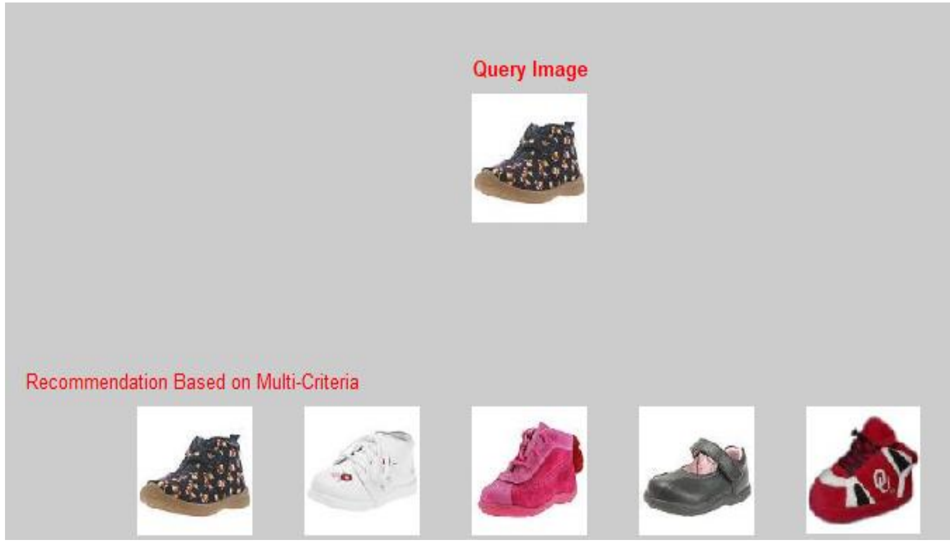


Figure 5-26: Sensitivity test for Image 5-D social factor weights with proximity weight =0.6

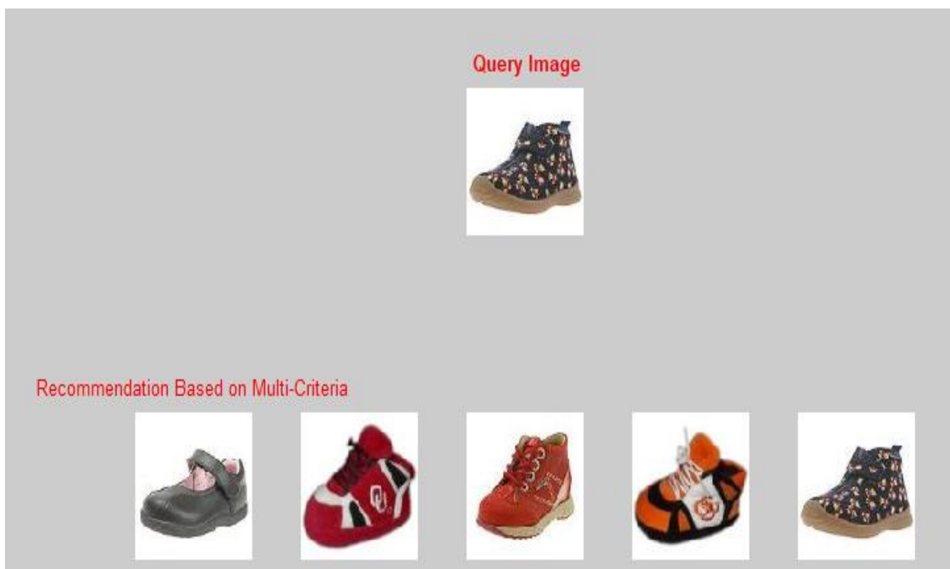


Figure 5-27: Sensitivity test for Image 5-D social factor weights with recency weight =0.6

Figure 5-28: Sensitivity test for Image 5-D social factor weights with price weight =0.6

The results from Figures 5-26 to 5-28 show that the proposed method increases the precision value of top-n recommendations for a small value of n (n=1 in this case). These results further strengthen the channel toward resolving the fourth research question of this study.

