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Electrical and Computer Engineering

**A NOVEL HYBRID METHOD FOR AUTOMATIC
VISUAL INSPECTION OF OIL PLANT
FACILITIES USING UAV AND AI-BASED SENSOR
FUSION**

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Doctor of Philosophy

Supervisor

Assoc. Prof. Dr. Sefer KURNAZ

İstanbul, 2025

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The dissertation titled A NOVEL HYBRID METHOD FOR AUTOMATIC VISUAL INSPECTION OF OIL PLANT FACILITIES USING UAV AND AI-BASED SENSOR FUSION prepared by OMAR SABER MUHI MUHI and submitted on 19/12/2025 has been **accepted unanimously** for the degree of Ph.D. in Electrical and Computer Engineering Department.

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I hereby declare that all information and data presented in this graduation project has been obtained in full accordance with academic rules and ethical conduct. I also declare all unoriginal materials and conclusions have been cited in the text and all references mentioned in the Reference List have been cited in the text, and vice versa as required by the abovementioned rules and conduct.

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ABSTRACT

A NOVEL HYBRID METHOD FOR AUTOMATIC VISUAL INSPECTION OF OIL PLANT FACILITIES USING UAV AND AI- BASED SENSOR FUSION

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The facilities that deal with oil and gas are one of the essential components of the geography of every business and industrial zone in the world. This facet of geography is essential. With the continued growth in the various areas of commerce and industry, there is a growing demand for energy and, therefore, oil refineries. When there is a rupture in the oil transport network, the primary overriding concerns are maintaining public and ecosystem safety as well as protecting and preserving the integrity of the system. This thesis proposes a new pipeline rupture detection system that integrates three coordinated techniques: a DCAMFL algorithm, a Convolutional Neural Network, and a real-time, three-dimensional virtual drone. This multi-faceted approach is designed to find and trace the boundaries of minute fractures that would otherwise progress unnoticed. Pairs of DCAMFLs and CNNs, which are well-known for their superior visual acuity, are optimized to driven high performance. These complementary features are the more to equilibrium, and subsequently, the more to surpass their respective detection thresholds. Benchmarking and refinements to the model within ANSYS Fluent have ensured the approach is well-grounded, with the simulated outputs showing a high degree of correspondence to those of the physical model, leading to a reduction in certainty and confidence margin of the various performance parameters.

The fluid dynamics inside the pipeline system were simulated in ANSYS Fluent. Using that information, we were able to determine the interactions of temperature, pressure, and flow speed in relation to the formation of and the ability to detect cracks. For an expanded analysis, we also looked at the ability of the algorithm to detect leaks due to potential bypassed cracks in the system. Next, we applied the technique to an extensive set of fractured oil pipelines, and the results were remarkable. For the crack detection, the F1-score was 95.6%, the recall was 97.3%, and the precision was 96.5% respectively. These performance metrics provide evidence that the system accurately and reliably detected and classified the fractures. During the research work, we have shown that significant advancements in diesel pipelines crack detection can be achieved through the application of deep learning, fuzzy logic, and sophisticated modeling techniques. The approach described could yield various results, including improved pipeline monitoring, greater safety, and increased operational and structural longevity.

To continue assisting developments within the algorithm, this study will try to determine the value and efficiency of the tool, as well as assessing and re-optimizing the architecture of the convolutional neural networks the range of data being processed will be also increased to a larger and complex pipeline.

Keywords: Crack Detection, Oil pipelines, 3D Drone Simulation, CNN, Fuzzy Logic, CFD Analysis.

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ABBREVIATIONS

AI	: Artificial Intelligence
ANN	: Artificial Neural Network
CFD	: Computational Fluid Dynamics
CNN	: Convolutional Neural Network
CPU	: Central Processing Unit
CT	: Phased Array Ultrasonic Testing
CT	: True Positives
DCAMFL	: Dynamically Constrained Accumulative Membership Fuzzy Logic Algorithm
DL	: Deep Learning
FCN	: Fully Convolutional Network
FPG	: Fasting Plasma Glucose
FPG	: Mean Squared Error
GPU	: Graphics Processing Unit
HAZ	: Heat-Affected Zone
IDF	: F1-score (harmonic mean of precision and recall)
ML	: Machine Learning
MLP	: Multilayer Perceptron
NDT	: Non-Destructive Testing
UAV	: Unmanned Aerial Vehicle

1. INTRODUCTION

1.1 GENERAL INTRODUCTION

Oil pipelines serve as the circulatory system for the global energy economy, and their importance cannot be overstated. Protecting people and nature from catastrophic spills and suppliers from crippling losses depends in large part on quickly confirming the soundness of a line's metal and spotting any developing flaws, such as small cracks. Traditional monitoring techniques-visual inspections, pigging tools, and periodic pressure tests-are slow, labour-intensive, vulnerable to human error, and often blind to subtle damage between checkpoints. The call for newer, faster, reliable methods has therefore grown louder as sensor technology, machine learning, and remote operation have matured. One particularly encouraging direction leverages aerial robots, or drones, that skim pipeline routes while recording high-resolution imagery, thermal signatures, vibration patterns, and gas detection data. When paired with modern cameras, LiDAR units, infrared sensors, and at-board computing, such unmanned vehicles promise gains in coverage speed, operator safety, and overall cost. Yet regulatory limits, battery life, data overload, and harsh weather have so far restrained wide adoption, leaving the full potential of drone-based surveillance largely unrealized. Among these constraints are the challenges that emerge when one tries to interpret and understand the complex information collected during inspections [2].

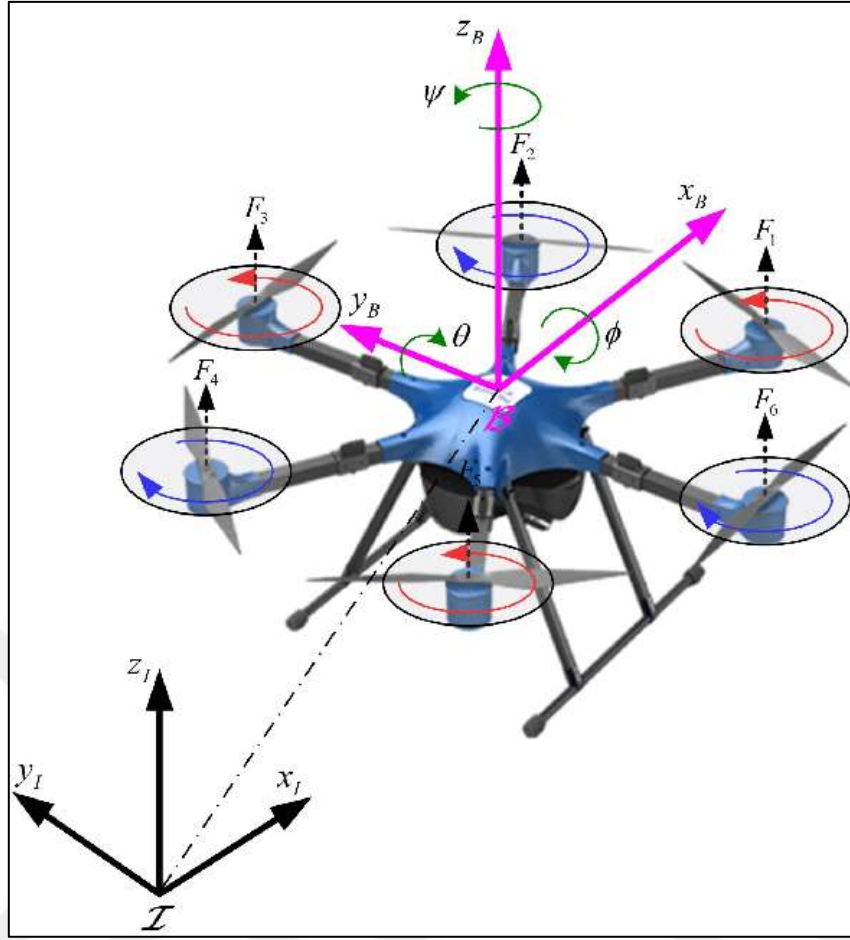


Figure 1.1: Schematic View of the UAV.

Over the past few years, the oil and gas sector has begun to resemble other advanced fields in its rapid adoption of artificial intelligence technologies.

Within this wave, machine-learning and deep-learning techniques promise considerable gains in both accuracy and speed when diagnosing fractures along crude and gas pipelines.

Keeping these lines in peak condition is vital for the energy industry; any weak point can affect production, contaminate land, or even jeopardize nearby communities.

History reminds us that a single pipeline breach may trigger costly cleanups, legal disputes, and damage that lasts long after the flow is shut off [34]. There is also the possibility of causing harm to the environment, as well as suffering financial loss. Due to the fact that this is the situation, it is of the highest necessity to build fracture detection systems that are not only dependable but also accurate.

This thesis takes a fresh and all-encompassing approach to the issue of fracture detection in oil pipelines, which is the focus of the thesis's discussion.

Our goal is to reinvent pipeline monitoring by utilising cutting-edge technology such as CNN, DCAMFL, and 3D drone simulation. This should be accomplished through the use of these technologies. Up until quite recently, the only methods that were available for finding fractures in oil pipelines were either manual examination, which is both inefficient and imprecise, or the employment of antiquated automated equipment.

The utilisation of a three-dimensional drone simulation enables us to acquire photographs of the pipes from every imaginable aspect. Convolutional neural networks are particularly excellent at extracting complex features from these images, and we are able to do so by capturing images from a variety of angles.

