IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received March 12, 2022, accepted March 25, 2022, date of publication March 28, 2022, date of current version April 4, 2022.

Digital Object Identifier 10.1109/ACCESS.2022.3163023

Fusion in Cryptocurrency Price Prediction: A Decade Survey on Recent Advancements, Architecture, and Potential Future Directions

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ABSTRACT Cryptographic forms of money are distributed peer-to-peer (P2P) computerized exchange mediums, where the exchanges or records are secured through a protected hash set of secure hash algorithm-256 (SHA-256) and message digest 5 (MD5) calculations. Since their initiation, the prices seem highly volatile and came to their amazing cutoff points during the COVID-19 pandemic. This factor makes them a popular choice for investors with an aim to get higher returns over a short span of time. The colossal high points and low points in digital forms of money costs have drawn in analysts from the scholarly community as well as ventures to foresee their costs. A few machines and deep learning algorithms like gated recurrent unit (GRU), long short-term memory (LSTM), autoregressive integrated moving average with explanatory variable (ARIMAX), and a lot more have been utilized to exactly predict and investigate the elements influencing cryptocurrency prices. The current literature is totally centered around the forecast of digital money costs disregarding its reliance on other cryptographic forms of money. However, *Dash* coin is an individual cryptocurrency, but it is derived from *Bitcoin* and *Litecoin*. The change in *Bitcoin* and *Litecoin* prices affects the *Dash* coin price. Motivated from these, we present a cryptocurrency price prediction framework in this paper. It acknowledges different cryptographic forms of money (which are subject to one another) as information and yields higher accuracy. To illustrate this concept, we have considered a price prediction of *Dash* coin through the past days' prices of *Dash*, *Litecoin*, and *Bitcoin* as they have hierarchical dependency among them at the protocol level. We can portray the outcomes that the proposed scheme predicts the prices with low misfortune and high precision. The model can be applied to different digital money cost expectations.

INDEX TERMS Cryptocurrency, price analysis, volume analysis, deep learning, machine learning, survey, ensemble model, fusion in metrics.

I. INTRODUCTION

Cryptocurrencies have been introduced to the market in 2008 when Satoshi Nakamoto rendered the first cryptocurrency named *Bitcoin*, through his white paper *Bitcoin*: peer-to-peer Electronic Cash System [1] intending to replace the old and widely used economic system. The traditional cash exchange system is entirely dependent on the centralized third-party financial institutions such as banks in order to validate and execute the monetary transactions. It is restricted to perform only a finite amount of money and possesses various issues such as trust, security, transparency, and flexibility. To overcome the aforementioned issues, a peer-to-peer (P2P) network-based currency namely cryptocurrency is a perfect

The associate editor coordinating the review of this manuscript and approving it for publication was Jolanta Mizera-Pietraszko.

solution [2]. It eliminates the involvement of centralized third-party banking systems. In this, each transaction has to be acknowledged (validated) by each peer using any suitable consensus algorithm such as proof of work (PoW), proof of stack (PoS), and many more. These algorithms internally uses the transaction hash and timestamps for transaction confirmation. It requires peers in the network to solve a complex mathematical problem to add a new block in the chain. Mining is the process of solving the problem, and miners get rewarded for their work through cryptocurrency. A specific block is of no use until it is not added to a chain. Here, the question arises whether the system of cryptocurrency can be carried out in a practical scenario?

The practicality of Bitcoin can be seen through its exponential growth in terms of transaction and volume. The first transaction was done in 2010, where 10000 *Bitcoins* were used to buy couple of pizzas [3] and as of April 2021, nearly 2 million transactions were executed. As the number of the transaction is increasing exponentially, we can say that the cryptocurrency is accepted by the public. Specialized hardware is required to make the mining process efficient. To carry out the mining, GPU plays an important role, which utilizes its CUDA cores for quick calculation of PoW problems by recalculating the valid hash using algorithms like SHA-256 and X11 as well mentioned by the authors in [4]. The GPUs utilized in this process are expensive and they require high power supply. Then, the organization started to use a system called pool, where many users come together to mine a coin by helping each other and get proportional reward based on their contributions [5], [6]. So, is there any way to generate profit from it?

The mining activities described above are profitable, which leads to the emergence of startups and draws the attention of big companies for mining cryptocurrency. However, the complexity of making a chain of hashes increasing day-by-day due to the limited number of coins available on the web. Apart from these, other factors like the market sentiments of also affect the coin prices. Such additional factors make the cryptocurrency prices highly volatile, and the mammoth institutes are getting high returns [7], [8]. The same observation can be sum up from the price timeline, i.e., the *Bitcoin's* price jumped from \$0.08 in 2010 to above \$64000 as of April 2021 [9], and the same trend is followed by *Ethereum*, *Ripple*, *Litecoin* and others as well. So, what will be the growth of the cryptocurrency market cap, and at present how many cryptocurrencies exist in the market?

Since the inception of *Bitcoin*, several cryptocurrencies have been introduced to the market having their advantages and disadvantages. As of April 2021, according to [9] nearly 4200 crypto coins are circulating in the market with a net worth of over \$2.23 Trillion, in which *Bitcoin* has a share of 78% followed by *Ethereum* with a total market share of 12%. High market esteem brings the consideration of organizations and people to put resources into them. The cryptocurrency market will boom with a minimum expected CAGR value of 11.9% that had been derived by [10] with a detailed analysis based on different market sizes, peoples sentiments, and many other factors as well. The given growth rate is functional till 2025. Considering that the market follows the same trends then the given growth rate can be effective for cryptocurrencies. Through FIGURE 1 we can see the expected future price changes of the crypto market till 2050.

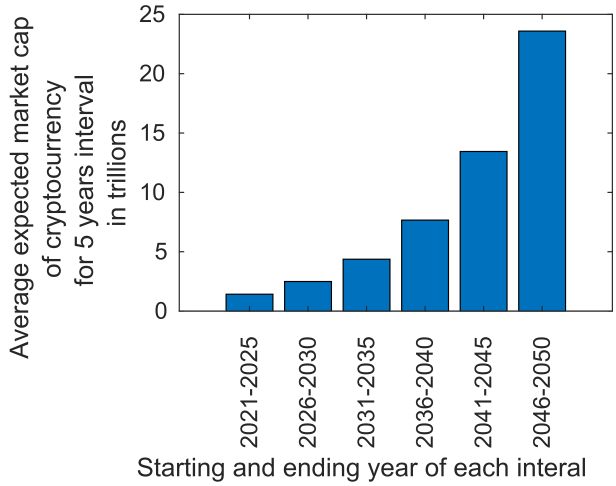


FIGURE 1. Timeline of cryptocurrencies market from 2020-2050.

High volatility in cryptocurrency prices invokes the interest of researchers across the academia as well as industries to predict their prices using the power of machine learning and deep learning algorithms [11]. The volatility of cryptocurrencies depends on factors like volume, mining difficulty, popularity, price of alternate coins, transaction cost, sentiment on the social platform, and the laws of a specific country as well stated in [12], [13]. Due to the involvement of numerous factors, price projection becomes a challenging task for the entire research community. To solve this challenging task, we put forward a fusion of cryptocurrencies, a deep learning-based scheme using a time-series model. The function of this model is to predict the price of a specific coin by utilizing the past prices of other cryptocurrencies. For example, the price forecasting of *Ethereum-Classic* can be done through prices of *Ethereum* and *Bitcoin*.

A. NECESSITY OF FUSION IN CRYPTOCURRENCY PRICE PREDICTION

The sudden surge in the market value of cryptocurrencies brings huge attention to the investors. The main activities involved in cryptocurrency market are selling, buying, and submitting PoW, PoS through mining. For analyzing its efficiency in the market, the hypothesis theorems like EMH and AMH were introduced. Now, we will get insights to this theorem in context of cryptocurrency market [14], [15]. To understand the EMH, consider a situation where prices of *Bitcoin* are reflecting by sentiment on the social platforms. However, the approval evidence of EMH has been arguable over a while. Oppositely, there is no approval evidence for EMH, the author of [16] has studied the cryptocurrency market through EMH and found good results. EMH being arguable for its utilization in the real scenario for determining dependency among factors. To overcome it, AMH comes with the inclusion of Behavioral finance. So now, what are AMH and behavioral finance hypotheses, and how it is important for our research?

Behavioral finance is the study of influence of psychology on the behavior of investors or financial analysts. The information by them creates a situation called herding, where the people's actions depend on market agents [7], [17]. The bias discussed above had an important role in determining cryptocurrency prices. During this kind of scenario, EMH does not work, because it assumes the market to be frictionless without any uncertainty and biases. Therefore, an alternative theory named AMH was introduced. The study in [18] checks the proficiency in the development of *Bitcoin* prices, and concluded that the proof of dynamic effectiveness sticks to the recommendation of the AMH. The authors of [18] concluded that the different factors mentioned in [12] played an important role in determining the cryptocurrencies prices, so there must be a careful selection of attributes to be considered together for improving the ability of the forecasting model. Integrating these features helps to build a robust model, where the shortcomings of a particular factor can be covered by other factors. The process of integrating and utilizing these features is term fusion. So now the question arises, how can the fusion algorithm be incorporated to build a prediction model?

The fusion can be carried out in two ways. One way of fusion is to integrate several forecasting models to make a hybrid or ensemble model [19]. Through this, the results of all models can be generalized to overcome the weaknesses of a single model. Another way of fusion is our novel idea, where we consider the inter-dependency among cryptocurrencies. Here, the interdependency may be technical or non-technical. Considering these ways significantly improves the performance of the forecasting model.

B. SURVEY METHODOLOGY

This section describes the methodology considered to carry out the survey. For this, we have followed the guidelines given by Kitchenham and Charters [20]–[22].

1) REVIEW PLAN

The exhaustive study needs some survey planning for this paper, a comprehensive study has been performed to provide insights into the concrete research done in the field of cryptocurrency price prediction by utilizing it's different depending factors. We begin with the review planing, identification of numerous research questions helping to narrow down our search criteria, reading of sorted articles for inclusion–exclusion criteria, and quality evaluation. We identified various relevant studies, articles, and publications to carry out this systematic survey. The identified material is first referred for quality before utilizing its data in the proposed survey.

2) RESEARCH QUESTIONS

The aim of this article is to systematically and comprehensively survey cryptocurrency price prediction using machine learning and deep learning algorithms and then propsed a novel method to increase the performance of the prediction model. For impelling it, various research questions were framed for this comprehensive survey as written down below:

- What are possible factors that are yet to be explored for cryptocurrency price prediction?
- What is the importance of explored factors for cryptocurrency price prediction?
- How to improvise new findings with existing work to make a powerful forecasting model?
- What are other possible fusion-based algorithms to make a robust forecasting model?
- What are the research challenges of the identified solution?

3) DATA SOURCES

Our study had been carried out through high-quality peer-reviewed research works from the reputed online databases such as Springer, Elsevier (Science Direct), ACM digital library, Wiley, IEEE Xplore, Google Scholar, and the company's official technical blogs.

4) SEARCH KEYWORDS

The vital keywords used for searching the related contents were: "cryptocurrency", "cryptocurrency price prediction", "price prediction using machine learning", "factors affecting prices of cryptocurrency", "blockchain factors affecting cryptocurrency prices", "time series based machine learning models", "regression based price prediction", "Bitcoin and Ethereum volume analysis", "Bitcoin and Ethereum price analysis", "Impact of price change on derived cryptocurrency", "Stakeholders in cryptocurrency market", "Companies and research organization involved in blockchain development", "market and sentiment trends on cryptocurrency market", "Correlation values between dervied factors", "types of cryptocurrencies", "Details of Zcash, Dash, Litecoin, Ripple, Monero, Bitcoin Cash Bitcoin SV, Ravencoin, Ethereum Classic, Qtum, Wrapped Bitcoin, Ripple and Binance Coin", "Normalization techniques for regression", "Working of RNN, GRU and LSTM", "Ensemble Models", "Performance evaluation metrices for price prediction models", "Transformers, Federated Learning and Reinforcement learning in field of price prediction", "Legal aspects and goverment policies on cryptocurrency", and "challenges in the field of cryptocurrency price prediction".

5) CRITERIA OF INCLUSION AND EXCLUSION

For making this survey impressive and effective, the recent and relevant papers of 2020 are included along with the early access articles. The other survey articles, tutorial papers, books, technical reports, blogs, and other resources are also included for wider coverage. The filtration process is divided into multiple stages based on the title, abstract, full paper, and investigations. Finally, we identified some relevant papers and focused on those having good citations. We have analyzed the works of curated papers and highlight the significance of papers in this field of research, incorporating various noteworthy studies in our article with our new fusion method for the prediction model.

C. SURVEY MOTIVATION

The properties like immutability, transparency, security, decentralization, and exponential growth make the cryptocurrency market an important part of the investment for investors and individuals. Because of its volatile nature with high returns, people started trading, which works similarly to the stock market. The study in [23] briefs about the crypto trading. FIGURE 2 concluded the same which reveals the exponential growth in the number of crypto wallets since 2011. However, the price is much more volatile compare to other investment areas because of its dependency on a vast number of parameters as discussed above. The above reason motivates us to work in the research field of cryptocurrency price prediction.

The state-of-the-art forecasting models uses machine learning and deep learning algorithms. But most of them focus on the limited and famous cryptocurrencies such as *Bitcoin*, *Ethereum*, *Ripple*, and *Litecoin* [19]. The factors they have considered are also limited and direct factors like opening and closing price, the complexity of mining problem, volume, and flow of the coins. Others have considered indirect factors like sentiments of cryptocurrencies on social platforms [24], socio-economic factors [25], epidemic modeling [26] and online social networks (OSN) models for detecting price bubbles. Apart from this, are there any significant factors that can be considered for designing a precise and robust model?

There exist several other properties that plays an important role while forging the forecasting model. One of the properties is the dependency of one coin on others. Although it is an indirect factor as most of them are derived from *Bitcoin* and *Ethereum* with additional features, so the price tendency of the derived coins is dependent indirectly on them. The inverse can be justified as the price changes of the derived coins can reflect their impact indirectly on the parent one. This factor is vital, which further motivates us to build a forecasting model utilizing the described feature. Our paper aims to incorporate this factor through fusion in state-of-the-art models to improve the performance of the price prediction algorithm.

D. RESEARCH CONTRIBUTIONS

Price volatility and the dynamic nature of cryptocurrency make the task of price forecasting hard and tedious. Several state-of-the-art models have been introduced by researchers across the globe that analyzed the dependency of several direct and indirect factors for the price prediction. Still, many

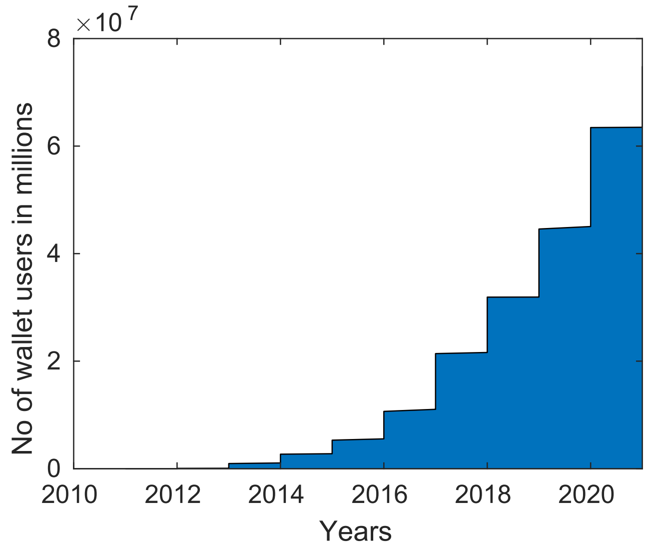


FIGURE 2. Growth in number of cryptocurrency wallet users till 2021 [9].

dependencies are yet to be explored. The existing studies have explored such attribute and following are the key objectives of the paper.