5.7 Implementation of Imaging Interface Prototype

The proposed system relies on 5-D image-based social factors to deliver a personalised recommendation to mobile users. Realising an equivalent dynamic interface is very challenging because of the dynamic nature of mobile users. The purpose of implementing and testing the effectiveness of an adaptive imaging interface that anchors on image content through a camera-enabled mobile device is to resolve the fifth research question of this study. The implementation of the recommendation system will serve as a proof of concept to demonstrate the feasibility of realising the required dynamic imaging interface using all the phone-gap technology tools earlier alluded to in Chapter 4. It is also worth mentioning that the proposed imaging interface followed the design considerations highlighted in Section 4.13. Consequently, a mobile shopping environment was created by building a local area network (LAN). The network is tagged *rsmnet, which was built with a* hotspot server named *rsm-server.* The mobile hotspot was built on a Samsung Galaxy ACE4 smartphone. The hot sport facilitates the internet phone connection sharing with the PC (server) and mobile client (Galaxy S4 in this case) through Wi-Fi tethering. This agreement transforms the smartphone into an equivalent of a broadband modem and router. This strategy works on most current Android and iOS phones. The *rsm-server* is currently running on 192.168.43.113 as shown in Figure 5-29.

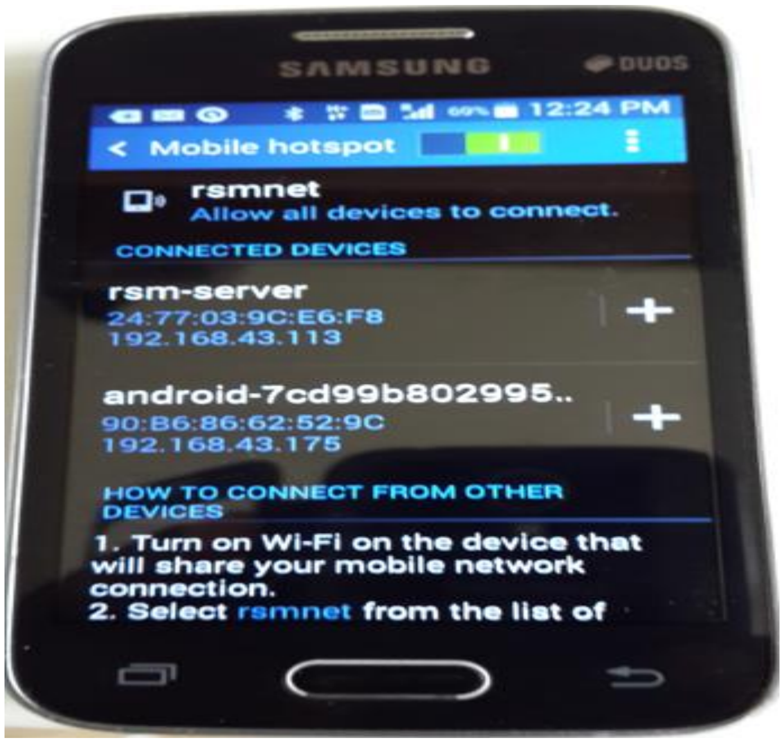


Figure 5-29: The Hotspot Server Name is -- rsm-server

The internet assigned numbers authority (IANA) is a part of a private network 192.168.43.0/24 that registers this IP address. The IP addresses in this private space are not assigned to any specific organisation and anybody may use these IP addresses without the consent of a regional Internet registry as described in RFC 1918, unlike the public IP addresses. The application project generates an android application (APK) after a successful compilation and execution of code. Figure 5-30 shows the generated APK on the client-side of the application. A mobile user or client can access this APK on the Admin page by typing 192.168.43.113 into the address bar of a web browser.