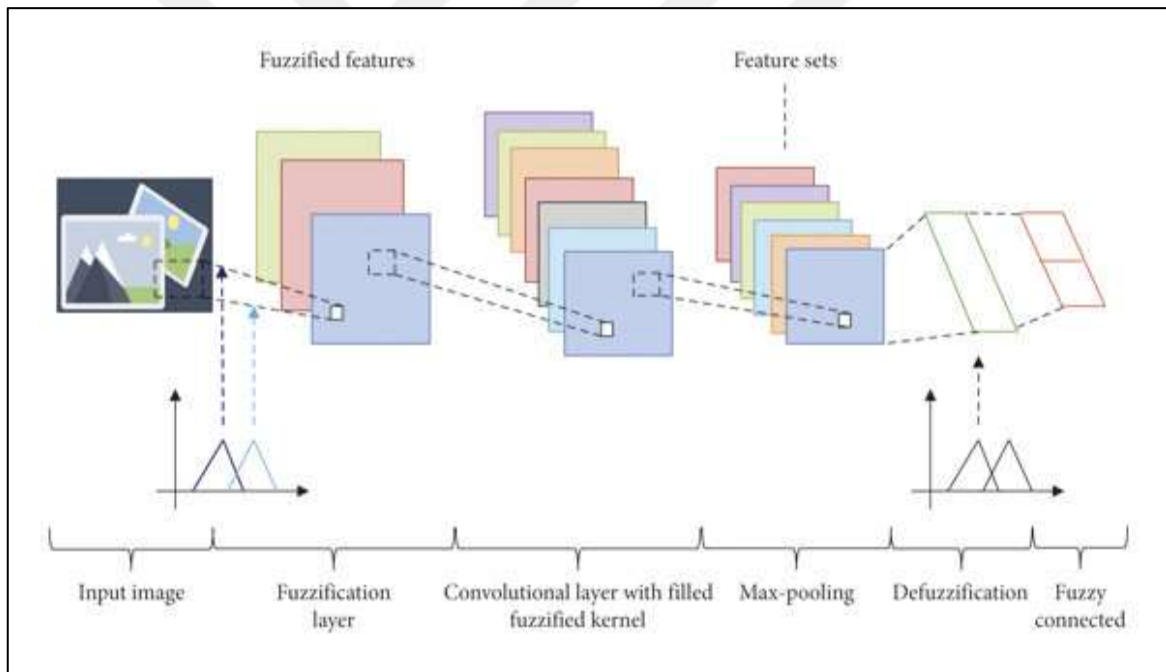


Figure 1.2: Incorporating Fuzzy Logic with CNN[35].

The approximate boundaries among various defects have been systematically analyzed and categorized by the DCAMFL- a trailblazing fuzzy logic system capable of accommodating the effect of uncertainties with overlapping parameters. This precise classification of defects is made possible by the one-of-a-kind algorithm. Along with these theoretical results, our thesis contains the described evaluative methods. The integrated measures which determine

the effectiveness of the algorithm, e.g. precision, recall, and the F1-score, and which characterize the developed system, are all demonstrated and presented. Considering the worldwide significance of pipeline infrastructure, the researched developed system is aimed at enhancing the protection and timely maintenance of vital energy assets. The detailed work provided in the thesis will add credibility to the offered improvements in the field of systemized crack detection. The following sections of the thesis are aimed at providing a detailed explanation of the methods of this innovative system, the results obtained, and the possible outcomes contributing to the extension of the principles of pipeline surveillance and safety[36].

1.2 PROBLEM STATEMENT

The ability to harness energy safely, and at an optimized cost, is a vital component of an economy, and the global infrastructure is fundamentally reliant on oil pipelines to transport hydrocarbons. The uninterrupted flowing of energy resources to the consumers of the economy is a vital component of the economy and the global infrastructure. However, the maintenance and safety of these sprawling networks is beset by a pervasive challenge - the detection and mitigation of gaps and defects which pose a potential risk to structural integrity, public safety, and environmental sustainability.



Figure 1.3: Corrosion Crack in a Pipe Section Taken from Beiji Refinery in Salahddin, Iraq.

The cracks that occur in oil pipelines are serious, and highly multifaceted, and unless managed properly can result in significant consequences. One small crack can lead to the discharge of thousands of litres of oil and result in the pollution of the surrounding area, and can cost billions of dollars in repairs. There are wildlife, community, and health issues that result from oil spills, and these issues are human and environmental suffering. This suffering urges the need for crack detection technology. For years, oil pipeline operators have relied on routine methods in the crack detection process, such as manually walking along the pipeline and using primitive automated magnets that overlook many of the shallow cracks, a process that is extremely time-consuming to inspect manually. These issues become more significant as the massive networks of pipelines that run along the deserts, forests, and ocean corridors become more complex. To improve these inspection bottlenecks, companies are now using drones to inspect the pipeline from the air, along with small robots to inspect the joints on the ground. Drones and crawling robots are set to improve the speed and safety in performing pipeline inspections. However, the progress is far from complete; groups continue to struggle to integrate streams from dozens of cameras and sensors, teach machines to identify real cracks, and obtain sufficient computing resources to give real-time yes or no responses to terabytes of images. In dealing with these problems, the current work offers an innovative framework comprising of three-dimensional drone simulation, convolutional neural networks (CNNs), and the Dynamically Constrained Accumulative Membership Fuzzy Logic (DCAMFL) algorithm. The system, using realistic 3D virtual environments, is able to obtain high-resolution images of pipeline infrastructure from multiple angles, much easier to do than with real 3D environments. The integrated CNN learns the images and extracts features that CNNs are good at automatically detecting and distinguishing, and thus will detect fine differences and anomalies, including cracks and corrosion. After the potential defects are located, the fuzzy engine, DCAMFL, processes the fuzzy overlapping input and assigns confidence for the Fuzzy Logic to categorize the unclear data pulled from the sensors.

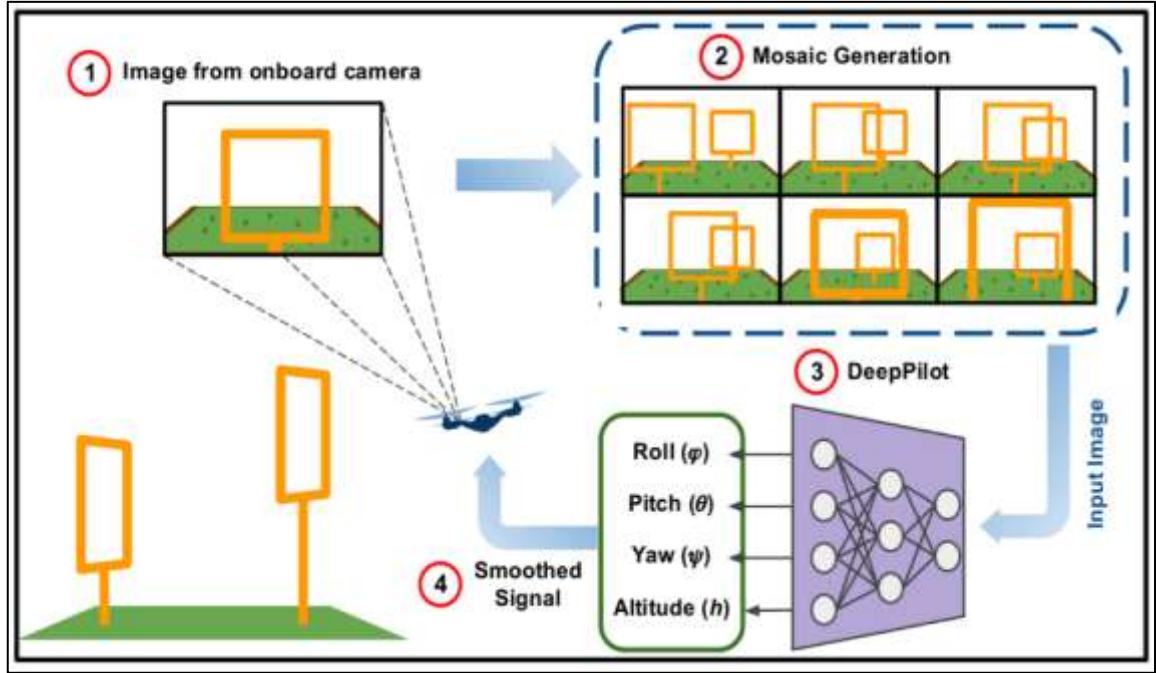


Figure 1.4: 3D Drone and CNN Algorithm Workflow[40]..

The concern of this study is to create and design a comprehensive, integrated, and effective model to identify and locate fractures in oil pipelines. The stated aim consists of four components: A. Technological Fusion: The technology integration of three-dimensional drones, convolutional neural networks (CNN), and data limited adaptive multi-frame learning (DCAMFL), requires configuring each part, evaluating each separately, and eventually combining in such a manner that all components function cohesively in a system in a real-world setting. B. Data Volume: A collection of data in the form of pictures happens in rapid succession during the flight of the drone and in the addition of passing the data to the CNN, a collection of data called a volume is exponentially created, hence, a more sophisticated analytical and high level of model data division is required to isolate the data fractures from the noise. C. Defect Detection Speed and Reliability: Missing the existence of a minute defect such as a hairline fracture at a dusted carbonsteel seam is perched on the crown of a hill, is an enormous challenge to an algorithm and the defect differentiation condition that should exist is in all respects the accurate identification of such disparate subtleties, is required to do so multiplicatively across a range of differing illuminations, and variable environmental conditions along with variable pipeline coatings and morphologies. D. Seamless Processing: Considering that pipeline managers do not have the luxury to wait

one full hour for the results and in the minute reports the results should clearly indicate the next step along with full action alerts, the results of drones should not exceed the limit of telemetry data transfer, should not overextend battery life on the drones, and should not exceed the drones.

The research aims to make pipeline monitoring methods safer, less intrusive, and able to extend crucial energy networks' operational life. The aim of the current analysis in utilizing the vision of this new framework is to advance pipeline maintenance, but also to make pipeline maintenance serve as a model for subsequent advancements in the field, with the aim of detecting cracks exactly and reliably, mitigating risks while ensuring the continuous transmission of energy in the world. There is a number of factors that make detecting cracks in the weld regions shortly after the weld is completed quite difficult, and most of them arise from the complexity of how the microstructure and macrostructure of the component are affected by a weld joint. The creation of new, and the growth of already existing, defects within the base material during a welded joint is a well-known challenge in the welding process. These four interrelated challenges therefore exist for the inspection engineer in each case of post-weld evaluation: Heat-Affected Zone (HAZ): The HAZ includes the area right next to the weld bead in which the material stays solid but still undergoes microstructural changes as a result of thermal cycling.