- We present a comprehensive study on various existing cryptocurrency price prediction models that uses both machine and deep learning approaches.
- We propose a novel deep learning-based fusion model to predict the cryptocurrency prices by considering their interdependencies among other cryptocurrencies.
- To evaluate the performance of the proposed fusion-based model, we consider different window sizes, i.e., 1, 3, 7, and 30 for previous cryptocurrency prices.

E. ORGANIZATION

FIGURE 3 represents the paper organization, where of this paper. The rest of the paper is organized as follows. Section II discusses the existing research work in the field of cryptocurrency price predictions. Section III gives the detailed analysis of major factors mentioned in [12], affecting the price of the cryptocurrency. Section IV describes the importance of stakeholders associated with cryptocurrency price prediction. Section V analyzes the important metrics that affect the prices of cryptocurrency. Section VI consists study of dependency among the cryptocurrency based on technical and non-technical factors. Section VII discusses problem formulation and making a system model for the proposed architecture. Section VIII describes the architecture of proposed fusion-based model. Section IX contains the performance of the proposed fusion-based model. Section X disucussed the threats that will harm the survey and measures done to prevent it. Section XI is based on the discussion of issues we have found during our study and suggesting its future directions. Section XII contains the conclusion of our work. Table 2 describes the acronyms along with their meaning.

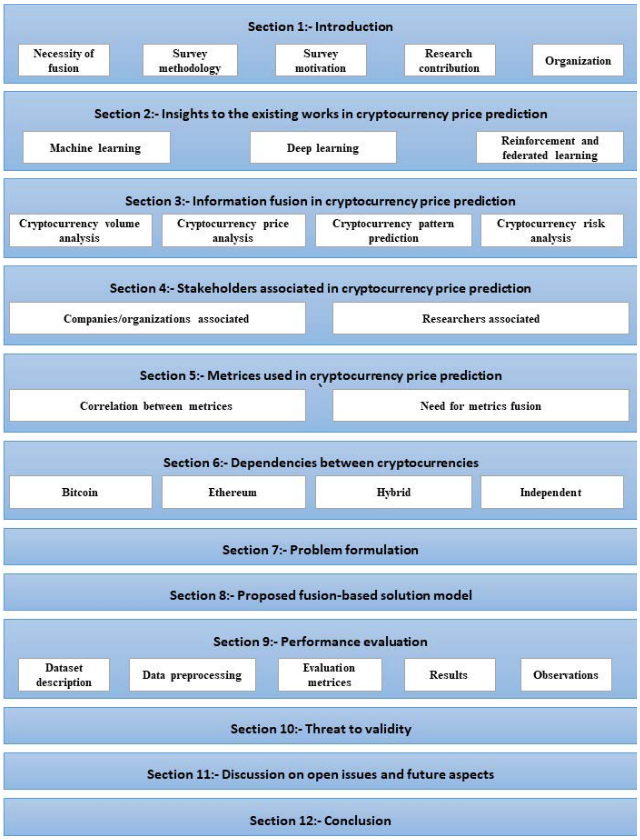


FIGURE 3. Organization of the paper.

The introduction section explains the working of cryptocurrency and factors affecting its price. It also focuses on the estimated growth of the cryptocurrency market between 2020-2050 with a CAGR value of 11.9% and its timeline in FIGURE 1. Following, a short explanation of the proposed forecasting model. After that, there is a brief description of factors influencing cryptocurrency price based on the EMH, AMH, and how a robust model can be built through a fusion by overcoming the demerits of one feature through other features. Consequently, we discussed a brief survey of a few research works and our motivation behind this model. After that, we described the role of each section in the paper.

II. INSIGHTS TO THE EXISTING WORKS IN CRYPTOCURRENCY PRICE PREDICTION

Due to the extreme fluctuation in cryptocurrency prices, their price prediction has become an attractive topic for the researcher since the last decade. High volatility in the prices of the cryptocurrency was noticed for *Bitcoin*. Researchers are successfully able to predict the price for the stock market but not able to predict the price of cryptocurrency with good accuracy compared to the stock market because of the large number of depending factors affecting the price of cryptocurrency significantly.

Average price, opening price, closing price, highest price, lowest price, and the volume traded of cryptocurrency for the past days are some of the main factors to forecast the next day's price significantly. The factors affecting the price of cryptocurrency also include social media sentiments-based comments/posts. Some researchers have tried to implement the relation of the cryptocurrency with gold and then try to predict the cryptocurrency prices. The change in the price of *Bitcoin* for the near future can be explained by the investor's sentiment significantly. This study was carried out by R. C. Philip in [47] that justify the behavioral finance property, which was also discussed in Section I. In [36], researchers have also concluded that there is a relation between *Bitcoin* price and search engines. The relationship between *Bitcoin* and search engines, was established based on the rank of documents from specific search engines. In terms of forecasting, machine learning and deep learning have made some essential contributions to researchers in recent years [48]. Deep learning algorithms recently became famous for forecasting purposes. Many researchers have implemented models using deep learning methods for forecasting cryptocurrency prices and get great results with short-term and long-term data. Substantial work has been carried out for cryptocurrency price prediction using machine learning and deep learning methods, but there is still a lot to be done.

This section gives insight into the existing work that has been done in the field of cryptocurrency price prediction.

A. CLASSIC MACHINE LEARNING-BASED PREDICTION

This subsection discussed the different machine learning algorithms [48], [49] used by various researchers to predict the cryptocurrency price. For example, Madan *et al.* in 2014, got an accuracy of *57.4%* using decision tree for *Bitcoin*, with a 10-minute sample price as the main input feature [50]. Then, Hegazy and Mumford [51] in 2016 predicted the price of *Bitcoin*, for every 8-minute interval and fed into the decision tree with an accuracy of *57.11%*. Further, Chen *et al.* implemented both machine and deep learning models to predict the price changes in *Ethereum* [27]. Study in [27] had used machine learning-based algorithms like linear regression, naive bayes, SVM, random forest, ARIMA, and deep learning-based models like RNN and NN. They got the highest accuracy using ARIMA *61.17%* for prediction.

Later, Connor *et al.* [52] used Naive Bayes, Regression models, and SVM for predicting *Bitcoin*, *Ethereum*, and *Litecoin* prices considering the sentiments of news and posts of social platforms. Using Google trends data and Twitter texts, Jethin *et al.* [24] tried to predict the price of *Bitcoin* and *Ethereum* where the Twitter data was considered as a main feature. Further, the data cleaning was performed using the hashtags like #btc and #eth respectively, where #btc represents the tweet data for *Bitcoin* and and #eth represents the tweet data for *Ethereum* After pre-processing, they have applied a regression model for price prediction. Then, the authors of [53] considered the daily price of *Bitcoin* for

TABLE 1. Comparative study of existing techniques for cryptocurrency price prediction.

Ref.	Year	Description	Fusion?	Technique used	Expected result	Merit	Demerit
[27]	2017	Machine learning based algorithms were used for *Ethereum* price prediction.	No	Logistic Regression, SVM, Naive Bayes, ARIMA, and RNN	ARIMA accuracy = 61.17%	Algorithmic changes on existing machine learning and deep learning algorithms done for *Ethereum* price prediction.	Not explored time-series-based models like LSTM and GRU.
[28]	2018	Authors had used different regression techniques for *Bitcoin* price prediction.	No	Theil-Sen Regression, Huber Regression, LSTM, and GRU	MSE = 0.00002, R2 = 0.992 (GRU)	Data Collection was focused on a 1-minute interval rate.	Ignored other impacting factors like sentiments.
[29]	2018	Encog framework was used by authors for cryptocurrency price prediction through ANN.	No	ANN	Accuracy = 75% - 97.3%	Prediction of cryptocurrencies prices on a hourly and daily basis.	Not explored other kind of machine learning and deep learning algorithms.
[30]	2018	Machine learning-based algorithms were used for price prediction.	No	ANN, SVM, Random Forest and Naive Bayes	Accuracy :- *Bitcoin* = 85%, *Ethereum* = 93.33%, *Bitcoin Cash* = 70%	Consideration of Altcoin for *Bitcoin* price prediction.	Not considered deep learning based model to find complex patterns.
[31]	2019	Authors had used RNN and LSTM to predict Bitcoin prices with 10-fold cross-validation.	No	RNN+LSTM, Random Forest and Linear Regression	LSTM MAE = 0.0043	They had implemented 10 cross-fold validation to make a robust prediction model.	Absence of other impacting factors like opinion mining-based factors.
[32]	2019	Authors had compared and studied various models like DNN, LSTM, CNN, DRN for price prediction.	No	DNN, LSTM and CNN	Accuracy, precision, recall, specificity, F1 score	Analysis of various hyper parameter factors and pre-processing function on model.	Absence of wallet users as factor for predicting price direction.
[33]	2019	Authors of the paper proposed a model by conducting research on efficiency of LSTM-NN.	No	LSTM	RMSE = 0.006 , MAE = 0.003	Implemented statistical test on LSTM based model.	Bi-directional LSTM can be considered before optimization .
[25]	2019	Relationship between Gold prices and *Bitcoin* price prediction had been incorporated by authors through deep learning algorithms.	No	CNN, LSTM and GRU	LSTM RMSE = 32.98	Established the relationship between cryptocurrencies with gold and twitter sentiments.	Absence of live dataset input streams of various parameters affecting *Bitcoin* prices.
[34]	2019	Price prediction for *Bitcoin* using Yahoo Finance data was carried out using LSTM.	No	LSTM	RMSE = 288.59866	Implemented a complex LSTM based model for good results.	RMSE value is quite high.
[35]	2019	Relationship between Twitter sentiments and *Bitcoin* price prediction had been incorporated by authors through VADER algorithm.	No	VADER algorithm	3 day window: test accuracy = 57.84%	Usage of Twitter sentiments for determining the direction of price.	Not considered data from Facebook, Bitcoin forums, and other social media platforms.
[36]	2019	Authors had incorporated CNN, LSTM based hybrid model for price prediction.	No	CNN-LSTM	Prediction loss: MAE = 209.89, RMSE = 258.31, MAPE = 2.35 direction prediction: Precision = 0.64, Recall = 0.81, F1 = 0.69	Technical indicators and macroeconomic variables were used for price prediction through hybrid model.	The loss for prediction is quite high compared to others.
[37]	2019	For cryptocurrency price prediction authors had used decision tree and regression techniques.	No	Decision tree and regression	Decision tree accuracy = 95.88013%, regression accuracy = 97.59812%	Explored decision-tree-based algorithm for cryptocurrency price prediction.	Deep learning based algorithms were not considered.
[38]	2019	Authors had done price prediction for *Bitcoin*, *Ethereum*, and *Ripple* using LSTM.	No	ANN and LSTM	MSE	Statistical analysis to justify the price prediction of cryptocurrency was worth it.	Hybrid or ensemble model can be utilized.
[39]	2020	Authors had used MLP and LSTM for cryptocurrency price prediction.	No	MLP, and LSTM	MAPE MAE RMSE MSE	Consideration of business sector information for *Bitcoin* price prediction.	Fine-tuning of hyper parameters is required to improve performance.
[40]	2020	Price prediction was carried out with a 2-day to 60-day window through RNN and MLP.	No	MLP, and RNN	MLP accuracy = 81.3%, precision = 81%, and recall = 94.7%.	Authors had done a detailed comparison of different window sizes for *Bitcoin* price prediction.	Instead of using RNN, the author can also go for LSTM-GRU for better long-term prediction.
[19]	2020	Ensemble model was used for *Litecoin* and *Monero* price prediction.	No	GRU-LSTM	MSE, RMSE, MAE, MAPE used for evaluation purpose for *Monero* & *Litecoin* for window size 1, 3 & 7 days	Introduced ensemble model for cryptocurrency price prediction.	Some technical factors from the protocol level can also be considered.
[41]	2020	Authors have demonstrate correlation between sentiments and cryptocurrencies prices through LSTM.	No	LSTM	MSE = 0.00030187	Sentiment-driven cryptocurrency price prediction.	GRU or bi-directional mode can be used for making more robust model.
[42]	2021	A deep learning-based hybrid model of LSTM and GRU used to predict the price of cryptocurrencies using inter-dependent relations with parents coin.	No	LSTM, and GRU	MSE	Dependencies of *Litecoin* on the major coins like *Bitcoin* were also considered.	The fusion of prices can be used as an input feature for better performance, which is not considered.
[43]	2021	The authors have used a hybrid model of LSTM, GRU, and TSN (Temporal Convolutional Networks) for price prediction based on historical data of *Ether*.	No	LSTM, GRU, and TSN	Accuracy:- 1-day: 84.2%, 1-week: 78.9%	A novel type of ensemble model was used, which was a combination of LSTM, GRU, and TSN for better prediction.	The proposed model was not tested for the higher window like 15 days or 30 days.
[44]	2021	The proposed model, LSTM and GRU-based model, was tested on two different types of data.	No	LSTM, GRU	RMSE, MAE	The performance of the model was tested on two different datasets.	The influence of other major coins was not considered.
[45]	2021	The authors have proposed an improved KNN-based model for price prediction of *Bitcoin*.	No	Improved KNN	RMSE = 5774.448	The model has proposed an improved KNN model which shows better performance compared to traditional KNN, and logistic regression.	The deep learning based hybrid model was not used and other factors than price was not considered.
[46]	2022	The authors have proposed a price prediction scheme based on long and short term integrated learning using SVR (Support Vector Machine).	No	Integrated learning with SVR	RMSE, R2	The performance of the model was tested on many cryptocurrencies like *Bitcoin*, *Binance Coin*, *Cardano*, *Dogecoin*, *Ethereum*, *Tether*, and *XRP*.	The authors can also considered other factors like influenced of major coin, which was not considered.
Our model	2022	The authors have proposed a deep learning-based hybrid scheme to predict the price of cryptocurrency with considering the impact of major coins like *Bitcoin*, and *Litecoin* on *Dash* using fusion techniques.	Yes	LSTM-GRU	MSE	Dependency of the target coins was on a major coin like *Bitcoin*, and *Litecoin* considered.	-

prediction purposes and applied more than three normalization techniques on the dataset. Forecasting was performed via feature selection and implemented machine learning models such as random forest and Bayesian models considering five features, which were block size, the total volume of *Bitcoin*, day high, day low, number of transactions, and trade volume. Further, in [37], the authors have applied decision tree and linear regression techniques for forecasting the price of *Bitcoin* and compared the result of both and found that the linear regression technique outperforms the other on price prediction with high accuracy.

B. DEEP LEARNING-BASED PREDICTION

Various existing works on deep learning-based forecasting models to predict cryptocurrency prices are discussed in this subsection. Deep learning approaches are highly accurate compared to the classic machine learning models [11]. It is because the deep learning models can able to find complex patterns in comparison to the classic machine learning models. For example, Sebastian *et al*. predicted the price of *Bitcoin* with a minute sample price as an input feature and passed to the feed-forward network to predict the directionality of *Bitcoin*, which gave *60%* accuracy [54]. LSTM with its vari-

TABLE 2. Acronyms.