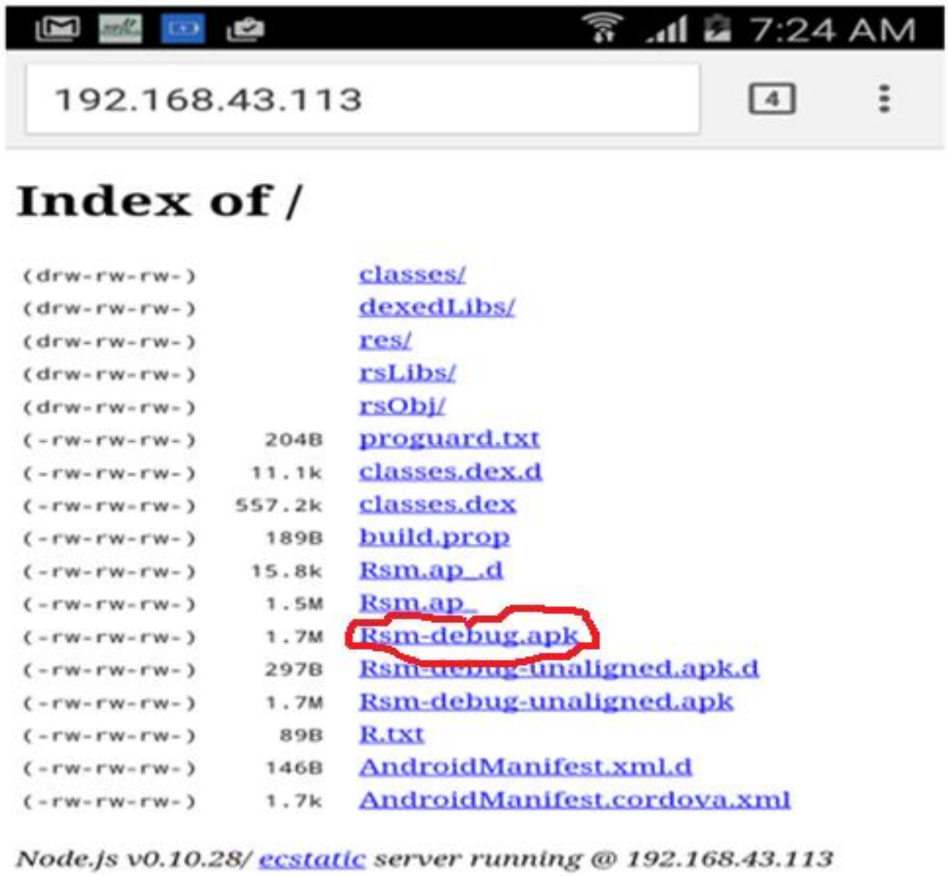
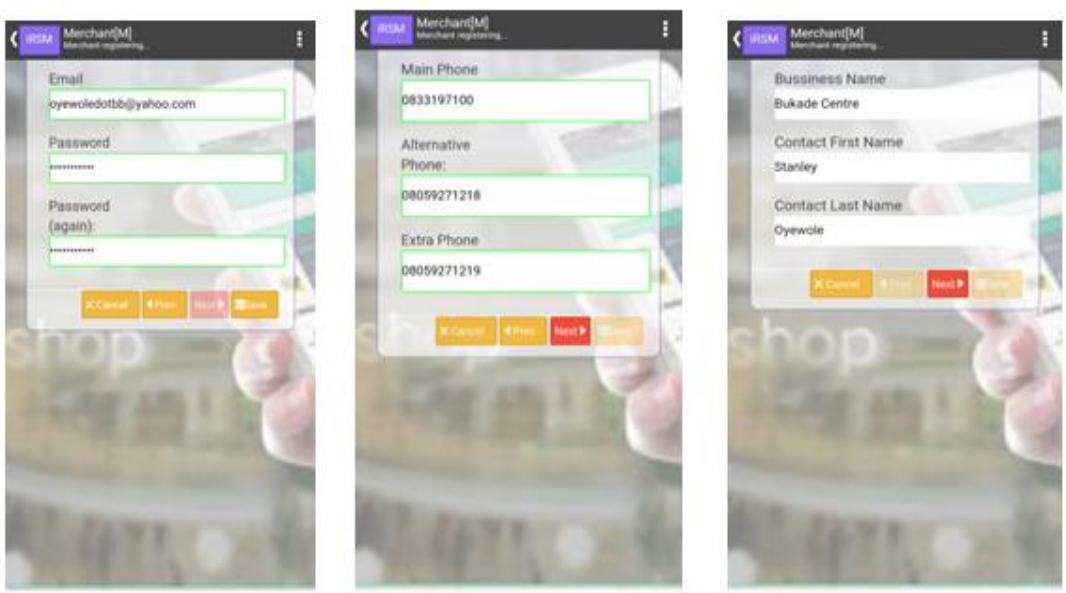


Figure 5-30: The Android application (APK) is generated on the client mobile

The APK is downloadable and installable. Any registered mobile user or merchant who intends to enjoy the services provided by this application may install it on his mobile for usage. After installing the '.apk' file, both fixed and mobile users will have full access to the application menus. In the following section, the components of the real-life functional interface are presented.