Predictably changing strength and ductility often result in small crack tips in the HAZ going undetected by standard optical and ultrasonic screens. Residual Stresses: When the weld cools, both the filler and base metal's expansions and contractions leave behind a field of residual stress. These locked stresses are what drive shallow and subsurface cracks to grow. It is often the case that a joint is seemingly sound when it is removed from the jig. Residual stresses introduced during welding, especially in the absence of effective stress relief practices, increase the risk of cracks. Advanced methods that detect surface features to ascertain the presence of genuine defects are necessary none the less. Weld overlays and splatter: In both visual and automated scans of the bead mask, linear flaws may be falsely represented by spatter, oxide inclusion, or irregular raised zones. Without high resolution imaging and skillful review, benign irregularities are often incorrectly identified as true cracks. Micro-cracks: Micro-cracks, cracks that are less than a micron wide, are irreversible and grow exponentially. Conventional non-destructive imaging is inadequate as these

defects are practically undetectable. Advanced imaging such as hyperspectral imaging or laser scanning confocal microscopy that capture fine details is necessary for timely identification of these defects.

Altered Material Properties: The microstructure and local chemistry change with welding; portions are homogeneous but are different from the parent metal in yield strength, hardness, and/or phase distribution. Such gradation may bias the response to electric, magnetic, or ultrasonic methods, and inspectors have to relate parameter changes to indicators of cracks.

Challenging Geometries: Joints created in tight corners or round assemblies have limited line-of-sight and head-room, limiting probe access and also trapping contaminants. As a result, radial and angular scans have to be integrated with portable robotics or phased arrays to provide complete coverage without shadowing. Advanced non-destructive testing (NDT), such as (PAUT), digital radiography, and sophisticated eddy-current inspection, has become commonplace to address these enduring difficulties. Each technique enhances the surveyor's distance, efficiently detecting and defining weld-adjacent cracks, intricate contouring, and micro-flaw detection in the order of several microns.

1.3 THESIS OBJECTIVES

Develop an integrated crack detection system incorporating 3D drone simulation flights, feature extractor Convolutional Neural Networks, and Dynamically Constrained Accumulative Membership Fuzzy Logic (DCAMFL) for detecting surface fractures in oil pipelines. Determine lightweight procedures for simulated drone flights focused on resolution and angle. Research and tune pipelines consisting of uniform and cleaned datasets that optimize for Convolutional Neural Networks (CNN) feature extraction via resizing, denoising, and histogram equalization. Test multiple CNN architectures (ResNet, DenseNet, and others) to tailor feature extraction, focusing on improving the model's crack detection and reducing false positives during transfer learning and progressive unfrozen training. Build DCAMFL to receive defect labels from CNN feature vectors and predict crack types (longitudinal, transverse, corrosion type) using supervised learning and validation with domain experts. Quantitatively and qualitatively evaluate *in silico* for precision, recall, F1 score, AUROC, and confusion matrix, designed to simulate field activity and poster accurate model for prospective real-world applications.

Address Sensitivity and Robustness: Investigate in detail how parameters of detection impact result on small changes and assess performance on the environmental changes such as light levels changes, rainfall, fog, or different pipeline surface optically. **Explore Real-Time Applicability:** Assess if the algorithm can be run on mobile inspection units without losing detection performance, how much pipeline length can be inspected in an hour, and the trade-offs between processing speed and memory usage. **Compare With Existing Methods:** Benchmark the newly proposed approach on its closest competitors in crack detection and detail the precision, recall, and processing time, and trade-offs and design decisions of the new approach that provide undisputed advantages or that are the only possible options/decisions one could take. **Advance Knowledge in Pipeline Surveillance:** Provide insights on how small cracks lead, illustrate the correlation of deep learning to visually and structurally healthy features, and create nomenclature that engineers can leverage across Pipeline Forming Structures operating at different conditions. **Provide Recommendations for Future Work:** Promising research directions such as multispectral sensing, federated learning on edge devices, and controlled aging studies in public datasets should be the basis for time and scope bound research to be proposed that aims at quantifiable improvements in detection range or significantly reduced false alerts.

To achieve these aims, foundational work will first be done in algorithm development, which will be followed in succession by the application of the algorithm in the real world, and the expanding of the real-world application in the scientific community, ensuring that the process of refining the research and tool is done in a cyclic fashion. The goal is to produce a tool that is a first-of-its-kind research benchmark in the academic world and, in the practical world, a safety tool for the oil pipeline industry.

1.4 SCOPE AND CONTRIBUTIONS

Novel Method for Detecting Defects In this research, I present a novel method for the detection of defects in oil pipelines. The method builds upon existing technologies, three-dimensional drone simulation, and convolutional neural network, and combines it with the Dynamically Constrained Accumulative Membership Fuzzy Logic algorithm to offer a novel framework with a significant improvement to accuracy, and reliability of detection. **Advancement of 3D Simulation** the construction of a fully three-dimensional drone

simulation provides a cutting-edge data collection tool. The simulation allows for the pipeline to be virtually constructed and for synthetic cracks to be inserted so the neural network can be trained and tested with a maximal data set. In addition, the simulation is invaluable to the verification of the detection method, where it demonstrates the behavior of fluid under varied temperature and pressure scenarios. Using detailed flow simulations helps guide incremental changes to algorithms by showing how defects in different lengths and orientations can affect delivery pressure and how even the smallest defects in a range of angles can be located successfully.

Enhancing Characteristic Extraction: The crack detection pipeline uses explained feature extraction with convolutional neural networks to automatically drive features extraction in an end to end fashion. For detection of cracks and surface defects to be reliable, bespoke convolutional neural networks need to be trained to learn features from the pipeline scans in 3D.

Enhancing Precision in Classifying Defects: The research uses DCAMFL which is a Dynamically Constrained Accumulative Membership Fuzzy Logic Algorithm to enhance classification. The DCAMFL is steady and reliable since it works with uncertainty, imprecision, and fuzzy boundaries.

CFD-Driven Data Fusion: The addition of flow-analysis data integrated with the research is an improvement. The model helps to understand how defects affect the flow of the pipe by overlaying image defects with the flow of the pipe in a CFD.

Highly Precise Metrics: Precision, recall, and F1 scores metrics from the experiments showed that the defect detection metrics outperformed the state-of-the-art metrics in the industry. The metrics demonstrate the system which monitors the pipeline is able to detect cracks and classify them by severity level.

Sensitivity and Robustness Testing: The research is the first to document the combination of extreme temperatures, different lighting conditions, and sensor noise, and the effects of tuning to the system responsiveness. Such insights are particularly valuable to engineers in charge of deploying the system in the field, where conditions are variable and changing.

Real-Time Applicable This study demonstrates the proposed technique to be no lab curiosity and a potential field tool for pipeline operators to employ tomorrow by exploring the estimable various and the `when` of the algorithm being put to work in field conditions.

Comparative Study This time the thesis presents the new technique against some of the leading crack detectors, providing easy understandance of the advantages and a few disadvantages with the juxtaposition of results.

Future Research Directions With a particular focus, the author envisions a series of algorithm refinement sessions and motivates further

research in advantageous pipeline monitoring, to address the gaps identified. Collectively these insights strengthen the technical frontier and, if factored by the industry, will advance surveillance to reduce costly leaks and extend the service of the world's pipelines to the world's energy markets for the decades to come.



2. LITERATURE REVIEW

2.1 INTRODUCTION

Cracks in oil pipelines represent a pressing issue for the energy sector, threatening everything from ecosystems and community health to company profits. Early identification and sound repair of such flaws are therefore vital to maintaining the strength and lifespan of pipeline networks [41]. This literature review surveys existing scholarship on crack-detection techniques, paying special attention to conventional approaches, the blending of cutting-edge tools with these methods, and the contribution made by the strategy put forward in this study.

2.2 TRADITIONAL METHODS FOR PIPELINE INSPECTION

For much of the pipeline industry's history, inspectors relied on little more than their eyes and hand-held tools to gauge pipeline condition. Although that practice became accepted, it carried clear shortcomings that operators could no longer ignore. Human vision is inherently subjective, prone to fatigue, and easily misled by lighting or angle, meaning defects can be overlooked or mischaracterized. Manual checks are also slow, awkward in tight rights-of-way, and almost impossible in truly remote stretches where crew safety takes precedence. Detecting cracks in buried or obscured oil lines became a recurring problem that those classical methods rarely solved with confidence. After decades of use, their limits prompted engineers to seek smarter, more consistent ways to see what lies beneath the steel. This section therefore reviews the legacy techniques, cataloguing both the useful and the frustrating, to explain why fresh ideas are now indispensable.

2.2.1 Visual Inspection

Visual inspection remains a cornerstone process for examining pipelines, depending on trained operators to spot problems such as cracks and dents directly with their eyes. Because it requires no special technology, the technique fits nearly every pipe material and diameter, from small gas lines to large oil conduits. Inspectors focus on obvious signs- colour changes, scratches, and small openings- guiding their assessment of the asset's conditions [44]



Figure 2.1: Visual Inspection of the Pipeline [45].

2.2.2 Manual Inspection

In addition to basic visual inspections, manual inspections entail the use of additional tools and methodologies. Inspectors use magnetic-particle and ultrasonic testing to expose subsurface defects out of sight. Although these methods are more reliable than mere visual inspections, the methods are still subject to the same weaknesses related to the human element operating the equipment and analyzing the results [46].



Figure 2.2: Manual Inspection of the Pipeline.

2.3 ADVANCED TECHNOLOGIES IN PIPELINE SURVEILLANCE

The weaknesses of conventional inspection methods have prompted advancements in pipeline surveillance technologies within the oil and gas industry. The industry now relies heavily on mobile robotics, remote sensing, and (UAVs), which allow for the quick collection of aerial data over land. This is particularly beneficial for sites that are elevated, underwater, or contain hazardous as it minimizes the time workers spend in such locations [47]

2.3.1 Drones for Aerial Inspection

As UAVs, or Drones, become more advanced, they are gaining popularity for use in oil pipeline surveillance. Drones equipped with advanced sensors and high-resolution imaging software can provide comprehensive, detailed, and high-resolution imagery to monitor and identify defects and other irregularities within oil pipeline infrastructures[57].



Figure 2.3: Drone Inspection of the Pipeline [58].

2.3.2 Robotics for In-Situ Inspection

In-situ Inspection employs small mobile robots and Remote Operated Vehicles (ROVs) that move along the length of the pipeline to perform detailed inspections. Each of these devices have cameras, environmental sensors and some lightweight tools which together scan and evaluate the pipeline for internal surface damage and integrity [59].