ARCH	Autoregressive Conditional Heteroskedasticity
AMH	Adaptive Market Hypothesis
ANN	Artificial Neural Network
ARIMA	Autoregressive Integrated Moving Average
ARIMAX	AutoRegressive Integrated Moving Average with Exogenous variable
BEP	Binanace chain Evolution Proposal
BFT	Byzantine Fault Tolerance
CAGR	Compound Annual Growth Rate
CNN	Convolutional neural network
CUDA	Compute Unified Device Architecture
DAO	Decentralized Autonomous Organization
DNN	Deep Neural Network
DRN	Dilated Residual Network
EMH	Efficient Market Hypothesis
ERC	Ethereum Request of Comments
FFNN	Feed Forward Neural Network
GASEN	Genetic Algorithm based Selective Neural Network Ensemble
GPU	Graphics Processing Unit
GRU	Gated Recurrent Unit
HMM	Hidden Markov Model
LSTM	Long Short Term Memory
MLP	Multi Layer Perceptron
MSE	Mean squared error
NGO	Non Govermental Organization
NN	Neural Network
PoS	Proof of Stack
PoW	Proof of Work
RNN	Recurrent Neural Network
SARIMA	Seasonal Autoregressive Integrated Moving Average
SHA	Secure Hash Algorithm
SVM	Support Vector Machine
VADER	Valence Aware Dictionary and Sentiment Reasoner

ant was used for forecasting the price of *Bitcoin* by Wu *et al.* in [55] and Tandon *et al.* in [31] with the same purpose of implementing the LSTM model along with the 10-fold cross-validation and got the MAE value of *0.0043*s. Another deep learning model ANN was used by Radiyo *et al.* in [56], which was optimized using a genetic algorithm to avoid local minima by optimizing the initial weights of ANN. One variant of the genetic algorithm GASEN was used with ANN ensemble approach for *Bitcoin* price prediction. A hybrid of the Hidden Markov model and LSTM was proposed by Hashish *et al.* in [57] and got improved results compared to the traditional approach of ARIMA and LSTM. *Bitcoin*, *Ethereum*, and *Ripple's* prices were analyzed using LSTM and ANN by Yiying *et al.* in [38]. Then, Mohil *et al.* in [19] proposed an hybrid LSTM and GRU-based scheme to predict the price of *Litecoin* and *Monero* with the RMSE of *2.2986* and *3.2715* respectively for 1-day prediction window, RMSE of *2.0327* and *5.5005* respectively for 3-day prediction window, and RMSE of *4.5521* and *20.2437* respectively for 7-day prediction window. Then, Rahmat *et al.* in [40] proposed an MLP and RNN-based scheme to predict the *Bitcoin* price for short and long time windows, where MLP showed the best accuracy, precision, and recall for both scenarios. However, Suhwan *et al.* in [32] implemented different combinations of deep learning models such as DNN, LSTM, CNN, and ResNet to forecast the price of *Bitcoin*. They also studied the effect of the window size prediction, the effect of using log values as inputs, the effect of data splitting, and the effect of normalization on classification and prediction problems. Then, Temiloluwa *et al.* in [33] applied different statistical tests to the LSTM model for better prediction because statistical tests are important for time series analysis and forecasting. In [25], the author considered the *Bitcoin* parameters and social parameters for forecasting purposes and compared the results of the deep learning models like CNN, GRU, and LSTM, and concluded that LSTM showed the best result among all with 4-layers. Then, the author of [34] used yahoo finance stock market data for predicting the price of *Bitcoin* using LSTM with *500* epochs and without a dropout layer achieved the RMSE of *288.59866*. Later, Serafini *et al.* in [41] proposed a sentiment-driven scheme using statistical and deep learning approaches. ARIMAX and LSTM-based RNN were trained to predict the sentiment-based price prediction of *Bitcoin* with different feature combinations like (i) BTC volume, sentiment, tweets volume, (ii) BTC volume, sentiment, (iii) BTC volume, tweets volume, (iv) BTC sentiment, tweets volume, (v) BTC volume, (vi) BTC sentiment and (vii) BTC tweets volume. The author found that ARIMAX outperforms well compared to LSTM-based RNN and has an MSE of *0.00030187* on new predictions. Tanwar *et al.* [42] proposed a hybrid LSTM and GRU-based deep learning model, which outperformed the state-of-the-art techniques, to predict the price of cryptocurrencies. They have also considered the influence of the major parent coins on other altcoins, such as *Bitcoin's* influence on *Litecoin* and *Zcash*. Politis *et al.* [43] has proposed an ensemble model of LSTM, GRU, and TSN (Temporal Convolutional Networks) to predict the price of Ether based on its historical price data and achieved 84.2% and 78.9% accuracy respectively for 1-day and 1-week. In the same manner, to predict the price of *Bitcoin*, *Ethereum*, and *Litecoin*, the author of the paper [44] proposed a system with LSTM and GRU. The price prediction was performed on two types of a data sample of *Bitcoin*, *Ethereum*, and *Litecoin*.

C. REINFORCEMENT AND FEDERATED LEARNING-BASED PREDICTION

Reinforcement learning is one of the types of machine learning techniques that focuses on learning based on its own experience and environment. It enables an agent that learns to achieve a goal in an uncertain, complex, interactive environment by trial and error using previous actions and experiences. It is mainly used in interactive environments like game-like situations where rewards and penalties are already set for the actions that the machine/computer performs and learns through that data to maximize the rewards. In the absence of training data, reinforcement learning can learn through its experience [58], [59].

To overcome the inability of prediction models to learn in real-time, federated learning is useful as it helps to work without any centralized system/server. Federated learning (also known as collaborative learning) is one of the machine learning techniques that are different from traditional ones. It helps to train algorithms/models on decentralized servers/devices through local data. This technique enables the different systems that build robust systems without sharing information which helps to increase the critical issues like the privacy of data and many more. It helps the model to learn from larger datasets at different places in no time and improves the ability of the model to learn [60].

These two machine learning techniques are much not explored yet compared to others as per the literature survey. Reinforcement learning can apply to cryptocurrency price prediction as it learns from the environment and experiences. As any remarkable changes occur in price it learns from the occurred changes and tries to make predictions more accurate. Through federated learning, as the size of the dataset increases, the model can learn significantly through decentralized training and helps in increasing the accuracy of the model.

This section discussed the work that was already being carried out to forecast the price of various cryptocurrencies. Starting off the section discussed why researchers find interest in this field of research. The relation of cryptocurrency price with gold, search engines, sentiment-based comments also tried to be established by researchers, discussed in the following section. Existing work on machine learning and deep learning techniques is also discussed in detail. Some methods that are not explored in literature and are available in suggested future research.

III. INFORMATION FUSION IN CRYPTOCURRENCY PRICE PREDICTION

This section revolves around the analysis of several factors involved in cryptocurrency price prediction. The prices are highly volatile, so a detailed analysis of important factors is necessary to build a robust forecasting model. Features like volume and past days' prices plays a crucial role in cryptocurrency price prediction. So, the statistical analysis of volume and prices are highly required. The importance of amount concerning cryptocurrency price is demonstrated in [61]. For price prediction, [57] utilizes Hidden Markov theory for making a price prediction model. According to Hidden Markov theory, there exist hidden patterns among the data and this pattern can be learned by the forecasting model. So, to statistically conclude these results, we have to perform a cryptocurrency price analysis. Through this, we can find the hidden pattern, which is statistically significant [62]. Popular choice among investors, cryptocurrency risk analysis is a must. Even organization like Forbes [63] has surveyed and analyzed the risks related to cryptocurrency. So, risks also play an important role in cryptocurrency prices, and their analyses play an important role in price prediction. Further discussion on this topic is done in the following subsections.

A. CRYPTOCURRENCY VOLUME ANALYSIS

The total volume of the cryptocurrency here is referred to as the volume that is actively traded and not actively traded. The mass of cryptocurrency keeps increasing over the period.

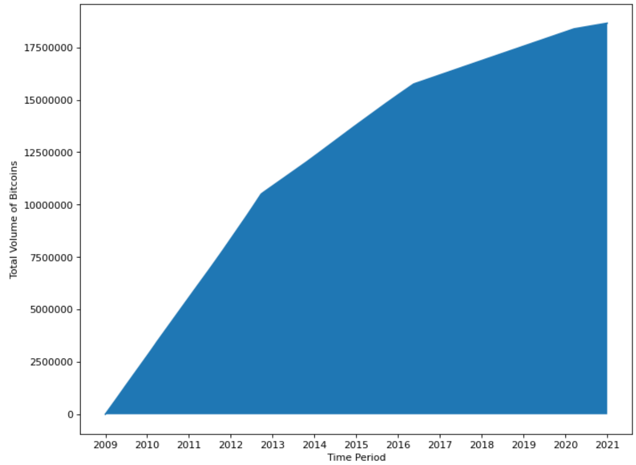


FIGURE 4. Growth in total Volume Of *Bitcoin* till 2021 [9].

FIGURE 4 shows the total volume of *Bitcoins* from the year the currency was introduced, till 2021, similarly FIGURE 5 shows the total volume of *Ethereum* coins from the year the currency was introduced, till 2021.Proficient merchants and chartists use volume to extraordinary benefit, following the formula that assuming the cost falls alongside volume, it by and large denotes a reason behind weariness, flagging an inversion will happen soon.

While then again, an ascent in cost with a drop in complete volume presents a more grounded case for the bears as they drag costs for a lower bid, typically after gathering a key opposition zone. By mining, you can earn cryptocurrency without using cash. Mining rewards are paid to the digger who finds an answer for a complex hashing puzzle first. The likelihood that a member will be the one to find the arrangement is identified with the segment of the absolute mining power on the organization. The *Bitcoin* reward is halved every *210,000* units or roughly four years [64]. A portion of the *Bitcoins* available for use are accepted to be lost perpetually or unspendable, for example in case of lost passwords, a wrong destination address, or mix-ups in the output contents [64].

B. CRYPTOCURRENCY PRICE ANALYSIS

In this section, we analyze the various highs and lows of the price of different cryptocurrencies. The analysis of the price history of cryptocurrency helps us to know the nature of that particular cryptocurrency. This will help us to establish an interdependence among the cryptocurrencies, which is an aim of the paper. So the fake bubbles and crashes for the prices of the cryptocurrencies are discussed in detail as follows:

1) BITCOIN PRICE ANALYSIS

Among the various assets such as gold, silver, cryptocurrencies, and other investment areas, the *Bitcoin* has a broad range of price variation in its trading history. The first time the insurgence in the price of *Bitcoin* was occurred in 2011, i.e., from \$1 in April to \$32 in June 2011, an increase of

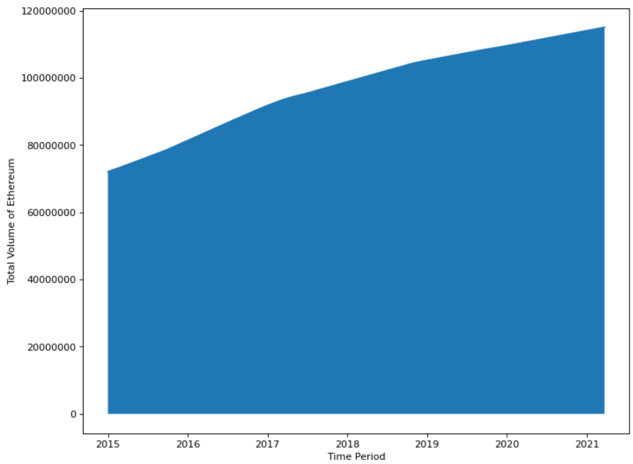


FIGURE 5. Growth in total Volume Of *Ethereum* till 2021 [9].

3200% [65]. This lofty increase in the price was followed by a sharp downturn in cryptocurrency prices. The price of *Bitcoin* reached to $2 in November 2011 [65]. Following year price of *Bitcoin* went from $4 to $13.5 from May to August 2012 [65] and become one of the important years for the price of *Bitcoin*. In 2013, from the past data, we observed two price bubbles. The first bubble happened at the beginning of April 2013, when the price of Bitcoin reached the skies of $220 from $13.5 at the start of the year [65]. Due to processing delays in payment processes in April 2013 by processors BitInstant and Mt.Gox, the price dropped from $226 to $76 and then again returning to $160 within 6 hours [9]. But it was followed by a steep decline within 15 days, *Bitcoin's* price reached to $70 in the mid of April 2013 [65].

Another price shot/bubble occurred nearly at the end of the year 2013. In October 2013, *Bitcoin* price was $123, but till the end of December 2013, the price shot up to $1156 and again slumped to $760 within the three days [65]. From this time, it started to show the volatility in the price of *Bitcoin*. Following years, the prices slumped many times, and at the beginning of 2015, the price reached $315 [65]. An increase in the price of *Bitcoin* was about to occur in the year 2017, which was the 5th bubble [65]. At the beginning of the year 2017, the trading price was $1000. After a decrease in the price for 2-months, in March 2017 the price was $975 [65]. But now there was a steep increase. At the end of the year, in December 2017 prices skyrocketed to $20,000 [65].

FIGURE 6 shows the same in graphical manner for better understanding. As seen from the FIGURE 6, for the next two years, the price of *Bitcoin* moved sideways, and there was not a big streak. In June 2019, the price surpassed $10,000, which created the hopes of another rally in *Bitcoin* prices. But the price declined to $7,112 in December 2019 [65]. In 2020 until the lockdown and economic shutdown occurred prices of *Bitcoin* came to the spotlight again. The economy shut down, and the government policies inset a fear in the investor's mind which then fuelled the rise in the price of *Bitcoin*. In November 2020, *Bitcoin* was traded at $18,000 [65]. Following the *Bitcoin* prices rose to $24,000 in December 2020 and $40,000 in January 2021 but within three days price declined to $30,253 [65].

FIGURE 6. Historical price data of *Bitcoin* over the period of years 2015-2022 [66].

2) ETHEREUM PRICE ANALYSIS

Ethereum is the second-biggest cryptocurrency, followed by *Bitcoin* based on its market cap. As of April 2021, according to [9], *Ethereum* has a share of 12% in cryptocurrency market cap. After its surge in 2015 with an initial supply of 72 million coins. After the surge of *Ethereum* in 2015, there was a bull run in the price of *Ethereum* till the 15th of January 2018. The same can be sum up from FIGURE 7. *Ethereum* prices show several ups and downs, and like other cryptocurrencies, it is also stochastic in nature. There is also a vast gap between the minimum and maximum annual returns. FIGURE 10 shows minimum annual return of −82.70% and max annual return of 9159.40%. So the analysis of *Ethereum* prices is required.

In this subsection, we will analyze *Ethereum* prices and relate its downfall with the factors listed in [12], [13]. Although the bull run of January 2018 was stochastic in nature, the prices of *Ethereum* increased from $0.67 to $1332.62 [9]. The first bull run jumps the cryptocurrency prices by 1988.98%. After this long bull, the prices start to fall, and within a year its prices fall to $92.65. This fall decreases the price of *Ethereum* by 93%. Forbes article [67] said that this downfall was because of ICO's projects. On the other hand, Financial Times [68] says that this fall was because of its enormous retail investors rather than the ICO projects. After this downfall, there is again a big and long bull run which increases its prices to $2346 at 18th April 2021. Although the bull run was stochastic in nature, the prices of *Ethereum* managed a jump of nearly 2532% from its last min price of $92.65. As of the latest trends, financial analysts [69] expect that this bull run is going on with a stochastic nature.