5.7.1 Interface for fixed user

At this state with the login interface design, fixed users who are the merchants or shop-owners can log in with their unique password and register all available items. The imaging interface also designs a new interface for the Merchants to register new items or update old ones during item registration. This interface opens a registration form for items, and one button enables the user to load the image or image information save along with others. Figures 5-31a to 5-31c show the required windows that allow the merchant to obtain access to the system.



a b c

Figure 5-31: Interface for Merchants

During the registration, all incentives that are pertained to item classes are extracted and submitted. Incentive scores used in this research are categorised based on scores. The product item with the assured guarantee is given an incentive score of 30%, product item that is on promotion is assigned an incentive score of 26%, product item that allows return is assigned a score of 20%, a product item that can be purchased on credit is allocated a score of 24%, item that can not be purchase on credit is assigned a score 0% and item price is indicated. The total incentive scores are shown in Figure 5-32 based on this scoring strategy is 50%. Customers were allowed to purchase an item on promotion (26%) and on credit (24%) to attract and retain more customers.

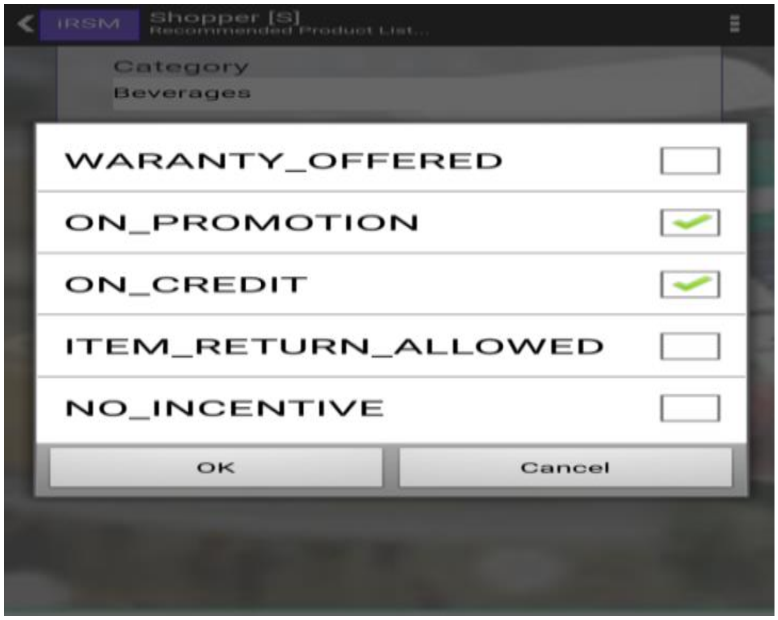
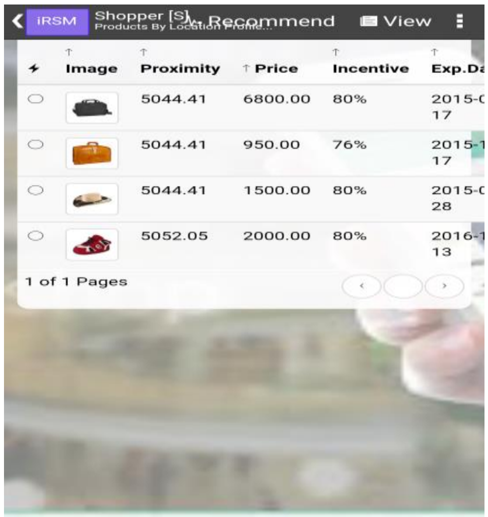
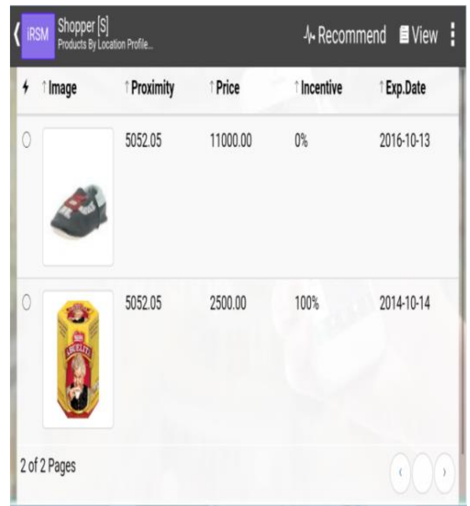


