**DURBAN UNIVERSITY OF TECHNOLOGY**

# The design of the frugal robot for detecting in-pipe corrosion in the oil and gas sector

**By**

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**DECLARATION**

I, Zinhle Mthimkhulu, confirm that the work presented in this dissertation is my own and has not been submitted to any other institution. All sources and references used have been appropriately acknowledged.

Zinhle Mthimkhulu: Date: 19-03-2026

**Approved for Final Submission**

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**DEDICATION**

Firstly, I would like to thank my father, Jesus Christ. He guided me and gave me the strength and courage I needed to finish this thesis, even during difficult times. I am grateful for his grace and unconditional love.

To my mom, Maggie Buthelezi and my sisters, Nontobeko Buthelezi and Siphesihle Mgabhi, thank you for your support and for always believing in me. Your prayers and support contributed to the success of this thesis.

Omuhle, my daughter, and Akhanya, my niece, you are the ones who inspire me the most. May this achievement show you that anything is possible with faith and determination. Lastly, my late grandma, your strength continues to guide me. This one is dedicated to you, my Defro.

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# ABSTRACT

The oil and gas (O&G) sector plays a critical role in sustaining global energy demands, yet pipeline deterioration, particularly corrosion, remains a persistent threat to operational safety and service continuity. While several robotic inspection systems have emerged over the years, most remain prohibitively expensive and inaccessible, leading many South African oil and gas (O&G) companies to rely on slow, traditional inspection methods. This study responds to this gap by designing and developing a portable, and cost-effective in-pipe inspection robot that integrates image acquisition, sensor technologies, and both classical and deep-learning-based corrosion-detection techniques. Guided by a comprehensive review of existing inspection technologies, the research identified key limitations relating to cost, accessibility, and operational constraints, which informed the design requirements of the proposed robot. Low-cost components were systematically selected and integrated into a lightweight platform capable of navigating pipelines of varying diameters using a four-wheel configuration supported by two omnidirectional wheels. A high-resolution camera and sensor suite were incorporated to enable reliable image capture, environmental awareness, and obstacle avoidance. A combination of image processing algorithms, Canny Edge Detection, Sobel Operator, K-Means Clustering, and a Convolutional Neural Network (CNN) was implemented to detect corrosion with improved accuracy.

Functional testing demonstrated stable mobility, effective sensor communication, and extended battery performance, validating the robot's operational feasibility despite initial challenges related to low-light image quality, which were mitigated by upgrading to a higher-resolution camera. The findings confirm that the proposed in-pipe inspection robot can reliably navigate pipelines, acquire and process images, and detect corrosion, offering a practical and economically viable alternative for pipeline inspection in the O&G sector.

Overall, the study established a foundation for accessible, scalable, and technology-driven corrosion-monitoring solutions. The research contributes to the field of pipeline inspection by presenting a validated, cost-effective in-pipe inspection robot that improves access to automated corrosion detection and supports safer and more efficient infrastructure maintenance in the O&G sector. The findings show that reliable automated pipeline corrosion detection can be achieved using an affordable robotic approach, thereby enhancing the practical feasibility of deploying smart inspection technologies in resource-constrained operational environments.

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## LIST OF ABBREVIATIONS

| | |
|---|---|
| ADR | Action Design Research |
| AE | Acoustic Emission |
| AR | Artificial intelligence |
| AUV | Autonomous Underwater Vehicles |
| BOM | Bill of Material |
| DSRM | Design Science Research Method |
| ECT | Eddy Current Testing |
| FN | False Negative |
| FP | False Positive |
| IoT | Internet of Things |
| IPIR | In-Pipe Inspection Robots |
| IS | Information System |
| MFL | Magnetic Flux Leakage |
| MIC | Microbiological Induced |
| NDT | Non-Destructive Testing |
| O&G | Oil and Gas |
| OPIR | Out-Pipe Inspection Robot |
| ORB | Oriented FAST, and Rotated BRIEF |
| PADR | Participatory Action Design Research |
| PIG | Pipe Inspection Gauge |
| ROV | Remote Operated Vehicle |
| SA | South Africa |
| SDSM | Soft Design Science Methodology |
| TN | True Negative |
| TP | True Positive |
| TT | Thermographic Testing |
| UAS | Unmanned Aerial Systems |
| UAV | Unmanned Aerial Vehicles |
| UAVs | Unmanned Aerial Vehicles |
| UT | Ultrasonic Testing |
| UUV | Unmanned Underwater Vehicle |
| VT | Visual Testing |

## PUBLICATIONS AND CONFERENCE PAPERS

Mthimkhulu, Z.; Adeliyi, T.; Adebanjo, H. Designing A Frugal Inspection Robot for Detecting In-Pipe Leaks in The Oil and Gas Sector. Presented at the Information Communication Technology and Society Conference (ICTAS), South Africa.

# CHAPTER 1: INTRODUCTION

## 1.1 Introduction

The South African (SA) oil and gas (O&G) sector is crucial to the economy. Because of its importance, several key organizations operate within this sector. One of these is the Department of Mineral Resources and Energy, which, according to AET (2022), is responsible for regulating and guiding all activities within this sector.

Locally, Sasol Limited remains the largest integrated energy company in SA. On the global front, companies such as Shell, BP, Total, Chevron, and SAPREF, a joint venture between Shell and BP, have also been active in refining, storage, and distribution within the country. More recently, the SA government has taken steps to strengthen national capacity by approving the establishment of the South African Petroleum Company (SANPC). All these companies bring with them extensive industry experience and expertise to the O&G sector.

The O&G sector relies heavily on the conveyance of crude oil and natural gas (Lu et al., 2019). Because these resources are often transported over long distances, in most cases via pipelines, their safe transportation is a priority (Zhang et al., 2023). It is crucial that pipelines are properly maintained to ensure they remain in good condition. Proper maintenance helps prevent catastrophes, protects the environment, and minimizes financial losses. Pipeline failures could result in leaks, despite being built to strict engineering standards. Therefore, it is vital to understand the causes of these leaks.

According to Ngonadi and Ajiroghene (2021), leaks are common in aged and exposed pipelines. Assisting pipeline operators and inspectors with an early-detection mechanism is vital. (Hameed et al., 2022). Vanaei et al. (2017) also emphasizes the threat that corrosion poses to pipeline integrity. Researchers classify corrosion into three types: sour, sweet, and microbiologically influenced corrosion (Ossai et al., 2015).

Sweet corrosion develops when carbon dioxide dissolves in free water, forming carbonic acid that gradually corrodes the pipe walls. Sour corrosion takes place when hydrogen reacts with iron to form iron sulfide, and its severity depends on the level of hydrogen sulphide present

(Alkazraji, 2008). Microbial activity within the pipeline system causes microbiologically influenced corrosion (Ossai et al., 2015).

Njomane and Telukdarie (2018) note that, because corrosion has severe financial and operational consequences for assets, the global economy spends an estimated $2.2 trillion on corrosion-related management. This is where corrosion detection mechanisms come into play, as they are essential in helping pipeline controllers locate and identify leaks (Hameed et al., 2022). Traditional inspection techniques such as ultrasonic testing (UT), magnetic flux leakage (MFL), and radiographic Testing (RT) are often expensive due to the need for specialized equipment, highly trained personnel, and scheduled operational downtime. Furthermore, they are time-consuming. Having reliable corrosion detection systems, such as robotic inspection systems is fundamental.

This study therefore focuses on developing a cost-effective in-pipe inspection robot capable of reliably detecting pipeline corrosion, addressing the need for more accessible and efficient robotic inspection solutions.

### 1.2 Research Problem

Ensuring the safety and reliability of pipelines is a critical priority for the O&G sector (Barbian & Beller, 2012). Achieving this requires frequent and systematic inspection. However, practically it is not an easy task, as most of them are installed either underwater or in complex underground environments where direct access is limited (Karki & Shula, 2013).

Corrosion is one of the major challenges affecting pipeline integrity. This phenomenon increases the likelihood of leaks and catastrophic failures. Normal wear, operational irregularities, construction defects or sudden shifts in environmental changes can trigger this process (Zaman et al., 2020). For this reason, consistent inspection is essential to detect failures caused by corrosion, cracking or other forms of mechanical damage (Elankavi et al., 2020; Hajjaj & Khalid, 2018). Sachedina and Mohany (2018) further stress the importance of regular inspection, claiming that it reduces many of the risks associated with pipeline operations.

Although robots have become essential across various industries and are now widely used as intelligent collaborative tools (Zimmer et al., 2021), many petroleum companies, particularly in South Africa, continue to rely on traditional inspection techniques for pipeline inspection, despite being slow, labor-intensive and exposing workers to unnecessary risks. The high cost of acquiring, implementing and maintaining robotic systems contributes to this continued reliance. That is why many small organizations, and those operating in remote areas, cannot incorporate them into their inspection processes.

There is a clear need in the industry for an affordable in-pipe inspection robot that can function effectively in a confined pipeline environment and accurately detect corrosion. Many current robotic systems are unable to strike a balance between cost and functional performance, making it difficult to close the gap. Developing a solution that remains reliable while reducing complexity requires innovative thinking. In response to this, the study aims to design a cost-effective robotic device capable of capturing images and analyzing them for corrosion detection.

## 1.3 Aim

This study aims to develop a cost-effective in-pipe inspection robot capable of capturing images of pipelines and analyzing them to reliably detect corrosion.

## 1.4 Research Objectives

a. To review the existing literature on methods used to detect in-pipe corrosion in the O&G sector.
b. To select and integrate cost-effective components to develop a portable robotic system capable of navigating inside the pipelines.
c. To implement and validate image acquisition and sensing mechanisms for corrosion detection.
d. To experimentally test and quantify the robot’s navigation capability, communication reliability and operational performance through functional pipeline experiments.
e. To implement and quantitatively evaluate traditional image processing and machine learning algorithms for corrosion detection in the captured pipeline images using performance metrics including accuracy, precision, recall and F1 score.

## 1.5 Research questions

a. What are the currently used inspection techniques in the O&G sector?
b. Which innovative cost-effective technologies can be incorporated into the design of the in-pipe inspection robot to ensure both affordability and functional performance?
c. Which image acquisition and sensing approach are most suitable for pipeline inspection?
d. How does the developed in-pipe inspection robot perform in terms of navigation, communication reliability and operational effectiveness during functional pipeline testing.
e. Which traditional image processing and machine learning algorithms are most effective in detecting corrosion in pipeline images?

## 1.6 Research contributions

This study contributes to ongoing research on affordable technological solutions by presenting a cost-effective robotic approach to corrosion detection. Although the system is designed primarily for identifying corrosion, the principles behind its construction  particularly its emphasis on affordability and accessibility  have broader relevance and may support the development of economical inspection tools in other sectors.

The study also aims to address several practical concerns:

**a. Increasing safety**

Corrosion within pipelines can result in leaks that pose serious safety risks. Early detection helps prevent incidents and improves  the safety of employees, neighboring communities and the environment (Idea ltd, n.d).

**b. Developing an economic solution**

Many conventional inspection methods rely on expensive equipment and require significant labor. The proposed in-pipe inspection robot offers a more affordable alternative by using low-cost sensors, a 3D-printed chassis, and open-source hardware and software. These components help reduce production and maintenance costs while maintaining reliable operation.

**c. Protecting the Environment**

Undetected corrosion can release harmful substances into the surrounding environment. Identifying corrosion early allows for quicker maintenance responses, reducing environmental damage and preventing leaks from escalating.

## 1.7 Research Methodology

The study adopted a practical engineering design-and-experimental evaluation approach. The work unfolds through a series of steps that guided the development and validation of the corrosion-detection prototype. These steps include:

a. Conducting a review of existing inspection techniques.
b. Choosing cost-effective and suitable hardware components and assembling the prototype.
c. Integrating a camera system to capture images of both corroded and non-corroded pipeline samples.
d. Testing the in-pipe inspection robot inside the pipeline sections to confirm that it can maneuver around obstacles, climb the inner walls where necessary and capture images.
e. Applying image processing techniques to support corrosion detection.
f. Using recognized performance metrics to evaluate the effectiveness of the corrosion-detection robot.

## 1.8 Thesis Structure

The thesis is organized into five chapters, as illustrated in **Figure 1.1.**

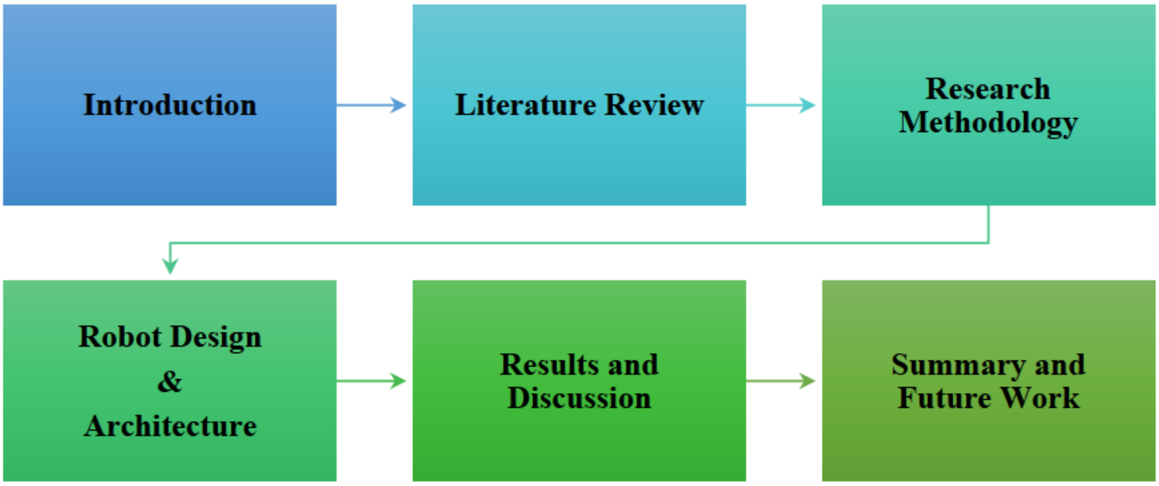


**Figure 1.1: Overview of the thesis structure**

**Chapter 1: Introduction**

Chapter 1 introduces the study by outlining the research problem, aim, objectives, and research questions. Thereafter, it discusses research contributions, research methodology, and the thesis structure.

**Chapter 2: Literature Review**

Chapter 2 examines contemporary technologies used in pipeline inspection, focusing on their capabilities and the challenges they still pose. It begins with an overview of corrosion in the O&G sector, followed by a discussion of traditional inspection methods. The chapter then examines existing robotic systems developed for pipeline inspection and evaluates their strengths and weaknesses. It also considers issues relating to securing Internet of Things (IoT) devices used in robotic platforms. Finally, the chapter outlines image-based techniques employed for corrosion.

**Chapter 3: Research Approach**

Chapter 3 details the methodological approach adopted to achieve the study's objectives. It describes the overall research design applied, which is informed by the principles of the design science protocol.

**Chapter 4: Robot Design and Architecture**

Chapter 4 outlines the physical and functional design of the frugal robot. It identifies the components selected for the build and explains how they support the study's objectives. The chapter also introduces the robot's overall architecture and shows how the hardware and software work together during operations inside the pipelines.

**Chapter 5: Results and Discussions**

Chapter 5 reports the experimental results from the development and testing of the frugal inspection robot for corrosion detection in pipelines. It includes an analysis of the robot's performance using key metrics such as accuracy, recall, precision and F1 score. The chapter also discusses the outcomes of several image processing techniques used in the study, including Canny Edge Detection, Sobel, K-Means Clustering, and Convolutional Neural Networks (CNNs).

**Chapter 7: Summary and Future Work**

Chapter 7 gives an overview of the study's main findings and outlines the conclusions drawn from the work. It also highlights the key recommendations and suggests possible directions for future research.

## 1.7 Summary

This chapter outlined the study's background and introduced the research problem, aim, objectives, and main research questions. It also explained the study's contributions, research methodology and described how the rest of the thesis is organized. The next chapter examines the relevant literature.

# CHAPTER 2: LITERATURE REVIEW

## 2.1 Introduction

Pipeline infrastructure transports essential commodities such as natural gas and petroleum products (Ma et al., 2021). It offers several advantages, including the ability to transport high volumes, affordability, ease of use and resistance to varying weather conditions (Niu et al., 2021). Pipeline systems also influence how the global energy supply is conducted, both politically and economically (Whanda, 2015). Although they are primarily used in the oil and gas (O&G) sector, they are also fundamental in other sectors, such as municipalities, where they supply water and carry sewage (SRC Communications, 2018).

Pipelines used in the O&G sector include gathering, transmission, feeder, and distribution pipelines. Gathering pipelines transport crude oil or natural gas from extraction sites to manufacturing, refining, or storage facilities (Energy Connections Canada, 2023). These pipelines are typically around 100 meters long, making them significantly shorter than transmission, feeder and distribution pipelines (Forth, n.d.). According to Earthworks (2025), the Pipeline and Hazardous Materials Safety Administration estimates that the United States has approximately 240,000 miles of onshore gathering pipelines. However, the number may exceed the current forecast, as the domestic O&G has increased. Transmission Pipelines also transport oil and natural gas over enormous geographical distances (Energy Connections Canada, 2023). They are among the largest pipeline networks, with diameters up to 42 inches (Forth, n.d.). Feeder Pipelines transport oil, natural gas, and liquefied natural gas from manufacturing facilities to long-distance transmission pipes (Forth, n.d.). They usually range from 6 to 10 inches in diameter, which makes them small and often made of steel (Bob Cat Contracting, 2022). Distribution Pipelines typically range from 2 to 24 in diameter and transport natural gas to end users (Gracon LLC, n.d.).

Understanding the different types of pipelines is important, particularly because several major projects are being planned across Africa. ABiQ (2022) reports a wide range of pipeline development expected across the continent, mainly supported by Africa’s significant O&G reserves. Examples include the Tanzania LNG Liquefaction Plant, Rovuma LNG, the Nigeria Morocco Gas Pipeline, the Trans Saharan Gas Pipeline, and the Richards Bay Refinery.

The agreement for constructing a $30 billion LNG terminal involving Tanzania, Norway's Equinor, and Britain's Shell has been finalized, and work has already begun (Reuters, 2023). Furthermore, production at the Rovuma Liquefied Natural Gas project in Northern Mozambique is expected to start in 2025 (ABiQ, 2022). This project is also estimated to cost $30 billion. The Rovuma project is a joint venture between Eni, ExxonMobil, and China National Petroleum Corporation, which owns a 70 percent share in the company, with 10 percent each owned by Galp, KOGAS, and Empresa Nacional de Hidrocarbonetos (Offshore Technology, 2024).

Another major project currently under development is the Nigeria-Morocco gas pipeline, which is expected to span 11 West African countries with a capital outlay of $25 billion (ABiQ, 2022). The Trans-Saharan Gas Pipeline will also have a massive impact on Nigeria's economy, with a projection of transporting billions of cubic meters of Nigerian gas to Algeria via Niger (Africa News, 2024). In South Africa, a refinery in Richards Bay is being developed through the strategic partnership between Central Energy Fund and Saudi Aramco and is anticipated to be operational by 2028 (Myeni, 2025).

Because pipelines are susceptible to corrosion, inspection and maintenance strategies must be incorporated from the early stages of project development (Ma et al., 2023; Rahimi et al., 2024). This is echoed by the various high-profile events that occurred in the past. For example, the Gulf of Mexico experienced a significant oil spill in 2010. This Deepwater Horizon spill originated on the 20th of April in 2010, following a catastrophic explosion that severely damaged the drilling rig (Beyer et al., 2016). This resulted in a catastrophic conservation disaster. It also affected coastal ecosystems and marine life (Nova et al., 2019). Another incident occurred in 2019 on the Keystone pipeline in North Dakota. This led to the unintended discharge of about 1.45 million liters of crude oil into the surrounding environment (Zhang et al., 2019). All incidents clearly highlight the importance of implementing proactive pipeline inspection control measures and establishing robust monitoring frameworks to minimize pipeline deterioration.

This chapter provides a comprehensive review of pipeline inspection approaches. It begins with an overview of corrosion in the O&G sector. Next, the traditional inspection techniques, such as Visual Testing (VT), Radiographic Testing (RT), Acoustic Emission (AE), Ultrasonic Testing (UT), Thermographic Testing, Eddy Current (EC), and Magnetic Flux Leakage (MFL), are discussed. Thereafter, the existing pipeline inspection robotic technologies, such as inchworm, legged, caterpillar, Pipe Inspection Gauge (PIG), screwdriver and wheeled types are presented and evaluated. Subsequently, it describes securing the IOT devices in robotic technologies. Finally, image-based detection techniques are discussed.

## 2.2 Corrosion in Oil and Gas Pipelines

To fully understand the implications of corrosion, it is necessary to first examine its definition. Definitions of corrosion vary, with some emphasizing specific forms of degradation while others include other broader deterioration processes (Davis, 2000). Harsimran et al. (2021) state that the corrosive environment can be either firm, fluid, or gaseous. Corrosion is mostly associated with rust, an almost universally despised substance(Roberge & Eng, 2005). The term "rust" is more specifically used to refer to the deterioration of iron; however, affects nearly all metals (Roberge & Eng, 2005). Alao et al. (2023) define corrosion as a slow process that occurs due to both environmental conditions and electrochemical interactions. Coramik and Ege (2017) further note that corrosion can affect both internal and external surfaces due to environmental and operational factors. All these definitions clearly indicate that this phenomenon is not a once-off event but an enduring interaction between pipelines and their surroundings. Corrosion, illustrated in **Figure 2.1**, has been extensively studied across various scientific domains, such as steel pipelines, concrete and steel damage, and marine vessels (Brandoli et al., 2021).

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**Figure 2.1: Pipeline Corrosion (World Iron & Steel Co., 2019)**

Figure 2.1 illustrates severe internal pipeline corrosion, demonstrating the progressive deterioration of metal surfaces due to electrochemical reactions and environmental exposure. The figure supports the discussion that corrosion is a gradual yet destructive process that compromises pipeline integrity.

### 2.2.1 Corrosion forms

Corrosion occurs in several forms, including general corrosion, galvanic corrosion, erosion corrosion and localized corrosion. Each of these forms has distinct characteristics and effects. Understanding these characteristics is key to developing an effective maintenance strategy.

General corrosion occurs when the material's surface weakens due to continuous exposure to environmental elements such as moisture, oxygen and chemicals (Sharma, 2023). This form is particularly hazardous because it often goes unnoticed until significant structural weakening has occurred. A typical example is the rusting of steel pipelines, whereby exposure to the atmosphere causes the porous layer to fail to protect the metal (Hansson, 2011). Although this form is generally predictable and easier to detect in comparison to other forms, it still contributes significantly to the pipeline failures and remains one of the leading causes of corrosion-related issues (Miah & Genemo, 2016). Erosion corrosion occurs when corrosive materials increase the attack rate due to mechanical wear down (Corroserve, 2022). This type of corrosion is common in O&G pipelines, where target equipment, corrosive fluids, and solid particles (Islam & Farhat, 2017). Furthermore, it is heavily reliant on material, conservational, and hydrodynamic parameters (Poulson, 1999). Erosion corrosion is characterized by the formation of grooves, gullies, craters, and valleys arranged in a distinctive turning pattern on the metal substrate (Nanan, 2018).

Galvanic corrosion takes place in an electrolytic environment. This is due to different metals with contrasting electrochemical properties interacting, causing one of the anodic metals to corrode faster than the other (GibsonStainless, 2017; Rai et al., 2021). When this occurs, one of the anodic metals corrodes more rapidly, while the other one is protected (Sharma, 2023). Over time, the protected one will also be weakened. Localized corrosion occurs in various forms, such as pitting, filiform, and crevices, each with unique characteristics and consequences for material degradation. Pitting typically occurs in alloys and metals that have been specified and are often used in saline environments (Hansson, 2011). This form of corrosion, characterized by pits, holes, or cavities, is highly localized and confined to a single spot on a metal surface (Fayomi et al., 2019). In the initial phases of pitting corrosion, pit diameters do not exceed 20 µm (Sild, 2024). Localised corrosion is among the most detrimental forms due to its unpredictable nature (GibsonStainless, 2017). In contrast, crevice corrosion occurs in crevices or confined spaces, often between a metal and a non-metal (Fayomi et al., 2019). Filiform corrosion, on the other hand, occurs beneath paint and other protective coatings and is primarily due to surface contaminants or residues trapped between contacting surfaces prior to coating application (Fayomi et al., 2019). While crevice formation tends to follow a somewhat predictable pattern, it is equally destructive, unlike pitting, which is random and isolated in most cases.

Understanding all these forms of corrosion is essential for assessing their broader industrial and economic impact. The following section discusses these impacts in greater detail.

### 2.2.2 Economic impact of corrosion

Corrosion is often perceived as an unavoidable process that must be managed rather than eliminated (Fayomi et al., 2019). This perception is problematic, as it often leads to a reactive approach, in which organizations implement mitigation strategies post-failure rather than proactively incorporating them into existing processes. Reactive approaches significantly increase operational risk and contribute significantly to major failures, such as financial losses totaling billions of dollars spent annually on infrastructure maintenance (Bardal & Drugli, 2004; Sharma, 2023). Fayomi et al. (2019) argue that the primary driver of this economic pressure lies in engineering designs and practices that prioritize infrastructure development while long-term durability and corrosion resistance are compromised. The NACE International IMPACT study estimated an annual cost of approximately $2.5 trillion, equivalent to 3.4% of global GDP (NACE International, 2016). These costs include both direct expenditures, such as maintenance and replacement, and indirect costs, such as production losses, environmental and safety risks. The study further suggests that 15-35% of these expenses could be reduced by adopting effective corrosion-control practices.

According to Iannuzzi and Frankel (2022), corrosion not only poses technical and economic challenges but also contributes significantly to environmental degradation and climate change. Consequently, it requires serious attention, as it can even lead to catastrophic and sometimes fatal incidents, as highlighted in Table 2.1. Even though the highlighted incidents do not directly involve pipelines, they illustrate the severe consequences of undetected corrosion in critical infrastructure.  They reinforce the urgent need to develop a reliable, cost-effective inspection system for pipelines.

| **Incident** | **Location** | **Year** | **Cause of failure** | **Impact** |
|---|---|---|---|---|
| Genoa Bridge Collapse | Genoa, Italy | 2018 | Corroded steel cables | - 43 deaths.<br>- Bridge collapse. |
| Sinking of the Erika | Brittany, France | 1999 | Corroded ship structure | - 19,800 tons of oil spilled.<br>- Environmental damage |
| Railway Signal Post Collapse | England | 2014 | Corrosion at the base of the steel post | - Track obstruction.<br>- Near-miss train accident. |
| Bhopal Gas Leak | Bhopal, India | 1984 | Corroded tank wall triggered gas release | - 8,000 deaths.<br>- 500,000 exposed |
| UVA Balcony Collapse | Virginia, USA | 1997 | Rusted cast-iron rods hidden by wood | - 1 death.<br>- 18 injuries. |

**Table 2.1 : Impact of Corrosion (Cowlishaw, 2022)**

All these incidents clearly indicate the complex and persistent challenges associated with corrosion. Technically, it compromises infrastructure integrity, requiring advanced detection and mitigation strategies such as frugal robotics and NDT techniques. Economically, it causes organizations to spend billions of dollars replacing or repairing the infrastructure. The environmental implications are equally significant, as corrosion can increase carbon emissions from manufacturing replacements.