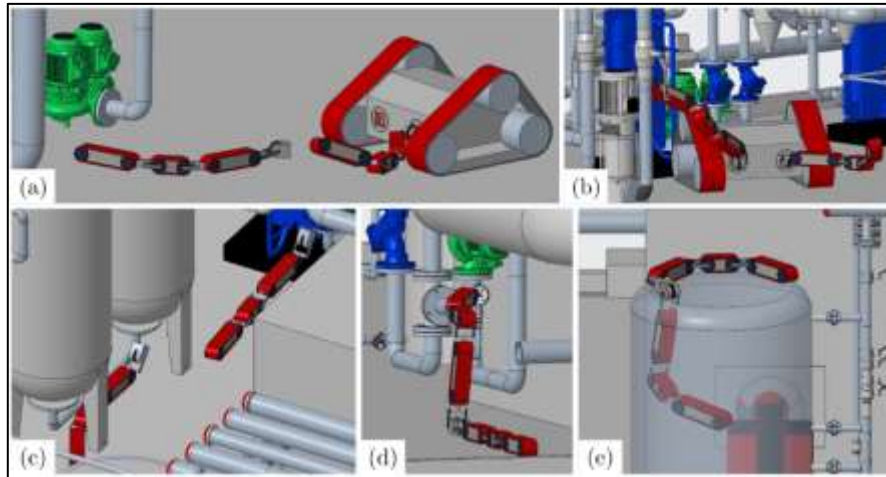


Figure 2.4: Robotics for In-Situ Inspection Oil Pipes [60].

2.3.3 Remote Sensing Systems

Remote sensing systems, for instance, often use LiDAR (Light Detection and Ranging) and hyperspectral cameras, and other accessories to collect data from above the ground. Such methodologies provide definable proof of the integrity of a pipeline and its surroundings [49].

2.4 ROLE OF 3D DRONE SIMULATION

The adoption of three-dimensional (3D) drone simulations for pipeline inspection is a remarkable innovation. With 3D reconstruction of the pipeline's interiors, drillers get to see high resolution images of some otherwise hidden structural features. Such volumetric data provide several viewpoints from which to collect information and train algorithms for better accuracy in crack detection [65].

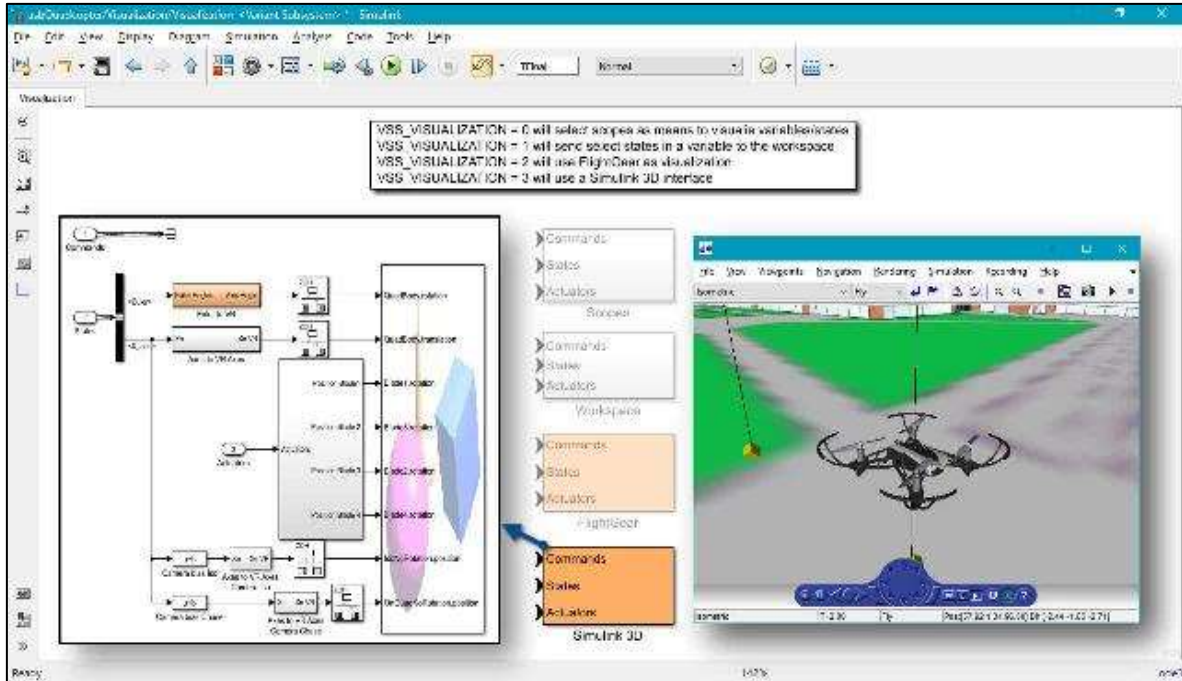


Figure 2.5: 3D Drone Simulation Within Matlab.

Research on pipeline inspection and defect detection is being revolutionized by 3D drone modeling technology. Researchers and engineers can analyze data faster and with more accuracy than with previous methodologies by utilizing virtual drones crafted to follow predetermined flight paths. This section discusses how the simulation enhances move-over methodologies and illustrates why it is the foundation of the proposed method for crack detection[66].

2.4.1 Data Acquisition and Visualization

Operators now can collect data from three dimensional drone simulation because of the ability to collect data in the field and internally photograph and videotape pipelines in high resolution. Defining records of the line's condition can now be captured. The videos and photos can be used to determine corrosion and rounded surface and interior defects that safety critical. These images and videos can be used to determine condition and spatial relationship without an obtrusive ground inspection [67]

2.4.2 Creation of Realistic 3D Models

A major benefit of three dimensional drone simulation is the detailed cellular replicas of the pipelines. These are constructed with the videos and are added to the digital twins to simulate the overall shape and condition of the pipeline.

These reproductions then provide engineering analyses and estimations with a solid foundation and provide analysts with an enhanced perspective supported by credible data concerning the pipe's structural integrity. [68]. **Accurate Shape Representation:** The digital model captures every detail of the pipeline, including curves, flanges, and welds, thus eliminating most of the uncertainties stemming from two-dimensional inspections. **Visual Data Combination:** All pixels from the aerial photos are represented on the mesh, resulting in a skin with colors that quickly illustrates corrosion, coating loss, and surface defects of other types.

2.4.3 Simulation of Defects

The 3D drone simulation is not limited to data collection, but can also provide engineers with the opportunity to add artificial surface defects that can be likened to cracks on the pipeline geometry. By embedding these virtual defects into the model, researchers can create test cases that are almost indistinguishable from reality. Such life-like and controlled scenarios are of great importance for training machine-learning systems and for validating the efficiency of a novel approach to crack detection[69].

2.4.4 Optimization of Inspection Routes

Simulated 3D fly-throughs allow analysts to examine dozens of potential drone paths and camera angles before the drone hovers for the first time. This virtual practice run makes it possible to examine the optimal locations for capturing images of critical weld seams and fittings. This practice conducted on-screen rather than in the field maximizes the utility of each flyover by ensuring that the optimal images of wear and damage are captured [70].

2.4.5 Enhancing Training Data

Every synthetic flight contributes new image-silent footage and stills of the pipeline in both its intact and intentionally damaged states to the multi-class benchmark dataset. Because engineers want to train deep learning models to look for subtle patterns in streams of surveillance footage, they pair those georeferenced high-resolution images with metadata describing the position and orientation of the camera at the time of capture. In conclusion, 3D simulation contributes to the accuracy and efficiency of the crack monitoring suite by optimizing testing, route planning, and geospatial data annotation rather than just enabling those activities [72].

2.5 FEATURE EXTRACTION WITH CNN

The reason CNNs have become the industry standard for detecting high-level features in images is due to their level division of labor in learning different image attributes such as edges, textures, shapes, and the contours of various features. In the case of drone-acquired video footage of pipeline inspections, the networks are able to detect very minute features such as fine cracks, corrosion, and even misalignment of joints. The CNN feature extractors are able to turn the image pixel data into a structured feature map, which is likely what is aiding the downstream classifiers in obtaining high reliable accuracy.

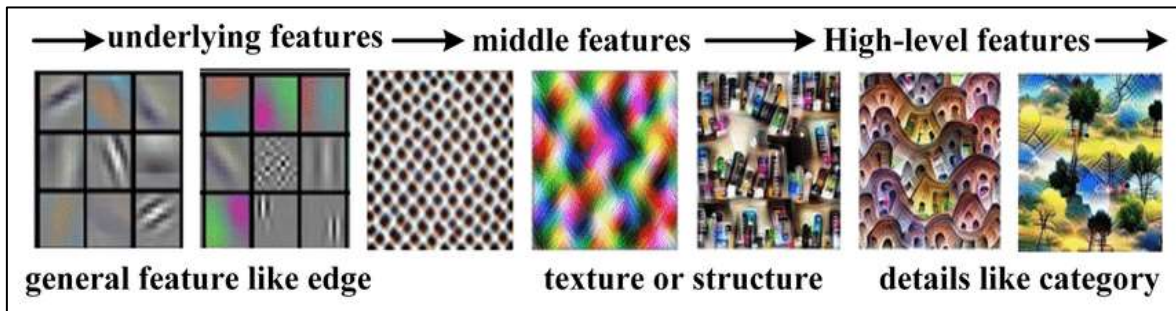


Figure 2.6: CNN Feature Extraction.

CNNs image feature extraction has set a new standard and their application in pipeline inspections is a remarkable and innovative advancement in the industry. In figures and descriptions, the subsequent segment illustrates the application of the networks in image feature extraction, which is vital to the proposed method for detecting cracks later in this paper [79].

2.5.1 CNN Architecture

Convolutional neural networks are some of the most popular deep-learning architectures due to their effectiveness on visual data. A standard CNN consists of convolutional, pooling, and fully connected layers, stacked in a hierarchical order. In the convolutional layers, a number of sliding filters that have been previously learned from the dataset capture image features. After the convolutional layers, the pooling layers of the hierarchy down-sample the image to remove unimportant details, conserving redundancy in the feature map. Finally, the fully connected layers are used to yield class scores from the features that have been pieced together.