Figure 5-32: List of Attached Incentive Options

5.7.2 Making Recommendation List to Mobile Users with Imaging Interface

This mobile client interface is developed and then deployed on Samsung Android Phone (Galaxy S4) 3GS devices running android version 5.0.1 operating system (O/S). On the client-side, the user interactively captures the product image of his choice using an imaging interface and sends it to the server for processing. The unique identification number that is used for each user is the phone international mobile equipment identity (*IMEI*). This is used to access and update user profiles accordingly. The imaging interface allows a *new user* to interact with the mobile recommendation decision engine by taking a picture of his desired shopping item and send. The recommendation decision engine jointly considered similarity scores of items and all other extracted details in determining the final preference of a shopper. It finally sends the recommendation list to the mobile device. Figures 5-33a and 5-33b show page 1 and page 2 of similar items to query based on the image captured with the imaging interface.





a b

Figure 5-33: Prototype of Recommendation Results on Galaxy S4 Mobile Phone

A user may wish to check the details about each of the images to enhance his/her selection. Figures 5-33a to 5-33c show an enlarged preview of interface windows for three products after capturing during item registration. The interface also provides the product price, name of this item, and shop location where respective items can be found, as shown in Figure 5-34. One of the dynamic features of the imaging interface is that a user can perform sensitivity analysis based on his preference on the result page offered to him by clicking on the pointed errors in any of the respective factors he so wishes. The results will be reordered accordingly based on the preference factor selected. The Next button shows further information.

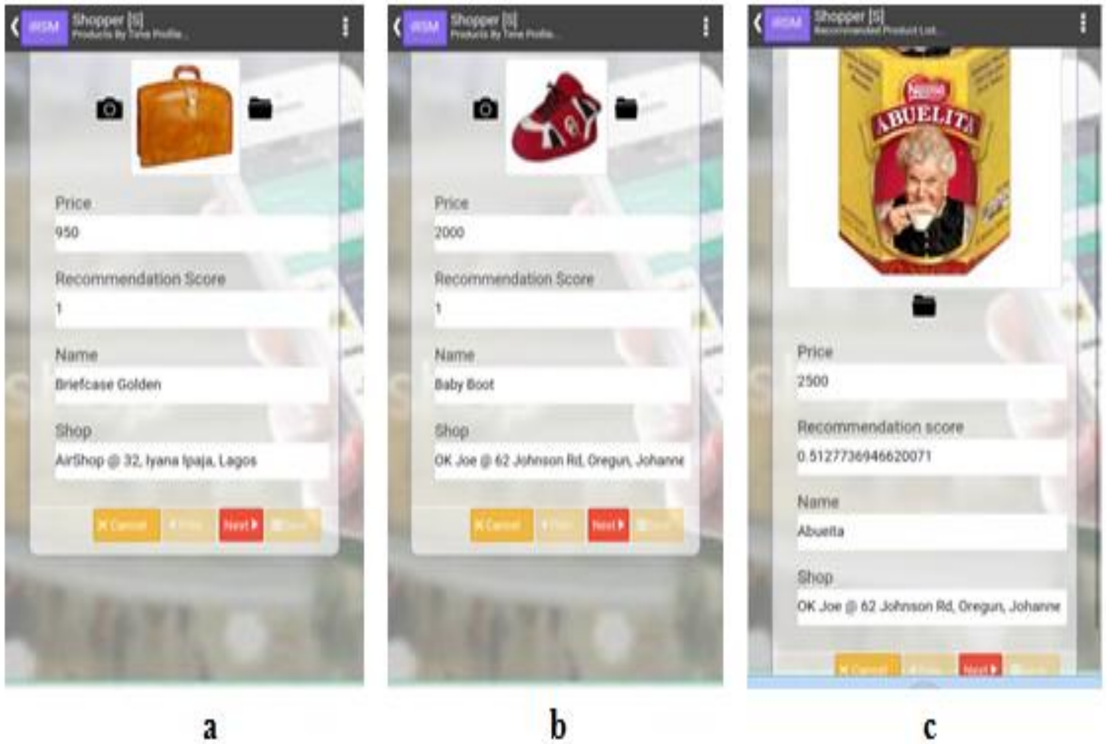


Figure 5-34: A wider view of an image during registration after Image capturing

The other important feature of the system is the ability to suggest diversified recommendations by generating complementary items to the initially selected item. These are lists of other items that can be purchased with the best item selected. Figure 5-35 shows the other complementary items selected by an active user that can be added, and the total amount required.