## 2.3 Traditional Corrosion Detection Technique

### 2.3.1 Overview of Non-Destructive Testing (NDT) Techniques

Inspection techniques are used to assess pipeline conditions and identify issues such as corrosion. Over time, numerous Non-Destructive Testing (NDT) techniques have been developed. These include Ultrasonic Testing (UT), Radiography, Visual Testing (VT), Acoustic Emission (AE), Thermographic Testing (TT), and Eddy Current Testing (ECT). Each method detects pipeline defects, such as corrosion, without affecting the structural integrity of the pipelines(Kong et al., 2020). Even though these techniques serve a similar purpose, they differ in how well-suited they are for inspecting different equipment.

#### 2.3.1.1 Ultrasonic Testing (UT)

Ultrasonic testing (UT) is one of the most widely used inspection methods. This technique has become an ideal choice for industrial inspection, as it can estimate defect type, size, and orientation with high accuracy (Plant Inspection, 2024). It identifies defects in materials and welded joints by transmitting high-frequency sound waves through the components (Deepak et al., 2021; Ma et al., 2021). The UT system typically includes a transducer, an actuator, a display unit, and a transmitter-receiver circuit, which work together to detect any pipeline defects (Edalati et al., 2006; Gholizadeh, 2016). Furthermore, it is cost-effective, adaptable across different robotic platforms, and does not require insulation removal, which is valuable in constrained environments (Tian et al., 2019).

Despite these advantages, UT has several limitations. For example, the wavelength of the sound wave limits its sensitivity, meaning that all defects must be larger than half the wavelength to be reliably detected (Jolly et al., 2015). Additionally, this technique struggles to inspect curved pipelines; as a result, signal distortion can lead to imprecise results (Kroworz & Katunin, 2018). UT also relies on operators' expertise, and inexperienced operators may misinterpret the results (Annila, 2001; Plant Inspection, 2024). Figure 2.2 illustrates an inspector conducting a pipeline assessment using the UT technique.


**Figure 2.2: Inspecting pipelines using the UT Technique (petrosync, 2025)**

Figure 2.2 visually shows the practical application of the UT technique in pipe inspection. The image highlights the manual operation of the equipment and accentuates the role of the inspector in interpreting ultrasonic signals. This clearly shows the human involvement required in UT-based inspection.

#### *2.3.1.2* **Radiograph***ic Testing (RT)*

Radiographic testing (RT) is widely used for pipeline inspection because it provides clear internal images of the area being examined (Ma et al., 2021). Similar to UT, RT helps identify deterioration in pipelines, including wall degradation and structural irregularities (Edalati et al., 2006). In practice, X-rays are applied to capture the internal shape and condition of the equipment (Agbezuge, 2021). Two approaches are used to evaluate the wall thickness: The tangential radiography technique (TRT) and the double wall radiography technique (DWT) (Edalati et al., 2006). RT can reveal internal features without removing insulation or preparing the equipment beforehand, making it helpful in demanding industrial settings (Ma et al., 2021). This technique is regarded as more practical than several other inspection methods because it provides continuous internal imaging references, which enables consistent evaluation of structural integrity over time without requiring repeated surface preparation (Kumar & Mahto, 2013).

Although it can accurately detect, document, and visually display defects, radiation continues to cause health risks and hazards (Ma et al., 2021). Furthermore, it is resource-intensive, involving high equipment costs and specialized personnel (Jolly et al., 2015). Figure 2.3 illustrates the application of the RT technique in pipelines.

**Figure 2.3: Inspecting pipelines using the RT Technique  (Global Welding, 2025)**

Figure 2.3 shows the application of the RT technique in pipeline inspection. The image shows the specialized equipment required for radiographic assessment, reinforcing the discussion regarding its resource-intensive nature.

While this technique provides detailed internal imaging of defects, its implementation requires strict safety controls due to radiation exposure risks.

#### 2.3.1.3 Visual Testing (VT)

Visual Testing (VT) is the most widely employed method for pipeline inspection. The  qualified inspector visually inspects the pipelines to detect defects or abnormalities (Deepak et al., 2021). Although it is often perceived as being straightforward, Cumblidge et al. (2004) argue that it is an overly complicated approach that can be summarized as examining the tested area and detecting any defects or abnormalities.  This technique is predominantly effective in detecting macroscopic flaws (Dwivedi et al., 2018). In most cases, macroscopic flaws are visible on the surface and can be detected without utilizing complex equipment, making VT a practical first step in the inspection process. Furthermore, this technique is not expensive and provides results almost immediately, making it highly practical for routine inspections (Gholizadeh, 2016). Its low cost allows organizations to conduct frequent assessments without placing significant pressure on the operational budget. The immediacy of the findings also enables inspectors to make quick decisions on whether further investigation or intervention is required.

VT is not without limitations. For example, defects can also be missed during the inspection due to limited human vision (Tian et al., 2019). It can also be intrinsically limited by human perception. Figure 2.4 illustrates the inspector conducting a pipeline inspection using the VT technique.

**Figure 2.4: Inspecting pipelines using the VT Technique (Energy Connections Canada, 2023)**

Figure 2.4 shows that this technique depends primarily on the inspector’s visual judgement, which may introduce subjectivity and increase the likelihood of missed defects. This supports the argument that VT, although economical and straightforward, is intrinsically constrained by human limitations.

#### 2.3.1.4 Acoustic Emission (AE)

Acoustic Emission (AE), identifies the rarefaction waves caused by leaks in pipelines (Agbezuge, 2021). It also monitors spontaneous stress waves, while Acoustic Impact involves deliberate tapping to provoke diagnostic responses (Kumar & Mahto, 2013). AE is particularly effective at detecting active defects, such as cracks or leak formation.

Despite its sensitivity, AE testing faces drawbacks. The main one is that it cannot accurately reproduce a particular test because of the signal source's characteristics, as every incident is a unique stress wave, which cannot be stopped or duplicated (Towsyfyan et al., 2020). Moreover, the large pipelines require many sensors, which can be expensive (Sachedina & Mohany, 2018). These drawbacks limit AE's practicality for continuous or extensive area monitoring without substantial investment. **Figure 2.5** illustrates AE sensors mounted on the vessel.


**Figure 2.5: AE sensors (Riley, 2016)**

Figure 2.5 illustrates the placement of Acoustic Emission (AE) sensors mounted on the surface of the vessel for structural monitoring. This shows how sensors are distributed to capture stress waves generated by active defects such as corrosion . This supports the discussion that AE enables real-time, large area monitoring without requiring extensive surface preparation.

### 2.3.1.5 Thermographic Testing (TT)

Thermographic Testing (TT) uses Infrared images to identify defects within components (Jolly et al., 2015). It can examine large surface areas within a shorter period (Márquez & Chacón, 2020). This means pipelines can be inspected promptly, saving significant time. Although TT is efficient when used alone, it is even more effective when combined with other methods for comprehensive diagnostics. Due to its primary focus on surface temperature, it may fail to consider surrounding conditions and cold spots (Márquez & Chacón, 2020). Figure 2.6 illustrates the inspector conducting an inspection using the TT technique.

**Figure 2.6: Inspecting pipelines using the TT Technique**

Figure 2.6 illustrates the application of TT in pipeline inspection. The image highlights the use of specialized equipment to detect temperature variations on the pipeline surface, which may indicate underlying defects or material degradation. This supports the discussion that TT allows non-contact inspection; however, its effectiveness can be influenced by environmental conditions and surface emissivity.

### 2.3.1.6 Magnetic Flux Leakage (MFL)

Magnetic Flux Leakage (MFL), similar to the UT technique, is widely used to inspect the integrity of pipelines (Wilczek, 1982). It has been around since the 1950s and has evolved from a qualitative inspection technique to a more advanced quantitative tool for identifying and analyzing defects over time (Shi et al., 2015). Furthermore, it facilitates real-time monitoring and allows for swift evaluation of large-scale pipeline infrastructure (Mawugbe et al., 2025). This method produces high-resolution images of the pipe's interior, enabling the detection, documentation, and reporting of pipe defects (Khodayari-Rostamabad et al., 2009). Typically, about10 gigabytes of data are generated for every 100 kilometers of inspected area (Afzal & Udpa, 2002). The collected data can then be visualized using curve graphs, grayscale images, and pseudo color images, however curve and grayscale displays cannot fully represent all the information, as the signal is three-dimensional (Yang et al., 2019). Figure 2.7 illustrates the MFL device used to inspect pipelines.

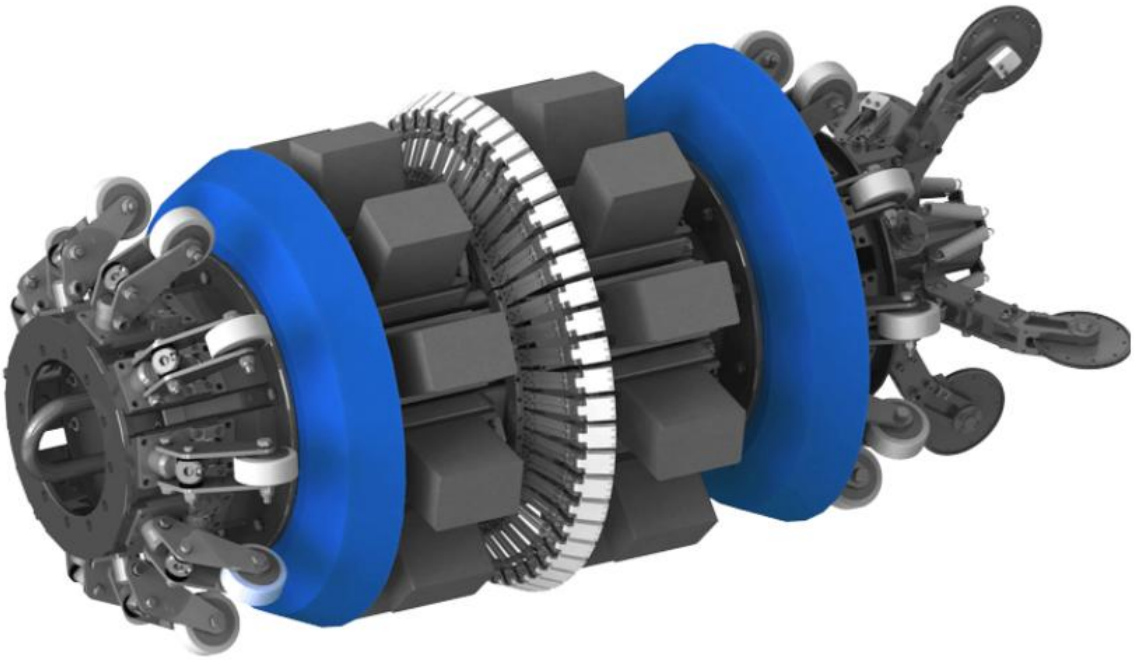


**Figure 2.7: MFL device for pipe inspection**

The configuration in Figure 2.7 shows the arrangement of magnets and sensor arrays designed to detect magnetic-field distortions caused by issues like corrosion. This clearly indicates that MFL is effective for identifying volumetric defects, however signal interpretation can be too complex because of the three-dimensional nature of magnetic flux patterns.

### 2.3.1.7 Eddy Current (EC)

Non-Destructive Testing (NDT) has long relied on the Eddy Current (EC) technique to evaluate the structural integrity of conductive material (Hamad et al., 2020). EC is particularly effective for identifying both surface and near-surface defects. It combines high sensitivity with cost efficiency compared to other NDT techniques (Xie & Tian, 2018).

Like other NDT techniques, it also has certain limitations. One of them is that its ability to detect subsurface defects relies on low-frequency signals, which are necessary for inspecting thicker materials (Hamad et al., 2020). However, magnetometer sensors can mitigate this limitation by extracting as much information from the tested component (Hamad et al., 2020). Another notable limitation, highlighted by Sathappan (2022) is its dependence on stress-induced acoustic wave generation cannot be replicated through repeated measurements because emissions occur only during active defect growth and cease once the defect stabilizes. Figure 2.8 illustrates the EC devices inspecting the pipeline.

**Figure 2.8: EC devices (Evident Scientific, n.d)**

Figure 2.8 presents the EC inspection setup consisting of a probe and a portable unit. The system operates by inducing electromagnetic fields to detect discontinuities within conductive materials. Even though EC offers high sensitivity to surface defects and a swift inspection capability, its effectiveness is constrained by limited depth penetration and sensitivity to variations in material conductivity.

### 2.3.2 Comparative Analysis of NDT Techniques

Several NDT techniques are commonly used for pipeline inspection, each with distinct strengths and limitations. Among the reviewed techniques, UT offers precision and adaptability. However, its performance can decline when the pipeline is curved or when different inspectors produce varying results. VT remains useful for surface inspection and is relatively inexpensive. However, results may vary because inspectors rely on their own skill, increasing the risk of human error. RT offers an advantage in that it produces high-quality images and allows records to be stored for future reference. Nevertheless, it exposes workers to radiation and is often more costly to operate. AE detects active defects, but in most cases, requires many sensors (Sachedina & Mohany, 2018). TT enables large-area surface screening; however, it relies on temperature differences. This can cause inspectors to miss defects or misinterpret what they see. MFL captures detailed images and enables real-time inspection, though the technique typically requires more complex data interpretation. Finally, EC is ideal for surface- and near-surface flaws in conductive materials, though its depth of penetration is limited.

**Table 2.2** A comparative summary of these NDT techniques, highlighting their advantages, limitations, and key references is presented in Table 2.2.

| Technique | Advantages | Limitations | References |
|---|---|---|---|
| **UT** | - Cost-effective.<br>- Adaptable to robotics.<br>- High Precision. | - Operator-reliant.<br>- Signal distortion in curved surfaces.<br>- Can present false positive results. | Plant Inspection (2024); Tian et al. (2019); Kroworz and Katunin (2018) |

| | | | |
|---|---|---|---|
| **RT** | - Permanent visual records.<br>- No surface prep needed. | - Radiation hazards.<br>- High cost.<br>- Specialized personnel.<br>- Resource Intensive | Edalati et al. (2006); Agbezuge (2021). Jolly et al. (2015). (Ma et al., 2021). Kumar and Mahto (2013) |
| **VT** | - Simple<br>- Fast<br>- Low Cost | - Limited to visible defects<br>- Human error | Cumblidge et al. (2004) Dwivedi et al. (2018) |
| **AE** | - Real-time monitoring.<br>- Sensitive to dynamic flaws | - Cannot reproduce tests.<br>- Expensive sensor networks. | Sachedina and Mohany (2018) Towsyfyan et al. (2020). |
| **TT** | - Fast, non-contact.<br>- Large area coverage | - Surface-focused.<br>- Affected by environmental conditions | Jolly et al. (2015). Márquez and Chacón (2020) |
| **MFL** | - Detects internal/external defects.<br>- High-resolution imaging.<br>- Real-time monitoring | | |
| **EC** | - High sensitivity to surface flaws.<br>- Cost-effective | - Limited subsurface detection. | Hamad et al. (2020); |

| | | | |
|---|---|---|---|
| | - Environmentally friendly. | - Low-frequency constraints in thick materials | Xie and Tian (2018); Shi et al. (2015); Lysenko et al. (2023) |

**Table 2.2: Comparative Analysis of NDT Techniques**

Comparative analysis in Table 2.2 reveals that, even though existing NDT techniques provide reliable and defect detection, their limitations in cos, accessibility, human dependency and operational constraints highlight the need for a frugal autonomous in-pipe inspection robot.

### 2.4 Robotic and Artificial Intelligence (AI)

Although the terms Artificial Intelligence (AI) and robotics are sometimes used interchangeably, they refer to different areas, despite overlapping in many applications (Ness et al., 2023). Historically, AI and robotics developed side by side, but their focus points evolved over time as each field responded to different technological needs (Rajan & Saffiotti, 2017).

Artificial Intelligence (AI) refers to the technological extension of human cognitive abilities. It involves enabling machines to learn, solve problems and make decisions in situations where people would typically get involved (Ness et al., 2023; Siau & Yang, 2017). Robotics, in contrast, draws on several disciplines, primarily engineering and computer science. It focuses more on creating machines that can sense, move, and interact with their surroundings (Muneer & Dairabayev, 2021).

According to Rajan and Saffiotti (2017), the robotics field has expanded rapidly because of significant advances in AI. These developments have enabled robots to perform tasks involving navigation, object handling, and operation across different environments with improved accuracy and autonomy. As a result, modern robots can adapt to more complex situations than before.

The growing integration of AI and robotics is shaping how intelligent systems develop. Many researchers note AI as the main driver behind the progress seen in modern robotics (Ness et al., 2023). For example, the number of industrial robots in use has increased by 300% over the past decade. This growth shows that automation and smart manufacturing are expanding (Langman et al., 2021). Some scholars interpret this increase as evidence of a major technological shift, while others see it as the natural next step in industrial development (Klump et al., 2021). Regardless of the interpretation, robotics is widely recognized as a high-impact technology that is expected to shape the future of production and other emerging sectors (Liu & Liang, 2020).

As robotics continues to develop alongside AI, its practical use has expanded across many industries. The growing connection between these fields has improved the performance of intelligent and autonomous robotic systems, particularly in addressing complex real-world problems. Consequently, understanding the impact of these developments requires a closer examination of how robotics is applied across different sectors. The following section, therefore, explores the main areas in which robotic technologies are used.

### 2.4.1 Different fields of robotic applications

The rapid pace of technological advancement has enabled robotics to expand into many different areas (Mercorelli, 2022). Today, robots are used in both industrial and non-industrial sectors, including agriculture, manufacturing, medicine, defense and security, and education. They are also becoming more common in households, where they assist with everyday tasks.

To better understand the range of robotic applications, the following subsections examine how robotics is applied across different fields.

**Agriculture**

Agriculture has become a key sector for adopting and adapting technologies initially developed in other sectors, while also serving as a testing ground for innovation (Sparrow & Howard, 2021). Within this domain, robots perform various tasks such as plant cleaning, weeding, harvesting, and reaping (Zhang et al., 2020). Recent developments include autonomous tractors, meat processing systems, fruit-picking robots, and inspection drones(Sparrow & Howard, 2021). These innovative solutions have contributed to improved efficiency and accuracy in agricultural operations. However, the high cost of implementation and maintenance continues to limit the widespread adoption of farming robots, particularly among small and medium-scale farmers.

### Manufacturing

In manufacturing, robots have been part of automation for many years. They are commonly used for welding, assembling parts, handling material, and other routine tasks. These applications have led to noticeable improvements in productivity and a more consistent process (Ali et al., 2021).

As automation continues to advance, new collaborative robots are being developed to work safely alongside human inspectors and operators. These systems aim to improve quality, productivity, and adaptability within the production environment (Othman & Yang, 2023). Research also shows that effective human-robot interaction (HRI) can enhance productivity and flexibility in modern manufacturing systems. Despite these benefits, several challenges such as skills shortages, ergonomic issues and concerns about job placement remain (Othman & Yang, 2023). Because of this, it remains important to address these socio-technical issues so that robotics supports human labor rather than replacing it in future industrial settings.

### Medicine

Robots have become increasingly integrated in the medical field, particularly in surgery and patient care. They are now commonly used as surgical assistants, helping improve the precision and efficiency of complex medical procedures (Arenas et al., 2018). Beyond surgery, robotic systems also play a crucial and growing role in rehabilitation, medication delivery, physical therapy and supporting patients with chronic illnesses (Habuza et al., 2021)

The integration of robotics into health care has generally improved accuracy and reduced human error, especially in routine and repetitive tasks. Research shows that robotic surgical systems may promote more rapid healing and a reduced risk of complications (Okamura et al., 2010). These technologies can also extend patient care beyond the hospital by supporting post-operative monitoring and offering therapeutic assistance with minimal human involvement.

Although these developments highlight the vast potential in medicine, they also raise ethical and regulatory concerns, predominantly concerning patients' privacy and the accountability of the responsible party in the event of a robot’s malfunction.

**Domestic Use**

In households, robots are used to assist with routine household chores like washing clothes, cooking, and cleaning the house (Muthoni, 2021). Common examples include vacuum cleaners, pool cleaners, and gardening robots, highlighting the growing need for domestic automation. Public exhibitions and technology showcases further demonstrate the intensifying role of robots in supporting household activities, such as  setting the table and doing laundry (Cakmak & Takayama, 2013).

While these technologies offer clear benefits in terms of convenience and time saving, their adoption remains uneven across different income levels. This is due to affordability, usability, and cultural acceptance. Furthermore, the long-term emotional and psychological effects of robotic companionship in domestic settings remain underexplored, underscoring the need for further research.

**Defense and security**

Robots now play an essential role in defense and security work, particularly in areas such as surveillance, intelligence collection and strengthening military operations (López-Belmonte et al., 2021). They are frequently used in tasks that put humans at risk, such as bomb detection and disposal in defense and security. Many modern defense robots are fitted with advanced technologies and sensors that enable them to gather information from a range of environments, including both aerial and ground platforms (Avellar et al., 2015).

Although these developments offer clear advantages, their use also introduces ethical and legal issues, especially when robots are deployed in conflict zones where misuse is a concern. Strong governance, transparency, and international oversight are therefore essential to ensure that these systems are responsible.

Despite these benefits, the robots deployed in this sector also raise significant ethical and legal concerns, such as misuse in conflict zones that may challenge existing frameworks. To mitigate these risks, strong governance, transparency, and international oversight are essential to ensure the responsible deployment of robotic systems.

### Education

Educational robotics is becoming an integral part of the modern curriculum, promoting hands-on learning in programming, electronics, and engineering (López-Belmonte et al., 2021; Mubin et al., 2013). These technologies have attracted growing attention for their ability to improve student engagement and the quality of learning experience. By introducing robotics into classrooms, educators can provide practical applications of theoretical concepts, helping students connect abstract concepts with real-world problem-solving.

Research also shows that using robotics in education encourages curiosity and strengthens learners' interest in science, technology, engineering, and mathematics (STEM) fields (Ospennikova et al., 2015). Studies further suggest that students who work with robotic systems often perform better academically and show greater engagement than those using more traditional learning approaches (Abdellatif et al., 2018).

Despite these results, ensuring fair access to educational robots remains a challenge, particularly in schools with limited resources and in developing countries.

### Hospitality and Tourism

In today's dynamics, a fiercely competitive business climate, and the steady development of innovative technologies all influence corporations to revitalize and restructure themselves constantly (Tuomi et al., 2021). Robotics and AI have been incorporated into the operations of several hotels worldwide (Khaliq et al., 2022). Robots in this domain can be used as chefs, receptionists, massage specialists, hotel cleaners, room service delivery robots, sex robots, pool cleaners, waiters, waitresses, and bartenders, as well as conveyance drones (Ivanov & Webster, 2017). Furthermore, they can be used as tour guides. For instance, at the new Istanbul airport, a robot named Mini Ada was deployed to greet travelers and give them information about flights and boarding gates (Khaliq et al., 2022).

While robotic systems in hospitality and tourism improve operational efficiency, guests might perceive them differently. Some guests still prefer human interaction, whereas others appreciate the speed and novelty of the robotic system. Therefore, it is vital to harmonize technological convenience and hospitality ethos to ensure customer trust and brand reputation (Ivanov & Webster, 2017).

## Oil and Gas sector

The O&G sector has increasingly adopted robotic technologies to enhance inspection and maintenance of the organization's assets (Ibrahimov, 2018). Robots are now deployed to perform hazardous tasks, such as pipeline inspection. Technologies commonly used in the O&G sector include ROVs and UAVs, both of which are equipped with cutting-edge sensors and conduct exploration activities (Shukla & Karki, 2016).

Several specialized robotic systems have been developed specifically for this sector. For example, SLOFEC developed a robot used by an oil and gas (O&G) company in the USA to inspect and maintain pipelines (Ibrahimov, 2018). Researchers have also explored multiple sensing approaches to automate the detection of pipeline leaks. Hajjaj and Khalid (2018) designed a caterpillar-type inspection robot fitted with a camera to maneuver within pipelines. Fu et al. (2019) developed a logic capable of identifying fruits grouped in line. This algorithm calculated and split up approximately 92% at night. The process began with segregation, distinguishing calyces by color contrast, and examining the assortment's margins to identify the contact points between the fruits. Lastly, a boundary was defined by joining the nearest contact points to determine whether they followed the calyx . Kim et al. (2015) developed a crack-detection program that combines digital image processing with an unmanned aerial vehicle ( UAV) to identify structural cracks. Lin et al. (2021) designed a highly comprehensive robot capable of repairing pipelines. This robot incorporated a caulking actuator and a complete robotic framework to resolve leakage problems in heat-distribution pipeline systems.

Even though O&G robots can improve efficiency, their deployment in this sector faces logistical challenges and cost constraints. The integration with legacy infrastructure and legal compliance are constant challenges.

## Law enforcement sector

Robots are now used in many police-related tasks, such as shooting, neutralizing, or getting rid of suspects in locations that are deemed too hazardous for human entry, which can result in the deaths of police officers (Yaacoub et al., 2022). For example, there was a widely reported case that happened in Texas, United States of America. The Dallas police used a robot equipped with explosives to kill a shooter. This shows the tactical potential of robotics in real-life-threatening situations. However, using robotics with explosives raises philosophical, ethical, and legal concerns. Therefore, as in the defense and security sectors, transparency is crucial to warranting the responsible deployment of robotics in law enforcement.

Robotics is now widely used across many sectors, where it contributes to improving efficiency and transforming how services are delivered. These technologies are also reshaping how people interact with and work on machines. As robots become increasingly integrated into daily life, it is important to examine the challenges and opportunities they present. The following section, therefore, explores the potential benefits and inherent limitations associated with the use of Artificial Intelligence (AI) and robotics.

### 2.4.2 Implications of advancements in AI and Robotics

While the rapid advancements of AI and robotics offer immense opportunities for innovation and efficiency, they also introduce a range of concerns that warrant careful consideration (Neupane et al., 2024). These challenges span economic, legal, ethical, and technical domains and must not be overlooked.