Table 2.1: CNN Types and Layer Parameters

	ResNet	LACE	CNN-BLSTM
Number of parameters	38 M	65 M	48 M
Number of weight layers	49	22	10
Input	40×41	40×61	$40 \times 7 \times t$
Convolution_1	[conv 1×1 , 64; conv 3×3 , 64; conv 1×1 , 256] $\times 3$	jump block [conv 3×3 , 128] $\times 5$	[conv 3×3 , 32, padding in feature dim.] $\times 3$
Convolution_2	[conv 1×1 , 128; conv 3×3 , 128; conv 1×1 , 512] $\times 4$	jump block [conv 3×3 , 256] $\times 5$	
Convolution_3	[conv 1×1 , 256; conv 3×3 , 256; conv 1×1 , 1024] $\times 6$	jump block [conv 3×3 , 512] $\times 5$	
Convolution_4	[conv 1×1 , 512; conv 3×3 , 512; conv 1×1 , 2048] $\times 3$	jump block [conv 3×3 , 1024] $\times 5$	
BLSTM			[blstm, cells = 512] $\times 6$
Output	average pool;	[conv 3×4 , 1] $\times 1$;	Softmax (9 k or 27 k)
	Softmax (9 k or 27 k)	Softmax (9 k or 27 k)	

Hierarchical Feature Extraction: Convolutional neural networks are distinguished from other deep-learning architectures by their novel feature learning methodology. CNNs learn features hierarchically, beginning with the most basic simple features, such as edges or textures, and combining them to identify progressively complex features, such as shapes or scene-level patterns.

Adaptive Feature Learning: Convolutional neural networks are also unique in the fact that their architectures learn to adapt on the fly, allowing the model to identify the most reliable

features of the data in a task-specific manner as data is fed to the model in the course of training.[82].

2.5.2 Detection of Subtle Visual Patterns

In the field of pipeline inspection, ConvNets (Convolutional Neural Networks) process high-resolution images to identify subtle visual cues associated with cracks and other surface defects. Using high-resolution 3D images obtained from drone flyovers, the network removes regular areas of the image and focuses on areas with irregular borders, which may indicate structural issues. The final image may contain several of these irregular areas. Marker removal thus becomes a key step in any automated pipeline for detecting and evaluating cracks. Utilizing ConvNets achieves a more detailed automated inspection than traditional systems owing to their ability to identify small features that may go unnoticed by inspectors[83].

2.5.3 Transfer Learning

As a feature extraction technique, convolutional neural networks (CNNs) utilize transfer learning, which has multiple applications. The technique starts with a model trained on a large dataset, usually ImageNet. The model is then adapted to a more specific task, e.g., crack detection. Then, the model has its weights transferred, which allows the network to obtain high-level representations and significantly improve the feature extraction capabilities in the new task[84]. Efficiency: This technique greatly reduces the dataset and compute time required to develop a CNN because it eliminates the need to train a CNN from scratch. Generalization: The model is able to generalize well and is able to adjust to different tasks in image classification because it has been trained on a diverse dataset containing millions of images.

2.5.4 Learning Spatial Hierarchies

Convolutional neural networks (CNN) learn layered, spatial features of images, which makes them appropriate to industrial inspections. Portions of a scene could look differently due to differences in orientation, scale, or illumination. For pipeline monitoring, a CNN's hierarchal (spatial) learning makes it possible to disentangle the relative position of pipes,

bends, flanges, and welds, even when the view is obstructed or corroded. Pipeline Structure Recognition: The network learns to classify each component, and differentiate fittings from straight runs, by training on sequences of annotated frames. Surface Abnormality Detection: Feature maps of typical appearances (no noise, consistent color, and clear geometry) invoke stronger responses. The system is responsive to previous features so in the presence of noise, color (discoloration), or shape alterations (geometric distortion), the system will detect cracks, damp corrosion, or the dent.

2.5.5 Algorithm Training and Validation

The features extracted from the images form the backbone of training and testing of the crack detection algorithm. To widen the training scope, drone simulations in 3D, with the cracks and other features incorporated, can be combined with the CNN extracted features to create a more rich and diverse training dataset. The system learns, during extensive training, to identify gaps in the surface of the data and 3D scans, which helps to improve the surface flaw detection. The training also shortens the time it takes to do future inspections and improves the accuracy of future inspections. During training, the features extracted using CNN assist the model in learning the patterns in the dataset which contain cracks and corrosion. For testing, the same feature set is used with a separate dataset to ensure the training does not overfit in the actual outdoor to real-world settings with actual varying lighting conditions, weather conditions, and scale. The use of neural feature extraction is, therefore, a critical aspect of the process as it enables the pipeline monitoring system to exploit the advantages of deep learning to identify fine details and complex patterns. By integrating single high-res images with predictions, the system can offer advanced real time monitoring of oil pipelines, saving detection time and costs in the process, while also enhancing the safety of oil operations.

2.6 FUZZY LOGIC IN CRACK DETECTION AND CFD ANALYSIS

Fuzzy-logic classifiers are widely used in industry because of their ability to capture ambiguity and overlapping terminology in defect recognition. The Dynamically Constrained Accumulative Membership Fuzzy Logic algorithm (DCAMFL) improves previous methods by tightening membership borders when the vocabulary is too fuzzy, enabling better

categorization. CFD software demonstrates that surface cracks in pipelines affect the flow and pressure of the fluid. Fuzzy sets improve the CFD data so that inspectors understand the flows associated with each defect and can prioritize based on the shape and the hydraulic consequences.

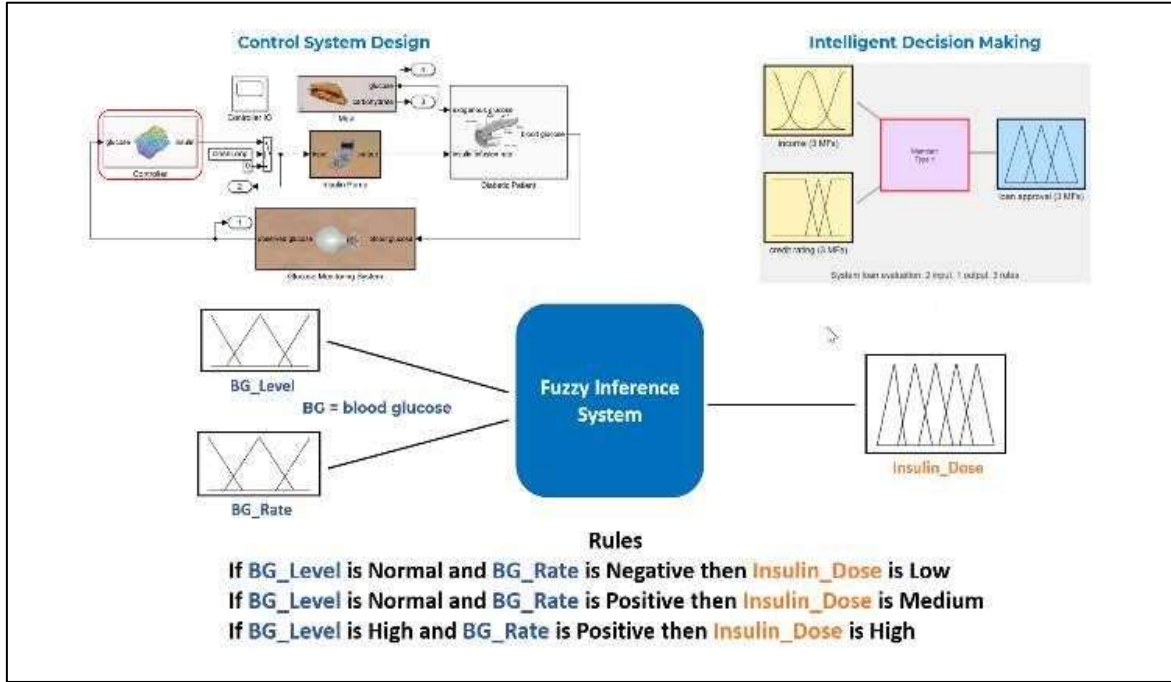


Figure 2.7: Fuzzy Logic System within Matlab.

The integration of fuzzy logic with CFD definitely enhances the precision and dependability of crack detection in oil pipelines. The current section first outlines the basic principles of fuzzy logic, describes its creative application in crack detection, and then explains how the CFD model reveals the flow distortions that such defects produce and how this model data guides the analysis of the inspection results.

2.6.1 Fuzzy Logic in Crack Detection

Fuzzy logic is one among many mathematical approaches that attend to uncertainty and vague information. While classical binary logic would require an answer that is either true or false, Fuzzy logic is able to handle partial truths and is thus far better suited to address many of the ambiguities in real world applications. With the systems that utilize this framework, imprecision in data is translated to usable information using linguistic variables and membership functions. Fuzzy logic systems used for crack detection in oil pipelines

allow for the efficient discrimination of actual defects, even in cases where the pictures are of poor quality or when the evidence is visually scanned. The detection system may inform users that an apparent defect is one of Small, Medium, or Large, using terms that people are used to. Quantitatively, membership functions determine how well an apparent defect fits each of the grades, and thus the engineers are provided with an approximation of how serious the defect is and its potential implications.

2.6.2 Integration of CFD Analysis

Numerical methods along with algorithms are used in fluid mechanics to predict the behavior and motion of liquids in real life situations. Within the context of oil pipelines, CFD tools allow engineers to visualize the fluid mechanics that would result from the operational defects such as cracks and dents that would otherwise cause catastrophic failures.