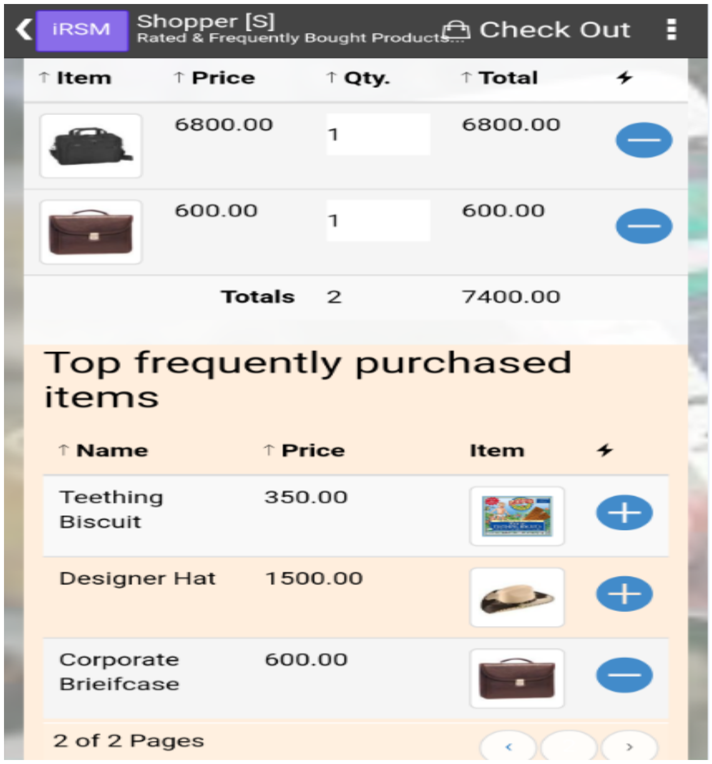


Figure 5-35: Recommendation Complementary Item

5.8 Chapter Summary

The proposed image-based representation algorithm has been broadly examined and assessed in detail. It has also confirmed that it satisfies all the necessary conditions for image representation that can be integrated into the recommendation system. One thing that is worth mentioning is the fact that realising image salient features or non-redundant feature components of a product image is very challenging. A large size feature will affect the recommendation process while a relatively small size feature may result in significant distortion in the resultant feature vector realised. As reported in Oyewole and Olugbara (2018), ECF produced state-of-the-art classification accuracy on the PI100 dataset with 100 classes of product items the proposed work in the thesis still outperforms it. In addition, it also generates compact features with colour Histogram descriptors as shown in Figures 6-10 through 5-17.

The incorporation of the ECFGT1-Histogram based classification model directly into the proposed product recommender system confirms that the introduction has a positive effect on the new cold-start user. In this research, this model only generates image class and image feature vectors as criteria. In making more personalised recommendations other images of social-context information (such as location, item-price, and attached incentive) are factored in, to achieve personalised recommendations to *new user*s. In addition, this chapter has presented a full implementation of an image-based mobile interface for personalised elicitation of shopping preferences of users. The proposed recommendation system relied on an image-based capturing approach to meet up with the dynamic nature of mobile users.

CHAPTER SIX

Conclusion and Future Work

6.1 Preamble

This chapter gives a summary of the research work reported in this thesis, including its contributions, limitations, and future work. As a recap, the overarching aim of this study was to elicit the drift preferences of users of a personalised recommendation system based on multiple criteria image content towards improving the system performance. The aim has been achieved as demonstrated through a recommendation model developed and tested through a series of experiments.

6.2 Summary of the Research

The research work presented in this thesis serves as an alternative approach to integrate multiple criteria and machine learning approaches to address a few open problems in product recommendation research.

Firstly, this research work proposes an enhanced image-based classification model to create implicit short-term profile information and reduce the search space of product items. The idea piggybacks on category theory and image-based semantic classification model. The classification model generates a very low MSE of 0.00061. Secondly, the same model is further explored to realise a discriminative item-class social factor. The item-class serves the purpose of improving other social factors. Experimentally, the study result generates a new state-of-the-art classification accuracy of 92.26% on the PI100 dataset. The number of product classes in the ground truth of the experimental database is 100, which is considerably huge. Achieving such an impressive new classification accuracy is encouraging because the performance of most machine learning algorithms often degrades with a large number of classes.

The TOPSIS algorithm that leverages multiple criteria decision theory was used to aggregate all social factors scores for the selection and recommendation of the best preference alternatives for a new user. This portion of the system addresses the elicitation process of user preference by projecting product item recommendations as a multiple criteria decision problem. The proposed method reported in this thesis presents 6 social factors to effectively characterise user preference. The final target and idea are because *new user*s do not have any preference information apriori, the 6-item social factors will generate what new users might likely want to buy, based on their initial preference item and contextual information. This philosophy handles the issue of inefficient user preference information, which is often regarded as the open problem of user cold start.