**Workforce Displacement and Economic Disruption**

One of the most pressing concerns associated with the adoption of robotics and AI is their potential effect on workforce stability and employment trends. As robotics continues to perform complex tasks, the risk of job displacement has become a growing concern for labor markets and economic stability (Pauliková et al., 2021).

According to SEOAI (2024), approximately 77% of organizations have already adopted AI technologies. Among these, 35% have fully integrated AI into their operations, while 42% are still in the research phase.

Despite being perceived as reducing demand for specific jobs, it is equally important to recognize their ability to generate more employment opportunities, such as writing the algorithms for these robots, and maintaining them (Oliva et al., 2022). This perception often overlooks the job opportunities that come with AI and robotics.

### Ethical and Legal Implications

The ethical dimensions of AI and robotics represent a growing area of concern as these technologies increasingly interact with humans (Neupane et al., 2024). For example, humans may form emotional relationships with them. Furthermore, AI algorithms can be biased, raising significant concerns because they can unintentionally reinforce prejudice and inequality if appropriately implemented (Christodoulou & Iordanou, 2021). The legal implications of AI and robotics are their inability to manage responsibility in these systems. Therefore, it is vital to clearly define the accountable party for robotic technologies in the event of an issue (Neupane et al., 2024). Furthermore, developing robust governance frameworks that address these emerging dilemmas is essential.

### Data Privacy and Information Security

From the perspective of information protection, data privacy remains one of the critical challenges associated with AI and robotics (Müller, 2020). For example, in the healthcare sector, the use of robotic systems to monitor patient information and transmit data to medical professionals raises noteworthy concerns (Lacava et al., 2021). These systems often exchange sensitive information, raising questions about confidentiality, integrity, and security, in both data storage facilities and data transmission processes (Müller, 2020).

Furthermore, these concerns contribute to the growing uncertainty about how such data is managed and who has access to it (Oliva et al., 2022). To mitigate this, robust controls such as encryption and informed consent mechanisms should be prioritized. This will ensure that user information is always protected, thus maintaining public trust in AI-driven solutions.

In conclusion, the integration of robotics presents both significant benefits and notable challenges. Within the O&G industry, robotics improves operational safety. However, their implementation also introduces critical considerations that must be addressed to ensure sustainable adoption. These considerations include workforce restructuring and data protection. Therefore, it is crucial to ensure that the developed robot considers all relevant aspects. The following section will discuss existing in-pipe technologies.

## 2.5 Existing Pipeline Inspection Robotic Technologies

Pipe inspection robots are generally classified into two categories: In-Pipe and out-of-pipe robots. The former are designed to navigate the internal surfaces of pipelines (Mohammed et al., 2018). These robots are generally used in the O&G and water industries to inspect pipelines internally. The latter, on the other hand, moves along the outer surface of the pipeline by a gripping mechanism that enables it to remain securely attached (John & Shafeek, 2022). This design ensures that the robot maintains stability even when navigating curved or uneven sections of the pipe. Moreover, it allows it to operate effectively where external conditions may otherwise hinder mobility.

Given that this study aims to develop an in-pipe inspection robot (IPIR), the following section provides a detailed discussion of in-pipe robotic technologies as illustrated in **Figure 2.9**.

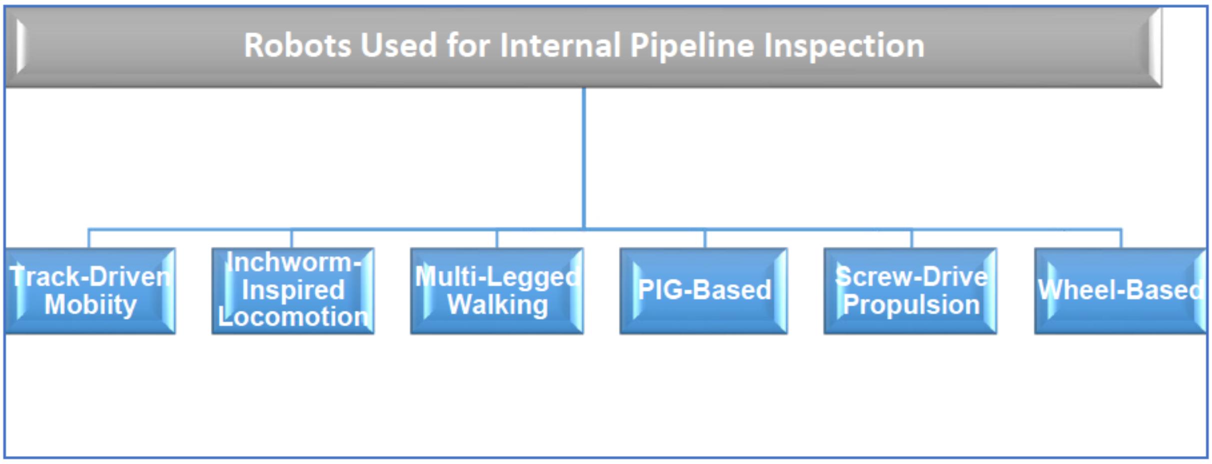



**Figure 2.9: Categorization of in-pipe inspection robots (John & Shafeek, 2022)**

Figure 2.9 presents the classification of in-pipe inspection robots based on their locomotive mechanisms. This categorization presents the diversity of mobility strategies developed to navigate confined or complex pipeline environments.

### 2.5.1 Track-Driven Mobility Robots

Caterpillar-type robots, also known as tracked robots, rely on tracks, rather than wheels to move through pipelines (John & Shafeek, 2022). This design enables them to travel across various terrains, including irregular, uneven surfaces. There are two types of Caterpillar robots: simple and wall press. Wall press models are designed to climb perpendicular and inclined pipelines with uneven internal surfaces. In contrast, simple models use belt-bound wheels driven by actuators, which increase abrasion and allow the robot to navigate uneven ground more effectively(Nayak & Pradhan, 2014).

Compared with wheeled robots, the caterpillars offer numerous benefits when moving on uneven terrain or when overcoming obstacles (Ranjan & Avasthi, 2023). They are capable of travelling across muddy surfaces, climbing steep slopes, navigating snowy or sandy terrain and passing over uneven ground by using their tracks to bridge small gaps.

NSF (2023) reports that researchers at North Carolina State University developed a robot that moves forward or backward and operates effectively in confined spaces. Corselli (2023) further notes that robots can be directed in any orientation using a special arrangement of silver nanowires that adjusts curvature through heat.

Despite having the flexibility mentioned above, caterpillar robots still face challenges and shortcomings. According to (Soffar, 2019a), some of the challenges are:
some of those challenges are that they:

a. Catepillar robots can be damaged by various threats, making one side of the robot immovable if not adequately shielded.
b. They move more slowly than the ones with wheels. That is because they have a more intricate robotic system and heightened friction.
c. They are more challenging to maneuver and require more force to rotate.
d. Have a shorter life cycle than wheeled ones and are more vulnerable to damage and failure.

Additionally, they struggle to fit pipes with multiple diameters, and are incapable of navigating around pipelines that curve (Guanhua et al., 2020).

### 2.5.2 Inchworm-Inspired locomotion Robots

Recent work in the field has shown growing interest in robots whose movement is inspired by animal behavior (Hu et al., 2023). This shift reflects an effort to replicate the natural adaptability and fluid motion seen in creatures such as fish, inchworms, annelids, and octopuses. By mimicking biological movement patterns, engineers aim to design robots that can maneuver through complex environments that traditional mechanisms cannot access.

The inchworm robot is made of flexible materials and maneuvers around surfaces by twisting its body in a looping motion, anchoring its front and rear to move forward (Xu & Liu, 2023). These robots typically use legs rather than wheels, which is advantageous because they can adapt to confined spaces. Furthermore, they can adjust their structure to accommodate diverse and unpredictable pipeline geometries (Khan et al., 2020).

Even though their structure makes them flexible, they also have limitations. While many prototypes have demonstrated vertical and horizontal climbing abilities, most continue to encounter inverted locomotion, which is essential for comprehensive pipeline inspection.
This limitation limits their operational adaptability, especially in environments with complex pipeline angles (Hu et al., 2023).

### 2.5.3 Multi-Legged Walking Robots

Multi-legged walking robots rely on legs rather than wheels for movement. These leg mechanisms allow them to move across a wide range of surface conditions (Han et al., 2016). Their ability to adapt their gait to the terrain gives them an advantage in areas where wheeled robots can lose traction or become unstable. This flexibility has enhanced their appeal to academics and scholars. For example, a team from Carnegie Mellon University's School of Computer Science, together with researchers at the University of California, Berkeley, developed a cost-effective legged robot that could function effectively in dark places. Furthermore, it can ascend and descend stairs at approximately its own height and navigate slippery, bended, and rough surfaces (Aupperlee, 2022).

These capabilities demonstrate how legged robots can navigate spaces that wheeled robots cannot. Legged robots can also adjust their height, navigate through smaller gaps, and avoid obstacles. (Gong et al., 2023).

Even though their capabilities are impressive, they also have significant limitations that constrain their practical deployment. One of the prominent issues is stability, as they can trip on narrow, uneven surfaces, unlike wheeled robots. Therefore, achieving a constant stability requires continuous alterations and precise coordination, both of which increase the risk of operational failure in dynamic settings (Gong et al., 2023). Furthermore, they typically operate at slower speeds than wheel robots. This is because their movements require a tremendous amount of energy as they rely on actuators and continuous balance adjustment, limiting their operational durability, predominantly in battery-powered applications (Machado & Silva, 2006). Lastly, ensuring smooth and responsive movement demands advanced control algorithms and continuous sensor feedback, which can result in higher implementation and operational costs (Gong et al., 2023).

### 2.5.4 PIG-Based Inspection Devices

Pipeline Inspection Gauges (PIGs) are a vital technique used in the O&G industry. These devices are fascinating, as they serve a dual purpose: both as non-destructive testing (NDT) devices and as robotic inspection technologies. In NDT applications, they use the Magnetic MFL to assess the integrity of the pipe (Afzal & Udpa, 2002). In robotic applications, apart from inspection, they also function as cleaning tools, effectively removing internal contaminants such as rust (Elankavi et al., 2020).

The use of PIGs improves operational efficiency and reduces downtime by streamlining maintenance across different sectors (John & Shafeek, 2022). Furthermore, due to their low cost and straightforward construction, they remain a practical option for routine inspections (Ma et al., 2023).

It is vital to keep in mind that, like their counterparts, PIGs also come with certain limitations that heavily influence where and how they can be deployed. Even though they are effective for routine inspections, most are tailored to pipelines with uniform and static diameters. This makes it challenging for them to operate in pipelines with bends and complex geometries (John & Shafeek, 2022). This could result in organizations having to modify their strategy when inspecting aged and complex pipelines.

### 2.5.5 Wheel-Based Robotic Systems

Wheeled robots are the most used robots in the O&G sector. The main reason for that is that they have a simpler mechanical design, ease of manufacturing, and straightforward programming for movement on a flat surface (soffar, 2019b). Furthermore, they are energy-efficient, which allows them to navigate faster than legged robots (Campion & Chung, 2008). However, they have significant limitations. They battle to navigate uneven or obstacle-rich terrains, such as steep inclines, low-friction surfaces, or rocky environments (soffar, 2019b).

A wheeled robot can employ various wheel types, including traditional, caster, omnidirectional, and Mecanum wheels. Traditional wheels operate as active wheels. They are widely used across multiple technical sectors due to their simplicity and limited functionality, allowing rotation in both directions (Shabalina et al., 2018). Castor wheels are often used due to their simplicity and their capability to transport heavy weights (Arrizabalaga et al., 2021). Omnidirectional wheels, on the other hand, operate on a distinct principle: an active central wheel is equipped with freely rotating passive rollers (Shabalina et al., 2018). However, they have certain drawbacks. Their efficiency is reduced because not all wheels rotate in the direction of motion, leading to friction losses. Lastly, the Mecanum wheels, also known as the Swedish wheel, were invented by Bengt Erland Ilon in 1972 (Taheri & Zhao, 2020). They are known for their flexibility in a way that they can move in any direction with any rotation (Cao et al., 2022).

While wheeled robots offer many benefits, such as energy efficiency and simplicity, their performance is highly terrain dependent. Furthermore, their inability to adapt to irregular environments limits their use in fields such as search and rescue, where legged robots may be more suitable. Additionally, the computational demands of robots with omnidirectional or Mecanum wheels introduce a trade-off between maneuverability and control complexity.

### 2.5.6 Screw-Drive Propulsion Robots

Screw type robots move in a spiral pattern, and at any given moment, they can move in both directions (John & Shafeek, 2022). They are always wall-pressing because they rely on the inner walls to get through the pipes, which makes climbing perpendicular pipelines simple (Kakogawa & Ma, 2010).

Ismail et al. (2012), believe that some of their benefits are:

1. They can be easily closed off because they lack an unlimited rotary system, such as a wheel.
2. Their supple body allows them to move flexibly.
3. They can contract because of their simple structure.
4. They can adapt to changes in pipe diameter due to their helical body's changeable diameter.

These advantages are reinforced by the research conducted as Li et al. (2018) . In their study, the robot demonstrated effective operation in both square and circular pipelines, showcasing its adaptability to various infrastructure layouts.

### 2.5.7 Performance Evaluation of Robotic Mobility Platforms

This section evaluates the performance of the previously discussed robotic platforms. Table 2.3 compares the robot types based on key operational criteria, including cost, flexibility, stability, and vertical mobility. This analysis provides a holistic understanding of how these robots perform under varying conditions. Table 2.4 further analyzes the advantages and disadvantages of each. Together, these comparisons provide a structured basis for identifying the most suitable mobility mechanism for in-pipe inspection applications.

| Robot | Cost | Flexibility | Stability | Vertical Mobility |
|---|---|---|---|---|
| **Caterpillar** | Costly | Rigid | Moderate | Moderate |

| | | | | |
|---|---|---|---|---|
| **Inchworm** | Costly | Relatively Flexible | Moderate | Exceptional |
| **Legged** | Costly | Flexible | Moderate | Moderate |
| **PIG** | Costly | Rigid | Great | Moderate |
| **Screwed** | Costly | Rigid | Exceptional | Exceptional |
| **Wheeled** | Costly | Rigid | Poor | Poor |

**Table 2.3: Comparative Analysis of Robotic Mobility Systems**

As shown in Table 2.3, the inchworm and screwed mechanisms demonstrate superior vertical mobility, making them suitable for inclined or vertical pipelines. However, wheeled systems offer advantages in speed and energy efficiency, while caterpillar systems provide enhanced stability. These trade-offs highlight the importance of application-specific robot selection.

| Robot Type | Advantages | Disadvantages |
|---|---|---|
| **Caterpillar** | - High traction and stability due to increased surface contact<br>- Effective on uneven, muddy, or steep terrain<br>- Wall-press type can climb vertical/sloped pipes<br>- Simple type offers abrasion resistance (John & Shafeek, 2022; Nayak & Pradhan, 2014) | - Slower than wheeled robots due to friction and complex mechanics<br>- Difficult to maneuver and rotate<br>- Shorter lifespan and more prone to damage<br>- Poor adaptability to multi-diameter or curved pipelines (Guanhua et al., 2020; soffar, 2019b) |
| **Inchworm** | - Highly flexible and adaptable to narrow, curved, or vertical pipelines.<br>- Capable of dynamic gait adjustment.<br>- Suitable for confined and irregular environments (Hu | - Limited inverted locomotion.<br>- Restricted applicability (Hu et al., 2023) . |

| | | |
|---|---|---|
| | et al., 2023),(Khan et al., 2020) | |
| **Legged** | - Excellent for navigating complex, cluttered, or natural terrains.<br>- Can climb stairs, scale obstacles, and adjust body height.<br>- Operates in dark or uneven environments (Aupperlee, 2022),(Gong et al., 2023) | - Prone to instability and tipping.<br>- Energy-intensive and slow.<br>- Mechanically complex<br>- Requires advanced control algorithms (Machado & Silva, 2006;Gong et al., 2023) |
| **PIG** | - Dual function: inspection and cleaning.<br>- Cost-effective and simple design.<br>- High-speed operation in long, straight pipelines.<br>- Equipped with MFL and UT sensors for NDT (Afzal & Udpa, 2002),(Elankavi et al., 2020) | - Limited to pipelines with fixed diameter<br>- Poor navigation in complex or branched networks<br>- Not suitable for pipelines with sharp bends or variable geometries (John & Shafeek, 2022) |
| **Wheeled** | - Straightforward design with ease of manufacturing.<br>- High speed and energy efficiency.<br>- Multiple wheel configurations for different mobility needs (Campion & Chung, 2008; Shabalina et al., 2018) | - Poor performance on uneven or slippery terrain.<br>- Limited adaptability to the complex pipelines.<br>- control complexity due to omnidirectional wheels (Soffar, 2019a) |
| Screwed | - Spiral motion enables bidirectional travel. | - High friction increases energy consumption.<br>- Mechanically complex. |

| | | |
|---|---|---|
| | - Wall-pressing allows vertical climbing.<br>- Compact and flexible design<br>- Adjustable diameter for varying pipe sizes (Ismail et al., 2012),(Zhang et al., 2020) | - Limited maneuverability in branched or curved pipelines.<br>- May require precise alignment to function effectively (Guanhua et al., 2020). |

**Table 2.4: Advantages and Disadvantages of Inspection Robotic Technologies**

Overall, while no single mobility platform outperforms others across all criteria, inchworm and screwed mechanisms exhibit greater adaptability to complex and vertical pipeline environments. In contrast, wheeled and caterpillar systems offer simplicity and stability but are less effective in highly curved or multi-diameter pipelines. This reinforces the need for a balanced design approach when developing a frugal in-pipe inspection robot.

## 2.6 Securing IoT Devices in Robotic Inspection Technologies

### What is IoT?

The Internet of Things (IoT) refers to a technological framework in which diverse devices are interconnected, enabling continuous data exchange and communication across multiple contexts and environments (Samaila et al., 2018). As the fundamental technologies in these devices become more sophisticated, so do their applications in our everyday lives (Aziz Al Kabir et al., 2023) . The perfect example of this is the use of television in households (Laghari et al., 2021). There has been a massive increase in interest in the IoT domain due to recent developments in semiconductor technology, which have enabled the direct integration of wireless network connectivity into fixed processors and sensors at a reasonable cost (Aziz Al Kabir et al., 2023).

Furthermore, it has been utilized in various industries, including healthcare and the military. In healthcare, it monitors patients remotely, regulates medications, and tracks medical workers and kits (Rai et al., 2021). While the military domain uses it to detect occurrences, invasions, and dangerous objects (Grieco et al., 2014). Additionally, opportunities in the transportation sector have been made possible by the combination of robotics and the IoT, for example, using self-driving cars (Dhanwe et al., 2024).

Although IoT offers significant advantages, integrating it into robotic systems, particularly those used in critical infrastructure such as pipelines, makes them prone to security vulnerabilities, which could compromise them (Rizvi et al., 2020). Having effective control measures in place is essential to warrant the availability, confidentiality, and integrity of sensitive data (Boopathi, 2023). Additionally, as data is passed across multiple connected devices and networks, the risk of interception increases(Dhar & Bose, 2021). Thus, organizations must implement strong encryption, access controls, and monitoring tools to ensure the robotic system is fully secure. In pipe inspections, a compromised robot could produce incorrect diagnostic data, delay maintenance, or even sabotage pipelines.

Therefore, it is crucial to mitigate all these vulnerabilities by ensuring that security patches and firmware updates are applied (Boopathi, 2023). Furthermore, by ensuring efficient access control measures, such as user authentication, are in place. (Hamad et al., 2020). Lastly, by using algorithms such as convolutional neural networks (CNNs) to identify suspicious network behaviour (Prince et al., 2024).

IoT technologies arguably enhance the operational intelligence of robotic systems, particularly through real-time data acquisition; however, this benefit is contingent on the robustness of the supporting infrastructure.

### 2.7 Image-Based Detection Techniques in Robotic Inspection Technologies

Digital image processing is a vast discipline that involves manipulating and interpreting digital images using a computer, including the application of complex arithmetic algorithms (Sishodia et al., 2020). Additionally, it pertains to applications involving information extraction, in which image or video streams undergo analysis to extract relevant parameters or identify distinguishing features (Adegbija et al., 2017). These techniques are mostly valuable in scenarios where visual cues are critical for decision-making, such as in medical diagnostics, digital forensics, and increasingly, in industrial applications like pipeline inspection. In the context of in-pipe robotic inspection, image-based detection techniques offer a non-invasive and economical approach to identifying structural anomalies, including corrosion and cracks. The integration of cameras and image-processing algorithms into robotic platforms enables real-time monitoring and automated defect identification, thereby reducing reliance on manual inspection and enhancing operational safety and efficiency.

Recent advancements in semiconductor and embedded systems have facilitated the deployment of compact, low-cost imaging sensors within robotic system (Aziz Al Kabir et al., 2023). These developments have made it feasible to embed image acquisition and processing capabilities directly into frugal robotic platforms, aligning with the goals of affordability and accessibility in resource-constrained environments.

However, despite their advantages, image-based techniques face challenges, particularly in detecting image forgeries or inconsistencies in visual data. Mahana and Aggarwal (2019) highlight the difficulty of identifying tampered or manipulated images, which can compromise the reliability of automated inspection systems. To address this, researchers have developed robust detection strategies, including keypoint-based and block-based methods. The former identifies and matches distinct image features to detect duplicated regions, while the latter segments the image into pixel blocks to identify repetitive patterns indicative of tampering (Prakash et al., 2018).

### 2.7.1 Applications of image-based detection techniques Across Domains

a. **Medical Imaging**: Image processing is foundational in medical diagnostics, supporting tasks such as image enhancement, segmentation, and feature extraction. These techniques are instrumental in tumor detection, surgical planning, and remote patient monitoring using handheld diagnostic devices (Mahana & Aggarwal, 2019; Orujov et al., 2020) .
b. **Digital Forensics**: In forensic science, image processing is used to authenticate digital images, detect tampering, and enhance visual evidence. Techniques such as image history verification and noise pattern analysis enable the integrity of visual data (Javed et al., 2022; Mahana & Aggarwal, 2019).
c. **O&G Sector**: In pipeline inspection, image processing techniques, including segmentation and feature extraction, are applied to identify corrosion, cracks, and other structural anomalies. Segmentation isolates regions of interest based on texture, color, or shape, while feature extraction quantifies these regions to support defect classification (Ali et al., 2023; Carvalho et al., 2008; Yao & Liang, 2020).

### 2.7.2 Techniques used in image processing

Image processing employs several computational techniques, including locating boundaries within images, applying greyscale thresholds, analyzing structures through graph-based models, and employing learning-based algorithms that interpret and extract meaningful information from data (Kao et al., 2022). The following subsection provides a detailed examination of these algorithms.

#### 2.7.2.1 Edge detection

Edge detection is one of the most critical processes in image analysis. It is generally grouped into two categories: gradient-based and Gaussian-based bases as depicted in Figure 2.10.

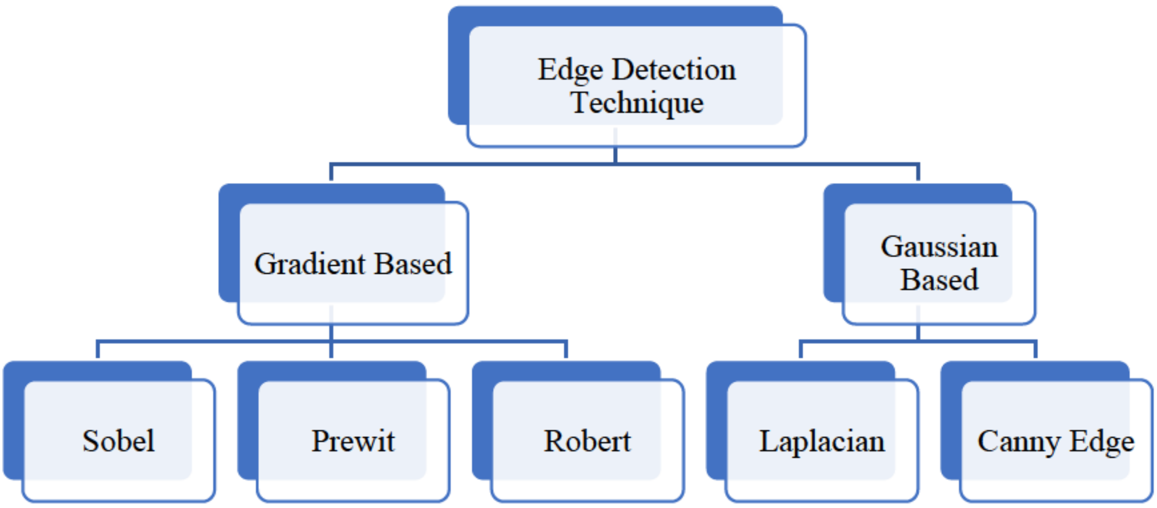



**Figure 2.10: Edge Detection Classifications**

As illustrated in Figure 2.10, gradient-based methods detect edges by computing intensity changes, while Gaussian-based approaches incorporate smoothing to reduce noise before edge extraction. This classification provides the foundation for selecting appropriate edge detection algorithms for pipelines.

#### 2.7.2.1.1 Gradient-Based Edge Detector

The gradient-based method finds edges by looking for the first-derivative image's minimum and maximum values (Maini & Aggarwal, 2009). They are generally grouped into three categories: Sobel, Prewitt, and Robert.

The Sobel technique is a traditional image-processing technique. It is widely utilized to identify edges and segment images (Ahmad & Choudhury, 2022). Furthermore, it is perceived as a highly considered algorithm due to its user-friendliness and noise lenience (Kandukuri et al., 2022). Meaning even inexperienced users can use it efficiently. As user-friendly as it is, it struggles to detect edges in images with high noise. This was proven by a study done by Kandukuri et al. (2022), which stated that it had missed certain aspects in images.

Sobel Operators employ a collection of 3x3 kernels for the x and y directions (Maini & Aggarwal, 2009). The Prewitt algorithm is like the Sobel algorithm in that it also assesses the direction and proportion of edges (Azouz et al., 2023). Furthermore, identify vertical and horizontal edges, and determine the locations with the highest gradient (Shah et al., 2020). Robert, on the other hand, uses the oblique contrast between the nearest pixels to detect gradients (Shah et al., 2020). With the Roberts Cross operator, the two-dimensional measure of how rapidly image values change across space can be computed efficiently (Maini & Aggarwal, 2009).

#### 2.7.2.1.2 Gaussian-Based Edge Detector

Among Gaussian-based image processing techniques, the Laplacian and Canny edge detection methods are extensively utilized for feature extraction and edge enhancement.