3) LITECOIN AND RIPPLE PRICE ANALYSIS

Among 4200 cryptocurrencies, there are only a few that gives a high return on investment. *Bitcoin* and *Ethereum* are the ones that are popular among investors because of their high returns. There are other cryptocurrencies like *Dash*, *Ripple*, *Litecoin*, which are good options for investment. As of April 2021, yahoo finance [70] sorted a few cryptocurrencies

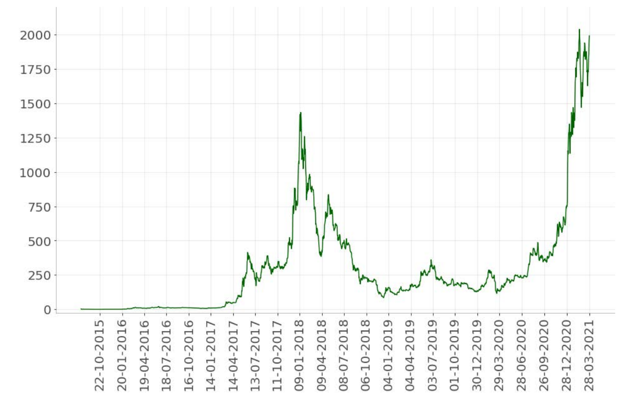


FIGURE 7. Price data of *Ethereum* for the period of (07/08/2015 - 01/04/2021) [66].

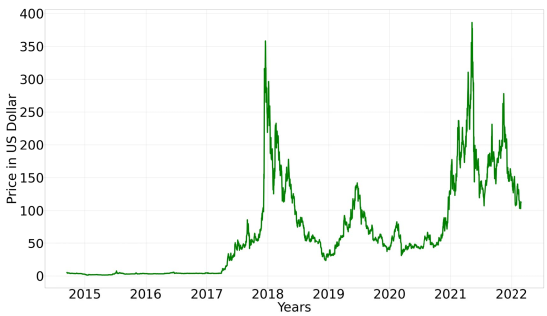


FIGURE 8. Historical price data of *Litecoin* over the period of years 2015-2022 [71].

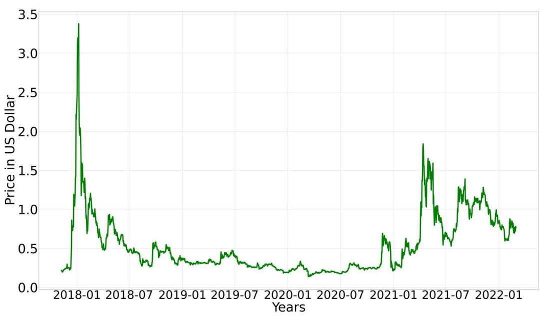


FIGURE 9. Historical price data of *Ripple* over the period of years 2018-2022 [72].

for investment. To generalize the analysis, we have taken *Litecoin* and *Ripple*. As seen from the FIGURE 8, *Litecoin* shows a great amount of surge in some specific period of time. Similarly, FIGURE 9 shows the historical data of price of *Ripple*. FIGURE 9 shows some similarity with the FIGURE 7, which shows similar behavior of *Ripple* as *Ethereum* for certain period of time. By analyzing data from [9], there was a bull run till January 2018, and after that, there was a fall down till March 2020. Now again, there is a bull run, and analysts [69] also consider that there will be a stochastic bull run ahead. *Litecoin* price behavior has a lot of short up and downfalls [9]. So we can say that till now, *Litecoin* has not properly shown its downfalls like *Ethereum* or *Ripple*. At present, the *Litecoin* in its downfall, but the analysts [69] considered that there is a stochastic bull run ahead.

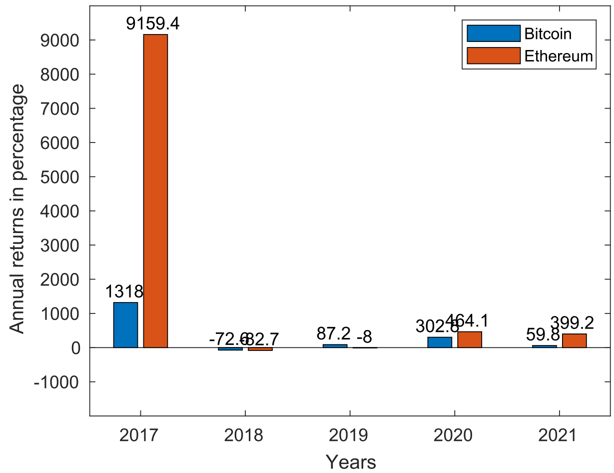


FIGURE 10. Comparision of annual return rate between *Bitcoin* and *Ethereum* over the period of 2017-2021 [73], [74].

C. CRYPTOCURRENCY PATTERN PREDICTION

In this subsection, we will analyze the price history of cryptocurrency and attempt to predict a pattern for increase and decrease in the price of the cryptocurrency. These patterns can be useful to determine the direction of the cryptocurrency prices. The knowledge can be utilized for analyzing the bullish and bearish trend running on is real or fake. And this will helps us statistically to justify the idea of a forecasting model for cryptocurrency price prediction. FIGURE 10 shows the annual return patterns of *Bitcoin* and *Ethereum*. Accordingly, the statistical pattern will help investors to notice the trend. The following paragraph discusses various statistical patterns to determine trends in cryptocurrency prices.

To predict the pattern of uptrend or downfall, we need to analyze the historical data of cryptocurrency. Here, we concentrate on the returns given by *Bitcoin* and *Ethereum* in past to determine future patterns. The daily return study of *Bitcoin* and *Ethereum*, over the last four years, was done by the authors in [73]. The returns in [73], were derived with an assumption that $1 of each asset was purchased on the same day, and all the dividends were reinvested in the market. However, as we can notice from the graph that both of them follow the same pattern of increase and decrease in the return value, which means when the return value of *Ethereum* increases at the same time, the return value of *Bitcoin* also increases. As we can see that the spikes and steeps were simultaneous in both currencies. From the studies of [73] conclusion can be carried out that both *Bitcoin* and *Ehtereum* must be interdependent in some manner because of the simultaneous increase or decrease in return percentage value.

Now, we will see some general patterns in cryptocurrency prices, which helps to predict the price movements from the graph. The graph patterns can be categorized into three classes: bullish, bearish, and reversal. Bullish patterns are the types of patterns, from which we can say that the price of the cryptocurrency is likely to go up and helps us to determine our profit margin. Similarly, bearish patterns are the opposite of bullish patterns. Whenever bearish patterns occur in the graph, cryptocurrency prices are likely to go. Through this analysis, investors can book early profits. Reversal patterns are the shapes of graphs through which we can expect the trend reversal in cryptocurrency prices. Further, the detailed knowledge related to the three patterns discussed here can be found in [62].

D. CRYPTOCURRENCY RISK ANALYSIS

The main distinguishing characteristic of cryptocurrency is, that they are not issued by any government or central authority. Hence, they have their advantages as well as disadvantages. The absence of backing by any central authority makes their value strictly volatile and leads to a loss of confidence among the investors and an abrupt price drop. The presence of a central authority guarantees the transaction comes with the facility to reverse the transaction in a condition of adversity. To maintain a unique security feature, no such facility is available in the case of cryptocurrencies. The lack of central authority means, if access to keys or an account is lost, then it can't be restored and money will be lost forever.

Many users store their cryptocurrencies with third-party services, they have the risk of getting compromised. There is a large pool of criminal community which can infuse computers with malware that steals the cryptocurrency. Similarly, bugs can also cause huge harm to the cryptocurrencies. It majorly affects when cryptocurrencies are combined with smart contracts, these are programs that automatically get triggered on the exchange of cryptocurrency. The first big catastrophic event once occurred when DAO tried to create an independent mutual fund. This system was affected by a bug that led the attacker to steal all the *Ethereum* in their account. The theft was in vain as the *Ethereum* developers soon released a new version of the system that invalidated the stolen cryptocurrencies [75]. There is no uncertainty that cryptocurrencies are going to stay as innovation progresses. Public acknowledgment and their trust will take some time yet, the dangers will continue as before. Some giving off an impression of being more material and raised for money and business [76].

This section was, based on the analysis of important factors related to cryptocurrency price prediction. Firstly, we discussed the importance of statistical analysis of important factors. After that, we have a brief analysis of cryptocurrency volume. Following is the detailed analysis of cryptocurrency prices especially *Bitcoin* and *Ethereum*. Following is the cryptocurrency pattern analysis where we discussed bearish and bullish patterns for cryptocurrency prices. Further through the last subsection, we discussed the risk involved with an investment in cryptocurrency, and its effect on the rates of crypto coins.

IV. STAKEHOLDERS ASSOCIATED IN CRYPTOCURRENCY PRICE PREDICTION

Stakeholders can be stated as all social actors that can be affected either positively or negatively due to decisions, objectives, and action plan of the company [77]. In spite of the fact that cryptocurrencies being transparent, secure, and decentralized systems. By connecting the dots, there is an inference that no organization can control cryptocurrency prices. But, somebody should be governing them otherwise it will cause havoc in the cryptocurrency market. These facts were studied by the author of [78] discussing the governance crisis of the cryptocurrency market. So, a collaborative organization like *Bitcoin* organization has been formed for its governance worldwide. Their main work is to make two users' software i.e. wallets, compatible with each other for transactions, but they don't have any control over its prices [79]. So now, are there any other stakeholders for cryptocurrency price prediction?

Yes, their are stakeholders are affecting the price of cryptocurrencies. Messages and tweets from stakeholders can manipulate the cryptocurrency prices. Sentiments of their messages and tweets influence the prices [25]. For the sake of understanding purpose, let's consider an imaginary situation where Barry Silbert, one of the major *Bitcoin* investors [80], stated from his Twitter handle that he convert all of his *Bitcoin* to USD. Considering the behavioral finance hypothesis, within few hours we might see a significant drop in *Bitcoin* prices. Similar types of features were used for making a sentiments-based forecasting model in [81]. So we can conclude that there are stakeholders associated with cryptocurrency price prediction. Based on [77], categorization of stakeholders is done into two categories:

- *Primary Stakeholders*: They are the one whose decision directly affect the price of cryptocurrency. Generally, developers of *Bitcoin* organization, N.G.O's like Bitcoin foundation dealing with countries government for making Bitcoin as a valid mode of transaction, but has been dissolved in 2015 [82]. Wallet companies like Coinbase, then venture capitalists or investors and miners are the ones considered as primary stakeholders. Few cryptocurrencies are also there, which is being controlled by its possessing company who had developed it like *Libra* is owned by Facebook [83].
- *Secondary Stakeholders*: They are the one whose work or research indirectly affects the price of a cryptocurrency. Associated with this category are companies or researchers working at the protocol layer of any cryptocurrency for improving specific factors like transaction time. Companies or researchers working on implementing a bot for cryptocurrency portfolio management like [84]. Companies or researchers working on forecasting models like the ones in Table 1 and this paper authors also fall under this category.

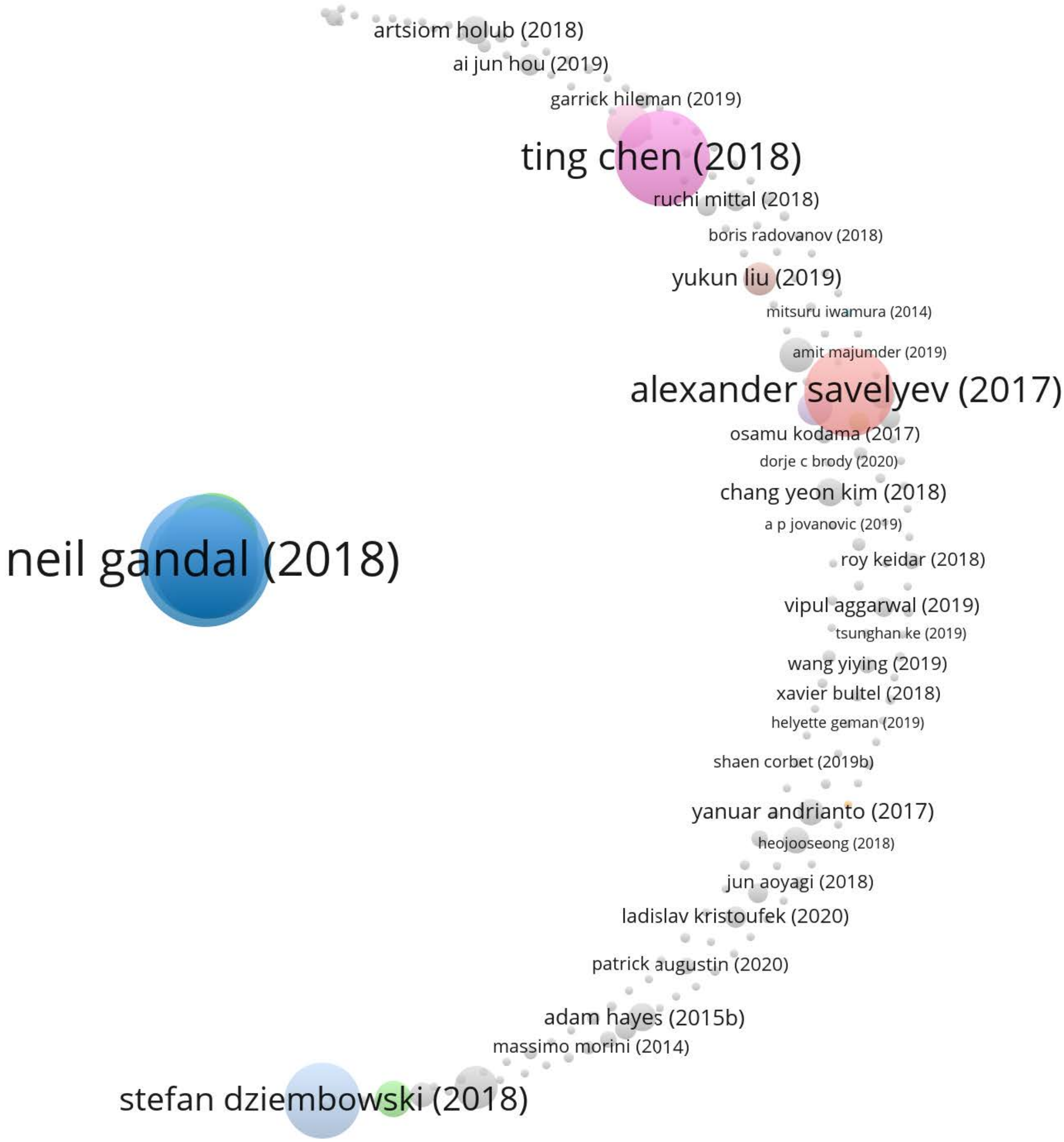


FIGURE 11. Bibliometric analysis of the researchers in field of cryptocurrency price prediction [85].

A. COMPANIES/ORGANIZATIONS ASSOCIATED

Companies associated with cryptocurrency price prediction are of both types. Few of the cryptocurrencies are still under the control of the companies who developed it like Air-Asia is the proprietor of *BigCoin* [86]. So they might have control over its price. Startups and companies designing protocols like *Ripple* [87] are also important stakeholders in price prediction. Their main work is at the core level so how are they important for the price prediction might come to your mind. Let's consider a hypothetical situation, where a *Ripple* makes few changes in its cryptocurrency by which it can make transactions three times faster than its previous generation. Through these, big giant companies started to make transactions through *Ripple*, leads to increase demand in the market. An increase in demand will make the prices of *Ripple* reach unbelievable limits. So yes, protocol companies and organizations play an important role in the prices of cryptocurrencies.