A new time-based similarity function has been devised with the major aim of improving content-based recommendations. In addition, the enhancement of the score of a particular image social factor attribute and user interest corresponds to a decay that takes place in a simple linear fashion. The time-lag function only delays the recommendation process in such a way that is not linear. It has been found that if user interest can be identified and a good shop to locate the desired items can be recommended, the personalisation of user interest exponentially takes place. In this research work, an imaging interface that meets the dynamic nature of a mobile *new user* has been developed. Mobile shoppers were allowed to dynamically capture any desired query image with the proposed imaging interface. The imaging interface relies on a native-based and phone-gap technology that was successfully implemented on a mobile phone.

6.3 Summary of Contributions

This thesis contributes to using image-content-based features representation to address the open problem of concept-drift and reduce the search space of product items. The thesis thus provides the most effective method to acquire user preference based on 6 social factors to improve the performance of a recommendation system. It also contributes to how to extract high-level features from low-level image features to improve the performance of a classification system. Generally, this thesis makes a significant contribution toward enhancing personalised recommendations, particularly when users are met with uncertain information needs scenarios. Generally, the main contributions of the research reported in this thesis are summarised as follows.

❖ **Contribution to a new colour image representation algorithm**

Extracting salient and dimensionality reduce features from images becomes an important contribution, especially in the world of today where image-content is believed to be a powerful complementary carrier to express user intent. The proposed image representation has as a component a novel 4-D colour model that does not only improve accuracy but also resolve difficultly involve in selecting the best colour model among several ones in the image retrieval domain. Results of the experiments conducted on visualization of image features show that the proposed algorithm generates high-level and low-dimensional image features, significantly generating higher accuracy than other 4-D features colour models.

❖ **Contribution to a new image-content-based preference elicitation model**

Most often individual personal data do reflect certain preferences; however, one of the challenging tasks in delivering personalised recommendations is how to acquire the preferences of a *new user*. This often exists mobile users who cultivate their preferences ‘on the go’ and most of the time do not know how to stylishly express exactly what they want. These two common scenarios do negatively affect the quality of the recommendation system and as well make accurate user profiling very difficult.

In this situation, *image-class* can be used to build an implicit-short term profile for the *new user*. The short-term implicit profiling method is faster and fit than the use of rating, particularly in the mobile domain. Towards realising this image-based classification model is proposed in this work. This model aims to improve the prediction accuracy of recommendation systems by realising image-class social factors. This classification model realises classification accuracy of 92.2% on PI100 with product images in 100 categories. The final classification model can simply be incorporated into any decision supportive application in any e-commerce domain. This model tends to reduce search space and improve recommendation accuracy.

- **Contribution to improve the multi-criteria approach for recommendation generation**

The report from recommendation literature has revealed that the two most popular recommendations are dread by user cold-start problem. In addition, the same literature hints that these two conventional recommendation systems relied on only single rating information. Thus, only the extracted image-content features or rating cannot produce quality product item recommendations.

This thesis proposed to integrate item-class social factors with item relevance, price, incentive, proximity, and time-band to improve the system accuracy toward overcoming these open problems. The result shows that the injection of image-class with other social factors can produce better-personalized recommendation accuracy results compared to those without image-class. This model has attended to both *multi-criteria decision problems* and the *new user* problem, which is a novel idea. It is novel because existing recommendation systems rely on classical retrieval systems that are plagued with many limitations.

To the best of our knowledge, nobody has integrated image-based classification with decision algorithms in recommendation technology.

- **Contribution to the effective realisation of mobile imaging interface**

Mobile devices play vital roles in our daily lives thereby becoming a recommendation terminal customised for individuals. Existing research works have predominantly focused on understanding the intent expressed by text. This is a typed word or text recognised from a voice sample. However, typing on the phone takes time and can be cumbersome for expressing user intent, especially in an urgent situation. An alternative is to leverage speech recognition techniques to support voice as an input. For example, popular mobile search engines enable a voice-to-search mode. However, the use of voice-to-search as an expression of user intent has two major limitations. First, it relies on a good recognition engine just like the proposed approach in this work, but it requires a moderately noiseless environment before it can work well (Zhang, et al 2015). Bearing in mind the nature of mobile users who are very dynamic both in time and their preferences, the existing static interface will not be able to accommodate their natural disposition and serve them appropriately. Moreover, translating from voice to text can be problematic for users of different native languages.