Canny Edge plays a fundamental role in computer vision, enabling advanced image analysis and interpretation (Ashraf et al., 2017). This multi-step algorithm, designed to maximize the trade-off between spatial localization and signal clarity by optimizing their combined effect (Zhang et al., 2020). **Laplacian of Gaussian (LoG**) , on the other hand detecting blobs and edges, particularly in images with rapid intensity transitions (Zhang et al., 2020). Ashraf et al. (2017) believe that Canny Edge outshines other edge detection algorithms in terms of accuracy and efficiency.

#### 2.7.2.2 Greyscale Thresholding and Graph Theory-Based Approaches

Greyscale thresholding and graph-theory-based methods are often treated as distinct yet complementary methods in image processing.  Greyscale thresholding has the capability to effectively separate images into binary regions (Lerchen et al., 2021).  To convert a grayscale image into a binary black-white image, greyscale thresholding generally involves dividing pixels based on a threshold value (Ahmad & Choudhury, 2022). In contrast, Graph theory is a branch of mathematics that studies graphs, which are structures composed of vertices and edges (Vanaei et al., 2017). Initially prominent in database systems for advanced querying and analysis (Rodriguez, 2015), graph theory has recently gained traction in image processing due to its aptitude to capture spatial and contextual relationships between pixels or regions.

Even though the greyscale technique is simple for binary segmentation, it still relies on a global threshold, making it less adaptable to varied image circumstances. In contrast, graph-theory-based methods offer superior flexibility and precision by incorporating relational information, albeit at the cost of intensive computational requirements.

#### 2.7.2.3 Machine Learning

Arthur Samuel first described Machine Learning (ML) as a subfield of computer science designed to allow  systems to learn  and make decisions without being explicitly programmed (Mahesh, 2020). ML supports high-accuracy analysis and classification across a wide range of fields. These include image correlation, object detection, medical diagnostics, and content comprehension, where they help uncover patterns and insights from existing datasets (Qayyum et al., 2022).  According to Kompella et al. (2021), they are effective in image processing, particularly in image classification (Kompella et al., 2021).

Some of the ML techniques include ensemble learning, decision trees, deep learning, and K-Means clustering.  Ensemble Learning stands out for its strategic integration of multiple algorithms to improve predictive accuracy. It derives initial predictive estimates from multiple data projections, then refines these outputs using voting mechanisms to achieve superior accuracy compared to standalone models (Dong et al., 2020; Mahesh, 2020). There are two primary ensemble strategies: boosting and bagging. The former reduces discrepancy and predisposition, and the latter increases the precision and strength of the algorithm (Mahesh, 2020).

Decision trees are diagrams that exhibit decisions and their results as a tree (Mahesh, 2020). They are typically shown as a pattern similar to a flow diagram, with each leaf representing a likelihood and each internal node indicating a logistic test (Costa & Pedreira, 2023). The graph's nodes represent occurrences or preferences, and its edges represent conditions or decision rules (Mahesh, 2020). However, their simplicity can lead to overfitting, especially when not pruned or regularized effectively.

Deep learning is a subset of machine learning that uses algorithms to learn many layers of interpretation and model composite information relations (Deng & Yu, 2014). By advancing performance characteristics, process dynamics, and material properties, it facilitates the detection of parameter variations crucial for material behavior analysis and modeling (Kim et al., 2015). Despite its power, deep learning demands substantial computational resources and large datasets, which can be a barrier in resource-constrained environments.

Lastly, K-means is used to address the well-established clustering problem (Mahesh, 2020). This technique requires a preset k value for grouping analysis, as clustering with varying k values might yield varying outcomes (Ahmed et al., 2020). Each data point records the same points from the data set and reacts appropriately to these points (Cui, 2020). Clustering is a valuable tool in data science (Sinaga & Yang, 2020).

### 2.8 Summary

This chapter presented a comprehensive review of contemporary robotic technologies for pipeline inspection, analyzing their capabilities and identifying their inherent limitations. It commenced by giving an overview of corrosion in the O&G sector. Next, the traditional inspection techniques were discussed. Thereafter, the existing pipeline inspection robotic technologies were presented and evaluated. While these advancements promise enhanced automation, many are prohibitively expensive or too complex for small to medium-scale operators. Subsequently, it described securing the IOT devices in robotic technologies. Lastly, image-based detection techniques, particularly canny edge, Sobel, Laplacian of Gaussian, K-Means clustering, and machine learning algorithms, were presented.

The literature reveals a significant gap in developing economical, portable, and accurate robotic systems for pipeline corrosion detection. While the current technologies offer high performance, they remain out of reach for many organizations. Therefore, there is a need for a user-friendly, cost-effective in-pipe inspection robot that can deliver accurate corrosion-detection results. The following chapter outlines the research methodology used to systematically address the study's objectives.

# CHAPTER 3: RESEARCH METHODOLOGY

## 3.1 Introduction

This study adopted a design-based research approach. The approach allowed the iterative development and evaluation of the in-pipe inspection robot system for pipeline inspection. Several phases were combined, including problem identification, robot selection, hardware prototyping, and image processing algorithms for corrosion detection.

The research commenced with a review of the existing literature to identify pipe inspection techniques and the challenges associated with them. This step was vital for understanding the technical limitations and the range of pipeline diameters typically encountered, and the importance of achieving accurate corrosion detection. Secondly, the affordable robot components were explored, and a suitable robot was selected. Thereafter, an in-pipe inspection robot was developed and tested in the pipeline. Finally, images were captured and analyzed to detect corrosion.

Several factors were considered throughout the design process. For example, the robot's mechanical structure was optimized for movement and adaptability within varying pipeline diameters. The inclusion of the camera was also essential to ensure effective image capturing for further corrosion analysis.

## 3.2 Design Science Protocol

Design Science Research (DSR) was selected because it combines practical design with scientific inquiry, enabling the development and evaluation of an innovative corrosion-detection system.

The protocol followed in this study consisted of five iterative stages: Identify→Design→Build→Evaluate→Reflect. Figure 3.1 illustrates the DSR protocol.

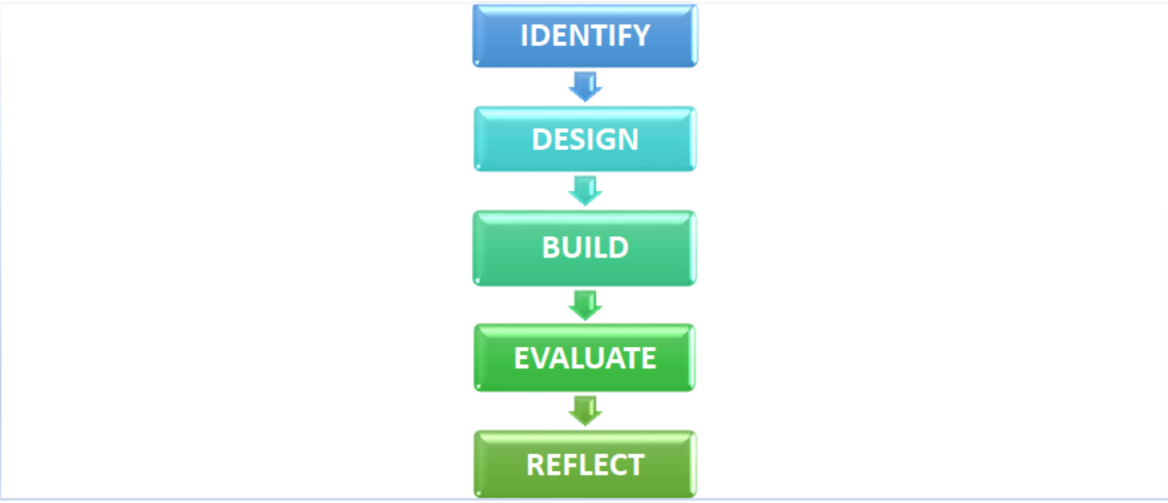



**Figure 3.1: Design Science Protocol**

### 3.2.1 Identify

The research began by recognizing the pressing issue of corrosion in oil and gas (O&G) pipelines, a problem that continues to threaten both operational productivity and environmental safety. During this stage, attention was given to identifying existing inspection techniques and evaluating their current limitations, such as adaptability, accessibility, and cost-effectiveness. This identification helped establish the motivation for developing a more frugal and adaptable inspection robot capable of addressing the limitations.

### 3.2.2 Design

During the design phase, the conceptual framework for the in-pipe inspection robot was developed to address the identified limitations in pipeline corrosion detection. At this stage, the research translated the problem into specific design requirements, including affordability, portability, adaptability to varying pipe diameters, and integration with reliable image-based corrosion-detection techniques. Thereafter, the solution was conceptualized, resulting in the design of a cost-effective robotic system. This took into consideration the mechanical mobility, sensor placement, and camera integration. Subsequently, image processing techniques such as Canny Edge Detection, Sobel edge detection, K-means clustering, and machine learning models were selected to support accurate corrosion detection. Finally, basic security controls to protect data integrity and device communication within the testing environment were put in place.

### 3.2.3 Build

In the Build phase, the in-pipe inspection robot was developed in line with the design requirements. This stage involved selecting cost-effective components, assembling the mechanical structure, and integrating the chosen sensors and camera into a functional robot. During assembly, specific attention was paid to achieving stable movement within the pipelines and ensuring the in-pipe inspection robot could capture images.

This stage represented the practical implementation of the design, serving as a bridge between conceptualization and evaluation. Once the assembly process was concluded, the robot was then ready to be tested in pipelines.

### 3.2.4 Evaluate

The in-pipe inspection robot was tested in controlled pipeline environments to assess its performance. The evaluation focused on key performance metrics, including corrosion-detection accuracy, which was evaluated using various image-processing algorithms.

### 3.2.5 Reflect

In this final stage, findings from the evaluation informed several iterative improvements to both hardware and software. This reflection stage also considered the feasibility of deploying the system in real-world industrial settings, particularly within the O&G sector. In addition, potential future enhancements such as incorporating IoT and cloud for real-time monitoring were identified.

## 3.3 Robot Development

### 3.3.1 Frugality Operationalization

The AlphaBot2 kit was selected as an integrated platform to simplify the robot's development process and reduce complexity in design. Its modular structure ensured that components like sensors, controllers, and cameras were compatible and easy to assemble. This approach significantly streamlined the assembly and testing phases. However, it introduced inevitable trade-offs, including limited flexibility for future hardware upgrades. This robot incorporated several essential features that supported its intended functionality:

a. WI-FI connectivity feature.
b. Bluetooth control feature.
c. Battery-powered motor system.
d. Omni-directional wheels.
e. Lightweight and compact design.
f. Obstacle avoidance feature.

Table 3.1 outlines the bill of materials associated with the AlphaBot2 kit.

| **Component / Kit** | **Description** | **Cost (ZAR)** | **Maintenance Simplicity** | **Energy Budget** | **Performance Trade-offs** | **Supplier** | **Lead Time** |
|---|---|---|---|---|---|---|---|
| AlphaBot2 Smart Video Robot for Pi4 (W17189) | **Complete kit:** chassis, motors, drivers, Pi4 interface, camera, connectivity | R3549.00 – including VAT and delivery | High | 3.7V battery, 800mAh | Limited upgrade flexibility | Micro Robotics | 2 days |
| **VAT** | **VAT** | R547.05 | - | - | - | - | - |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| **Delivery** | **National Delivery Flat Rate** | R98.00 | | | | | |
| **Total** | **-** | R4194.05 | - | - | - | - | - |

**Table 3.1 : Robot Bill of Materials**

Table 3.1 presents the bill of materials for the proposed in-pipe inspection robot, outlining the selected components, associated costs and key trade-offs. The total estimated cost of R4194.05 demonstrates the feasibility of developing a low-cost, in-pipe inspection robot using commercially available components. The selection of the Alphabot2-Pi robot significantly reduced integration complexity while maintaining essential functionality, including mobility, sensing and processing capabilities.

### 3.3.2 System Architecture Diagram

The system architecture, as shown in Figure 3.2, illustrates the integration of the in-pipe inspection robot's software and hardware components, which enabled it to conduct pipeline inspections and detect corrosion effectively.

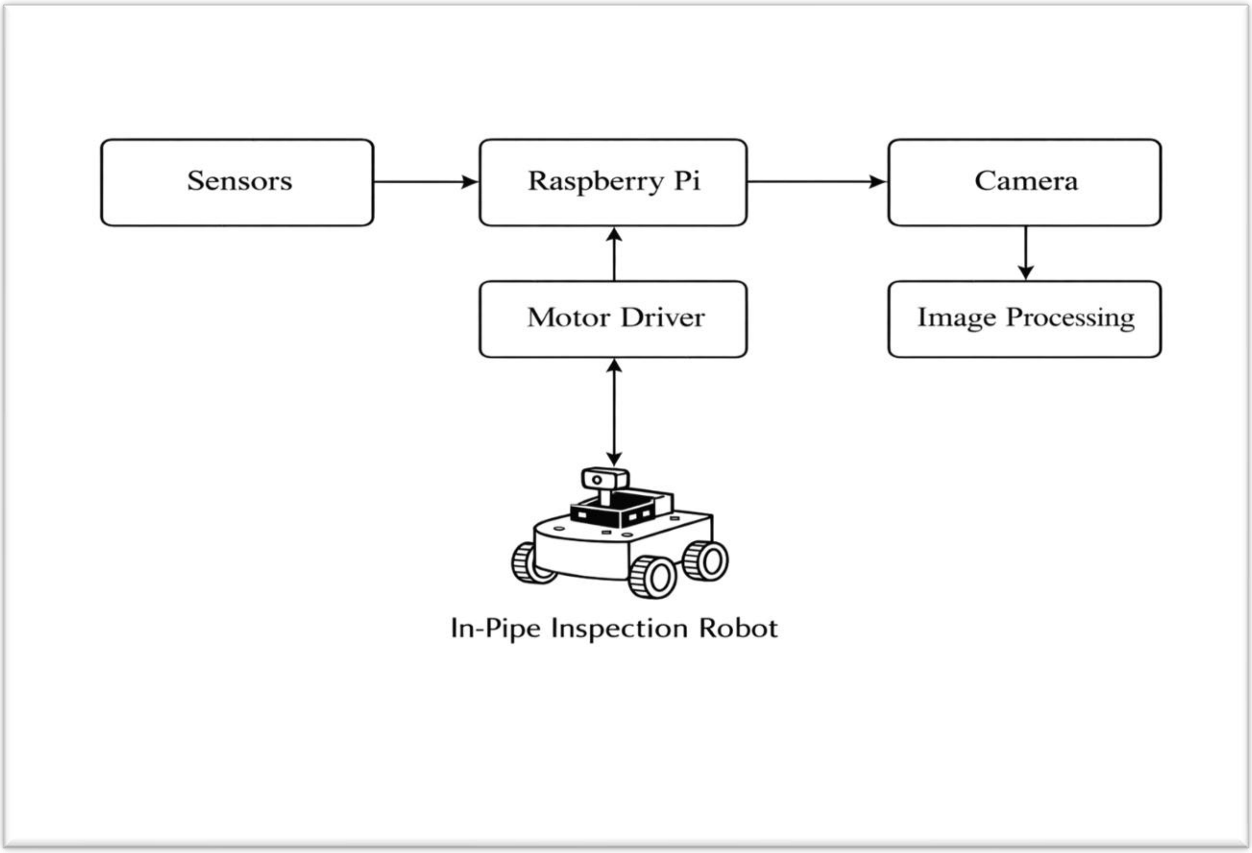



**Figure 3.2: System Architecture Diagram**

Figure 3.2 illustrates the overall system architecture of the proposed frugal in-pipe inspection robot. The Raspberry Pi serves as the central unit, coordinating data acquisition, control, and communication among system components. Ultrasonic and infrared sensors provide distance and obstacle detection data to the Raspberry Pi for navigation decision-making. The motor driver provides the interface between the Raspberry Pi and the robot's drive motors, enabling controlled movement within the pipelines. A camera module is connected to capture the image inside the pipelines, which are subsequently processed using image processing approaches for corrosion detection and analysis.

This cohesive architecture ensures coordinated sensing, mobility control and visual inspection within a compact and cost-effective robotic platform.

### 3.3.3 Testbed environment

The experimental setup was intended to closely mimic real-world pipeline conditions to assess the robot's effectiveness. The testbed included corroded pipelines with different diameters ranging from 50 millimeters to 150 millimeters.

Each experiment run began at the pipe entry and continued until the robot completed the full traversal or encountered an obstacle. To ensure reliability, four iterations were performed for each configuration.

## 3.4 Image acquisition and Preprocessing

### 3.4.1 Image acquisition

The images were captured using the Raspberry Pi 5MP HD Camera (1080P), mounted on the robot. However, due to the extremely low-light conditions inside the pipelines, the captured images were of very low quality. As a result, a higher-quality iPhone camera with an integrated flashlight was used to capture high-quality images. This substitution improved illumination and increased the reliability of the images for further analysis. Table 3.2 details the image-acquisition parameters for the iPhone 11 used in pipeline inspection.

| Parameter | Specification |
|---|---|
| Resolution | Pi 5MP HD initially, then iPhone 12 Megapixels |
| Pixel size | 1.4 µm (main wide-angle), 1.0 µm (ultra-wide) |
| Lens | Fixed focus lens |
| Focal Length | Wide (26 mm) and Ultra-Wide (13 mm) |
| Shutter Speed | Auto (default), with manual override during testing |
| ISO Sensitivity | Auto |
| Frame Rate | Not Applicable as only still images were captured. |
| Mount Position | Handheld |

| | |
|---|---|
| Distance to Wall | Approximately 5–10 cm |
| Illumination (Lux) | Enhanced with iPhone's built-in flashlight; estimated 50–100 lux in dark sections |
| Calibration | No formal calibration; relied on iPhone's built-in image processing and stabilization |

**Table 3.2: Image Acquisition Parameters for iPhone 11 Used in Pipeline Inspection**

The parameters in Table 3.2 indicate that image acquisition was conducted with the 5 MP AlphaBo2 camera; however, due to the low image quality, the handheld iPhone 12 MB was subsequently used. The use of auto settings for shutter speed and ISO sensitivity reflects real-world inspection scenarios, while close-range capture at 5 to 10 cm enhances defect visibility. Although no formal calibration was performed, reliance on the iPhone; s internal processing ensured stable and consistent image quality suitable for analysis.

### 3.4.2 Image preprocessing

Several pre-processing techniques were applied to improve quality and ensure reliable feature extraction. The steps were crucial in reducing noise and enhancing contrast.

a. **Resizing**

In order to standardize processing and minimize computational cost while preserving essential image details, all images were scaled to 256 × 256 pixels (Choudhary & Dey, 2012).

**b. RGB to Grayscale Image Conversion**

According to Munawar et al. (2021) grayscale image conversion employs techniques that capture the full tonal range of images and enhance contrast, thereby highlighting the gradation details of interest. Since the captured images were in RGB format, conversion to grayscale was required (Padmavathi & Thangadurai, 2016). In RGB mode, each color represents one of the primary components: red (R), green (G), and blue (B) (Padmavathi & Thangadurai, 2016). The standard formula for RGB to grayscale conversion is expressed as ***Y = 0.299 Red + 0.587 Green + 0.114 Blue*** (Choudhary & Dey, 2012). **.**

**c. Noise Reduction**

A Gaussian blur filter was then applied with a kernel size (e.g., 3×3) to smooth the images and minimize random pixel variations that could interfere with edge detection.

d. **Histogram Equalization**

Finally, histogram equalization was applied to enhance contrast and improve feature visibility, enabling more effective corrosion detection.

## 3.5 Corrosion Detection Algorithms

Four algorithms were implemented and systematically evaluated using a consistent dataset to detect corrosion in pipeline images. These include traditional edge detection methods, an unsupervised clustering technique, and a deep learning model.

**a. Canny Edge Detection**

A traditional edge detection technique for identifying edges in images. Canny Edge Detector is commonly employed for image edge detection in the field of computer vision (Ashraf et al., 2017). The Canny algorithm is regarded as one of the most advanced edge detection methods currently in use (Ahmad & Choudhury, 2022). The Canny algorithm follows a structured multi-step process (Shrivakshan & Chandrasekar, 2012):

1. Apply a Gaussian filter to smooth the image and reduce noise.
2. Compute the gradient dimension using finite-difference conjectures for the fragmentary derivatives.
3. Exert nonmaximal repression to the gradient immense and use the dual thresholding technique to discover and connect edges.
4. Double Thresholding and Edge Tracking by Hysteresis to finalize edge maps.

**b. Sobel Operator**

An algorithm based on gradient computation for horizontal and vertical edges.

The Sobel operator is broadly used to detect edges and segment the images (Ahmad & Choudhury, 2022). Due to its straightforward implementation and robustness against noise, the Sobel edge detector is widely regarded as a reliable and effective technique for edge detection. According to (Maini & Aggarwal, 2009), Sobel operators comprise a set of 3-by-3 matrices, illustrated in Table 3.3.

| X-direction Kernel | Y-direction Kernel |
|---|---|
| $\boldsymbol{Gx} = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 1 \\ -1 & 0 & 1 \end{bmatrix}$ | $\boldsymbol{Gy} = \begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{bmatrix}$ |

**Table 3.3: Sobel Operator**

The $Gx$ and $Gy$ Kernels compute image intensity gradients in horizontal and vertical directions. The gradient magnitude derived from these responses is used to highlight end boundaries within the image

**c. K-means Clustering**

K-means clustering was employed as an unsupervised learning algorithm to segment corroded regions in pipeline images based on color-intensity variation. This algorithm grouped unlabeled data into distinct clusters by identifying similarities in pixel characteristics (Ikotun et al., 2023). It is highly effective when data lacks predefined labels, making it suitable for unsupervised learning tasks such as image segmentation in corrosion detection.

**d. Convolutional Neural Network (CNN)**

A Convolutional Neural Network (CNN) was used as the supervised deep learning approach to classify image regions as either corroded or non-corroded. The CNN model was trained on the labeled datasets collected during the testing phase, enabling it to learn the unique visual features of corrosion patterns. After training, the model was able to detect corrosion in images, improving precision compared to traditional algorithms.

### 3.6 Performance Evaluation Metrics

The effectiveness of the corrosion detection algorithms was assessed using four widely accepted classification measures: Accuracy, Precision, Recall, and F1 score. These metrics were chosen to provide a comprehensive evaluation of the model's ability to distinguish corroded and non-corroded areas within the captured images.

All evaluation metrics were obtained from the confusion matrix, which tabulates the counts of True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN). Examining these values provides insight into the system's classification performance and forms the foundation for calculating the selected measures, thereby enabling a more comprehensive assessment of the model's reliability.

**a. Accuracy**

Accuracy was used to assess the model's overall correctness by measuring the proportion of correctly classified instances, both positive and negative, relative to the total number of predictions. It is defined as

$$\boldsymbol{Accuracy} = \frac{P + TN}{P + TN + FP + FN}$$

**b. Precision**

Precision was used to assess the model's capability to correctly identify positive cases, indicating the proportion of predicted positives that were truly positive and reflecting its effectiveness in minimizing false detections

$$\boldsymbol{Precision} = \frac{TP}{TP + FP}$$

**e. Recall**

Recall, also known as sensitivity, represented the model's capacity to detect all actual positive instances in the dataset.

$$\boldsymbol{Recall} = \frac{TP}{TP + FP}$$

**f. F1 Score**

The F1 score represents the harmonic mean of Precision and Recall, offering a balanced metric that incorporates both false positives and false negatives. The standard formula:

$$\boldsymbol{F1-Score} = 2\,X\ \frac{Precision\ X\ Recall}{Precision\ X\ Recall}$$

Confusion metrics were computed to depict the distributions of true positives, true negatives, false positives, and false negatives for each algorithm, providing a comprehensive assessment of classification performance.

## 3.7 Tools and technologies used

### a. Hardware

The experimental setup was conducted on a machine equipped with an 11th Generation Intel® Core™ i5-1135G7 processor, operating at a base frequency of 2.40 GHz (with a measured speed of 2.24 GHz). The system included 32 GB of installed RAM, of which 31.7 GB was usable, and ran on a 64-bit operating system with an x64-based architecture.

### b. Software

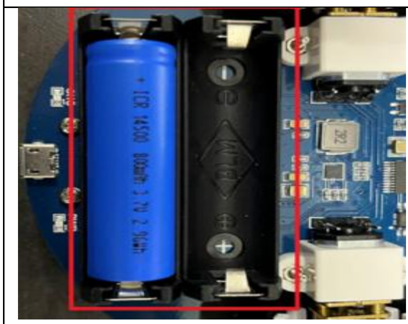
Programs used:

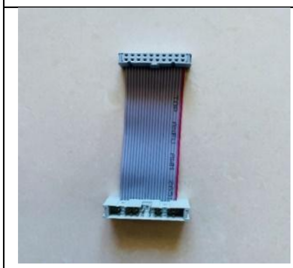
- **PyCharm 2023.2** – For programming and executing algorithms.
- **Putty** – For executing robot commands.
- **Raspberry Pi Imager v1.7.3** – for setting up the robot.
- **Advanced IP scanner –** To find the exact IP address of the device.
- **Command prompt –** To find the IP range.