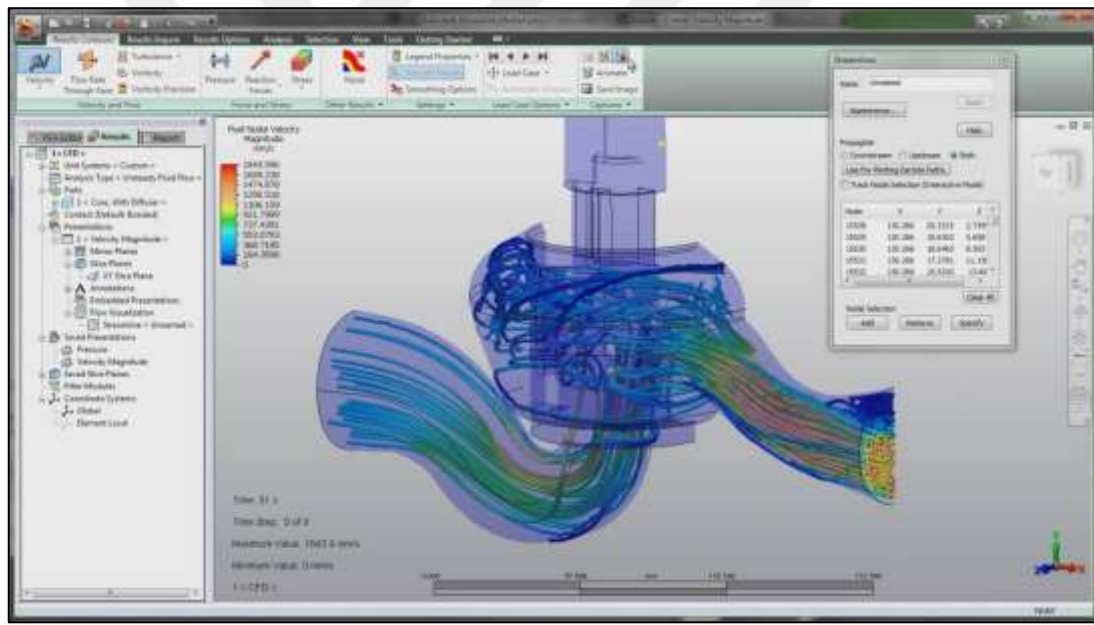


Figure 2.8: 3D CFD Analysis within ANSYS Fluent.

Integrating computational fluid dynamics (CFD) into discrepancy detection workflows enhances the understanding of how imperfections influence the operation of pipelines. CFD models showcase the flow within a pipeline and how it alters (or does not alter) concerning pressure, flow, velocity, and other attributes. When there is a defect in the flow of a pipeline, these attributes change, and the resulting signature can be analytically processed to be attributed to a specific defect location and depth in the pipeline [88].

2.6.3 Novel Integration for Crack Detection

The aerophotography received by 3D scanners of pipelines is the first to a fuzzy classifier, which sequenced the image into its constituent visual elements. The new combination of fuzzy logic and CFD provides a disparate way of modeling the location and a grade of defect in a pipeline. Meanwhile, the CFD model provides the expected values of how a deficient pipeline behaves. The integration of these flows allows the system to balance visual and hydraulic parameters, and therefore diagnostic attestation. The system alleviated the disparity between the visualized and the hydraulic within the pipeline.

2.7 EXISTING CRACK DETECTION METHODS

The current literature showcases various methods for detecting cracks, ranging from machine learning to fuzzy logic. Each strategy exhibits varying degrees of accuracy, speed, and versatility for use in operational pipelines. Each method has unique pros and cons, and overall effectiveness often depends on the particular characteristics and limitations of the pipeline. The last several years have seen the adoption of more advanced techniques in the discipline, focussing on integration of sophisticated modeling and simulation, deep learning, and fuzzy logic for advanced and more reliable inspections. Automation of manual processes has been the objective, seeking to improve workflow efficiency in maintenance. Zhou et al. (2020) demonstrated the effectiveness of this approach in their study, in which a convolutional neural network framework autonomously identified pipeline fractures with high accuracy. The process required hundreds of thousands of images to be manually annotated, emphasizing the highly data-driven approach to modern defect detection.

Recent research validating deep learning's application in pipeline monitoring is encouraging, given the network's ability to identify both large and small cracks with accuracy [4]. Li and Chen (2021) have followed the line and investigated the combination of support vector machines (SVM) and image-processing techniques to detect cracks on the surface of oil pipelines. Their method involved two image preprocessing techniques, namely adaptive thresholding and histogram equalisation, before the images were presented to the SVM classifiers. When implemented, the SVM classifiers in the experiments showed a good level of detection [5]. In the most recent work, Khan et al. (2022) describe the use of AE sensors to monitor fractures and to combine them with artificial intelligence [9].

2.8 GAPS IN THE EXISTING LITERATURE

A major gap identified in the review is that there is no literature covering a fully integrated approach to 3-D modeling, convolutional neural networks (CNN), and fuzzy logic theory applied to the problem of oil pipeline crack detection. Therefore, there is an immediate need to consider new approaches. Traditional inspections, while rudimentary to the oil industry and oil and gas pipeline operations, have well documented detractors. There is a visual component to pipeline inspections that is ultimately subjective. Additionally, visual inspections are, in most cases, unable to penetrate the surface coatings and may, have a degree of rapid degradation and require intermittent sophisticated experts that are not always readily available to the pipeline where miles and miles of pipeline goes unmonitored. As a result of these things, there is a perceived lack of speed, consistency and, the ability to detect flaws that are hidden or not directly visible, no matter the method employed magnetic, ultrasound, or even, aerial surveying. These things have lead to the creation of experimental systems. The use of drones to create 3 dimensional maps and then apply a CNN to determine the images of defects and fuzzy logic systems to determine the degree of certainty about the defects is the system described in the following section (4). 3D imaging, deep learning and fuzzy inference systems may lead to a more accurate system but, the systems that need to be deployed to achieve these things will be very difficult to create. The difficulty is caused by large data volumes, near real-time demands, multitasking sensor systems, and integration to existing systems.

There have been significant advances in several interconnected fields, and based on the latest breakthroughs in processing, data, and automation, practitioners and researchers could realize the full potential of the fields.

Table 2.2: Summary of the Research Gaps in the Literature Review.

Study Reference	Crack Detection Methodology	Gap Details
Zhou et al. (2020)	Convolutional Neural Networks (CNNs)	Automated detection of pipeline cracks using CNNs trained with labeled pipeline images.
Li and Chen (2021)	Support Vector Machines (SVMs)	Image preprocessing (histogram equalization, adaptive thresholding) followed by SVM classification.

Table 2.3: Summary of the Research Gaps in the Literature Review. “Table Continued”

Khan et al. (2022)	Acoustic Emission (AE) Technology + AI	AE signals from cracks are processed and classified using AI for real-time pipeline monitoring.
Huang and Liu (2022)	Reinforcement Learning (RL)	RL-based drone system for optimal drone navigation to inspect pipelines, maximizing crack detection accuracy.
Present Study	3D Drone Simulation + DCAMFL	A novel approach combining 3D drone simulation with Dynamically Constrained Accumulative Membership Fuzzy Logic Algorithm for crack detection.
Literature References for Other Methods	Various Machine Learning Approaches	Pattern recognition and machine-learning methods have been applied in different studies for various purposes.

2.9 SUMMARY

This literature review attempts to detect cracks in oil pipelines and examines the evolution of the domain from traditional methods of inspection to contemporary methods. The review looks at the potential of three- dimensional simulations from drones and convolution neural networks to extract valuable information from data. Fuzzy logic and computational fluid dynamics are valuable in the enhancement of the analysis. The integrated methodology of the review is designed to address fundamental issues and improve surveillance of the oil pipelines.

3. PIPELINE CRACKS AND AI

3.1 INTRODUCTION

This chapter is dedicated to discussing the various oil delivery methods. The several varieties of oil pipelines suitable for use in this context are also shown here. A more in-depth explanation of leakage detection methodologies and processes will be provided. Following this, a complete examination of the various techniques of detection that are now accessible will be offered. A variety of today's most well-liked oil leak detectors will be shown in this exhibition.

3.2 GENERAL PRESENTATION OF THE NETWORKS

3.2.1 Definitions

In an oil distribution network, different pipes are interconnected and arranged in a circuit according to their intended use and, more specifically, their diameter. This allows the product to travel from its origin to its destination [91].

A. Oil Mains

Pipes go from the city's purification facility or pumping stations to each neighborhood. They often have a diameter of 350 millimeters or more.

A. Secondary Lines

They have a 250 or 300-mm diameter and are linked to significant pipes, creating interconnected networks. Separation is about a kilometer. c. Local pipes Despite being the smallest sewers in a system, local sewers must have a minimum diameter of 150 mm to meet fire safety regulations. Few local streets are serviced by the oil mains[92].

3.2.2 Types of Oil Distribution Networks

This is a set of armed pipes. The selected system and the idea of pipe connections are used to categorize these networks[93].

a. Branched Networks

The Forked System figure (3.1) depicts a main line with linked branch lines parallel to it. It's a tree-like (branched) network with no means of distributing profits evenly. If there is a problem with the main, everyone living farther downstream will be without oil.

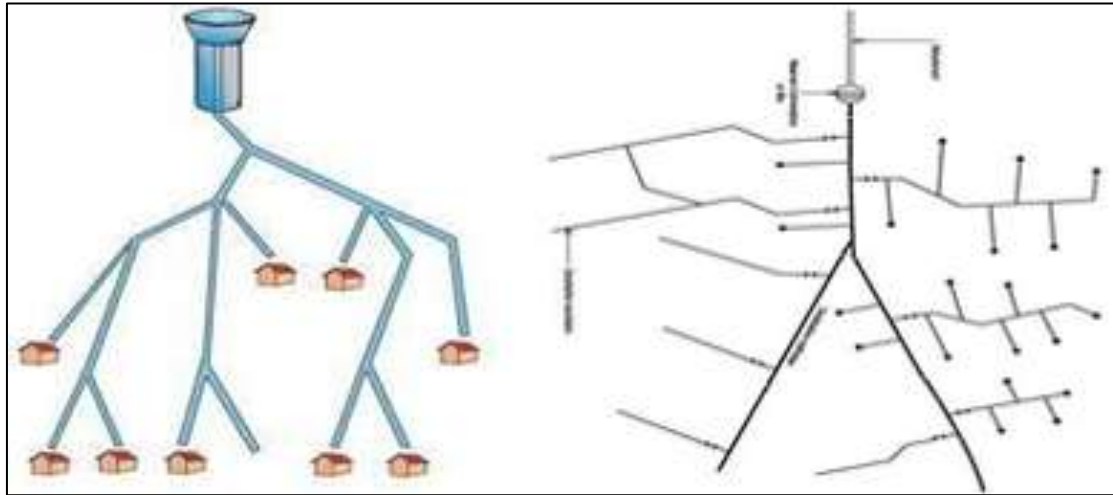


Figure 3.1: Diagram of a Branched Oil Distribution Network [94].

b. Mesh Networks

For city oil distribution, this is the most common choice of network. Oil for irrigation purposes is also available from this source. The "on-demand" model of distribution works well for them. Due to the ability to guarantee flow at any node in the network in either direction and to deliver a decreased flow from the other end of the mouth in the case of a pipe break, mesh networks increase operational security [95].