Investors, startups, organization, and individuals plays an important role in cryptocurrency price prediction. It is because, they are the one who creates a demand and supply chain in it [88]. As discussed above, based on the behavioral finance hypothesis, their statement can cause a shift in the market. Mining organizations like Genesis-Mining, are also prime stakeholders for price prediction because they are the ones who generate volumes of cryptocurrencies in

FIGURE 12. **Graphical representation of how stakeholders associated with cryptocurrency price prediction [91], [96]–[98].**

the market. Mining-based startups are versatile, a couple of them like BitFury [89] generates revenue by making and selling mining machines and rigs in the market. On the other hand, companies like Genesis-Mining [90] is a cloud platform where users can mine cryptocurrency by paying the cost of hardware power consumption they utilized. Companies like BitMain generates revenue by mining *Bitcoin* only [91]. Wallet companies also play a crucial role in the market, because they control the transaction. If these companies stop making transactions subsequently, there will be no value of the cryptocurrency stored in the users' wallets. Last, governments and authorities of countries play an important role too. Many countries' governments have kept the ban on cryptocurrencies because of security reasons. So, the decision's regarding this ban and other legal aspects also plays a vital role in the cryptocurrency price prediction.

B. RESEARCHERS ASSOCIATED

Researchers associated with cryptocurrency are categorized as secondary stakeholders. The field of research in the domain of cryptocurrency and blockchain is vast. So, researchers from a different area other than price prediction are also cover under the secondary stakeholders. Article [92] gives a detailed explanation regarding the research development in the discipline of cryptocurrency and blockchain. A couple of them plays a crucial role as stakeholders. The evolution of cryptocurrency is also one of it. The discussion of this factor is essential because whenever a new cryptocurrency is initiated they are derived from other cryptocurrencies with few changes. Simultaneously, the introduction of new crypto coins increases the market capitalization and volatility of the cryptocurrency market too. For example, *Bitcoin Cash* has been derived from *Bitcoin*, based on price analysis, when *Bitcoin Cash* set in motion during 2017 after one year in a period of 2018 a cryptocurrency market crash has happened. In this market crash, *Bitcoin* was the worst affected. As *Bitcoin Cash* was just inaugurated, they faced the worst during the end of the year, forcing the developers to split into two parts, namely *Bitcoin Cash* and *Bitcoin* [93]. Although, there are many other factors as well [94], from present drift whenever *Bitcoin* price escalates, *Bitcoin Cash* price also rises simultaneously.

Researchers are also involved in the zone of designing forecasting systems, similar to the prediction model stated in Table 1 and portfolio management bot like [84] have a major contribution to cryptocurrency price prediction. Big investors and organizations use the statistical output of forecasting models to conclude whether they should invest or back off their money from the market. Their research works are indirectly affecting the price of cryptocurrency. The same goes for the research work done in the field of portfolio management bot. Through their past learning, the bot can invest clients' money or back off their money from the market to obtain profit. Based on the demand-supply concept [95] when thousands of such bot conclude the same result from the environment videlicet from the market, it can cause a sudden surge or fall in the price of the cryptocurrency. So, indirectly the researchers working in this field of research also affect the cost of the cryptocurrency. FIGURE 11 gives the bibliometric analysis of researchers associated with the domain of cryptocurrency price prediction, the data is retrieved using Microsoft Academic API.

The beginning of the section defines various stakeholders and how they are important for cryptocurrency price prediction. Followed by the categorization of stakeholders, FIGURE 12 gives insights into it. Data for FIGURE 12 is referred from [77], [79], [82], [89], [90]. Following are two subsections as part of the first subsection, we surveyed types of organizations associated as stakeholders for cryptocurrency price prediction. The second subsection discusses our survey of the researchers associated with cryptocurrency and especially those whose workings indirectly affect the cryptocurrency price prediction.

V. METRICES USED IN CRYPTOCURRENCY PRICE PREDICTION

Many factors that affect the change in cryptocurrency prices and this section discusses those metrics in detail. Some factors affect the price of cryptocurrency directly and some which affect it indirectly. Public perception is one of the most significant factors that indirectly affect the change in the price of any cryptocurrency. In [99], D'Alfonso *et al.* in 2016 studied the relation of online news with *Bitcoin* and findings proved that the increase in the price of *Bitcoin* is caused by the number of online talk increases, which means that positive talk about *Bitcoin* leads to an, increase in price and negative talk about *Bitcoin* lead to a decrease in price. Google search is also one of the indirect factors that affect cryptocurrency price. Google trends for *Ethereum* show that there is a high relationship between the number of Google searches and *Ethereum's* price [100]. The government's decision indirectly plays a significant role in the price changes of the cryptocurrency. They are the ones to determine the legality of cryptocurrency. As the status of legal currency or illegal currency is the decision of individual governments, and any decision related to it leads to ups and downs in the cryptocurrencies prices. 'Opinion Mining' is also associated with public perception, in a simple word known as sentiment analysis [30], which indirectly affects the price of cryptocurrency significantly. The above-discussed ones are a few of the indirect factors that significantly affect the price of the cryptocurrency in one or another way.

An increase in the number of users on exchange forums shows their interest in trading information and help them to make decisions related to investment and trades [30]. So, this kind of trading data may affect the price of the cryptocurrency indirectly and helps to determine the fluctuated price. Similarly, the price volatility can also be determined through past data. Patterns from historic prices help to find the expected change in the price with proper attributes. Price forecasting can be done, through machine learning and deep learning techniques by utilizing the above-discussed factors. These features are the data for every day's opening price, closing price, minimum price, maximum price, average price, and the total traded volume. In sentiment-based models, one can find features as crowd-sourced data having sentiment-based comments from the online social platform like Google Trends, and Twitter. The utilization of factors from the blockchain part can be helpful for cryptocurrency price prediction. A similar approach is done by the author of [32] for predicting the price of *Bitcoin*. They also found the correlation between various features and *Bitcoin* prices in the right amounts.

Apart from the factors mentioned above, some other factors have a significant impact on the price of cryptocurrency. They are as follows:

- *PoW:* It is one of the most important metrics that affect the price of cryptocurrency significantly. For each mining process, miners should submit the PoW having genuine work. A new cryptocurrency has modified PoW and name it as a PoS having rewards for the miners based on their holdings.
- *Volume:* In cryptocurrency price prediction, the volume of any cryptocurrency plays an important role as it can be broken down in many ways. By observing the volume change, the researcher can find the probable movements and direction of the coin.
- *Closing and Opening Price:* Many researchers have successfully implemented the model having closing price and opening price of the cryptocurrency data day wise. Closing price and opening price pattern also helps to determine the probable ups and downs of price.

A. CORRELATION BETWEEN METRICES

Several correlations have been found among factors stated in [12]. Volume and price correlations are altogether famous among the traders as mentioned in [101]. The author of [101] also concluded that the relationship between volume and price is inversely proportional. Next comes the analysis of volume and mining algorithms, two factors that affect the volume of newly introduced cryptocurrencies. To study the affecting attributes, we have chosen *Bitcoin*. Firstly the mining rate of the new *Bitcoin* is fixed. New *Bitcoins* are introduced into the market when miners process blocks of transactions. The rate at which new coins are introduced by miners is slowing over time [102]. If we analyze the above statement, we can derive the rate at which the volume of cryptocurrency introduced to the market is inversely proportional to the complexity of mining algorithms (PoW or PoS). Since price is inversely proportional to the supply of a cryptocurrency, we can also conclude that price and mining algorithms are directly proportional. The studies in [102] also stated that indirect factors like market sentiments, opinions, regulations and legal matters, and other factors are also directly proportional to the price of cryptocurrency.

B. NEED FOR METRICS FUSION

As discussed above, there is a correlation between different cryptocurrency price-predicting metrics. Through the discussion in the previous subsection, we can say that the price of cryptocurrency not only depends upon one or two factors. So, the prediction model should consider the combination of the metrics specifically, there is a need for the fusion of metrics. Many cryptocurrencies were, derived from another cryptocurrency like *Bitcoin Cash* is one of the derived cryptocurrencies from *Bitcoin*. So, this reason concludes that the price of *Bitcoin Cash* is also affected by the factors affecting *Bitcoin* prices. During price prediction of the *Bitcoin Cash*, the fused metrics of the *Bitcoin* and *Bitcoin Cash* are required. The interdependencies can be found between derived and parent cryptocurrencies very often. Correlation among the factors can be found very easily which leads to thinking of fusion of the same to improve the accuracy of the predictive model. The next section is devoted to discussing the dependency of cryptocurrency and factors that affect the price.

In the beginning of the section, we have done a short analysis of existing work and discusses important metrics related to cryptocurrency price prediction. After that, we have tried to find the correlation between the important metrics like prices, volume, and complexity of a mining problem. After that we have done a thorough discussion on the requirement of metrics fusion and also have an overview for our next section.

VI. DEPENDENCIES BETWEEN CRYPTOCURRENCIES

The forecasting model proposed in this paper through fusion has considered dependency between the cryptocurrencies as an important metric. Top 100 cryptocurrencies based on their market cap [9] has been considered to study dependency among them. From the price analyzes, we found that cryptocurrencies are of two types:

- *Stable cryptocurrency*: This type of cryptocurrency price is always fixed, specifically their exchange rate is always equal to 1 USD. Cryptocurrencies like *Tether*, *USD Coin*, and *Paxos* are a few of the examples.
- *Unstable cryptocurrency*: This type of cryptocurrency price keeps fluctuating similar to stocks, in other words, their exchange for 1 unit keeps on changing minutes by minutes. Cryptocurrencies like *Bitcoin*, *Ethereum*, *Litecoin*, and *Ripple* are a few of the examples.

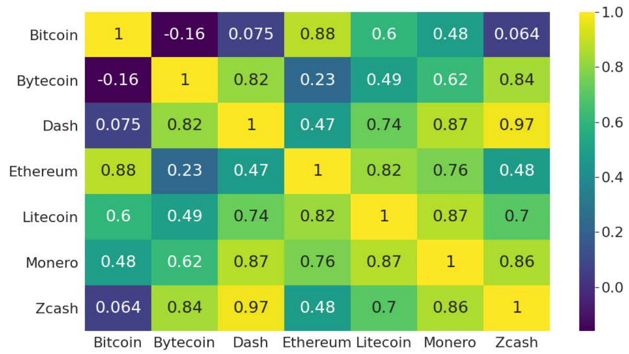


FIGURE 13. Heat map representing the correlation among popular cryptocurrencies [66].

Based on the above categorization, the forecasting model can be used only for unstable cryptocurrencies. As there is no requirement to predict the price of a stable one because their prices are always fixed. Although, the forecasting model for the exchange rate of stable coins for other countries' currencies like Rupees, Euros, and Pounds keeps fluctuating. This factor is not from cryptocurrency volatility but is from the volatility of a specific country's currency with respect to U.S. Dollar. Models similar to [103], [104] [105] can be utilized to predict exchange rates for a specific country's currency with USD. This can be incorporated as a forecasting model for stable cryptocurrencies concerning a country's currency other than USD. So, the research field on the forecasting model revolves around unstable cryptocurrencies only. For the statistical inference, FIGURE 13 shows the correlation among *Bitcoin*, *Bytecoin*, *Dash*, *Litecoin*, *Monero*, *Ethereum*, and *Zcash*. In the following subsections, there is a brief analysis of main or parent cryptocurrencies.

A. BITCOIN

Bitcoin being the first most cryptocurrency, is considered as the parent for most of the other cryptocurrencies. The newly introduced cryptocurrencies made a few changes in their protocol to improve the performance in terms of anonymity, speed of transaction, and other crucial features. *Bitcoin* holds nearly *78%* value of the market cap during April 2021 [9], and its effect on other cryptocurrencies makes it a popular choice as a crypto coin for researchers to determine the performance of the forecasting model. There are many cryptocurrencies derived from *Bitcoin,* further we discuss the major ones in the following paragraph.

Bitcoin Cash is one of the derived cryptocurrencies from *Bitcoin* by improving the size of the block to increase scalability and performance of transaction [93]. *Litecoin's* is also among the cryptocurrencies that are derived from *Bitcoin*. *Litecoin* developers aim to increase the speed at which new blocks are added to blockchain [106]. *Bitcoin SV* is derived from *Bitcoin Cash* [107], and *Bitcoin Cash*, furtherly derived from *Bitcoin* [93]. So, indirectly *Bitcoin SV* depends on *Bitcoin*. In addition, SV stands for "Satoshi Version" [106] and aims to restore the original version of *Bitcoin* introduced in [1] with the belief of cheaper fees. *Bitcoin Gold* is also the one forked from *Bitcoin*. *Bitcoin Gold* developers aim to change the PoW algorithm to democratize mining processes [106].

Zcash is a fork of a *Bitcoin* code-base. *Zcash* developers did not change anything at the protocol level, but they introduced a new option for users where they can make their transactions public [106]. This feature has attracted many governments because the dealings can be kept visible with the will of users. Through this government can trace the fraud easily which is not possible for other cryptocurrencies [108]. *Ravencoin* is a fork of a *Bitcoin* code-base. *Ravencoin* developers had made four crucial changes: they modified the issuance schedule (with a block reward of *5000 Ravencoin*), the block time reduced to one minute, their coin supply capped at *21* billion (ten times more than *Bitcoin*), and finally, a new mining algorithm (KAWPOW, formerly X16R and X16RV2 respectively) intended to mitigate the centralization of mining through Application-specific integrated circuit (ASIC) hardware [109]. *Dash* is a fork of *Litecoin*, through which it is indirectly a fork of *Bitcoin* [9]. There are many others as well with slight changes in the *Bitcoin* code-base. Through this, we observe the importance of *Bitcoin* in cryptocurrency's market cap. And their influence both technically and financially on other cryptocurrencies.

B. ETHEREUM

Ethereum is one of the famous and second-most versatile cryptocurrencies contributing nearly *12%* to cryptocurrencies market cap [9]. *Ethereum* resembles a similar feature with *Bitcoin* [110]. However, it is not forked from the *Bitcoin* code-base. On the other hand, the motivation of its introduction is different from *Bitcoin*. *Bitcoin* was introduced as a digital currency, on the other hand, *Ethereum* is a ledger technology that companies are using to build new programs, and *Ethereum* coin is a part of this ledger. *Ethereum* is far more robust than *Bitcoin* [111]. Many other properties at the protocol level are also different, such as decrement in the amount of time for confirmation of the transaction, developers of *Ethereum* had used *ethash* instead of SHA-256 [110]. For this reason, we have considered *Ethereum* as a separate cluster from

Bitcoin, and also there are a large number of cryptocurrencies forked from Ethereum. In the following paragraph few of them will be discussed.