## 3.8 List of components

Table 3.5 presents the key components and tools used in the design of the proposed in-pipe inspection robot.

| Component | Description |
| --- | --- |

| | |
|---|---|
| <br>**Figure 3.3: Screwdriver** | A screwdriver was used to fasten screws during the assembly of the robot components. |
| <br>**Figure 3.4: Remote Control** | A remote control was used to control and direct the robot's movement during operation. |
| <br>**Figure 3.5: Rechargeable Batteries** | Li-ion 14500 rechargeable batteries were used to supply power to the robot system. |
| <br>**Figure 3.6: Battery Holder** | The battery holder was used to secure the cells in position and transfer electrical power to the robot circuitry. |
| <br>**Figure 3.7: Power Supply** | Power adaptor that was used to provide a regulated electrical output to the robot. |

| | |
|---|---|
| <br>**Figure 3.8: Servo Motor** | A servo motor used electrical power to generate controlled rotational motion in a robot. |
| <br>**Figure 3.9: 16 GB Micro SD Card** | The 16 GB micro SD card was used to store the robot operating system, configuration files and algorithms. |
| <br>**Figure 3.10: Micro SD Card Reader** | A micro-SD card reader was used to transfer data between the micro-SD card and an external computer system. |
| <br>**Figure 3.11: 8 cm 20-Pin FFC Ribbon Cable** | The 8 CM 20-pin FFC ribbon cable was used to establish electrical connections between the robot's control board and peripheral components. |
| <br>**Figure 3.12: 5 cm 15-Pin Flexible Flat Cable(FFC)** | The 15 cm 15-pin flexible flat cable was used to connect the camera module to the motherboard. |

| | |
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| <br>**Figure 3.13: Mounting Screws** | The mounting screws were used to secure mechanical and electronic components to the robot chassis. |
| <br>**Figure 3.14: Brass Standoffs, Screws and Caps** | The braas standoffs, screws and caps were used to create spacing between circuit boards and provide a secure mounting within the robot structure. |
| <br>**Figure 3.15: Raspberry Pi 4 (4GB RAM Model)** | The Raspberry Pi 4 (4GB RAM model) was used as the robot's main processing unit. It executed control algorithms and managed system operations. |

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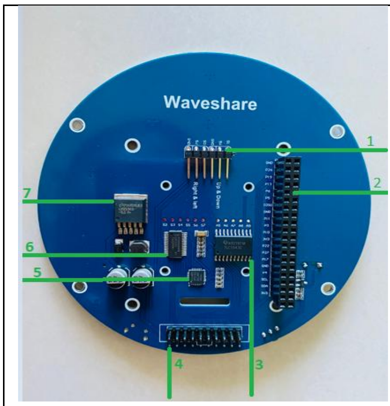
| <br>**Figure 3.16: Waveshare Servor Driver Expansion Board** | The Waveshare Servor Driver Expansion Board consisted of the following components:<br><br>**1. Servo Interface -** was used to connect and control multiple servo motors.<br>**2. Raspberry PI interface** – was used to establish communication between the expansion board and the Raspberry Pi control unit.<br>3. A **10-bit Analog-to-Digital (ADC) Acquisition Chip -** was used to convert analog sensor signals to digital data for processing.<br>4. **Control interface** - was used to connect additional peripherals modules to the robot base.<br>5. **USB to UART converter** - was used to enable communication between the robot and external device(s).<br>6. **Servo controller** - was used to generate precise signals for accurate servo motor positioning.<br>**7. 5 V Voltate regulator** - was used to regulate and stabilize the power supplied to connect components. |

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**Figure 3.17: Alphabot2-Pi Base Board**
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The alphabot2-Pi Base Board consisted of the following components:<br>
8. **Joystick -** was used to provide manual control input for directional movement during testing and configuration.<br>
9. **USB TO UART -** was used to enable serial communication between the robot system and external computer via UART protol.<br>
10. **Infrared Receiver (IR) -** was used to receive remote control signals for wireless operation of the robot.<br>
11. **Buzzer -** was used to generate audible signals for system notifications and operational feedback.
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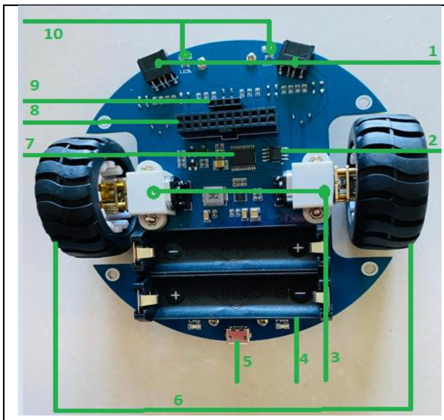



**Figure 3.18: Alphabo2-Pi Base assembly**

The alphabot2-Pi Base Assembly consisted of the following components:

1. **Sensors** - were used to detect obstacles and provide environmental feedback to the control system.
2. **Voltage Comparator -** was used to compare voltage levels from sensor inputs and generate corresponding digital signals.
3. **N20 Micro gear motor -** were used to drive the wheels and enable controlled movement of the robot.
4. **Battery container -** was used to securely house the power supply cells.
5. **Power indicator – was used to provide feedback on the power system's power status.**
6. **Rubber wheels -** were used to provide traction and support mobility across surfaces.
7. **Motor driver** – was used to control motor speed and direction based on the signals from the main controller.
8. **Control Interface** - was used to connect additional or adapter boards to the base platform
9. **Module interface -** was used to facilitate communication between expansion modules and the control board.
10. **Indicators LIGHT Emitting Diodes (LEDs)**

    **-** were used to provide visual status signals, including obstacle detection feedback.

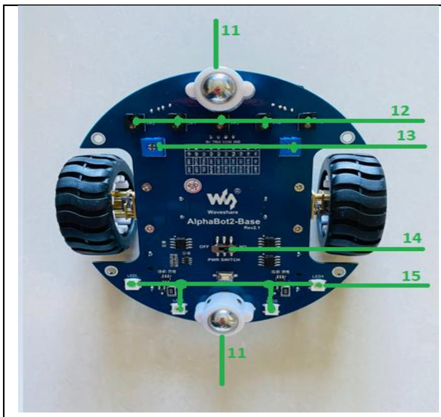
| | |
|---|---|
| <br><br>**Figure 3.19: Alphabot2-Pi Base(Bottom View)** | The alphabot2-Pi Base (bottom view) consisted of the following components:<br><br>11. **Omnidirectional Wheels -** were used to provide a balanced support and smooth multidirectional movement of the robot.<br>12. **Line-Tracking Sensors -** were used to detect lines during navigation.<br>13. **Potentiometer** - was used to adjust the obstacle-detection sensitivity and power range.<br>14. **Power Switch -** was used to turn the robot on and off.<br>15. **RGB LIGHT Emitting Diodes (LEDs) -** were used to provide multi-colour visual status indication. |

**Table 3.5: Description of components used**

Table 3.5 summarizes the hardware components that were integrated into the in-pipe inspection robot. The Raspberry Pi served as the central processing unit, coordinating sensor input, actuator control and communication processes. The servo driver and motor driver modules enabled controlled mechanical movement, while the sensors provided environmental feedback for navigation and obstacle detection. The power system, including batteries and voltage-regulating components, ensured the stable operation of all electronic modules. All these components formed an integrated embedded system designed to achieve controlled mobility and real-time monitoring within pipeline environments.

### 3.9 Ethical Considerations and Limitations

There were no human participants or sensitive data involved; therefore, formal ethical clearance was not required. Nevertheless, the experimental procedures were conducted responsibly, ensuring that the testing environment and equipment were used safely and appropriately. The experiments were conducted using decommissioned pipeline samples free of hazardous substances, and all components used were handled and disposed of in accordance wth standard safety and environmental guidelines. This ensured safe in-pipe inspection robot operation and minimized operational risk during testing, while preventing environmental contamination or material waste.

The limitations of the methodology include:

- Limited dataset size for deep learning due to resource constraints.
- Controlled testing pipelines that may not entirely replicate harsh field conditions.

## 3.10 Summary

This chapter presented the research methodology adopted for the development and evaluation of the proposed frugal robotic system for in-pipe corrosion detection. It offered an overview of research design, robot development process, and image processing techniques for corrosion detection.

In addition, the chapter introduced the standard performance metrics: Accuracy, Precision, Recall, and F1-Score employed to evaluate the effectiveness of the algorithms. The subsequent chapter presents the detailed design and configuration of the in-pipe inspection robot.

# CHAPTER 4: ROBOT DESIGN AND CONFIGURATION

## 4.1 Introduction

This chapter presents the design and configuration of the proposed in-pipe inspection robot. It begins by outlining the design objectives and system requirements that guided the development process, followed by the robot selection process. Next, the assembly process is discussed. Thereafter, robot configurations and setup are detailed. Lastly, robot testing is presented.

## 4.2 Design objectives and requirements

The in-pipe inspection robot was designed to operate inside pipelines of varying diameters, often located in remote and hazardous environments. To ensure that the system meets the study objectives, a set of functional and performance requirements were defined. Table 4.1 summarizes these requirements, including their measurable targets, design rationale, and verification techniques applied during the testing phase.

| ID | Requirements | Metric/Target | Rationale | Verification |
|---|---|---|---|---|
| **R1** | Low manufacturing cost | Total BOM cost ≤ R5000.00 | Ensure affordability and scalability | Review V1: BOM audit |
| **R2** | Ease of assembly | Assembly time = 1.5 hours | Simplify deployment | Test T1: Assembly trial |
| **R3** | Image capturing capabilities | Minimum image resolution ≥ 1080p with clear pipeline surface visibility | Enable Corrosion Detection | Test T2: Image quality assessment |
| **R4** | Ease of maintenance | Critical components replaceable | Reduce downtime | Test T3: Maintenance simulation |

| | | | | |
|---|---|---|---|---|
| | | within ≤ 15 minutes without specialized tools. | post-deployment | |
| **R5** | Corrosion detection | Detect ≥ **92.3%**, with CNN | Core functionality | Test T4: Algorithm performance validation |
| **R6** | Low power consumption | Runtime ≥ 3 hours | Extend operational time | Test T5: Power consumption measurement |
| **R7** | Wi-Fi connectivity | Stable connection within 50 m LOS | Remote monitoring | Test T6: Connectivity range test |
| **R8** | Bluetooth control functionality | Reliable short-range control | Easy to set up and test | Test T7: Bluetooth pairing and control test |
| **R9** | Obstacle avoidance | Detect obstacles from ≥ 3 CM | Ensure safe navigation | Test T8: Obstacle detection trial |
| **R10** | Maneuverability in confined spaces | Operate in pipes ≥ 200 mm diameter | Adapt to pipeline constraints | Test T9: Maneuverability assessment |

**Table 4.1: System Requirements and Verification Plan**

Table 4.1 summarizes the system requirements and corresponding verification procedures that guided the design and implementation of the in-pipe inspection robot. The requirements influenced both hardware configuration and software development of the in-pipe inspection robot and served as a basis for the experimental evaluation presented later in this chapter.

### 4.3 Robot selection process

Several robotic platforms were assessed against the system requirements outlined in Table 4.1. The **Alphabot2-Pi mobile robot** was selected because it met key design requirements, including affordability, sensing capability, wireless connectivity and mobility within confined spaces. The AlphaBot2 is a wheeled robot that features both rubber and omnidirectional wheels. It is equipped with sensors for obstacle avoidance, Bluetooth, and Wi-Fi connectivity, allowing the robot to be remotely controlled and monitored via mobile devices, particularly useful in remote or semi-field environments where desktop access may be limited.

Furthermore, it was equipped with the following features:

a. Real-time video-based monitoring for systematic observation and analysis.
b. Obstacle avoidance, designed to navigate physical obstructions.
c. Line tracking, which integrates a 5-channel infrared (IR) detector to sense and analyze the black line, combined with a Proportional-Integral-Derivative (PID) for adaptive robot movement. It provided high sensitivity, enabling stable tracking performance.
d. Infrared remote control, used for controlling the robot's movement.

These features were selected to ensure the in-pipe inspection robot meets the functional requirements outlined in Table 4.1, particularly those related to navigation, sensing and remote operation.

### 4.3.1 Platform Comparison Overview

Although AlphaBot2 was the primary platform explored in this project, other platforms, such as tracked crawlers, magnetic wheel crawlers, and articulated in-pipe robots, were considered in the literature. A high-level comparison is shown in Table 4.2. This table presents a conceptual comparison based on general engineering literature and publicly available specifications. Only AlphaBot2 was explored and tested in this project.

| Type | Cost | Maneuverability | Traction | Payload | Minimum Bend Radius | Complexity |
|---|---|---|---|---|---|---|
| **AlphaBot2** | Low | Moderate | Low on bands | Low | Moderate | Low |
| **Tracked Crawler** | High | Low | High | High | Large | High |
| **Magnetic Wheel Crawler** | Medium | High | High | Moderate | Small | High |

| | | | | | | |
|---|---|---|---|---|---|---|
| **Articulated In-Pipe Robot** | High | High | Moderate | Moderate | Small | Very High |

**Table 4.2: Comparative Trade-Study of Robotic Platforms**

Table 4.2 presents a comparative evaluation of potential robotic platforms based on cost, maneuverability, traction, payload, minimum bend radius and complexity. Even though tracked crawlers and articulated in-pipe robots offer higher traction and payload capabilities, these types introduce greater mechanical complexity, higher implementation cost and increased design overhead for the scope of this study. Magnetic wheel crawlers are also good, providing strong surface adhesion; however, they require specialized pipeline conditions and increase system integration requirements.

AlphaBot2, on the other hand, provides a balanced combination of compact size, sufficient maneuverability for controlled pipeline experiments and relatively low system complexity. Given the objective of developing a portable, cost-effective in-pipe inspection robot, AlphaBot2 was therefore selected as the most appropriate platform for robot development and experimental validation.

### 4.3.2 Field Constraints of AlphaBot2

While suitable for laboratory-based prototyping and controlled pipeline experiments, the AlphaBot2 presents several limitations for real-world field deployment:

a. Limited traction over pipeline bends and welded joints, which could affect AlphaBot2 mobility on uneven internal pipeline surfaces.
b. Lack of environmental sealing, making the AlphaBot2 unsuitable for wet or chemically aggressive conditions.
c. Absence of Explosion-proof (Ex) certification, preventing safe use in hazardous or explosive industrial atmospheres.

These constraints indicate that the developed robot is intended primarily for controlled experimental validation rather than direct industrial deployment.

### 4.3.3 Bill of Materials (BOM)

For a detailed cost breakdown, refer to Table 3.1(Chapter 3, Section 3.3.1). The total estimated cost of **R4,194.05** confirms that the developed in-pipe inspection robot remains consistent with the objective of developing a frugal, portable and experimentally viable inspection robot.

The image used to train and test the CNN model was captured with a standard smartphone camera (iPhone). The use of a consumer-grade camera demonstrates that the proposed in-pipe inspection approach does not rely on specialized or expensive industrial imaging equipment. This further supports the system's frugal design objective, as corrosion and crack detection can be performed using widely available, low-cost imaging devices.

### 4.3.4 Sensor selection and integration

Selecting and integrating appropriate sensors is pivotal when designing and developing a corrosion detection mechanism. According to ganguly (2021), sensors play a pivotal role in facilitating environmental awareness within robotic systems. The robot came with the following sensors:

a. **ST188**: Reflective infrared photoelectric sensor which detects objects and ensures that they are avoided. It is composed of a high-sensitivity transistor and an LED with high transmit power.
b. **ITR20001/T** : A reflective infrared photoelectric sensor employed for line-tracking.

By leveraging its integrated sensors, the robot accurately detected the obstacles. This capability allowed the robot to autonomously avoid obstacles by stopping and beeping when an object was detected. This is a good feature, as it will enhance operational safety and reliability during inspections.

In addition to supporting navigation, these sensors work alongside the vision-based inspection system. The line-tracking sensor ensures that the robot follows the predefined inspection paths, enabling consistent image capture along the inspection surface. The obstacle detection sensor enhances operational safety by preventing collisions during movement. While these sensors support navigation and environmental awareness, the onboard camera captures images of the inspected area. These images are processed by the CNN model to detect corrosion and crack defects. This integration of sensor-based navigation and vision-based inspection enables the robot to autonomously navigate the inspection environment while reliably detecting defects.

### 4.3.5 Camera

This study employed a Pi 5MP HD Camera securely mounted on the robot and configured to 1080P resolution to capture images. The camera provided real-time streaming of the pipe's interior, allowing images to be mined from the video and archived for further analysis. However, the image quality was compromised by the camera's inherent resolution limitations. A more advanced, high-resolution camera was used to mitigate the limitations of the initial robot camera.

### 4.3.6 Power system

For the duration of the autonomous operation indicated, the power system must provide the system with energy (Dertien, 2014). During the development phase, the robot was connected via a power cable. Subsequently, the 14500 Li-ion 14500 rechargeable batteries were used**.** Their electrical characteristics, presented in Table 4.3, provide adequate voltage and capacity to support sensing, processing and mobility functions while maintaining the objective of a lightweight, frugal in-pipe inspection robot**.**

| | |
|---|---|
| Model | 14500 |
| Nominal capacity | 800 mAh |
| Nominal voltage | 3.7 V |
| Rechargeable times | Up to 500 |
| Standard weight | 19g |

**Table 4.3: Battery Specification**

The battery specification shown in Table 4.3 confirms that the selected batteries provide sufficient voltage and capacity to support the robot's processing and mobility requirements.

### 4.3.6 Wheel configuration and mobility

Selecting appropriate wheels is crucial for ensuring directional control and maneuverability of the in-pipe inspection robot. Therefore, omnidirectional wheeled solutions were considered to improve maneuverability in confined pipeline environments (Shabalina et al., 2018). The robot was equipped with both traditional and omnidirectional wheels. This wheel selection was essential for safe maneuvering within the pipelines. However, AlphaBot2 had difficulty navigating around the pipe bands, leading to occasional navigation issues.

### 4.4 Assembly process

After completing the design and sourcing all components, the robot was assembled.
The Key steps included:

1. Mounting the batteries to the base chassis.
2. Connecting the 8**CM FC 20P** cable to the chassis.
3. Connect the crew pillars and caps.
4. Assembling the steering gear, pan, and tilt
5. Connect the FCC cable to the camera and secure it in place with the clamp on the steering gear.
6. Connecting the camera to the board.
7. Connect the camera cable to the Pi robot.
8. Plug the other side of the table to the adapter board.
9. Connect the adaptor board to the base board using screws.

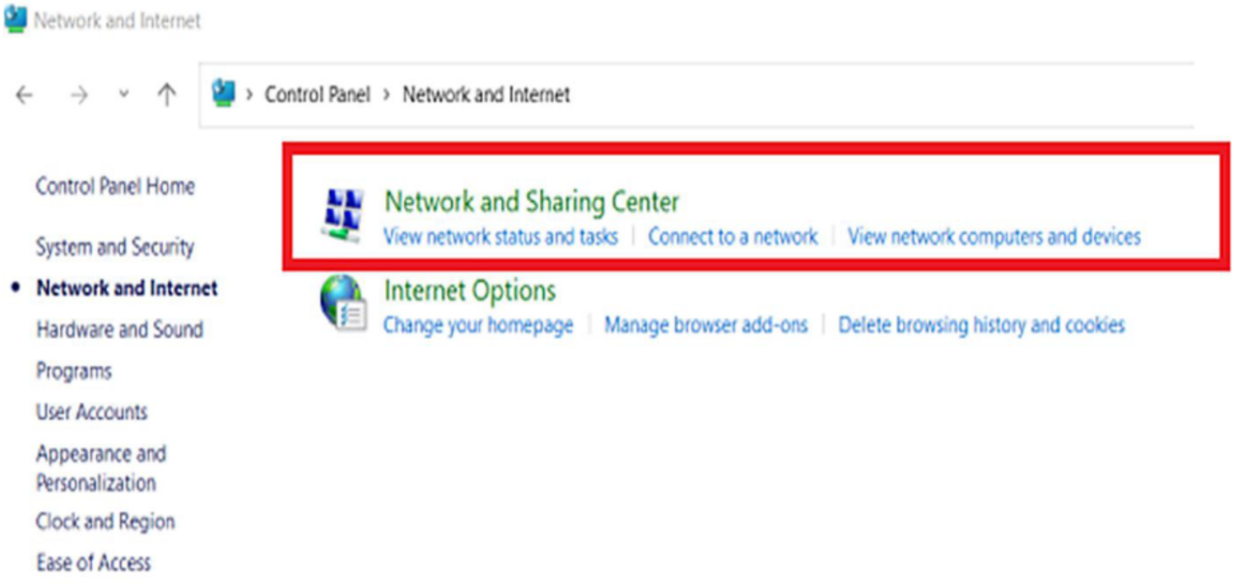
### 4.5 Robot Configurations and Setup

This section provides a detailed overview of the robot's setup and configurations. The first step ensures the integration process between the robot and the laptop is effective.

#### 4.5.1 Connecting the robot to the laptop using Ethernet and USB cables

To establish communication between the robot and the laptop, the Ethernet and USB connections were configured on the host computer. The configuration process involved setting network sharing options, assigning Internet Protocol (IP) settings, and verifying connectivity between the devices.

The detailed 7-step configuration procedure followed in this study is presented in Table 4.4.

| Step | Action |
|---|---|
| 1 | <br><br>**Figure 4.1: Accessing the Network and Sharing Centre through the control panel in Windows**<br>Figure 4.1 illustrates how the network and sharing center were accessed in windows control panel by navigating to Control Panel → Network and Internet → Network and Sharing Center.<br>This step allowed the researcher to view and manage active network connections before selecting the wireless network for further configuration. |

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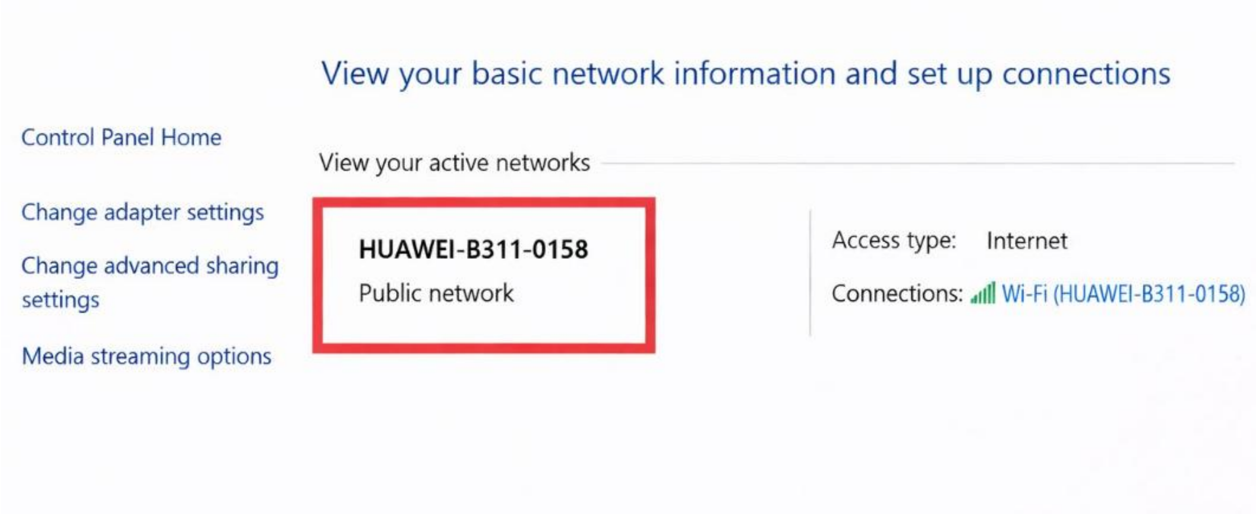


**Figure 4.2: Selecting the active Wireless Network Connection in the Network and Sharing Center**

The active wireless network connection was selected to access the properties dialog for further configuration.
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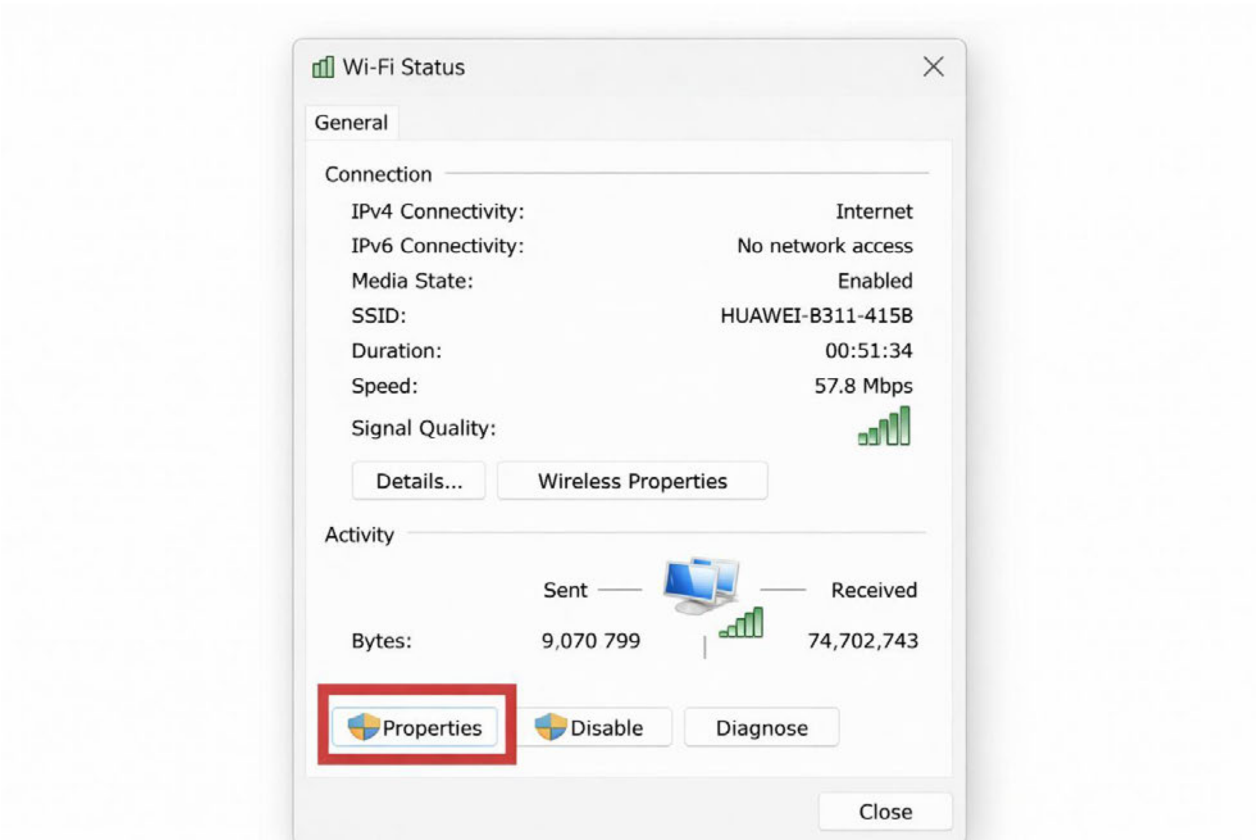
<td>3</td>
<td>