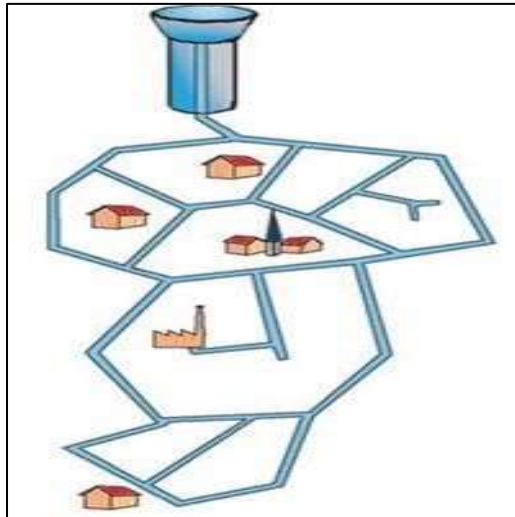


Figure 3.2: Diagram of a Meshed Oil Distribution Network [96].

c. Mixed Networks

These systems may be divided into forks at the primary and secondary conveyance levels (canals and pipes, respectively) and interconnected at the tertiary level [97].

d. Tiered Networks

Profound distinctions define the tiered network structure. This causes abnormally high pressures at the reservoir's lowest point (the pressure standards are not being followed). A second reservoir supplied from the first must be established to control the network pressure.

The network's topology will largely determine which canals and pipes are used to create it. However, in this scenario, the channels are always situated upstream of the pipes.

3.2.3 Characteristics of A Distribution Network



Figure 3.3: Ductile Iron Pipe.

a. Steel/ Galvanized Steel

Piping and fittings made of steel or galvanized steel oil pipelines (figure 3.4) may carry either hot or cold oil. Corrosion from the elements may cause problems for this task, both technically (affecting the installation's capacity to operate and last) and sanitarily (lowering the quality of the oil provided). It revealed that low-quality steels and their galvanization might be at the root of these disorders, in addition to problems connected to the design of the installations, the characteristics of the oil transmitted, or the operation of the installations [101].



Figure 3.4: Galvanized Steel Pipe.

b. Reinforced concrete with sheet metal core

Because of its cheap cost, passivity, low corrosion, self-supporting capabilities, appropriateness for trenchless, jacking methods, and lifespan, the pipe with a steel sheet core and a double reinforced concrete liner (Figure 3.5) is becoming more popular, especially in large sizes. Particular types of cement and internal and exterior coatings, similar to those used for other pipe materials, may be utilized under high circumstances of aggressiveness and/or corrosion of the oil or dirt. It is possible to use cathodic protection on the central sheet metal core [102].



Figure 3.5: The Reinforced Concrete Pipe with a Sheet Metal Core.

c. C. Network accessories

a. Tank

The reservoir acts like a basin, filling up during low daily usage and draining during high demand.

The reservoir's capacity will depend on how the upstream works are managed and how demand fluctuates. The reservoir may be submerged, semi-buried, or raised depending on whether the town is on the plain or the hills.

b. Seals

Their job is to keep water and oil out of the pipe connections while withstanding pressure and chemicals. They need to be a precise fit for the area allotted to them. Because of their

flexibility, the joints shown in Figure (3.4) are particularly susceptible to mechanical wear due to pipe movement. Chlorinated compounds in oil and drying contribute to joint aging. Mechanical, socket, and flange joints are the most common [103].

Under the ground, pipes are connected using mechanical or spigot connections, whereas flange joints connect pipes inside buildings like pumping stations, treatment facilities, etc.



Figure 3.6: Oil Pipe Joints were Taken from the Beiji Refinery in Iraq.

- d. D. Age of the pipes
 - a. Materials decay or become weak over time; the climate changes and the ground shifts contribute to the inevitable deterioration of pipes and their accessories. However, the factors that contribute to a pipe's deterioration are not limited to its age alone:
 - b. Environmental factors: some pipes are over a century old and still functioning well, while others are only five years old and have already been deemed obsolete. They are

situated on unforgiving or hostile terrain; the materials have inherent flaws, such as low corrosion resistance or inadequate surface covering.

- c. Network construction and operation issues, including oil hammer and backfilling done with subpar materials and no safety considerations [104].

3.3 LEAKS

3.3.1 Definition of A Leak

A decline in quality, manifesting as a measurable physical loss of the distributed fluid, puts a network in danger of failing. Leaks occur at valves, connecting points, joints, and the pipe itself, and they cause mechanical and acoustic vibrations owing to the pressure changes of the fluid in the pipe.

3.3.2 Types of Leaks

Smaller diameters tend to shatter transversely, whereas larger diameters tend to break longitudinally or develop pits. Pipes with greater diameters leak at the joints, whereas smaller-diameter pipes tend to spring leaks. Table 3.1 displays the most prevalent distribution pipeline rupture types [105].

Table 3.1: Failure Modes of Distribution Pipelines.

Type of Leak	The Cause
Circular crack	- Bending stress due to frost.
	- Flexural stress due to swelling clay.
	- Thermal contraction.
	- Longitudinal stress near valves and fittings.
Longitudinal break	- Peripheral stress due to internal oil pressure.
	- Annular stress from surcharge exerted by the ground cover.
	- Peripheral stress due to frozen oil.
	- Annular stress due to traffic overload.
Disengagement	- Expansion of the seal material.
Shearing of the socket	- Excessive pressing of the cord into the socket.
	- Bending stress.
Spiral break	- Combination of bending stress and peripheral stress due to internal oil pressure.
Breakdown / burst	- Peripheral stress due to internal oil pressure.
	- Corrosion of steel prestressing wires in concrete suppression pipes.
Through hole	- Pitting corrosion.
	- Imperfection in the moulding.

3.3.3 Cause of Leakage

- a. Leaks cause the majority of distribution losses in a canal. There are several origins for them:
- b. Construction, earthwork, backfilling, or compaction may destabilize the soil around the pipes, leading to leaks.
- c. • High pressure in the distribution network • Improperly installed pipes or work flaws
- d. Excess pressure .c:aised by hydraulic shock (due to the quick closing of a valve or other device; also known as the "oil hammer" phenomenon). Soil conditions change over time, compromising the integrity of the pipes [106].
- e. Seals' advancing years
- f. Connections to public infrastructure that are both cheap and poorly executed
- g. Due to corrosion, steel pipes may rust from the inside or outside, depending on the soil and humidity level.

3.3.4 Leakage Rate

The quantity of fluid leaking from its container may be used to quantify the problem. The rate of leakage is stated as a volume per unit of time, with 1 m³ per second being the standard unit of measurement).

3.3.5 Beiji Oil Refinery Cracks

The uneven distributions of stress along the components of the oil refinery affect the reliability and safety of the Beiji Oil Refinery. Operational stress and environmental conditions also lead to the uneven distributions of stress. The primary types of Cracking occurring at the refinery and their causes, effects, and potential solutions will be described in this paragraph.

3.3.5.1 Manufacturing flaws

The refinery could have meticulous systems in place to examine the structural design and systems of their pipelines and storage tanks, and the design could still be flawed. and lead to the creation of defects that could later lead to the creation of cracks. Within the systems to examine the design of the pipelines and storage tanks, there could be tight systems of

quality control, and the systems could still lead to the creation of defects that serve as the 'germ' or starting point of uneven degradation. The subtle imperfections that could stem from the systems could lead to uneven degradation of the structure that will become obvious along the economic life of the structure and become obvious later along the economic life of the structure.

3.3.5.2 Corrosion-Induced Cracks

Corrosion has occurred on the piping of the refinery and the storage tanks. These get worse in the presence of external temperature changes and cyclic mechanical loading. There are two specific types of cracking that can result from this phenomenon: stress corrosion cracking (SCC) and sulfide stress cracking (SSC). SCC starts primarily on the welded joints. SCC causes noticeable surface cracks when stress and corrosion are present along with heat.

3.3.5.3 Stress and Fatigue Cracks

The mitigation strategy for both types of this phenomenon considers three factors: the use of specific alloys that are hydrogen resistant, the planning and timing of the nondestructive testing, and the replacement of parts that are found not to meet both mitigation requirements.

3.3.5.4 Hydrogen-Induced Cracking

SSC, on the other hand, takes aim on the more harder welded joints and fine grained microstructures by losing its tensile strength on the alloys. Many cycles of loading, whether from normal processes or incidental hits to the steel, create what is termed fatigue cracks. These fatigue cracks are known to originate from surface imperfections such as dents or bad welds. The more surface imperfections are present and the more systematic inspection, the more preventive benefits can be realized before the cost of repairs to the steel increase significantly.

3.3.5.5 Weld and Nozzle Cracks

Another hydrogen-related concern for sour conditions is when a wet hydrogen-sulfide environment saturates the steel surface with atomic hydrogen. When hydrogen enters the

steel, it diffuses, creates blisters in the subsurface, and ultimately results in cracking, a process termed hydrogen-induced cracking, HIC, or its more directional derivative, stress-oriented hydrogen-induced cracking, SOHIC. Cracking is typically at weld seams and nozzle attachments, often the result of poor-quality welding or the presence of localised stress concentration. Such deficient conditions are even more likely without adherence to mandatory welding specifications and thorough post-weld inspections. As a result, the Beiji oil refinery does not rely solely on the accepted industry standards, but uses a comprehensive range of monitoring strategies to verify accurate and timely detection and mitigation of existing and potential structural weaknesses. These measures protect the Beiji oil refinery from unnecessary expensive standby periods.

Table 3.2: Types of Cracks in Beiji Oil Refinery in Iraq.