Ethereum Classic is the one that has been emerged from the *Ethereum* blockchain. Initially, *Ethereum Classic* and *Ethereum* were the same till the incident of DAO. After that, few developers had made a hard fork of *Ethereum* and introduced *Ethereum* crypto coin. And other developers decided to use the existing code-base, with no changes as *Ethereum Classic* [112]. *Binance Coin* initial release had incorporated the ERC-20 token, the same token used in *Ethereum* Blockchain. However as of now, ERC-20 tokens are replaced with BEP-2. Developers replace PoW with BFT, so mining is not possible [9]. *Chainlink* is also based on ERC-20 tokens with additional ERC-223 for transfer and call functionality [9]. *Aave* utilizes ERC-20 tokens of *Ethereum* ledger with open source implementation [113]. Currently, they are transferring the PoW algorithm with PoS algorithm [9]. There are many others as well who made a fork from *Ethereum*. From this, we can observe the importance of *Ethereum* to cryptocurrency's market cap. And its influence both technically and financially on other cryptocurrencies.

C. HYBRID

Till now, we have seen that cryptocurrencies were derived from popular or versatile cryptocurrencies like *Bitcoin* and *Ethereum*. However, many developers tried to combine two or many cryptocurrencies at the protocol level to make a hybrid one. This subsection discusses a few of them. *Wrapped Bitcoin* is the tokenized version of *Bitcoin* running on *Ethereum* Blockchain [9]. The main motive of its developers is to use *Bitcoin* in the *Ethereum* decentralized environment [114]. *Qtum* is another cryptocurrency that is a hybrid of *Bitcoin* and *Ethereum*. *Qtum* tokens were derived from *Ethereum* tokens, specifically ERC-20. And their transaction model is UTXO derived from *Bitcoin* [9], [115].

D. INDEPENDENT

Till now, we have seen how new cryptocurrencies are derived from other ones. But there are cryptocurrencies from which new ones were derived, so their study is also required. This subsection discusses a few of them. *Bitcoin* is the first cryptocurrency introduced in [1], which makes it an independent one. *Ethereum* is the first and original smart contract-based blockchain project. *Ethereum* is independent because of its ERC-20 token derived from the *Ethereum* blockchain. *Binance Coin* during their initial period was derived from *Ethereum*. But as of now, *Binance Coin* is independent. They introduced their own token BEP-2 [9]. *Bytecoin* being the first cryptocurrency based on cryptonote technology makes it an independent cryptocurrency [116]. Cryptocurrencies like *Monero* [9] and *Dashcoin* [117] are derived from *Bytecoin*. *Ripple* is another independent cryptocurrency that runs on Ripplenet and Ripple ledger [9].

This section analyzes the facts and discusses interdependency among cryptocurrencies. Initially, we have categorized cryptocurrencies into two categories based on their price or exchange rates. Later, in two subsections we discuss cryptocurrencies that are directly or indirectly derived from *Bitcoin* and *Ethereum*. After that, we had a brief discussion on hybrid cryptocurrencies. This kind of cryptocurrency was formed by combining the properties of two or more cryptocurrencies. Following is a subsection that discusses the cryptocurrencies that are independent of other cryptocurrencies. Their independent nature can be analyzed, through their codebase, protocols, and other technical aspects.

VII. PROBLEM FORMULATION

The proposed model is based on the fusion of cryptocurrencies in the context of interdependency among them. From the discussion in Section VI, we have picked out that there is an interdependency among *Bitcoin* and *Litecoin*, *Litecoin*, and *Dash*. So, hierarchically there is an interdependency between *Bitcoin* and *Dash*. To justify the fusion, we consider the prediction of *Dash* based on the prices of *Dash* with the inclusion of *Litecoin* and *Bitcoin* prices as well. The forecasting problem is a supervised learning problem. And under supervised learning, it is a regression problem. As we are predicting prices, the output from the model will be the predicted price for that particular day. But what will be feed as an input to the model?

We have the price history of all cryptocurrencies. This data can be incorporated to forecast the price of the present day. Let the cryptocurrency prices at the individual timestamps be $p_0, p_1, p_2, p_3, p_0, \ldots, p_n$, where p_i denotes price at time stamp i. Let the input window length be w, the input vector be ip, price of *Bitcoin* be pb, price of *Litecoin* be pl, price of *Dash* be pd and the output be o, mathematically ip and o can be denoted as:

$$ip_{pb} = [pb_{i-w+1}, pb_{i-w+2}, pb_{i-w+3} \ldots .pb_{i-2}, pb_{i-1}] \quad (1)$$
$$ip_{pl} = [pl_{i-w+1}, pl_{i-w+2}, pl_{i-w+3} \ldots .pl_{i-2}, pl_{i-1}] \quad (2)$$
$$ip_{pd} = [pd_{i-w+1}, pd_{i-w+2}, pd_{i-w+3} \ldots .pd_{i-2}, pd_{i-1}] \quad (3)$$
$$ip = [ip_{pb},\ ip_{pl},\ ip_{pd}] \quad (4)$$
$$o = pd_i \quad (5)$$

where w is the window size, ip_{pb} is the preprocessed input of *Bitcoin*, ip_{pl} is the preprocessed input of *Litecoin*, and ip_{pd} is the preprocessed input of *Dash*. Our motive is to predict output o using input vector ip, which contains prices of past w days value of *Bitcoin*, *Litecoin*, and *Dash*. The data for training and testing is arranged into multiple input-output pairs as shown in (4) and (5) respectively.

FIGURE 14 shows the working of the proposed system model. For training, the data is collected from Investing.com [66] and then preprocessed. For preprocessing we have normalized through a division operator. Let x be the current price and $x_{\max}$ be the maximum price seen till now, and y is the difference between the number of digits in 1 and

x_{max}, and x_{new} be the normalized prize then x_{new} can be denoted as:

$$x_{new} = \frac{x}{10^y}$$
$$y = Number\ of\ digits\ in\ x_{max} - 1 \tag{6}$$

Through the normalization used (6), values will be in the range of *0* to *10*. After preprocessing, the merging of data is done according to (4) to make an input tuple. After merging, the data is further divided into two parts training and testing data. Model weights are trained using training data and their performance is evaluated using testing data. For predicting price at i^{th} day, we have to feed past w days (window length) data of all dependent cryptocurrencies (here *Bitcoin*, *Litecoin*, and *Dash*). The forecasted price is fed into the model with past $(w - 1)$ days of prices to predict the $(i + 1)^{th}$ days price consequently. This process is repeated several times equal to the prediction window length. The new w days price is compared with test data to evaluate the performance. The proposed scheme uses a hybrid model combining GRU and LSTM. In the following subsection, we will see the working of LSTM and GRU neurons and why the classic RNN is not used for making system models.

1) RECURRENT NEURAL NETWORK

RNN is a type of feed forward neural network, whose output is derived from the input features and the outputs of all hidden neurons of that RNN layer at the previous timestamp or previous stage. This special property helps the RNN to solve the problems where the result of the present situation is based on the past scenarios. Price prediction, text classification, and language generation are the few problems that can be solved using RNN [118]. Mathematically RNN is denoted as [119]:

$$a_t = \sigma\left(W_{hidden}\, a_{t-1} + W_{input} x_t + b_a\right) \tag{7}$$
$$y_t = \sigma\left(W_{output}\, a_t\right) \tag{8}$$

where x_t is the input at timestamp t, a_t is the output of hidden neuron at timestamp t. W_{hidden}, W_{input} and W_{output} are the weights of hidden neuron, input neuron and output neuron respectively. Activation function in both hidden and output neuron is sigmoid function. Detailed mathematical description of RNN is given in [120], and [121] gives the overview of RNN. FIGURE 15 represents graphical structure of RNN neuron. So, is the RNN sufficient to solve our forecasting problem?

The specialty of RNN helps us to solve many problems, including the forecasting problem. But, there are few drawbacks. The RNN is, trained through back-propagation. They are cyclic in nature which makes them difficult to train and take time to converge [121]. They also suffer from a vanishing gradient problem due to which we cannot get proper output for long sequences or long window size [122], [123]. To overcome the vanishing gradient problem few steps in preprocessing [124] or mathematical operations like gradient clipping might help. However, this also fails when the data is having long sequences or window sizes. Two new models

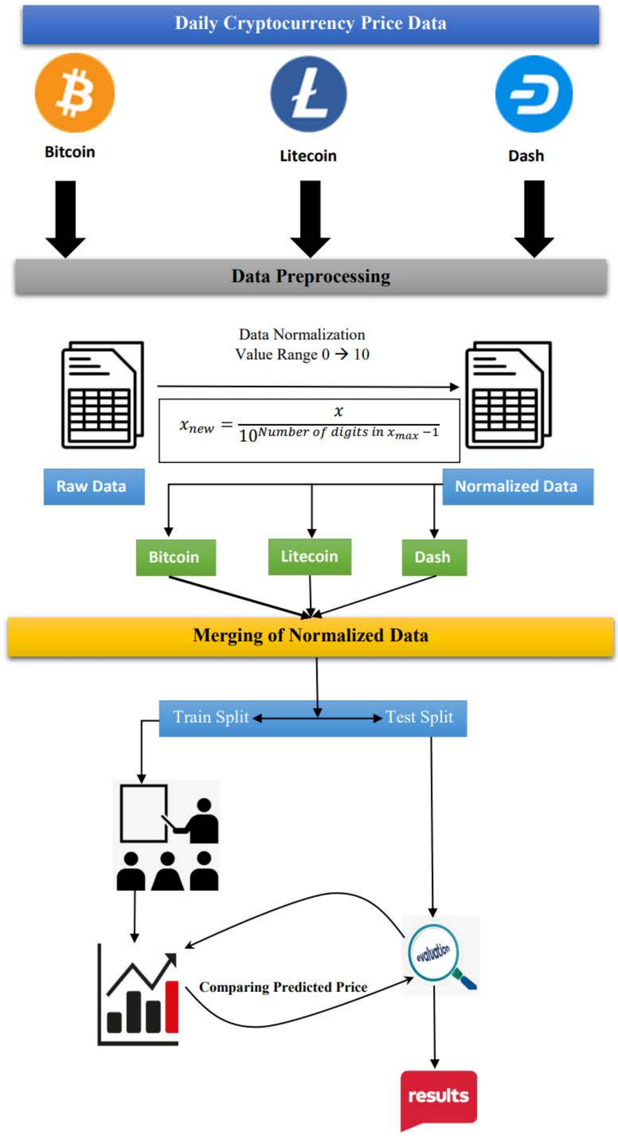


FIGURE 14. Pictorial flowchart for the working of proposed Fusion-based cryptocurrency price prediction model.

LSTM [125] and GRU [126] are introduced. They are derived from RNN with an additional feature called memory cell. This memory cell helps them to avoid vanishing gradient problems by remembering the essential past features only. Both of them also works well while feeding long sequences or long window size of data. In the following subsection, we will take a brief look at LSTM and GRU structure.

2) LONG SHORT TERM MEMORY

LSTM is a variant of RNN that contains memory cells in it [125]. Each neuron of LSTM consist of four other sub neurons in it which act as a memory cell. The weights of these sub neurons helps LSTM to remember long sequences. A classic LSTM cell consist of an input gate, forget gate, and

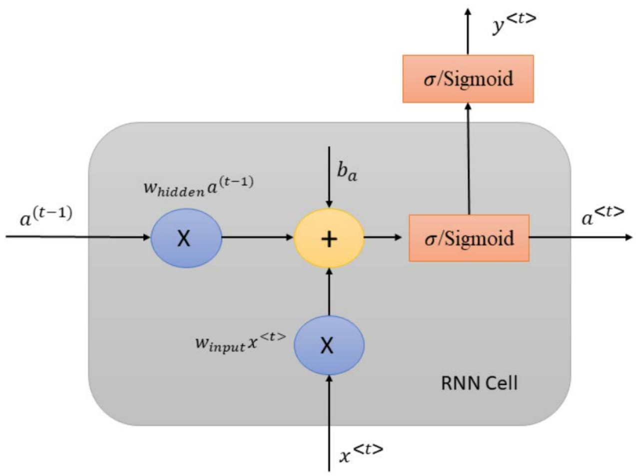


FIGURE 15. **Graphical representation for internal working architecture of RNN [119].**

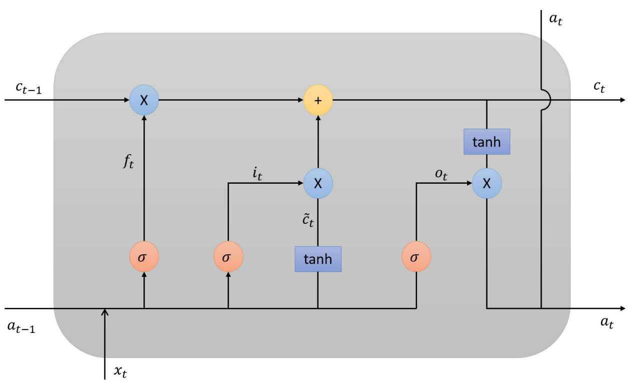


FIGURE 16. **Graphical representation for internal working architecture of LSTM [119].**

output gate. (9), (10), and (14) represents mathematical form of the respective gates. Their mathematical equation can be denoted as [119]:

$$i_t = \sigma(x_t U_i + a_{t-1} W_i) \tag{9}$$
$$f_t = \sigma(x_t U_f + a_{t-1} W_f) \tag{10}$$
$$o_t = \sigma(x_t U_o + a_{t-1} W_o) \tag{11}$$
$$\tilde{C}_t = tanh(x_t U_g + a_{t-1} W_g) \tag{12}$$
$$C_t = \sigma(f_t * C_{t-1} + i_t * \tilde{C}_t) \tag{13}$$
$$a_t = tanh(C_t) * o_t \tag{14}$$

where x_t, $a_{t\text{-}1}$ and $C_{t\text{-}1}$ will be the inputs, and a_t and C_t will be the output from the cell. Symbols i is for input gate, f is for forget gate, and o is for output gate. And symbols W, and U are the weights of each sub neuron or memory cells. FIGURE 16 represents graphical structure of the LSTM cell.

3) GATED RECURRENT UNIT

GRU is the latest variation of RNN introduced by [126]. The working of GRU is similar to that of LSTM. Even though, the structure is similar but [126] remove one hidden sub neuron and one gate from LSTM. GRU has three sub neurons and two gates which helps them to resolve the vanishing gradient problem. Two gates are an update gate and a reset gate. Like LSTM, the gates in GRU controls the flow of information through the network. Update or output gate controls information flow from the past that needs to be passed further. The reset gate determines the amount of information to forget. (15), and (16) represents mathematical representation of respective gates and output of GRU is represented by (18). Their mathematical equation are [119]:

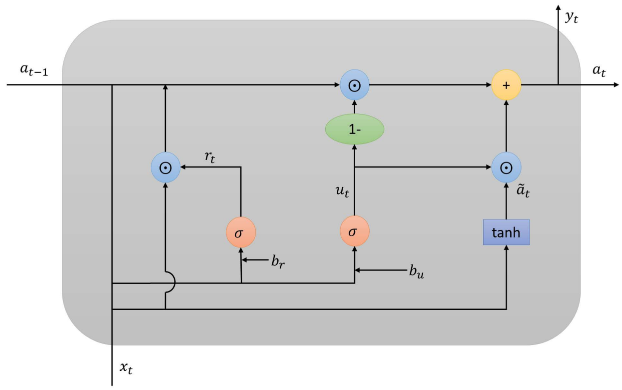


FIGURE 17. **Graphical representation for internal working architecture of GRU [119].**

$$u_t = \sigma(U_u x_t + W_u a_{t-1} + b_u) \tag{15}$$
$$r_t = \sigma(U_r x_t + W_r a_{t-1} + b_r) \tag{16}$$
$$\tilde{a}_t = tanh(U_o x_t + W_o(r_t \odot a_{t-1}) + b_o) \tag{17}$$
$$a_t = (1 - u_t) \odot a_{t-1} + u_t \odot \tilde{a}_t \tag{18}$$

where x_t, o_t, u_t, and r_t is the input, output, update gate output, and reset gate output respectively. Symbols denotes the Hadamard product and U, W, and b are the weights and biases matrices. FIGURE 17 represents graphical structure of the GRU cell.