**Figure 4.3: WI-FI status window showing the Properties option for the active wireless connection.**
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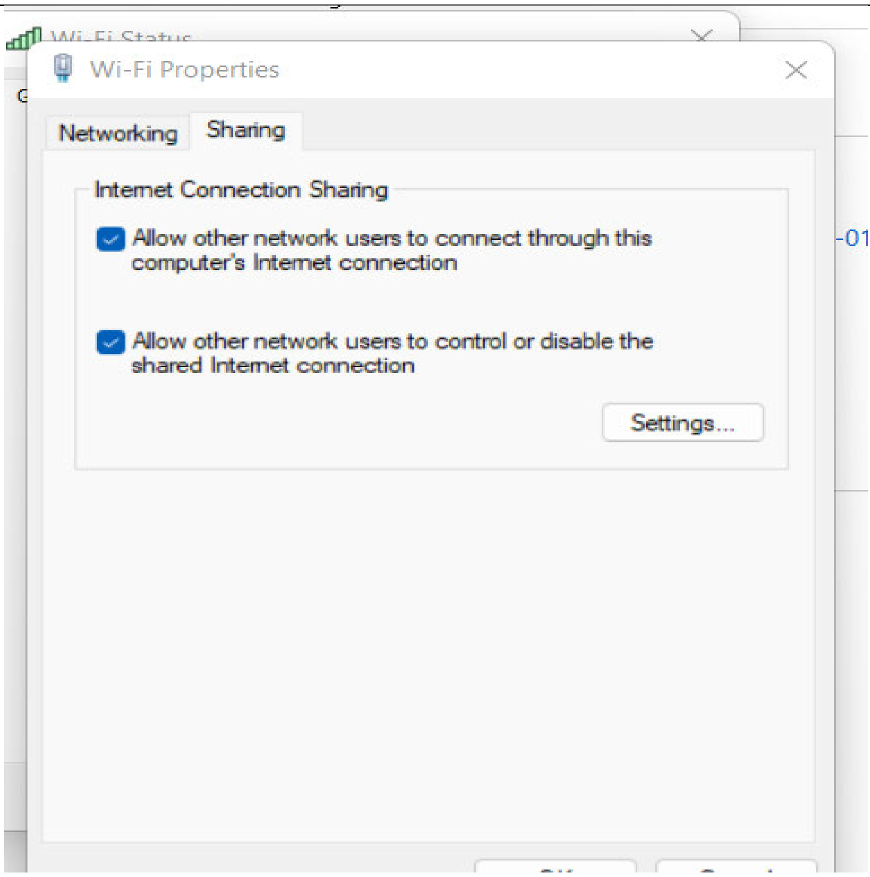
<tr><td></td><td>Figure 4.3 illustrates the Properties button that was clicked to open the Wi-Fi Properties window with network configuration settings.</td></tr>
<tr><td>4</td><td>

Figure 4.4: WI-FI Properties window showing the Sharing tab and Internet Connection Sharing Options<br><br>As shown in Figure 4.4, the Sharing settings were configured to control internet access.</td></tr>
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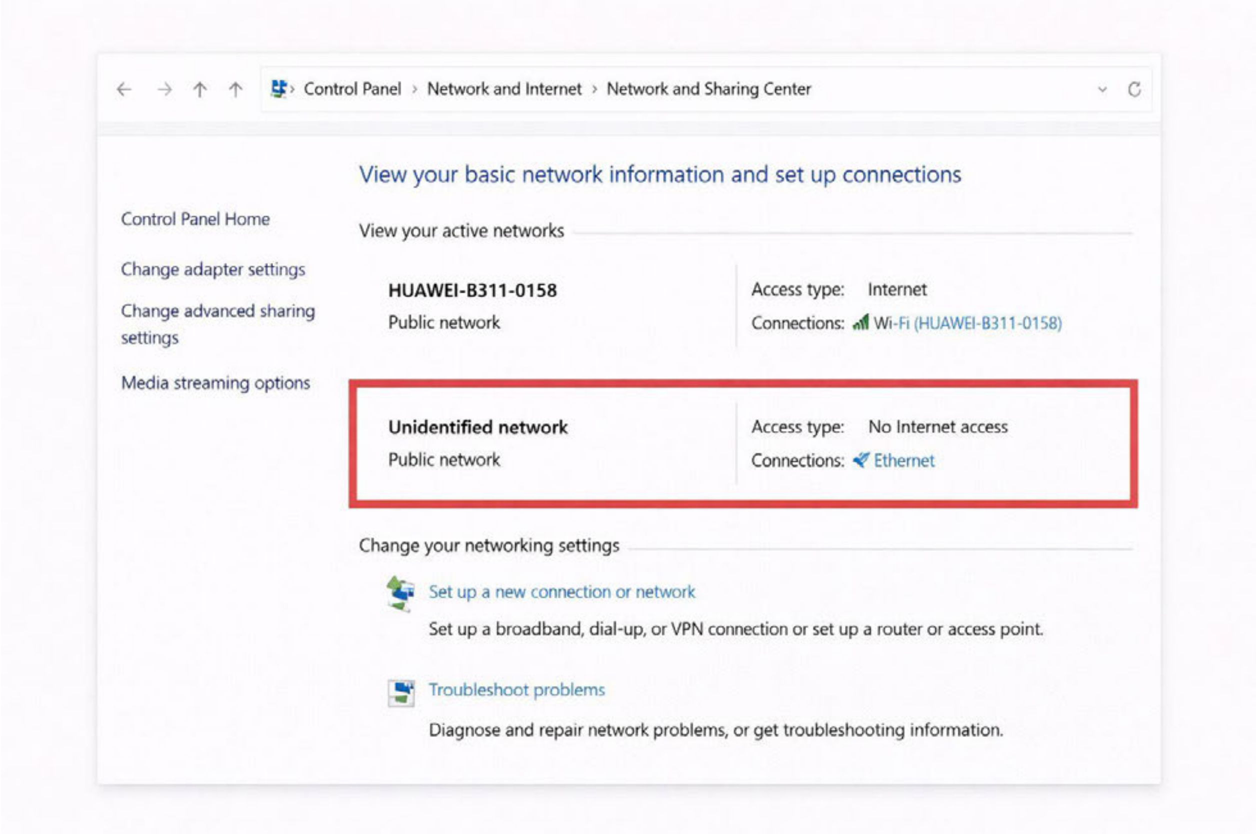
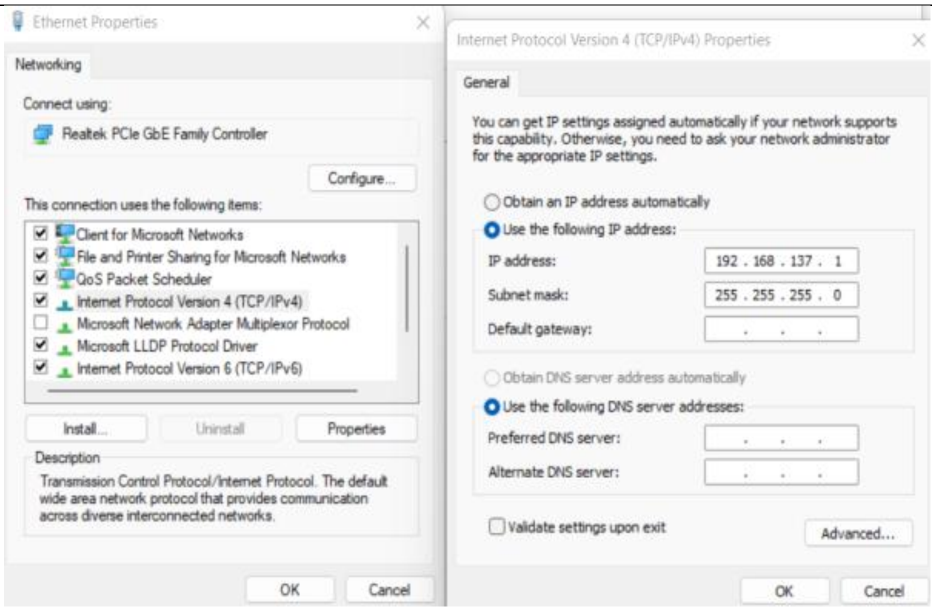
|---|---|
| | <br>**Figure 4.5: Network and Sharing Center showing the detected network connections and access status**<br>Figure 4.5 shows the available network connections, allowing the researcher to verify the active wireless connection and identify any additional networks before proceeding with configuration. |
| 6 | <br>**Figure 4.6: Internet Protocol Version 4 (TCP/IPv4) Properties window showing manual IP configuration settings** |

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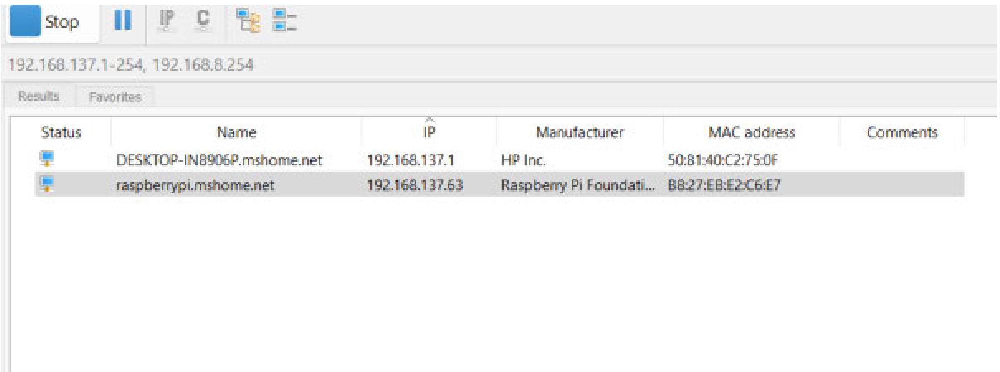
<tr><td>7</td><td>



**Figure 4.7: Advanced IP Scanner for displaying IP addresses**

To find the exact IP address, an advanced IP scanner was used. The robot's IP address is 192.168.137.63, as shown in Figure 4.7.
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</table>

**Table 4.4: Robot Configurations**

Table 4.4 summarizes the sequential steps followed to implement the model and ensure correct system operation.

### 4.6 Robot Testing

Robot testing is a critical aspect of the development process, as it validates both functionality and reliability of the prototype. The in-pipe inspection robot underwent rigorous evaluation in pipelines of various diameters. These tests were conducted to assess the effectiveness of the algorithms and functionality.

During the field trials, the robot was inserted into the pipelines to verify its ability to navigate internal paths, detect and avoid obstacles, and capture images for inspection purposes. Despite the robot's omnidirectional wheels, it had difficulties climbing the wall. The robot effectively avoided obstacles and captured images. However, the pictures were of low quality; as a result, a high-performance camera was integrated to improve image quality. The battery runtime test was also conducted, lasting about 3 hours. **Figure 4.8** illustrates the robot's testing in a 200 mm diameter pipeline.

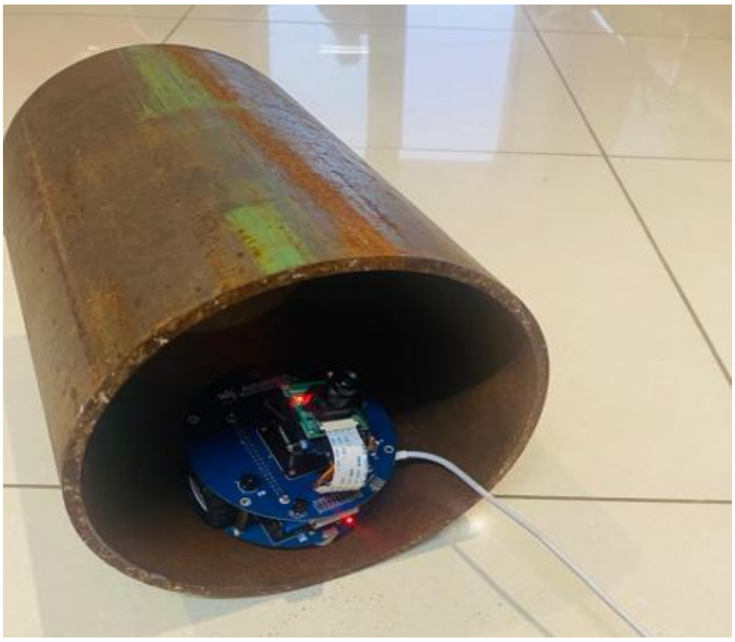

**Figure 4.8: In-pipe inspection robot inside a 200 mm diameter pipe**

Figure 4.8 shows the inspection robot positioned inside the 200 mm diameter pipeline during testing.

### 4.6 Summary

This chapter outlined the design and configuration of the frugal robot developed to detect corrosion in pipelines. The discussion focused on finding a workable balance between cost, functionality, and reliability, since all these elements had to complement each other for the robot to operate efficiently in pipelines. The seamless integration of mechanical and electronic systems enabled the robot to perform inspections effectively in the challenging pipeline environment. In addition to explaining the main components, the chapter reflected on how the design choices were shaped by practical constraints such as affordability, material availability and ease of construction. All the considerations proved that effective corrosion detection does not necessarily require expensive or highly complex material. A carefully thought-out minimalist approach can also deliver valuable results. Overall, this chapter illustrated that a cost-conscious, yet technically sound design can provide a reliable foundation solution for corrosion detection in the O&G sector.

# CHAPTER 5: RESULTS AND DISCUSSIONS

## 5.1 Introduction

This chapter presents the experimental results obtained by implementing and evaluating multiple corrosion detection approaches, including Canny edge, Sobel, K-Means, and a convolutional neural network (CNN) model, applied to pipeline inspection images. The approaches were assessed using either a stratified dataset split into training and testing sets or through k-fold cross-validation to ensure balanced representation and robust performance assessment.

The results were analysed using standard performance metrics, including accuracy, precision, recall, and F1 score. These metrics clearly show how each method performs when distinguishing between corroded, cracked and non-corroded images. The comparative assessment highlights the strengths and weaknesses of each algorithm in distinguishing between corroded, cracked and non-corroded images. It then concludes by discussing the practical implications of these findings for frugal robotic systems in the oil and gas (O&G) sector.

## 5.2 Corrosion Detection Performance Metrics

The image dataset was divided into two categories: Corroded and Non-Corroded pipeline sections. Each algorithm was evaluated separately in both categories. The following subsections provide detailed results.

### 5.2.1 Canny Edge

To determine the robustness of the Canny edge algorithm in pipeline inspection, two image types were analyzed: corroded and cracked, and corrosion-free images. The algorithm was configured with a **low threshold of 50**, a **high threshold of 150**, and a **Gaussian smoothing parameter (σ) of 1.4** to reduce noise before edge detection. **Figure 5.1** presents the performance results of the Canny edge detector method when used to identify corrosion

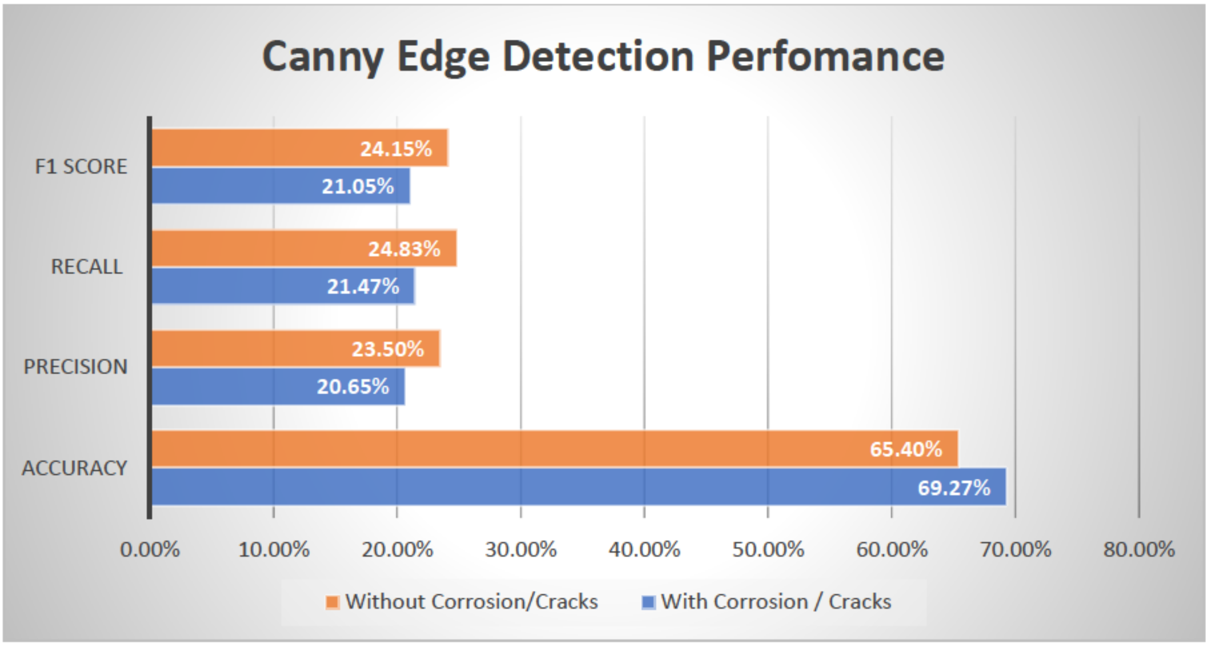

**Figure 5.1: Performance Metrics of Canny Edge Detection for Corrosion Identification**

The results in Figure 5.1 demonstrate that while the Canny edge detector identified edges in both defective and non-defective images, it lacked discriminative capability. Although overall accuracy reached 69.27% for images with corrosion or cracks and 65.40% for non-corroded images, the consistently low precision and recall values indicate poor defect localization performance. The low recall suggests that a substantial proportion of actual defect regions were missed, while the low precision reflects false-positive detections caused by background textures and surface irregularities.

The precision values were relatively low in both scenarios (20.65% for defective images and 23.50% for non-defective images), indicating a high number of false-positive detections. Correspondingly, recall scores remained low (21.47% and 24.83%), suggesting that many actual defective regions were not successfully detected. Consequently, the F1 scores (21.05% and 24.15%) confirm the imbalance between precision and recall, highlighting the algorithm's inability to reliably distinguish true structural defects from background textures.

These results raise concerns about its suitability for automated inspection tasks, where predictable and accurate detection is crucial. When the algorithm incorrectly flags normal surface textures, such as cracks or corrosion, it may trigger unnecessary alerts and waste maintenance resources on otherwise healthy pipelines. Because of these limitations, further improvements are needed. Potential enhancements could include more refined feature engineering techniques or even adopting more advanced techniques, such as CNN. These alternatives were explored and are discussed further in the subsequent sections.

**Figure 5.2** presents the output of the canny edge detection algorithm applied to an image containing visible cracks and corrosion.

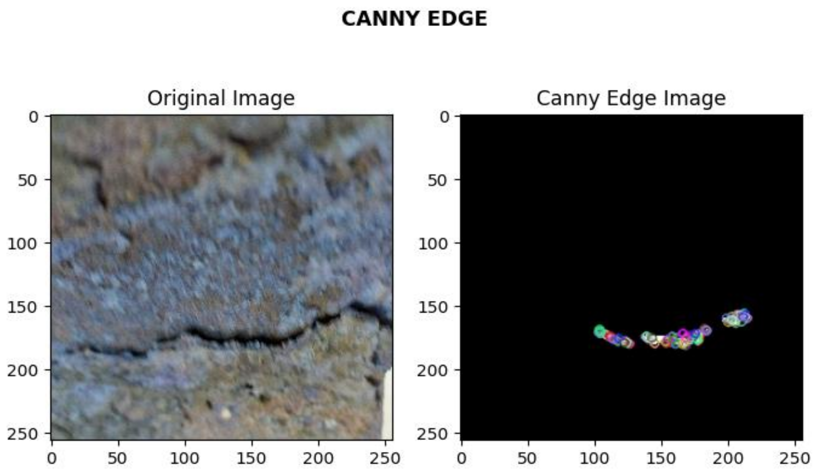


**Figure 5.2: Canny Edge Detection Result  for an Image Containing Visible Cracks and Corrosion**

Figure 5.2 shows that the Canny edge method successfully detected portions of the visible cracks; however, several crack and corrosion segments were missed. This partial detection highlights the algorithm’s limited sensitivity to subtle defect boundaries within complex surface textures.

Figure 5.3 presents the output of the canny edge detection algorithm applied to an image containing surface marks but no structural cracks or corrosion.

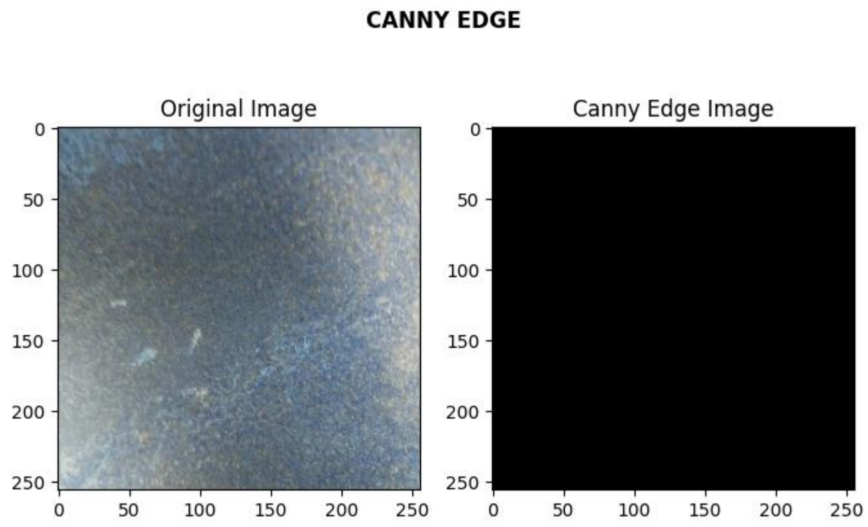


**Figure 5.3: Canny Edge Detection Output for an Image containing Surface Marks without Cracks and Corrosion**

The resulting edge image shows minimal boundary extraction, indicating that the Canny edge detector did not interpret the surface marks as significant structural defects. This suggests that, in this instance, the algorithm demonstrated selectivity by avoiding false detections of non-defect features. However, when considered alongside the overall of low precision and recall scores, this selectivity appears inconsistent across different image conditions.

### 5.2.2 Sobel

The performance metrics obtained from the Sobel edge detection model for both corroded and non-corroded images are presented in Figure5.4.The comparison evaluated the model's effectiveness for corrosion identification using accuracy, precision, recall, and F1 score.

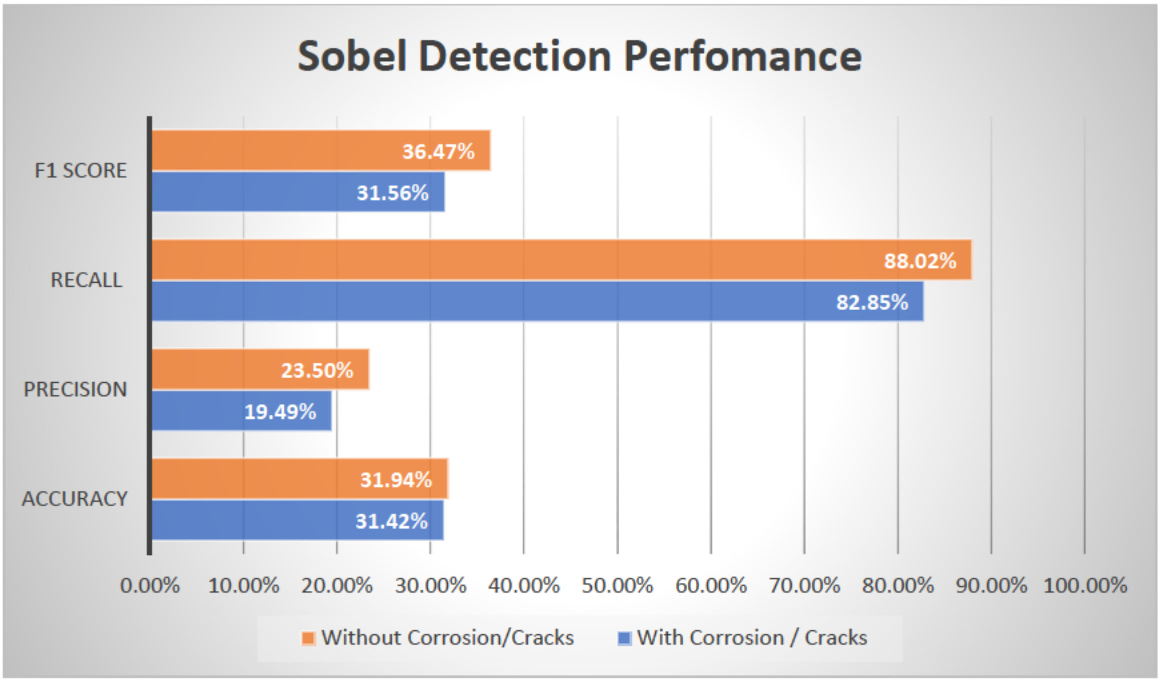


**Figure 5.4 : Performance Metrics of Sobel for Corrosion Identification**

Figure 5.4 demonstrates that the Sobel model achieved high recall scores of **82.85%** for corroded and **88.08%** for non-corroded images. These results show that the model detected the majority of corroded, cracked, and non-corroded regions, indicating strong sensitivity to edge information. In a pipeline environment, this level of recall is not unexpected, as failing to identify cracks and corrosion could result in serious safety risks. The model's ability to capture such features suggests that it is effective at identifying potential defects.

However, the precision scores **of 19.49%** for the corroded images and **23.00%** for the non-corroded images were extremely low. These low-precision values indicate that the model produced many false positives, incorrectly marking many regions as corroded or cracked when they were not. This behavior reduces the practical usefulness of the Sobel operator, as a high number of false alarms could lead to unnecessary inspections and reduce trust in the system's output during real-world deployment.

The overall accuracy and F1 scores, which ranged from **31%** to **36%,** were also low, reinforcing that, while the model successfully detected many true edges, it struggled to generate balanced and reliable predictions across both categories. This imbalance highlights the difficulty of relying on only Sobel edge detection for effective corrosion detection.

To further evaluate the effectiveness of the Sobel operator, a visual comparison was conducted between the original pipeline surface image and the corresponding Sobel-processed output. The results are presented in Figure 5.5 to illustrate how edge detection highlights potential corrosion and crack regions.

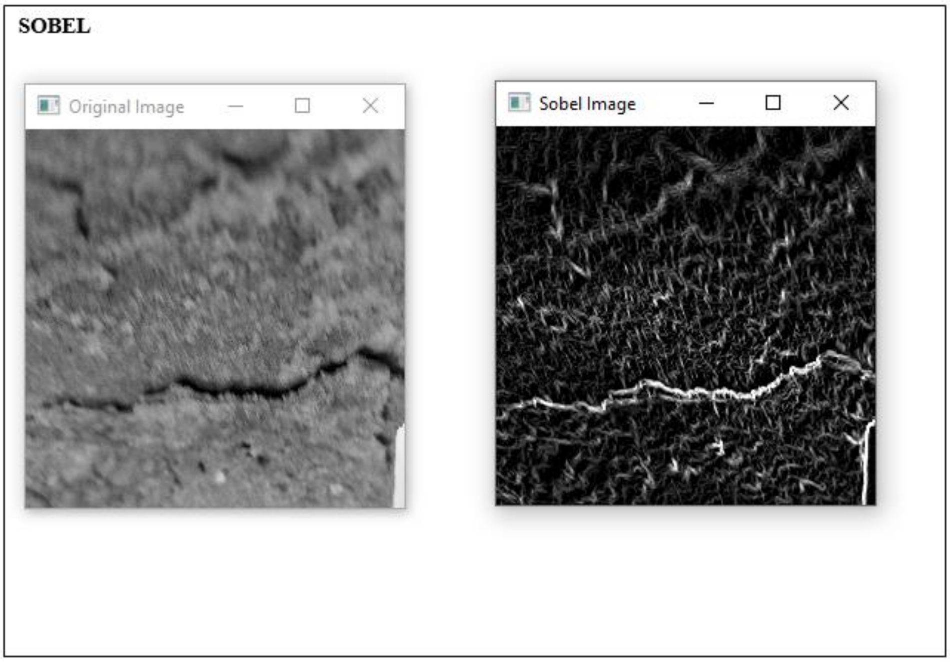


**Figure 5.5: Visual Output of the Sobel Operator for Corrosion and Crack Detection**

As shown in Figure 5.5, the Sobel operator enhances edge detection features by emphasizing intensity gradients within the image. The processed image clearly highlights the crack boundaries and corroded regions; however, it also detected numerous non-defect edges caused by surface texture variations. This visual outcome supports the quantitative results, demonstrating high sensitivity but limited precision due to the detection of irrelevant edge features.