This thesis contributes by developing an imaging interface that can accommodate the dynamic nature of mobile *new users* with a new design and implementation of a cross-platform-imaging interface to anchor the above recommendation framework in a mobile shopping domain. The new interface allows mobile shoppers to dynamically capture any image of their choice and send for effective recommendation making. This approach improves the quality of item recommendations to overcome the intrinsic problems of the orthodox text or voice-based recommendation methods. The proposed architecture has been tested on e-commerce product images mined from a popular database. The queried item is obtained from captured item images on camera-enabled mobile devices. The use of an image as input boycotts inherent limitations of text-word as input, which to date is still a challenge to mobile users. One can observe that this research work has contributed immensely to effectively delivering personalised recommendations of product items to mobile users by addressing the open problems of limited content analysis and *new users*.

6.4 Limitations and Future Work

Most good research, in general, presents an area of limitation for further research to address. This section of the thesis will discuss the limitations of the present research work and possible future expansion that can be researched. The highlights of the work done are presented as follows and point out the study limitations for future work.

- ❖ The novel state-of-the-art classification accuracy was realised in this study with 100 item classes. This mimics the real-life e-commerce application domain that presents multiple types of product items. However, there is still more to do in this area because several thousands of e-commerce products are available. Consequently, it is important to further develop and validate a single recommendation system that recommends thousands of product items. Future work can employ emerging deep learning and graph embedding methods whenever an advancement in the product databases reaches a maturity stage, which is currently of low progress.
- ❖ The thesis suggests an approach of addressing both the *new user* scenario and limited content analysis situation. However, the work did not consider the issues of scalability and sparsity. These are areas, which could be researched further in the future. Finally, the researcher believes that on a conceptual level, these limitations are not dire. The issues are vital when dealing with real-world implementation deployment with real datasets, hence the possibility of future expansion of the study.

- ❖ The lack of quality and sufficient mobile item or spatial databases is one major limitation for future research. This important issue has been rightly identified in the literature, as most of the existing mobile item databases, like movies music, and books are domain-specific (Pimenidis, Polatidis, and Mouratidis, 2019).

The satisfaction of users with product recommendations is of paramount importance in any recommender system. Therefore, this thesis focuses on how to utilise the relationship that exists between user satisfaction and the pretty multiple attributes information on product items. This relationship provides a prospective enhancement in the recommendation-making process. This connection could be further used to increase the recommendation performances and its limitations. On this background, plans on how to extend the proposed work in this study have been made. The target is to produce other novel algorithms by strengthening the relationship between the above-mentioned entities, together with other classification methods.

The proposed image representation technique ECF_GT1 with Eigenvalue >1 performs effectively when integrated with the classification framework and likewise in multiple criteria recommendation system, but its efficiency was not determined. The efficiency of a recommendation system is certainly a critical need considering the nature of the mobile user. An imaging interface has been proposed to anchor the proposed architecture. The interface is built using phone-gap technology, which enables it for cross-platform ability. However, the thesis did not cover other mobile phones such as iOS and Windows Phone apart from Android. In the future, more experiments and comparisons will be conducted on other smart mobile devices. This will allow an in-depth study into how the proposed system performs in all the different mobile operating systems. The introduction of imaging interface particularly into the mobile recommender systems arena is still a relatively new area that still needs more research effort.

6.5 Conclusion

The overarching aim of this study was to elicit the drift preferences of users of a personalised recommendation system based on multiple criteria image content towards improving the system performance. Consequently, a mobile recommendation system has been developed and tested in this study to achieve the set aim. A new mobile user who is just coming newly to use the recommendation system must first gain access through the newly designed imaging interface and then capture the image of his preferred item. The captured image is then sent through the imaging interface to the mobile recommendation engine where image features and other attributes are extracted for effective representation. An implicit short-term profile is built, and this is compared with those image features in the database. Thereafter, the system returns the list of similar product items that is suitable enough to meet the dear needs of a new user. The social factors proposed in this study to elicit the drift preferences of users of the developed personalised recommendation system are item relevance, item-class score, price of an item, product recency, attached incentive and, proximity attribute score information. The aim of the research reported in this thesis has been fulfilled.

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