In this section of the paper, we mathematically defined our forecasting problem and after that, we explore the type of architecture that can use to solve the problem. We explore RNN's advantages and disadvantages and to overcome them, how we can use LSTM and GRU.

VIII. PROPOSED FUSION-BASED SOLUTION MODEL

In this section, we elaborate the proposed fusion-based cryptocurrency price prediction model. To represent fusion, through dependency among cryptocurrencies, we predict the price of *Dash* based on the previous days' prices of *Dash*, *Litecoin*, and *Bitcoin*. In section VI, we have seen that *Litecoin* is derived from *Bitcoin* and *Dash* is derived from *Litecoin*. The model for the prediction task is based on LSTM and GRU. RNNs are well known to remember sequential data, but as discussed in Section VII it suffer from vanishing gradient problem. LSTM and GRU overcome this problem with memory cells which makes them fit for this task.

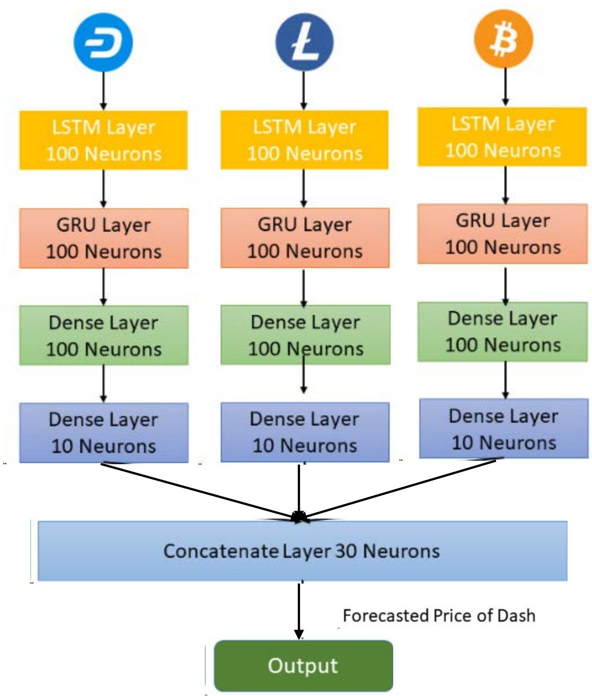


FIGURE 18. Graphical representation for architecture of proposed fusion based model.

The authors in [28], [32], [34], [39] managed to get good results using RNN, LSTM and GRU.

First of all, data available with us are continuous historical data. The prices of *Bitcoin* are in the range of $*60,000* whereas *Litecoin* and *Dash* are in the range of $*200*. This vast gap between the range of prices will makes the task complicated, and requires a lot of computational time for model training. So, we have normalize the data using (6) that make every data in the range of *0* to *10*. Reasons for not using standard normalization technique like Min-Max normalization is, discussed in Section IX. After normalization, the data is arranged in a suitable format of input-output pairs as per (4) and (5). The input is a sequence of past w day's prices of all three cryptocurrencies and output will be the present-day price of *Dash*. Here w is a window size which is a hyper-parameter. These multiple input-output tuples are divided into two parts. The first part is used to calculate the optimal values of parameters for the model, and the second part was used to determine its robustness and performance.

The next step is to train the the model using training data and analyze its performance on the test data. The model consists of three sub-models one for each cryptocurrency. Through these three sub-models, latent features are extracted and after that, all three latent features are concatenated to make a dense model. This dense model is further give us the forecasted price. Input is fed to the *100* neurons LSTM layer. The output of this LSTM layer is passed to the *100* neurons GRU layer. After that, we have *100* neurons of the dense layer and after that another dense layer of *10* neurons. Now we have *10* latent features from each crypto coin. So, in total, we have *30* latent features after the concatenation layer. Following the concatenation, we have a single neuron dense layer, which is the output layer that gives us the forecasted price. All the layers except the last layer that has ReLU as an activation function, and the last layer has a linear activation function. The difference between the output from the model and actual value will be used to determine loss, and through adam optimizer this loss will be decreased to a global minimum value. The model has been trained for *50* epochs. FIGURE 18 is the graphical representation of above described fusion-based model.

After training, the losses are compared to determine its performance. To justify our model, we train our model with various input patterns such as *Dash* only, then *Dash* and *Litecoin*, and after that *Dash*, *Litecoin*, and *Bitcoin*. For comparison purposes, we have used an MSE as our loss function. And for justifying the use of the (LSTM + GRU) model, we compared the loss with LSTM and GRU. In the below subsection, there will be a graphical comparison among LSTM, GRU, and (LSTM + GRU). The comparison was carried out through window sizes of one, three, seven, and thirty.

IX. PERFORMANCE EVALUATION

This section gives an insight to the dataset used for the proposed prediction model, feature selection for various cryptocurrencies, data preprocessing phase for each cryptocurrency, evaluation measurement for the proposed fusion-based model, and the final result is obtained by the proposed model which is described in detail analysis.

A. DATASET DESCRIPTION

The data was collected from the global portal *Investing.com* [66] for research purposes, which provides real-time data like the news and analysis of the financial market. The data for cryptocurrencies like *Bitcoin*, *Bytecoin*, *Dash*, *Ethereum*, *Litecoin*, and *Monero* was collected daily which adds features as follows.

- *Price:* Average price of each cryptocurrency day-wise
- *Open:* Opening price of each cryptocurrency day-wise
- *High:* Highest price of each cryptocurrency day-wise
- *Low:* Lowest price of each cryptocurrency day-wise

Data for each currency were collected for January 24, 2018 - April 01, 2021 (1164 data points). The proposed fusion-based model takes average daily prices of *Bitcoin*, *Dash*, and *Litecoin* as an input feature and FIGURE 13 concluded their dependency.

B. DATA PREPROCESSING

In the proposed fusion-based model, we pass the price data of *Bitcoin*, *Litecoin*, and *Dash* as an input for predicting the price of *Dash*. The range of price data of each currency is not the same and varies a lot. Due to these reasons, we cannot use the data directly for training purposes. We found some major issues with the existing normalization techniques and their applicability to this type of data for predicting prices. Techniques like min-max normalization are popular among the research community. To predict the price of *Dash*, if we provide input as the min-max normalized form then the model will not able to predict the price of *Dash* when it gets higher than the maximum value of training data and lower than the minimum value of training data. Due to this, we cannot use this kind of normalization technique and eventually can not fulfill our purpose for predicting the price accurately. (19) is mathematical presentation of min-max normalization [127].

$$x_{min-max\ normalized} = \frac{x_{original} - x_{min}}{x_{max} - x_{min}} \tag{19}$$

where $x_{\text{min-max normalized}}$ is the transformed value, x_{original} is the original input value, $x_{\min}$ is the minimum value from the input data and $x_{\max}$ is the maximum value from the input data. To avoid the above-discussed situation and for aligning price data in one range we have incorporated weighted normalization technique where is already explained in the above section, (6) that transforms the data in the range of *0* to *10*. After normalization, we select price as a primary feature for the proposed fusion-based model and give input as the price of *Bitcoin*, *Litecoin*, and *Dash*.

C. EVALUATION METRICES

Evaluation of the proposed fusion-based model is done using loss function namely MSE, which is observed for the singular model, dual dependency model, and hierarchical dependency model. Mathematically an MSE can be denoted as [128]:

$$MSE = \frac{1}{N}\sum_{i=0}^{N}(\hat{p}_i - p_i)^2 \tag{20}$$

where $\hat{p}_i$ represent the predicted price, p_i represents actual price, and N is the number of observations (data points).

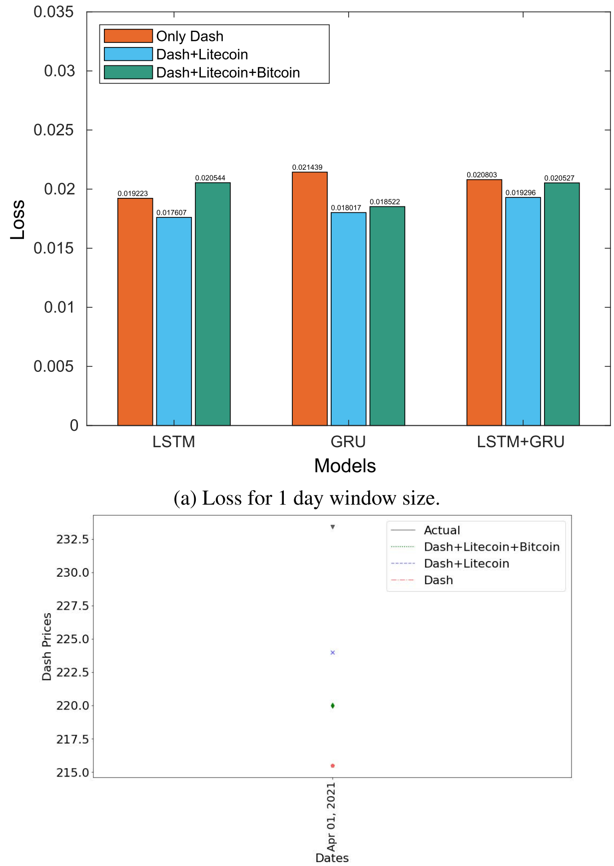
D. RESULTS

The result of the proposed model and various simple models compared in this subsection. The fusion-based proposed model experimented with different predicting window lengths: *1* day, *3*-days, *7*-days, and *30* days. We provide *1000* data points for each cryptocurrency as input for training, and testing data is different from training data on which the prediction task was performed. Training dataset length fixed for all window size that is *1000*, and testing dataset length is variable that are as follow:

- *1 day:* Test dataset length: *163* data points
- *3 days:* Test dataset length: *161* data points
- *7 days:* Test dataset length: *157* data points
- *30 days*: Test dataset length: *134* data points

To predict the price of *Dash*, two models were implemented besides the fusion-based prediction model. Without considering any dependency, the simple model having *Dash* price as an input feature implemented. Considering dual dependency, the second model with an input feature price of *Dash* and *Litecoin* implemented. The final fusion-based model is implemented by considering the multiple hierarchies, and have the price of *Dash*, *Litecoin*, and *Bitcoin* as input features. These three models were implemented with three varieties of the model that are as follows: only LSTM, only GRU, and fusion of LSTM and GRU models.

A simple model, for predicting the price of *Dash* with a different window size was implemented on LSTM, GRU, and LSTM-GRU based model with *1000* data points for the training. A single dependent model takes two input features, i.e., the price of *Dash* and *Litecoin's 1000* data points of each for training, whereas in the hierarchical dependent model the *1000* data points of each of *Bitcoin*, *Litecoin*, and *Dash* are given as an input feature.



(a) Loss for 1 day window size.

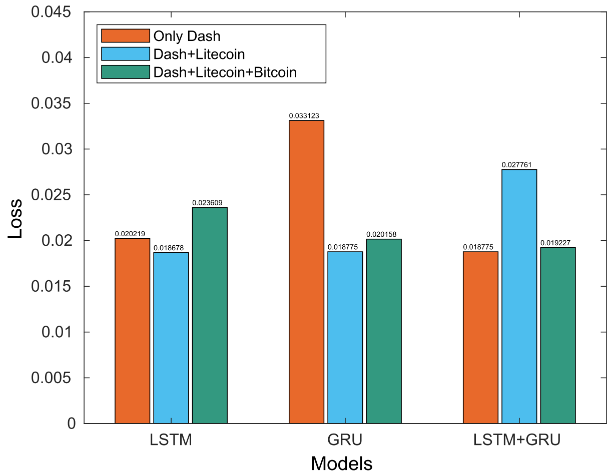
(b) Prediction of LSTM + GRU for 1 day window size.

FIGURE 19. Performance of Fusion-based model using previous day prices for price prediction.

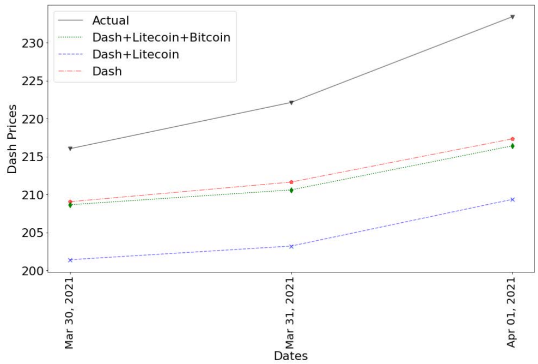
1) SCENARIO 1: 1-DAY PRICE PREDICTION

In a *1*-day price prediction window size, *1000* data points passed as input for training and *163* data points for testing purpose to calculate loss. In the *1*-day price prediction window size, the *1*-day price passed as an input, and the price of the next day is estimated.

A simple model with input as a *Dash's* price with LSTM unit gives an MSE loss of *0.0192*. A GRU unit produces an MSE loss of *0.0214*, and (LSTM + GRU)-based model

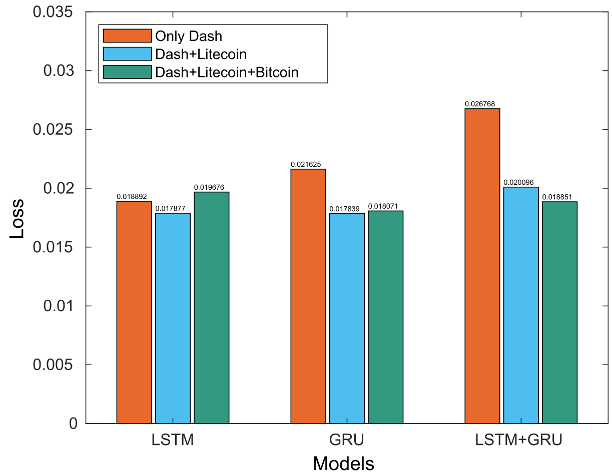


(a) Loss for 3 days window size.

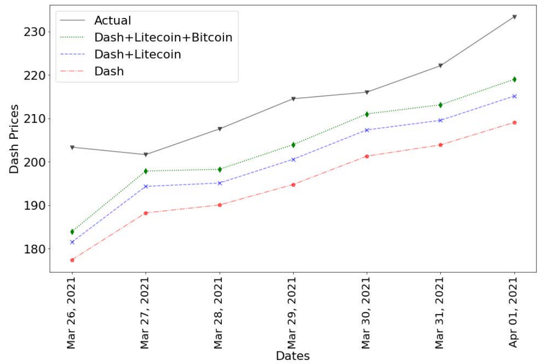


(b) Prediction of LSTM+GRU for 3 day window size.

FIGURE 20. **Performance of Fusion-based model using last 3 days as window size for price prediction.**



(a) Loss for 7-day window size.



(b) Prediction of LSTM + GRU for 7-day window size.

FIGURE 21. **Performance of Fusion-based model using last 7 days as window size for price prediction.**

delivers the MSE loss of *0.0208*. A single dependent model with input as *Dash* and *Litecoin's* price with LSTM unit gives the MSE loss of *0.0176*. A GRU unit produces an MSE loss of *0.0180*, and LSTM+GRU based model delivers an MSE loss of *0.0192*. A multiple dependent model with input as the price of *Dash*, *Litecoin*, and *Bitcoin* with LSTM unit gives the MSE loss of *0.0205*. A GRU unit produces an MSE loss of *0.0185*, and LSTM+GRU based model delivers an MSE loss of *0.0205*. The loss observed by all prediction models for *1*-day window size is displayed in FIGURE 19a, and FIGURE 19b shows the actual price and predicted price by our proposed fusion-based model (LSTM+GRU) in USD.