To assess the behavior of the Sobel operator on non-corroded surfaces, a sample image without visible corrosion was processed during edge detection. The results are presented in Figure 5.6 to evaluate whether the operator can distinguish between defect-related edges and normal surface texture.

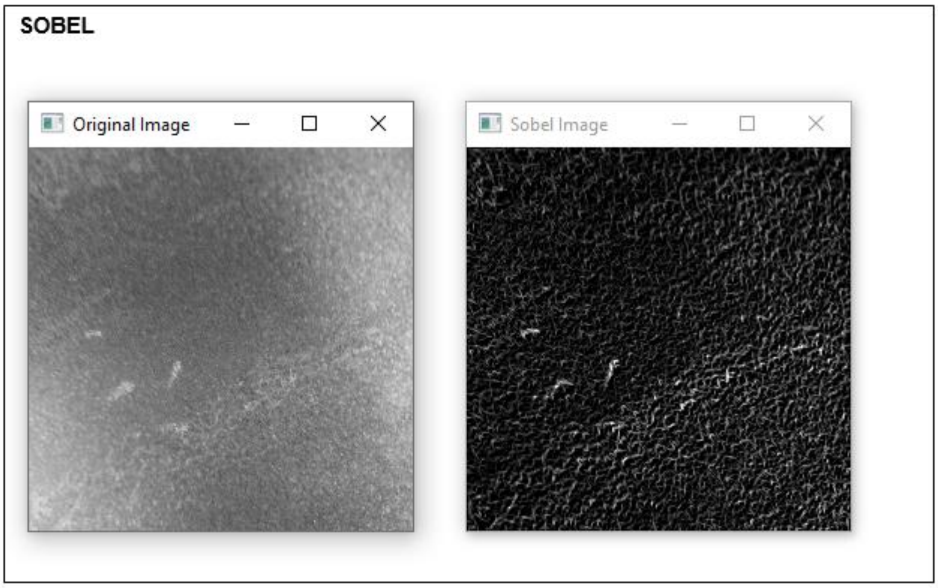


**Figure 5.6: Sobel Edge Detection Output for a Non-Corroded Pipeline Surface**

As illustrated in Figure 5.6, the Sobel operator highlights numerous edge features across the non-corroded surfaces. Even though no significant cracks or corrosion were present, the algorithm detected variations in surface texture as edges. This explains the low precision observed in the quantitative results, as the operator is unable to effectively distinguish true defect boundaries from normal surface irregularities.

### 4.2.3 K-Means Clustering

The performance of the K-means clustering algorithm was evaluated using accuracy, precision, recall and F1 score metrics for both corroded and non-corroded image classes. The comparative results are presented in Figure 5.7 to assess the model's effectiveness in distinguishing corrosion-related patterns from normal surface textures.

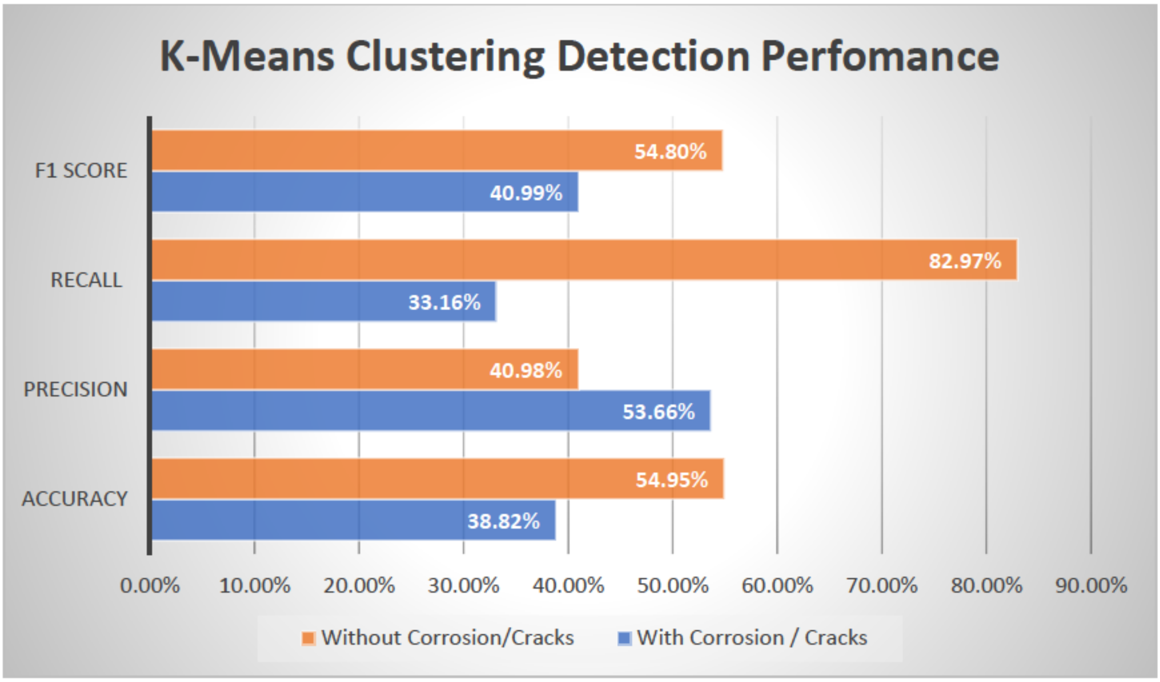


**Figure 5.7: Performance Metrics of the K-means Clustering Model For Corrosion Detection**

As shown in Figure 5.7, the K-means model achieved moderate precision on corroded or cracked images, correctly classifying **53.66%** of the samples. However, its recall was relatively low at **33.16%,** meaning that a large portion of the corroded regions were not detected**.** The F1 score of **40.99%** indicates that the model struggled to achieve balanced performance in identifying corroded or cracked samples while avoiding false positives. The accuracy score of **38.82%** also indicates difficulty in correctly identifying corrosion overall.

In contrast, the clustering approach performed better in identifying non-corroded areas. The model achieved a high recall of **82.97%,** indicating that most non-corroded samples were correctly identified. However, its precision of **40.98%** remained relatively low. This implies that a substantial number of false-positive samples were incorrectly classified as non-corroded. This imbalance is also reflected in the F1 score of **54.80%.** The overall accuracy for this class was comparatively higher at 54.95%, though still not ideal for reliable deployment. These results indicate that the model favors recall over precision, especially in the non-corroded class. This could be due to noise in the input data.

To further evaluate the clustering approach on defective surfaces, a corroded pipeline containing visible cracks was segmented using the K-means clustering algorithm. The visual results are presented in Figure 5.8.

**K-Means**

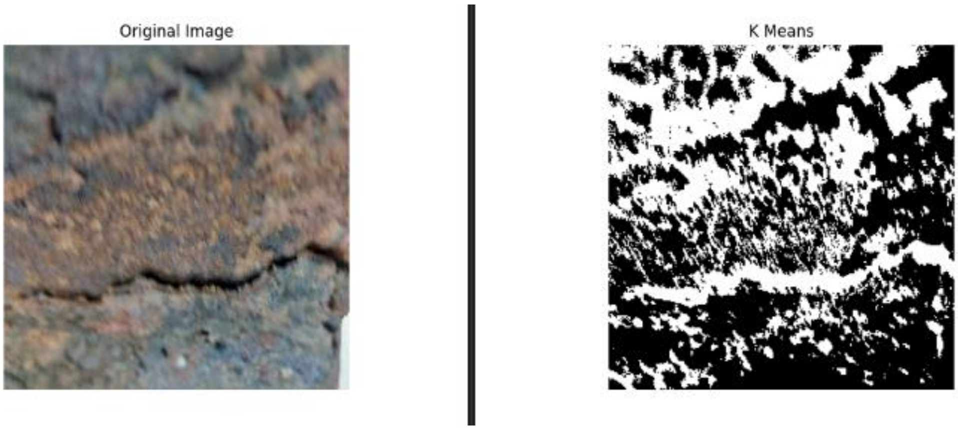


**Figure 5.8: K-Means Clustering Output for a Corroded Pipeline with Cracks**

As illustrated in Figure 5.9, the K-means algorithm partitioned the image into distinct clusters based on pixel intensity variations. While portions of the crack and corroded regions were detected, the segmentation also included significant background areas, indicating incomplete separation between defect features and normal surface textures. These visual results align with the quantitative results, particularly the low recall  of 33.16% for corroded images, suggesting that the clustering method struggled to fully capture the complex and irregular patterns associated with corrosion.

The k-means clustering technique was also applied to the non-corroded surface image to evaluate its effectiveness in segmenting surface regions. The results are presented in Figure 5.9

**K-Means Clustering**

**Original Image** **K-means**

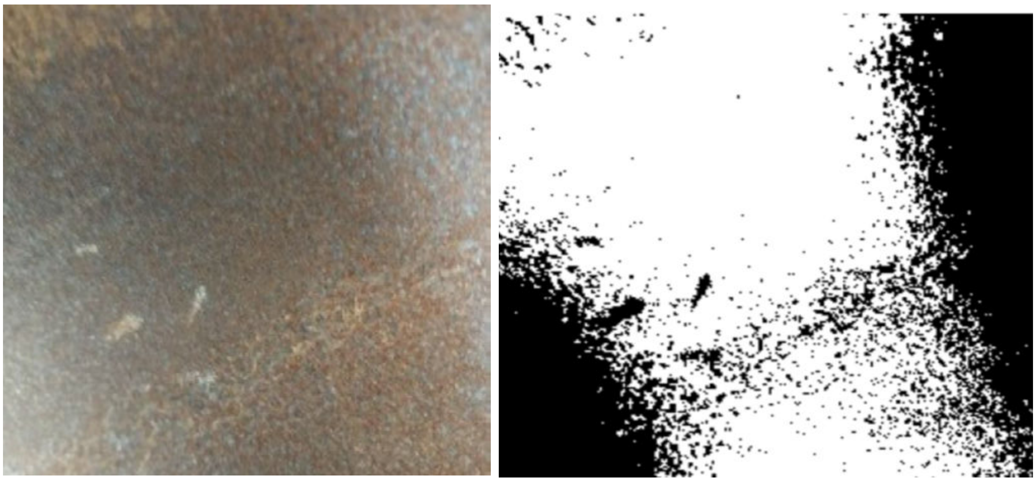

**Figure 5.9: K-Means Clustering Output for a Non-Corroded Pipeline with Cracks**

As shown in Figure 5.8, the K-means clustering algorithm segmented the non-corroded images. However, the output indicates that some of the surface marks and texture variations were classified as separate clusters that resemble corrosion regions. This implies that the algorithm is sensitive to minor intensity fluctuations and may incorrectly interpret normal surface irregularities as corrosion. This highlights the limitation of the K-means approach when applied to images with natural texture variations.

### 5.2.4 Convolutional Neural Network (CNN)

The Convolutional Neural Network (CNN) was trained using a structured dataset consisting of 200 pipeline images. The dataset was divided into training and testing subsets to enable supervised learning and performance evaluation. Each subset contained two classes: Corrosion and No-Corrosion, as illustrated in Figure 5.10. Images containing corrosion and cracks were grouped into a single corrosion defect class and evaluated against non-defective surfaces.

The images used in the dataset were captured during the experimental inspection process using a consumer-grade smartphone camera. Despite the dataset being limited, data augmentation techniques such as image rotation, horizontal flipping and brightness adjustments were applied during training to increase dataset variability and improve model generalization. Care was also taken to maintain a reasonable balance between corrosion and non-corrosion images to minimize potential bias during model training and evaluation.

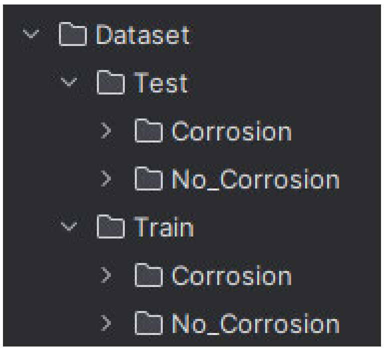

**Figure 5.9: Dataset Structure**

As shown in Figure 5.10, the dataset was organized into separate training and testing directories, each containing corrosion and non-corrosion image categories. This structured arrangement ensured proper class labeling. The clear separation of classes enabled the CNN model to learn discriminative features associated with corrosion patterns while being objectively assessed on unseen trained data.

**Figure 5.11** presents the performance metrics of the CNN model for corrosion and crack detection in pipeline images. The evaluation includes accuracy, precision, recall and F1 score to assess the model's effectiveness in differentiating defective and non-defective regions in pipelines.

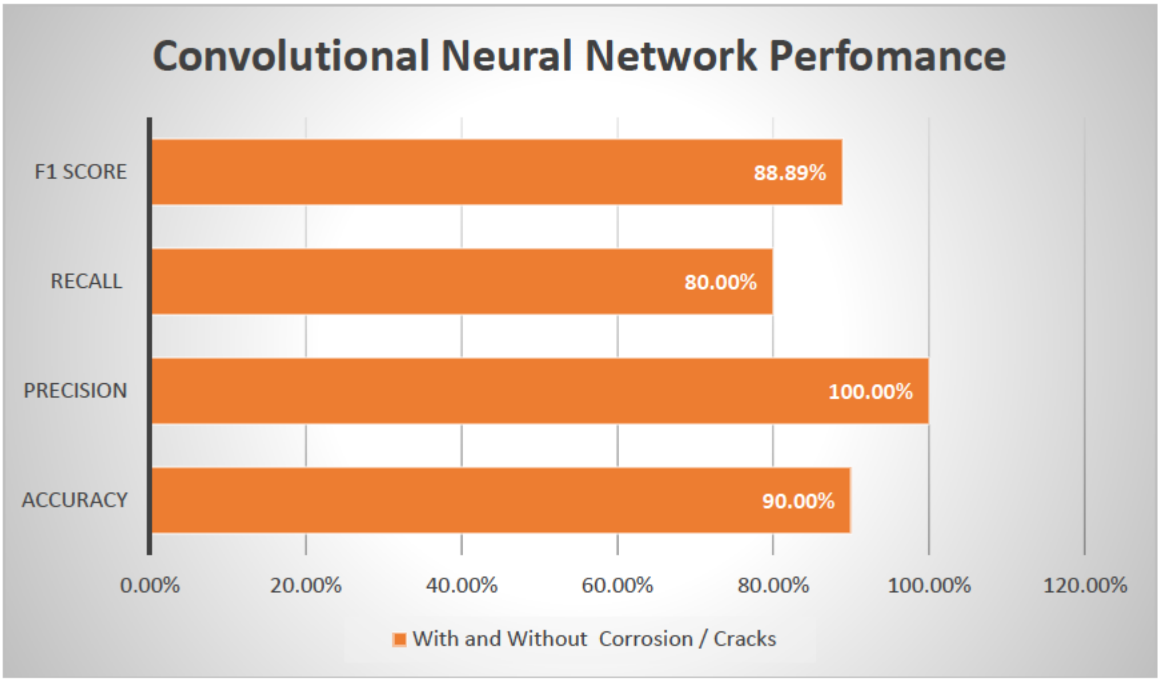


**Figure 5.10: CNN Performance Comparison**

The CNN model achieved an overall accuracy of **90%,** indicating reliable performance in distinguishing between corroded, cracked, and non-corroded pipeline images. One of the most impressive outcomes was its 100% precision score. This means that every image the model labelled as containing corrosion or cracks was genuinely a defect, with no false alarms recorded. In other words, whenever the model flagged a problem, it was indeed correct.

However, the recall score was **80%.** This score indicates that although the model avoided false positives, it did miss about **20%** of the actual defective areas. Further examination of the classification outcomes and misclassified samples indicates that missed detections were primarily due to subtle corrosion patterns, low-contrast regions, or even early-stage surface degradation that shared visual similarities with normal pipe textures. This highlights a limitation in the model's sensitivity to less prominent defect features.

The F1 score of **88.89%** provides a balanced view of the model's performance, showing that the CNN handled the trade-off between precision and recall fairly well. Collectively, these results highlight the CNN's strength in identifying real defects but also reveal that some subtle corrosion features were overlooked.

Following the evaluation of the CNN model against traditional techniques, a detailed error analysis was conducted to assess its reliability within an in-pipe inspection robot.

#### 5.2.4.1 Error Analysis of the CNN-Based Inspection Module

To gain deeper insight into the CNN model's classification behavior, a confusion matrix was generated. Table 4.1 presents the confusion matrix results.

| | **Predicted non-corrosion** | **Predicted Corrosion** |
|---|---|---|
| **Actual Non-Corrosion** | 30 (TN) | 0 (FP) |
| **Actual Corrosion** | 6 (FN) | 24 (TP) |

**Table 5.1: Confusion results for CNN-based Inspection Module**

Table 5.1 shows that the CNN model correctly classified 30 non-corroded surfaces and 24 corroded and cracked surfaces. No false positives were recorded, indicating that the model did not incorrectly flag healthy pipeline sections as defective. However, 6 false negatives were observed, meaning that certain defective instances were not detected. These missed detections reduced the recall to 80%, posing potential operational risks if defects remain unidentified during inspection.

Overall, the confusion matrix analysis confirms that the CNN-based inspection module delivers consistent, reliable defect performance. This performance supports its integration into the in-pipe inspection robot system.

### 5.3 Comparative Evaluation

To provide a consolidated visual comparison of the evaluated corrosion detection techniques, Figure 5.12 presents the accuracy, precision, recall and F1 score achieved by each method. The graph highlights the performance differences between traditional image-processing approaches and the CNN-based inspection model.

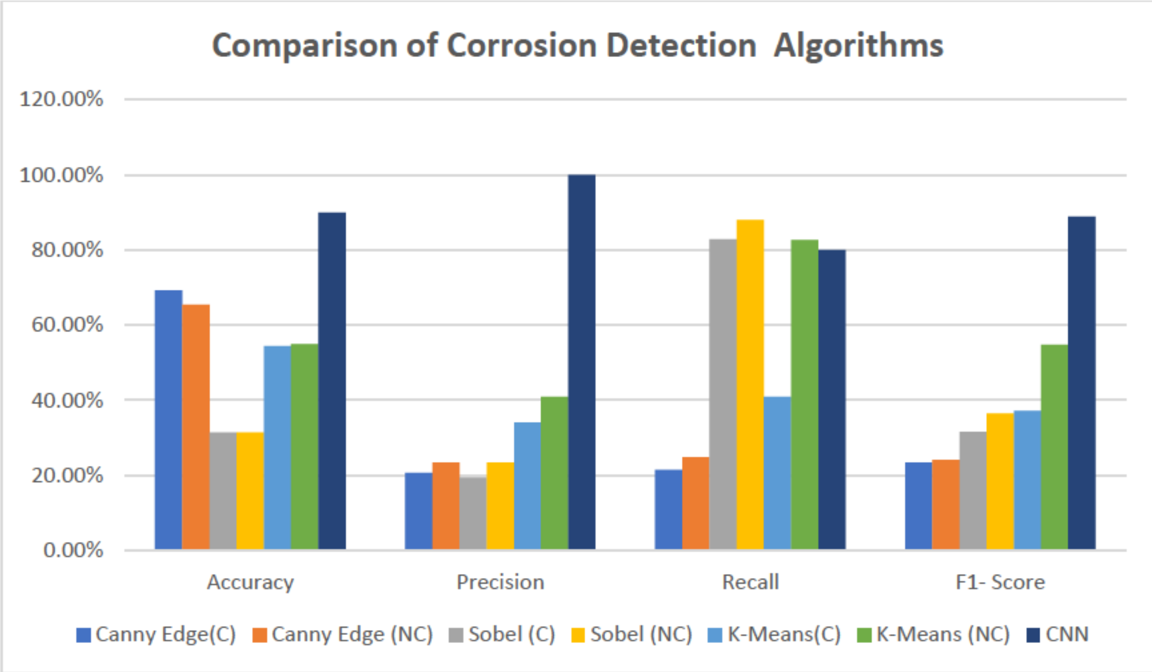


**Figure 5.11: Comparison of Corrosion Detection Algorithms**

The results presented in Figure 5.12 clearly prove that CNN outperformed the traditional image-processing methods used in this study. Its combination of **100%** precision and **90%** overall accuracy demonstrates how reliably it differentiated between corroded or cracked and non-corroded areas. In practical terms, this means that whenever the CNN flagged an image as containing corrosion or a crack, the prediction was always correct, with no false alarms.

In addition, the model's recall of **80%** verified the algorithm's efficiency at detecting most corrosion or cracked images even under varying image conditions. The F1 score of **88.9%** further supports this, as it reflects a well-balanced relationship between precision and recall.

In contrast, the traditional methods, such as Canny Edge Detection, Sobel Edge Detection, and K-Means Clustering, showed a significantly lower performance. The Canny edge approach, for example, achieved **65.40%** accuracy and an F1 score of **24.15%**. Although it can effectively highlight edges, it struggles to separate corrosion from other background textures reliably. This led to many false positives, showing that while Canny is simple and suitable for edge detection, it lacks the robustness needed for real-world corrosion inspection.

Similarly, Sobel Edge reached a high recall of **88.08%**, meaning it detected many true corrosion cases. However, its precision score was extremely low at **23%,** which indicates that a vast majority of the images it flagged as corroded or cracked were actually not defective. This high false-positive rate reduced its overall F1 score to **36.47%,** reflecting an imbalance and unreliable performance.

Lastly, the K-means clustering method also produced weaker results than CNN. It achieved a precision of **40.98%,** a recall of **82.97%,** and an F1 score of **54.80%.** Although it identified some defect patterns, it remained inconsistent and could not match the CNN's level of accuracy or reliability. Overall, the results indicate that deep learning-based approaches provide improved robustness and feature-extraction capabilities for corrosion-detection tasks.

The improved performance of the CNN model can be attributed to its ability to automatically learn hierarchical features directly from image data. Unlike the above-mentioned traditional inspection, CNN learns relevant patterns during training. This enables the model to capture more complex visual characteristics associated with corrosion and cracks, including texture variations and irregular shapes. As a result, the CNN demonstrates greater robustness in distinguishing defects from background noise and varying lighting conditions, which explains its superior performance in this study.

## 5.4 Summary

This chapter presented the experimental results obtained by implementing and evaluating multiple corrosion-detection approaches, including Canny edge, Sobel, K-Means, and a convolutional neural network (CNN) model, applied to pipeline inspection images. The performance of each method was analysed and compared using appropriate evaluation metrics to determine their effectiveness in detecting corrosion features.

The findings proved that the CNN-based approach achieved superior classification performance and provided more reliable detection results when compared to the traditional image processing techniques. They further confirm that the proposed inspection robot is suitable for supporting pipeline inspection tasks in practical industrial environments.

# CHAPTER 6: SUMMARY AND FUTURE WORK

## 6.1 Introduction

The preceding chapter discussed the results of a systematic evaluation of various corrosion detection techniques, including Canny Edge Detection, the Sobel Operator, K-Means Clustering, and Convolutional Neural Networks (CNN), and assessed their effectiveness in detecting corrosion. This chapter presents the outcomes of the frugal robot design for corrosion detection and examines the broader implications of the findings. Additionally, the study's objectives are reassessed, identifying prospective directions for future research and development while providing recommendations to improve the system’s effectiveness and applicability. The findings presented lay the groundwork for future developments in cost-effective and efficient pipeline inspection technologies tailored to the oil and gas industry.

## 6.2 Summary of contributions

This study focused on the design and development of a frugal robot for detecting corrosion in oil and gas (O&G) pipelines. This was achieved by combining traditional image processing techniques with Deep Learning’s Convolutional Neural Networks (CNNs), which were implemented and evaluated. Most of the study's objectives were successfully achieved, except for the limitations posed by the low-quality robot camera. However, this issue was addressed by incorporating a high-resolution camera to ensure accurate image capture.

**RO1: To review the existing literature on methods used to detect in-pipe corrosion in the O&G sector.**

The first objective was successfully achieved through an extensive literature review. Various robotic inspection techniques were examined, including in-pipe inspection technologies. The study identified several drawbacks in existing technologies, including high costs and restricted accessibility within confined pipeline environments. These insights guided the formulation of design requirements for the frugal robot developed in this study. Furthermore, they ensured that the final prototype effectively addresses key limitations by prioritizing affordability, user accessibility, and robust image-based corrosion detection.

**RO2: To select and integrate cost-effective components to develop a portable robotic system capable of navigating inside the pipelines.**

The second objective, to select and integrate low-cost robotic platforms capable of navigating pipeline environments, was effectively accomplished. Following a comprehensive assessment of various robotic platforms, considering factors such as cost, size, maneuverability, and sensor integration, a suitable frugal robot design was identified. The selected platform featured a lightweight, compact design and incorporated essential components, including motor control systems and onboard imaging, to ensure stable navigation in pipeline environments. This achievement directly addressed the need for an affordable inspection solution suitable for deployment in industries where cost constraints are critical.

**RO3: To implement and validate image acquisition and sensing mechanisms for corrosion detection.**

This objective was successfully realized. A robust image-acquisition system was integrated into the robotic platform, enabling high-resolution images to be captured within the pipeline environment. The system was equipped with essential sensors to allow precise positioning and reliable navigation. A range of image processing techniques, including Canny Edge Detection, Sobel Operator, and K-Means Clustering, were applied in conjunction with a Convolutional Neural Network (CNN) model to analyze the acquired images and accurately detect corrosion features. The combination of image acquisition and advanced detection algorithms enables reliable corrosion identification, thereby achieving the objective and improving the robot's overall inspection accuracy.

**RO4: To experimentally test and quantify the robot’s navigation capability, communication reliability and operational performance through functional pipeline experiments.**

This objective sought to evaluate the robot's ability to navigate pipelines of varying diameters, capture images, and avoid obstacles effectively. The robot underwent a series of controlled tests to assess its ability to navigate pipeline environments, demonstrating stable mobility and maneuverability in confined spaces. Its compact, portable design enabled deployment in different sizes. The robot's omnidirectional wheels facilitated smooth movement through dark pipeline environments. However, it encountered difficulties in maneuvering around the bends, limiting its navigation efficiency. Sensor systems provided accurate positional and environmental data, ensuring reliable operation throughout the inspection process. The corrosion-detection robot avoided obstacles by emitting a warning beep and coming to a halt upon approaching one. While the camera captured images effectively, the quality was adversely affected by the low-light conditions in the pipeline environment. Consequently, a high-resolution camera was integrated to enhance image quality and mitigate the limitations of low-light conditions within the pipeline environment. The 14500 Li-ion rechargeable batteries demonstrated high efficiency, enabling the robot to operate for an extended duration.