2) SCENARIO 2: 3-DAY PRICE PREDICTION

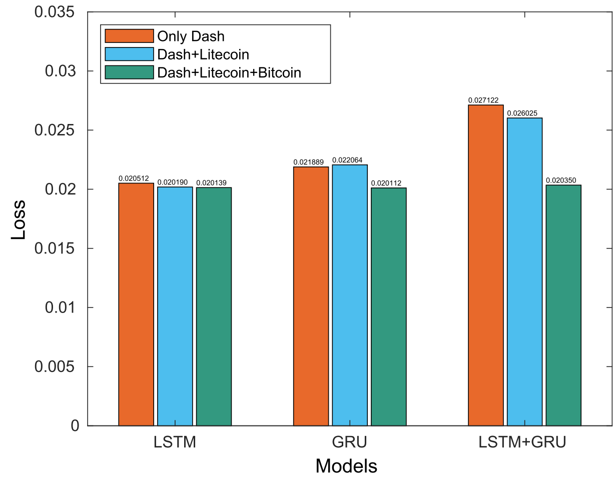
In a *3*-day price prediction window size, *1000* data points passed as input for training and *161* data points for testing purpose to calculate loss. In the *3*-day price prediction window size, the *3*-day price passed as an input, and the price of next day is estimated

A simple model with input as *Dash's* price with LSTM unit gives the MSE loss of *0.0202*. A GRU unit produces an MSE loss of *0.0331*, and (LSTM+GRU) based model delivers an MSE loss of *0.0187*. A single dependent model with input as *Dash* and *Litecoin's* price with LSTM unit gives the MSE loss of *0.0186*. A GRU unit produces an MSE loss of *0.0187*, and (LSTM+GRU) based model delivers an MSE loss of *0.0277*. A multiple dependent model with input as *Dash*, *Litecoin*, and *Bitcoin's* price with LSTM unit gives the MSE loss of *0.0236*. A GRU unit produces an MSE loss of *0.0201*, and (LSTM+GRU) based model delivers an MSE loss of *0.0192*. The loss observed by all prediction models for *1*-day window size is displayed in FIGURE 20a, and FIGURE 20b shows the actual price and predicted price by our proposed fusion-based model (LSTM+GRU) in USD.

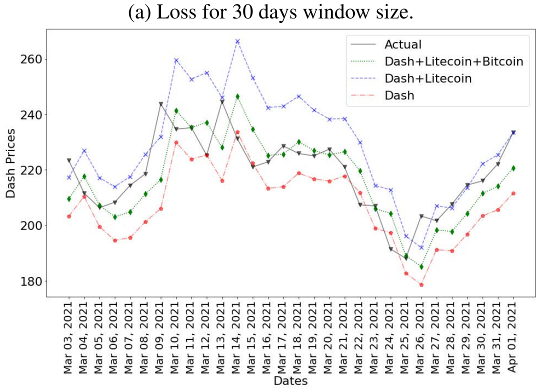
3) SCENARIO 3: 7-DAY PRICE PREDICTION

In a *7*-day price prediction window size, *1000* data points passed as input for training and *157* data points for testing purpose to calculate loss. In the *7*-day price prediction window size, the *7*-day price passed as an input, and the price of the next day is estimated.

A simple model with input as *Dash's* price with LSTM unit gives the MSE loss of *0.0188*. A GRU unit produces an MSE loss of *0.0216*, and (LSTM + GRU) based model delivers an MSE loss of *0.0267*. A single dependent model with input as *Dash* and *Litecoin's* price with LSTM unit gives the MSE loss of *0.0178*. A GRU unit produces an MSE loss of *0.0178*, and (LSTM + GRU) based model delivers an MSE loss of *0.0200*.



(a) Loss for 30 days window size.



(b) Prediction of LSTM+GRU for 30 day window size.

FIGURE 22. Performance of Fusion-based model using last 30 days as window size for price prediction.

A multiple dependent model with input as *Dash*, *Litecoin*, and *Bitcoin's* price with LSTM unit gives the MSE loss of *0.0196*. A GRU unit produces an MSE loss of *0.0180*, and (LSTM + GRU) based model delivers an MSE loss of *0.0188*. The loss observed by all prediction models for 1-day window size is displayed in FIGURE 21a, and FIGURE 21b shows the actual price and predicted price by our proposed fusion-based model (LSTM + GRU) in USD.

4) SCENARIO 4: 30-DAY PRICE PREDICTION

In a *30*-day price prediction window size, *1000* data points passed as input for training and *134* data points for testing purposes to calculate loss. In a *30*-day price prediction window size, the *30*-day price passed as an input, and the price of the next day is estimated.

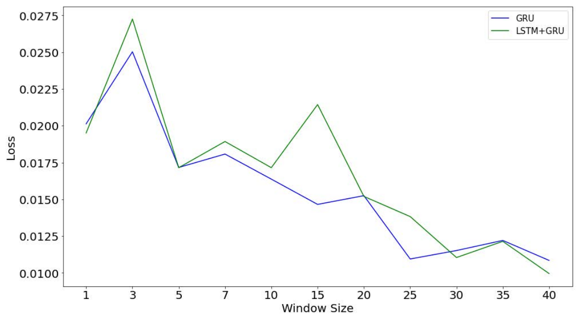
A simple model with input as *Dash's* price, with an LSTM unit, gives the MSE loss of *0.0205*. A GRU unit produces an MSE loss of *0.0218*, and (LSTM + GRU) based model delivers an MSE loss of *0.0271*. A single dependent model with input as *Dash* and *Litecoin's* price with an LSTM unit gives the MSE loss of *0.0201*. A GRU unit produces an MSE loss of *0.0220*, and the (LSTM + GRU) based model delivers an MSE loss of *0.0260*. A multiple dependent model with input as *Dash*, *Litecoin*, and *Bitcoin's* price with LSTM unit gives the MSE loss of *0.0201*. A GRU unit produces an MSE loss of *0.0201*, and (LSTM + GRU) based model delivers an MSE loss of *0.0203*. The loss observed by all prediction models for *1*-day window size is displayed in FIGURE 22a, and FIGURE 22b shows the actual price and predicted price by our proposed fusion-based model (LSTM + GRU) in USD.

E. OBSERVATION OF RESULTS FROM GRAPHS

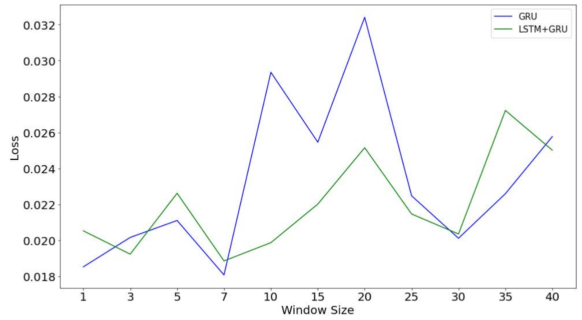
In this subsection, we are going to mark down some important observations captured from FIGURE 19, 20, 21, and 22. One of the main observations observed from all the graphs is that the proposed fusion-based hierarchical model and dual-dependency model performs better than the simple model for *Dash* price prediction. The hierarchical model shows the least variation in the loss amongst the dual-dependent and simple fusion-based algorithms for all model architecture and chosen window sizes.

For a *1*-day window size, it was observed from FIGURE 19b that the dual-dependency model performs better than the other two models. For a *3*-days window size, the GRU model for dual-dependency outperforms by having more than 40% less loss compared to the simple *Dash* prediction model where neither hierarchical model nor dual-dependent model performs better than the simple *Dash* prediction model for the fusion-based model of (LSTM + GRU). For a *7*-days window size, the GRU model gives the lowest MSE loss for dual-dependency approach that is *0.0178*. Performance increment of *30%* is observed for (LSTM + GRU) by loss values, which is the highest increment amongst rest models for the hierarchical model. FIGURE 21b provides the evidence for the above statement. For the I-days window size, the GRU model gives the lowest MSE loss for the hierarchical approach, which is *0.0201*. The performance increment of *25%* is observed for (LSTM + GRU) by loss values, which is the highest increment amongst rest models for the hierarchical model. FIGURE 22b provides the evidence for the above statement.

From the above study, we can conclude that the fusion-based forecasting model in the context of the interdependency of cryptocurrency gives better results compared to the simple forecasting model. We have proposed the (LSTM + GRU) architecture based on the fusion of the cryptocurrency prices. To justify this, a particular model is compared with the simple LSTM and simple GRU fusion-based model. From the figures, it's evident that most of the time GRU and (LSTM + GRU) give better performance compared to the LSTM model. The observation leads us to confusion about the performance of models as we find the GRU and (LSTM + GRU) both perform well for the hierarchical models. To provide an evidence that the (LSTM + GRU) performs better than the GRU model, we perform the prediction based on the hierarchical model for GRU and (LSTM + GRU) for *1, 3, 5, 7, 10, 15, 20, 25, 30, 35*, and *40* days window sizes. We found that (LSTM + GRU) is more promising than the GRU model for forecasting the price of cryptocurrency *Dash* based



(a) Train loss of GRU and LSTM+GRU for different window size.



(b) Validation loss of GRU and LSTM+GRU for different window size.

FIGURE 23. Comparison of training and validation loss for GRU and (LSTM + GRU) model.

on previous days price of *Dash*, *Litecoin*, and *Bitcoin*. FIGURE 23a shows the comparison of training performance while FIGURE 23b shows the comparison of validation performance.

X. THREAT TO VALIDITY

This section discusses threats to the validity for recognizing it and counter them in a research design for a robust study.

- *Scholarly and analysis articles*: The articles and analyses done by financial institutes played a big role to carry out the survey done in this paper. Somehow, if the surveyed articles are false or wrong, it will pose a threat to the survey. To tackle it, we have considered scholarly articles from reputed peer-reviewed journals, and analytical articles were derived from the reputed financial institutes. Moreover, the filtration of articles was done based on the number of citations, quality of the journal, and several views on it.
- *Dataset validation*: For the proposed model, the dataset play an important. A slight change in the price history will affect the performance at a drastic rate. The price history used were compared with other websites and then it's been considered to do a performance evaluation of our proposed work.
- *Architecture validation*: Proposed model uses a sophisticated algorithm. If the algorithms' implementation was wrong, the whole performance evaluation became useless. So, the standard and open-source libraries were used while setting up the whole environment to calculate the performance metrics of the proposed framework.

XI. DISCUSSION ON OPEN ISSUES AND FUTURE ASPECTS

This section discusses various future research challenges and open issues in cryptocurrency price prediction. Some of the major issues are discussed below.

A. ARCHITECTURAL ADVANCEMENT

The proposed model comprises of simple LSTM and GRU layers, which significantly improves the efficacy of cryptocurrency price prediction. But, there is a scope to further improve the prediction accuracy and robustness using ensemble learning, bidirectional layers, or the present trending transformers-based models. Research community can also go for Federated Learning as after few years the amount of data will be vast and it will be hard to train model on one single machine.

B. STOCHASTIC NATURE OF CRYPTOCURRENCY PRICES

The prices of cryptocurrency are stochastic. As, most of the times it follows random walk hypothesis, which is independent of time. External changes affect the price significantly that make the forecasting highly complex and tedious. This can be resolved to some extent by considering the fusion of multiple features by creating a robust forecasting model. In the proposed work we have used price of other but similar cryptocurrency for price prediction, further this can be fused with market sentiments, costs of mining hardwares, volume of cryptos in the market, current active users, worldwide governments policy and many more. The model might become complex and harder to train, but if all this features are fused with proper mapping and weightage, researchers can create a robust price prediction model.

C. LOW UTILITY OF FORECASTING MODEL

Based on the literature, the prediction models predicts the price of one cryptocurrency only. But, in fusion-based model, there can be multiple inputs, which comprises of diverse cryptocurrency prices. Thus, this can improve the models efficacy, which predicts the price of multiple cryptocurrencies at the same quantum of time.

The paper we have surveyed in Table 1 are kind of one-to-one price prediction model, i.e. the price history of Dash is used to predict current price of Dash. The model we have proposed is many-to-one, the price history of Litecoin, Bitcoin and Dash is used for price prediction of Dash. Now, we can also explore the path where many-to-many model can be implemented, to put it another way the price history of Litecoin, Bitcoin and Dash will predict the upcoming prices of all three cryptocurrencies based on each others history, through this we have completely cut off training time of 3 different models to one model and also the weights of models are efficiently used for prediction of different cryptocurrency.

D. ALGORITHMIC ADVANCEMENT

The proposed fusion-based model considered the interdependency among the cryptocurrencies and further improved the accuracy by considering various other factors (except the past prices) like market sentiments and opinion mining to improve the robustness and accuracy of the prediction model. The accuracy can further be improved by incorporating reinforcement learning that train the model in real-time by considering the environmental factors.

E. LEGAL ASPECTS

Although, the cryptocurrencies becomes a popular choice for investors nowadays, but there is no regulatory body that controls its circulation. In recent times, many countries legally accept cryptocurrency as a medium of transaction with numerous rules and laws. Few countries also started to ban cryptocurrency because of their belief that the anonymous nature of cryptocurrency is a boon for organizations that are involved in illegal businesses and terrorist activities. These factors affect public perception, which indirectly affects the prices of cryptocurrency.

XII. CONCLUSION

Price prediction of any cryptocurrency is quite challenging and popular among researchers due to its volatile nature and its dependency among various internal and external factors, as discussed in Section I. For price prediction, time-series-based models are used because of their dependency on past-day prices. Researchers have explored various machine learning-based time-series models like ARIMA, SARIMA, ARCH, ARIMAX, and other regression-based models for cryptocurrency price prediction. Since the introduction of deep learning-based algorithms in the time-series prediction field, researchers have also started to incorporate their functionality in this field of research. Several variants of deep learning-based algorithms like MLP, LSTM, GRU, CNN, and hybrid or ensemble models had been used by the researchers for cryptocurrency price prediction as discussed in Section II. In consideration of price prediction, statistical analysis on the price history of cryptocurrency is also important with the risks related to their prices as discussed in Section III. The study of companies, startups, organizations, and researchers related to the cryptocurrency market is also to be considered as they impact cryptocurrency prices as discussed in Section IV.

From the literature, we found that the researchers have not considered the interdependency among the crypto coins. But, we have considered this as our main factor for the proposed model. To find the appropriate factors for the proposed model, we have analyzed various existing factors and dependencies among the cryptocurrencies. In this paper, we have proposed an LSTM and GRU-based fusion model with a detailed comparison in terms of performance with existing models. For performance evaluation, we have considered the price prediction of *Dash* with the inclusion of daily price data from *Dash*, *Litecoin*, and *Bitcoin*. Based on the performance for predicting *Dash's* price, our proposed model works better compared with the model trained using only *Dash* price and other model trained using data from *Dash* and *Litecoin*. Hence, to increase the performance of the forecasting model, hierarchical dependency among cryptocurrencies was found useful. The concept of hierarchical dependency has termed the concept of fusion.

In the future, we will further improve the accuracy of the cryptocurrency price prediction using federated and distributed learning.

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