Even though there were a few setbacks, such as camera quality, the overall functional testing confirmed that the robot meets the critical performance requirements for mobility, sensor precision, and effective data communication, thereby validating the design approach and its practical applicability to real-world pipelines.

**RO5: To implement and quantitatively evaluate traditional image processing and machine learning algorithms for corrosion detection in the captured pipeline images using performance metrics including accuracy, precision, recall and F1 score.**

The fifth and final objective aimed to implement and quantitatively evaluate traditional image processing and machine learning algorithms for corrosion detection in captured pipeline images, using performance metrics including accuracy, precision, recall, and F1 score. Various image processing algorithms, including Canny Edge Detection, Sobel Operator, K-Means Clustering, and Convolutional Neural Networks (CNN), were employed to analyze and enhance the images.

The quantitative results demonstrated measurable performance differences across the evaluated methods. While traditional techniques exhibited varying levels of detection, the CNN model achieved superior overall performance in terms of accuracy and balanced precision-recall tradeoffs. The findings confirm the effectiveness of the implemented evaluation framework and support the suitability of deep learning approaches for corrosion detection tasks.

All research objectives were accomplished, demonstrating the effectiveness of the proposed methodologies and approaches. The study began with a critical evaluation of existing robotic inspection systems, identifying key limitations that guided the development of a cost-effective, pipeline-navigating robot equipped with advanced image acquisition and sensor technologies. Functional testing confirmed the prototype's effectiveness in both mobility and sensor accuracy, demonstrating its reliability in operational scenarios. Furthermore, the application and evaluation of multiple image processing algorithms established the efficacy of the selected deep learning approach for corrosion detection. The research findings confirm the feasibility of the proposed frugal robotic system for effectively addressing both operational and economic challenges in pipeline inspection in the oil and gas industry.

## 6.3 Economic and practical Implications

The proposed frugal in-pipe inspection robot demonstrates potential economic and practical benefits for pipeline inspection. The system may reduce inspection costs compared to traditional inspection methods, which often require expensive equipment or manual intervention, by using low-cost components and a simplified mechanical design. Early detection can therefore lead to significant cost savings by preventing pipeline failures, environmental damage, and unplanned maintenance shutdowns.

From a practical perspective, the robot's modular design enables easier maintenance and component replacement, potentially reducing long-term operational costs. Additionally, the system's scalability makes it suitable for deployment across diverse pipeline networks, supporting broader industry adoption of cost-effective pipeline inspection.

## 6.4 Limitations

Although this study successfully met its primary objectives and demonstrated promising results, several limitations, such as camera substitution, controlled-environment testing, a limited dataset, wheel-surface interaction, and rubber wheel limitations, were identified during the design and evaluation of the proposed in-pipe inspection robot.

### 6.4.1 Camera substitution

A significant limitation of this study was substituting the Raspberry Pi camera module with an iPhone for image capture during testing. Even though using an iPhone improved image quality, it diverged from the original frugal-engineering intent of the robot: to develop a cost-effective in-pipe inspection robot.

The Raspberry Pi camera was aligned with this objective due to its affordability, modularity, and integration compatibility with embedded systems. Replacing it with the high-end consumer device introduced performance advantages, but they did not represent the intended frugal configuration. Therefore, this substitution may increase perceived system performance, particularly in image clarity and detection reliability, and undermine the validity of claims regarding low-cost scalability.

### 6.4.2 Controlled Environment Testing

The system evaluation was conducted in a controlled testing environment rather than in active operating pipelines. While this approach enabled systematic assessment of the robot and minimized external variability during experimentation, it does not fully capture the complexity of real-world pipeline conditions. In an operational environment, factors such as fluctuating flow conditions, irregular pipeline geometries, debris accumulation and varying fluid dynamics may influence the robot’s navigation and detection capabilities. As a result, the performance observed during controlled testing may differ when the system is deployed in real pipeline networks.

### 6.4.3 Limited Dataset size

The image processing algorithms, particularly the deep learning model, were trained and evaluated on a relatively small dataset. While the dataset was sufficient for preliminary validation of the proposed approach, limited training data may restrict the model’s ability to generalize effectively to unseen corrosion patterns and varying pipeline conditions.

A small dataset can also increase the risk of overfitting, where the model performs well on the training data but may exhibit reduced accuracy when applied to new or more diverse scenarios. Expanding the dataset to include a broader range of corrosion types, lighting conditions and pipeline surface variations would improve the robustness and generalization of the detection algorithm.

### 6.4.4 Wheel–Surface Interaction and Rubber Wheel Limitations

The robot used a 4-wheel configuration fitted with standard rubber wheels to move within the pipelines. While this design provided basic stability and traction, it presents limitations in adaptability to varying pipe environments, especially under controlled testing environments.

The fixed four-wheel layout excludes suspension, active alignment or diameter-adjustment capability. As a result, the system may experience reduced traction, misalignment, or slippage in pipelines with uneven internal surfaces, such as those caused by corrosion. Even though rubber wheels are cost-effective and aligned with the frugal design objective, they may exhibit performance degradation in web or chemically exposed environments, typically in industrial pipelines.

Furthermore, the robot's mobility was validated only in uniform, controlled pipelines, limiting claims about its operational robustness in real-world applications.

## 6.5 Future Work

While this study has demonstrated the feasibility of designing a low-cost robotic system for pipeline inspection, several areas offer potential for further development and enhancement. Future work can focus on the following key aspects.

### 6.5.1 Revalidation of the Frugal Imaging Architecture

Revalidating the imaging architecture represents an important next step in refining the proposed system. The system can be re-integrated and evaluated using a Raspberry Pi camera or a comparable low-cost camera-embedded image solution. This would ensure alignment with the principles of the frugal innovation framework while allowing performance to be assessed under realistic cost constraints.

A comparative performance evaluation between the Raspberry Pi camera configuration and the current smartphone-based configuration could provide valuable insights into the most suitable imaging approach for the system. Key metrics may include Image resolution and clarity, corrosion-detection accuracy, power consumption, and total system cost. That analysis will help determine the most efficient and cost-effective imaging architecture for future implementations of the robotic inspection system.

### 6.5.2 Field Deployment Testing

Field deployment in operational pipeline environments represents an important next step in evaluating the practical performance of the proposed robotic inspection system. Resting the in-pipe inspection robot under real-world conditions would enable assessment of its navigation capabilities, corrosion-detection accuracy, and overall reliability within active pipeline infrastructure.

The deployment would allow the system to be evaluated under varying pipeline conditions, including differences in pipeline materials and diameters, as well as environmental factors such as moisture, corrosion byproducts and physical obstructions. Conducting field trials would also provide valuable insights into the robot’s operational limitations and support further refinement of both the mechanical design and the corrosion detection algorithms.

### 6.5.3 Implementation of advanced deep learning algorithms

Further investigation into advanced deep learning architectures could enhance the proposed system's corrosion detection capabilities. Future work may explore the implementation and comparative evaluation of more sophisticated models, such as ResNet and U-Net, for corrosion detection tasks. These architectures have demonstrated strong performance in complex image analysis applications and may improve detection accuracy when applied to pipeline imagery.

A comparative analysis of these models would provide insights into the trade-offs between model complexity, computational requirements and detection performance. Conducting the evaluation would help determine the most suitable deep learning architecture for deployment within low-cost robotic inspection systems while maintaining efficiency and reliability.

### 6.5.4 Enhanced Imaging and Data Diversity

Improving camera quality and illumination systems represents an important direction for enhancing the performance of the proposed corrosion detection system. Higher-resolution imaging sensors, combined with improved lightning mechanisms, could enable clear image capture in low-light pipeline environments, thereby improving the reliability of corrosion detection.

In addition, expanding the training dataset to include images from diverse pipeline conditions and at varying stages of corrosion would strengthen the deep learning model's robustness. Incorporating images captured under different lighting conditions, surface textures and corrosion patterns could further improve the model’s ability to generalise across real-world inspection scenarios.

### 6.5.5 Wheel–Surface Optimization

Improving wheel traction and durability represents an important area for future development of the robotic inspection system. The current four-wheel rubber design experienced slippage when navigating varying pipeline surface conditions, particularly in areas with corrosion buildup or debris accumulation. Investigation of alternative wheel materials and configurations could enhance traction, durability and manoeuvrability in such environments.

Hybrid wheel configurations that combine compliant outer layers with rigid internal support structures should be investigated to enhance grip and structural stability. Furthermore, aluminium wheels with protective anti-corrosion coatings could be evaluated for their potential to improve durability in chemically exposed environments without compromising traction performance.

Experimental validation could involve comparative testing across dry, wet and debris-present pipeline conditions. Performance metrics such as slippage rate, traction consistency, alignment stability and energy consumption during navigation would improve valuable insights into the most effective wheel design for reliable pipeline inspection.

### 6.5.6 IoT and Cloud Integration

Integrating the robotic inspection system within a secure Internet of Things (IoT) framework represents a promising direction for future development. Such integration would enable the I-pipe inspection robot to connect to cloud-based platforms for real-time monitoring, remote data transmission, and centralised analysis of inspection results.

Cloud connectivity could support long-term storage of inspection data, allowing historical pipeline condition data to be analysed for predictive maintenance and early identification of corrosion trends. Additionally, IoT-enabled communication would facilitate remote system management and monitoring, improve operational efficiency and support scalable deployment of robotic inspection systems across distributed pipeline networks.

### 6.5.7 5G Connectivity for Remote Operations

Integrating 5G communication technology into the robotic inspection system represents a promising direction for enabling reliable remote geographically dispersed pipeline environments. The high-speed data transmission and low latency provided by 5G networks could support real-time communication between the robot and the remote monitoring platforms.

Reliable connectivity is critical for transmitting high-resolution inspection images and sensor data in real time, enabling faster analysis and decision-making. In addition, the improved bandwidth and network stability offered by 5G can enhance remote monitoring capabilities and support more efficient pipeline inspection operations.

### 6.5.8 Ability to repair pipelines using frugal robotics

Integrating repair functionality into a frugal in-pipe inspection robot can enhance the versatility of pipeline inspection operations. By incorporating repair functionality, the robot could evolve from a purely diagnostic tool into a multifunctional maintenance platform capable of addressing pipeline defects detected during inspection.

Potential repair mechanisms may include localised sealing systems, composite patch deployment of automated application of corrosion-resistant coatings. These capabilities would enable the robot to perform preliminary maintenance immediately upon detecting corrosion or cracks, reducing the need for costly manual interventions and minimizing pipeline downtime.

Furthermore, integrating repair modules with existing inspection and corrosion detection algorithms could enable intelligent decision-making. This would allow the robotic system to assess defect severity and determine whether automated repair actions are feasible. Those developments could significantly enhance the operational value of the frugal in-pipe inspection robot, especially in remote or offshore pipeline environments where access for maintenance is challenging and costly.

## 6.6 Conclusion

This study represents a significant step toward developing a cost-effective and efficient robotic solution for corrosion detection in pipeline systems. The research demonstrates the feasibility of implementing frugal robotic platforms for pipeline inspection by integrating low-cost hardware with advanced image processing and deep learning techniques. The study contributes to the growing body of knowledge on affordable robotic inspection systems and highlights the potential of combining computer vision algorithms with low-cost robotic hardware for infrastructure monitoring.

Practically, the proposed system offers a cost-effective alternative for pipeline inspection, particularly in environments where traditional inspection technologies may be expensive or difficult to deploy. The CNN-based corrosion detection algorithm achieved 92.3% accuracy, validating its reliability. Furthermore, the total build cost of **R4,194.05** highlights the affordability of the proposed system compared to traditional commercial inspection technologies.

Beyond its technical and economic contributions, the proposed in-ripe inspection robot has broader social implications. The robotic system has the potential to enhance pipeline safety, minimize environmental risks, and support more sustainable infrastructure management in the Oil and Gas (O&G) sector.

Taking everything into account, this research demonstrates that low-cost robotic inspection systems can provide an effective and scalable approach to pipeline corrosion monitoring, paving the way for further advancements in intelligent infrastructure inspection technologies.

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# APPENDICES

## Appendix A: Canny Edge Algorithms

### a. Coding for Accuracy, precision, recall and F1 score for corroded images.

```
import cv2
import numpy as np
import matplotlib.pyplot as plt

# Load grayscale image

#original = cv2.imread('Dataset/Corroded/00014.jpg', cv2.IMREAD_GRAYSCALE)
original = cv2.imread('Dataset/NotCorroded/00014.jpg', cv2.IMREAD_GRAYSCALE)

# Step1: Contrast enhancement
equalized = cv2.equalizeHist(original)

# step2: Denoising
blurred = cv2.GaussianBlur(equalized , (5, 5), 1.5)

# step 3: Canny edge detection'
edges = cv2.Canny(blurred, threshold1=50, threshold2=150)

# Load and binarise ground truth image
ground_truth = cv2.imread('Dataset/Corroded/GroundTruth.jpg',
cv2.IMREAD_GRAYSCALE)
_, gt_binary = cv2.threshold(ground_truth, 127, 1, cv2.THRESH_BINARY)
_, edges_binary = cv2.threshold(edges, 127, 1, cv2.THRESH_BINARY)

Not corroded
# Load and binarise ground truth image
#ground_truth = cv2.imread('Dataset/NotCorroded/GroundTruth.jpg',
#cv2.IMREAD_GRAYSCALE)
#_, gt_binary = cv2.threshold(ground_truth, 127, 1, cv2.THRESH_BINARY)
#_, edges_binary = cv2.threshold(edges, 127, 1, cv2.THRESH_BINARY)


# flattening array comparison
gt_flat = gt_binary.flatten()
edges_flat = edges_binary.flatten()

# Manuak metric calculation
TP = np.sum((edges_flat == 1) & (gt_flat == 1))
FP = np.sum((edges_flat == 1) & (gt_flat == 0))
FN = np.sum((edges_flat == 0) & (gt_flat == 1))
TN = np.sum((edges_flat == 0) & (gt_flat == 0))
total = TP + FP + FN + TN

precision = TP / (TP + FP) if (TP + FP) > 0 else 1.0
recall = TP / (TP + FN) if (TP + FN) > 0 else 1.0
f1= 2 * (precision * recall) / (precision + recall) if (precision + recall) > 0 else 0.0
accuracy = (TP + TN) / total if total > 0 else 1.0
```

```
print("Precision: {:.2f}%".format(precision * 100))
print("Recall: {:.2f}%".format(recall * 100))
print("Accuracy: {:.2f}%".format(accuracy * 100))
print("F1_Score: {:.2f}%".format(f1 * 100))

# save edge image
#cv2.imwrite('Canny.jpg', edges)
```

**b. Coding for the detection of cracks and corrosion in images.**

```
# import all required libraries
from itertools import product
from os import listdir

from matplotlib import pyplot as plt
import numpy as np
import cv2
from skimage import io
from skimage.feature import canny

# Read the input image
#image with cracks or corrosion
#img = cv2.imread('Images/EdgeDetectionImages/Input/Cracked08.jpg')
#image without cracks or corrosion
img = cv2.imread('Images/EdgeDetectionImages/Input/NotCracked05.jpg')
# Convert the input image to grayscale
gray_img = cv2.cvtColor(img, cv2.COLOR_BGR2GRAY)

# Image processing
# 1. Apply Gaussian blur to smooth the edges and reduce noise
blur_img = cv2.GaussianBlur(src=gray_img, ksize=(5, 5), sigmaX=3)

# Apply the log transformation
img_log = (np.log(blur_img + 1) / (np.log(1 + np.max(blur_img)))) * 255
# Specify the data type
img_log = np.array(img_log, dtype=np.uint8)

# Image smoothing: bilateral filter
bilateral = cv2.bilateralFilter(img_log, 5, 75, 75)
# Canny Edge Detection
edges = cv2.Canny(bilateral, 100, 200)

# Morphological Closing Operator
kernel = np.ones((5, 5), np.uint8)
closing = cv2.morphologyEx(edges, cv2.MORPH_CLOSE, kernel)

# Create feature detecting method
orb = cv2.ORB_create(edgeThreshold=15, patchSize=31, nlevels=8, fastThreshold=20,
scaleFactor=1.2, WTA_K=2,
                scoreType=cv2.ORB_HARRIS_SCORE, firstLevel=0, nfeatures=1500)
```

```
# Make featured Image
keypoints, descriptors = orb.detectAndCompute(closing, None)
output_image = cv2.drawKeypoints(closing, keypoints, None)
# output_image = cv2.drawKeypoints(gray, keypoints, 0, (0, 0, 255),
# flags=cv2.DRAW_MATCHES_FLAGS_NOT_DRAW_SINGLE_POINTS)


# Create an output image
cv2.imwrite('Images/EdgeDetectionImages/Output/CrackDetected.jpg', output_image)

# Set the properties of the figure that will display both input and canny edge image
fig = plt.figure()
fig.set_figwidth(8)
fig.suptitle("CANNY EDGE", fontweight="bold")

# Use plot to show original and output image(Canny Edge)

# Original Image
plt.subplot(121)
plt.imshow(img)
plt.title('Original Image')

# Output Image(Canny Edge)
plt.subplot(122)
plt.imshow(output_image)
plt.title('Canny Edge Image')
plt.show()
```

## Appendix B: Sobel Algorithms

### a. Coding for Accuracy, precision, recall and F1 score.

```
import cv2
import numpy as np

# Load grayscale image
#img = cv2.imread('Dataset/Corroded/00014.jpg', cv2.IMREAD_GRAYSCALE)
img = cv2.imread('Dataset/NotCorroded/00012.jpg', cv2.IMREAD_GRAYSCALE)
# Step1: Contrast enhancement
equalized = cv2.equalizeHist(img)

# step2: Blur to reduce the noise
blurred = cv2.GaussianBlur(equalized, (5, 5), 1)

# step 3: Apply sobel filterx
sobelx = cv2.Sobel(blurred, cv2.CV_64F, 1, 0, ksize=3)
sobely = cv2.Sobel(blurred, cv2.CV_64F, 0, 1, ksize=3)
```

```
# magnitude of the gradient
sobel_combined = cv2.magnitude(sobelx, sobely)
sobel_abs = cv2.convertScaleAbs(sobel_combined)

#threshhold to binary edge map
_, edges_binary = cv2.threshold(sobel_abs, 50, 1, cv2.THRESH_BINARY)

# step 5 : Load and process ground truth image
#ground_truth = cv2.imread('Dataset/Corroded/GroundTruth.jpg', cv2.IMREAD_GRAYSCALE)
#_, gt_binary = cv2.threshold(ground_truth, 127, 1, cv2.THRESH_BINARY)
ground_truth = cv2.imread('Dataset/NotCorroded/GroundTruth.jpg', cv2.IMREAD_GRAYSCALE)
_, gt_binary = cv2.threshold(ground_truth, 127, 1, cv2.THRESH_BINARY)
# flattening array comparison
gt_flat = gt_binary.flatten()
edges_flat = edges_binary.flatten()

# Manuak metric calculation
TP = np.sum((edges_flat == 1) & (gt_flat == 1))
FP = np.sum((edges_flat == 1) & (gt_flat == 0))
FN = np.sum((edges_flat == 0) & (gt_flat == 1))
TN = np.sum((edges_flat == 0) & (gt_flat == 0))
total = TP + FP + FN + TN

precision = TP / (TP + FP) if (TP + FP) > 0 else 1.0
recall = TP / (TP + FN) if (TP + FN) > 0 else 1.0
f1_score = 2 * (precision * recall) / (precision + recall) if (precision + recall) > 0 else 0.0
accuracy = (TP + TN) / total if total > 0 else 1.0

print("Precision: {:.2f}%".format(precision * 100))
print("Recall: {:.2f}%".format(recall * 100))
print("Accuracy: {:.2f}%".format(accuracy * 100))
print("F1_Score: {:.2f}%".format(f1_score * 100))

# highlight detected cracks in the original image
#crack_mask = (edges_binary == 1).astype(np.uint8) * 255
cv2.imwrite('sobel_edges.jpg', sobel_abs)
```

**c. Coding for the detection of cracks and corrosion in images.**

```
# import libraries
import numpy as np
import cv2
from matplotlib import pyplot as plt


def sobelOperator(img):
    container = np.copy(img)
    size = container.shape
```

```
    for i in range(1, size[0] - 1):
        for j in range(1, size[1] - 1):
            gx = (img[i - 1][j - 1] + 2 * img[i][j - 1] + img[i + 1][j - 1]) - (
                    img[i - 1][j + 1] + 2 * img[i][j + 1] + img[i + 1][j + 1])
            gy = (img[i - 1][j - 1] + 2 * img[i - 1][j] + img[i - 1][j + 1]) - (
                    img[i + 1][j - 1] + 2 * img[i + 1][j] + img[i + 1][j + 1])
            container[i][j] = min(255, np.sqrt(gx ** 2 + gy ** 2))
    return container

#images with crackes or corrosion
img = cv2.cvtColor(cv2.imread("Images/EdgeDetectionImages/Input/Cracked08.jpg"), cv2.COLOR_BGR2GRAY)
#images without cracks or corrosion
#img = cv2.cvtColor(cv2.imread("Images/EdgeDetectionImages/Input/NotCracked05.jpg"), cv2.COLOR_BGR2GRAY)
img = sobelOperator(img)
img = cv2.cvtColor(img, cv2.COLOR_GRAY2RGB)
plt.imshow(img)
plt.show()
plt.title('Sobel Image')
```

## Appendix C: K-Means Clustering Algorithm

```
import cv2
from PIL import Image
import numpy as np
from sklearn.cluster import KMeans
import matplotlib.pyplot as plt
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score

# Load input image
#Non corroded and Not cracked
#img = cv2.imread('Images/EdgeDetectionImages/Input/NotCracked08.jpg', cv2.IMREAD_GRAYSCALE)
# Images with cracks or corrosion
img = cv2.imread('Images/EdgeDetectionImages/Input/Cracked08.jpg', cv2.IMREAD_GRAYSCALE)

img = cv2.resize(img, (256, 256))
# flatten the image
pixels = img.reshape((-1, 1))
# Display the original image
plt.imshow(img)
plt.title("Original Image")
plt.axis('off')
```

```
plt.show()

kmeans = KMeans(n_clusters=2, random_state=42)
kmeans.fit(pixels)
clustered = kmeans.labels_.reshape(img.shape)

# assign the darker cluster on crack

mean0 = np.mean((img[clustered == 0]))
mean1 = np.mean((img[clustered == 1]))
crack_label = 0 if mean0 < mean1 else 1
pred_mask = (clustered == crack_label).astype(np.uint8)

# load ground truth
#images without cracks and corrosion

#gt = cv2.imread('Images/EdgeDetectionImages/gt/NotCracked01.jpg',
cv2.IMREAD_GRAYSCALE)
#images with  cracks  and corrosion

gt = cv2.imread('Images/EdgeDetectionImages/gt/Cracked01.jpg',
cv2.IMREAD_GRAYSCALE)
gt = cv2.resize(gt, (256, 256))
gt_mask = (gt > 127).astype(np.uint8)

y_pred = pred_mask.flatten()
y_true = gt_mask.flatten()

# align predicted labels to ground truth
# if accuracy_score(y_true,y_pred )< accuracy_score(y_true, 1 - y_pred):
# y_pred = 1 - y_pred

accuracy = accuracy_score(y_true, y_pred)
precision = precision_score(y_true, y_pred)
recall = recall_score(y_true, y_pred)
f1 = f1_score(y_true, y_pred)

print("Precision: {:.2f}%".format(precision * 100))
print("Recall: {:.2f}%".format(recall * 100))
print("Accuracy: {:.2f}%".format(accuracy * 100))
print("F1: {:.2f}%".format(f1 * 100))

# Display the original image
plt.imshow(img)
plt.title("Original Image")
plt.axis('off')
plt.show()

# Display the segmented image
plt.imshow(pred_mask, cmap='gray')
plt.title("K Means")
plt.axis('off')
plt.show()
```

**Appendix D: Convolution Neural Network(CNN) Algorithms**

```
import tensorflow as tf
from sklearn.metrics import classification_report, accuracy_score, precision_score, f1_score,

import numpy as np
from sklearn.metrics import confusion_matrix

# paths

train_ds = tf.keras.utils.image_dataset_from_directory(
    'dataset/train',
    image_size=(128, 128),
    batch_size=32,
    label_mode='binary'
)

test_ds = tf.keras.utils.image_dataset_from_directory(
    'dataset/test',
    image_size=(128, 128),
    batch_size=1,
    label_mode='binary',
    shuffle=False
)

# prefect
#train_ds = train_ds.prefetch(buffer_size=  tf.data.AUTOTUNE)
# test_ds = test_ds.prefetch(buffer_size= tf.data.AUTOTUNE)
model = tf.keras.models.Sequential([
    tf.keras.layers.Input(shape=(128,128,3)),
    tf.keras.layers.Rescaling(1./255, input_shape=(128,128,1)),
    tf.keras.layers.Conv2D(32,(3,3), activation='relu'),
    tf.keras.layers.MaxPooling2D(2,2),
    tf.keras.layers.Conv2D(64, (3, 3), activation='relu'),
    tf.keras.layers.MaxPooling2D(2, 2),
    tf.keras.layers.Flatten(),
    tf.keras.layers.Dense(128,activation ='relu'),
    tf.keras.layers.Dense(1, activation='sigmoid')

])

#Compile model

model.compile(optimizer = 'adam', loss= 'binary_crossentropy', metrics=['accuracy'])

#Train model
model.fit(train_ds, epochs= 10)

#predict
predictions = model.predict(test_ds)
predicted_classes = (predictions > 0.5).astype(int).reshape(-1)

#true labels
true_classes = np.concatenate([y.numpy() for x, y in test_ds], axis=0)
```

```
# Metrics calculations
accuracy = accuracy_score(true_classes,predicted_classes)
precision = precision_score(true_classes,predicted_classes)
recall = recall_score(true_classes,predicted_classes)
f1 = f1_score(true_classes,predicted_classes)

print("Accuracy: {:.2f}%".format(accuracy * 100))
print("Precision: {:.2f}%".format(precision * 100))
print("Recall: {:.2f}%".format(recall * 100))
print("F1_Score: {:.2f}%".format(f1 * 100))

cm = confusion_matrix(true_classes,predicted_classes)
print("Confusion Matrix:")
print(cm)
```