1-	Reactors in CCR units	Causes of Cracks:
		1- Stress Corrosion Cracking (SCC):
		2-Fatigue Cracking:
		3- Hydrogen-Induced Cracking (HIC):
2-	piping network	Corrosion: External and internal corrosion can weaken the pipe material over time.
		Stress and Fatigue: Cyclic loading, temperature variations, and stress concentration points contribute to cracks.
		3- Hydrogen-Induced Cracking (HIC): Hydrogen diffuses into the material, leading to internal blistering or cracks. Wet H ₂ S environments are particularly prone to HIC.
		4- Sulfide Stress Cracking (SSC): SSC occurs in hard weldments and microstructures due to exposure to aqueous hydrogen charging and can weaken the pipe material over time.
3-	cracks in storage tanks	1- Longitudinal Cracks: These run parallel to the length of the tank. They often result from stress, corrosion, or poor welding during construction.
		2- Circumferential Cracks: These encircle the tank. They may occur due to overpressure, temperature fluctuations, or material defects.
		3- Radial Cracks: These extend outward from a central point. Radial cracks can form due to localized stress or corrosion.
		4- Shell-to-Bottom Joint Cracks: Located at the junction where the tank shell meets the bottom. Poor weld quality or stress concentration can cause these cracks.
		5-Nozzle Cracks: Associated with openings (nozzles) on the tank. Stress concentration, corrosion, or improper design can lead to nozzle cracks.
		6- Weld Seam Cracks: Result from welding imperfections. Proper welding techniques and inspections are crucial to prevent these.

Table 3.2: Types of Cracks in Beiji Oil Refinery in Iraq “Table Continued”.

4-	cracks in pressure vessels	1- Wet H2S Cracking:
		Cause: Wet H2S cracking occurs under acidic conditions, such as those in oil field applications or refinery environments with a pH around six or higher (due to ammonia presence).
		2- Sulfide Stress Cracking (SSC): Affects hard weldments and microstructures.
		3- Hydrogen Blistering: Formation of hydrogen blisters within the material.
		4- Hydrogen-Induced Cracking (HIC): Internal cracking due to hydrogen diffusion.
		5- Stress-Oriented Hydrogen-Induced Cracking (SOHIC): Cracks influenced by stress1.
		Mitigation: Proper material selection, inspection frequency, and timely replacement are crucial.

3.4 ARTIFICIAL INTELLIGENCE

according to [86], Artificial Intelligence in Engineering aims to develop intelligent machines based on the concepts and applications that govern them. As examples of intelligent machines, it is possible to mention natural language processing systems, used to understand excerpts of written and spoken language, automatic specialized consultation systems, which can identify diseases and even determine potential ore deposits, and systems of theorem proof, whose function is to deduce theorems from other previously proven theorems [87]. Such systems emulate intelligent behaviors through computational processes [88]. In the scientific context, AI can be described as a theory of intelligence that comprises intelligent behavior observed in people and other animals, as well as in artificially developed machines, through the formulation of terms and concepts that help achieve this degree of understanding [89]. AI definitions can address issues of reasoning and knowledge acquisition procedures, as well as behavioral issues. Such definitions can also consider aspects of human action and concepts of intelligence. Representing, estimating, and learning when they are in contact with the environment.

3.4.1 Machine Learning

Machine Learning (ML) is a subdivision of AI that is closely related to the fields of data mining and statistics. As a result of the constant increase in the amount and availability of data in different research areas, methods capable of extracting patterns and learning automatically are increasingly required [92]. These techniques that analyze data

automatically are characterized as Machine Learning methods. According to [93], “machine learning is a set of methods that can automatically detect patterns in data and then use the discovered patterns to predict future data or to perform other types of decision making under uncertainty.”.

Problems involving pattern recognition in the field of machine learning can be categorized into three main types: Supervised, Unsupervised, and Reinforcement Learning. According to Murphy (2012), solving problems in the supervised category consists of learning to relate the inputs x to their respective outputs y , since the labeled set of Eq. 3.1 is given, where D corresponds to the training data set, and N refers to the total number of training samples.

$$D = \{ (x_i, y_i) \}_{i=1}^N \quad (3.1)$$

The inputs x_i , comprised in the space of labeled instances, can be either D -dimensional vectors, called attributes, or more complex data structures, such as feature vectors, images, and even time series. On the other hand, the outputs y_i , referring to the label space, can be represented, in most applications,

by categorical variables (in a finite set of categories $y_i \in \{1, \dots, n\}$ to $n \in \mathbb{N}$) or by real variables, where y_i assumes continuous values ($y_i \in \mathbb{R}$). When y_i is categorical, you have a classification or pattern recognition problem; when y_i is real, you have a regression problem. If y_i is real and ordered, it is an ordinal regression problem [94].

According to [96], the training data set with N samples is used to adjust the parameters of the adaptive model applied to solve the supervised problem. Thus, in the training stage, the machine learning algorithm aims to determine an output function $f: X \rightarrow Y$. After training, the model can be applied to the test set, where new input variables are found.

In Unsupervised problems, only the input is known, Eq. 2.2, and there is no labeled input-output set to train the model. In this way, this type of problem is solved by determining patterns in the input data whose relationships are not previously provided [95].

$$D = \{ x_i \}_{i=1}^N \quad (3.2)$$

Finally, Reinforcement Learning methods consist of seeking to maximize reward through the process of taking actions that lead to distinct states in a specific environment. Such

algorithms are based on the concept of trial-and-error, in which it is necessary to interact with the environment to find the sequence of optimal actions and states [95].

The next topic presents Machine Learning algorithms called Artificial Neural Networks (focusing only on supervised learning) and fundamental concepts for more complex networks such as CNNs.

3.4.2 Artificial Neural Networks

According to [96], Artificial Neural Networks (ANNs) are mathematical models implemented computationally that seek to reproduce the functioning of the nervous system of living beings. ANNs became the research target more frequently in the early 90s and are still widely studied in applications such as pattern recognition and classification, control of robotic systems and electronic devices, data grouping, and associative memories, among others [97]. Furthermore, when applied, ANNs present the following characteristics: adaptation by experience, learning capacity, generalization ability, data organization, fault tolerance, distributed storage, and ease of prototyping[98].

The nervous system of living beings is composed of neurons that are cells capable of capturing, processing, and transmitting information in the form of electrical impulses (generated by physical-chemical processes) through their elementary structures: dendrites, cell body, and axons, respectively [99]. From this, the functioning of artificial neurons, which are the basic units that process information in an ANN, is based on the way biological neurons operate, but in a more simplified way. [100]. were responsible for developing the first artificial neuron structure, which, as can be seen from the

Fig 3.5 is composed of input signals $[x_1, x_2, \dots, x_n]$, synaptic weights $[w_1, w_2, \dots, w_n]$, linear combination $[P]$, activation threshold $[\theta]$ and activation potential $[u]$, activation function $[g]$ and output signal $[y]$.

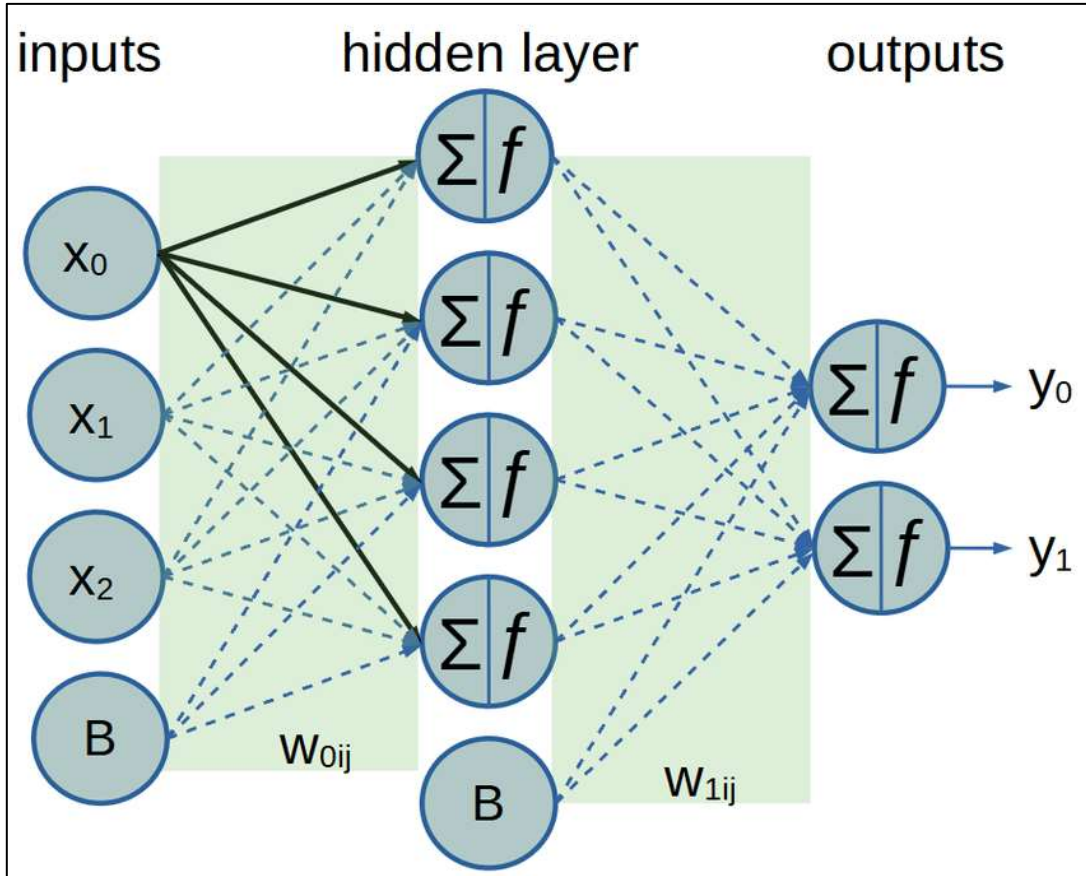


Figure 3.7: Representation of the Perceptron Network.

Thus, during training, this type of neuron receives data for each input, which are weighted by their respective synaptic weights. Subsequently, the weighted sum of the input variables is subtracted from the activation threshold, as can be seen in Eq. 3.3. Finally, the neuron's output signal is limited by applying an activation function to the values obtained for the activation potential. The most used activation functions are shown in Fig. 3.5.

$$u = \sum w_i x_i - \theta \quad (3.3)$$

As for the architecture, classical ANNs have an input layer, where data arrives at the network (no neurons), hidden layers, where features are extracted from the input data, and an output layer, which comprises neurons that generate network predictions. Fig 3.5 illustrates a feedforward network architecture (data flow occurs only in one direction) with only one neural layer (single layer). Such an architecture can be observed in Perceptron networks.

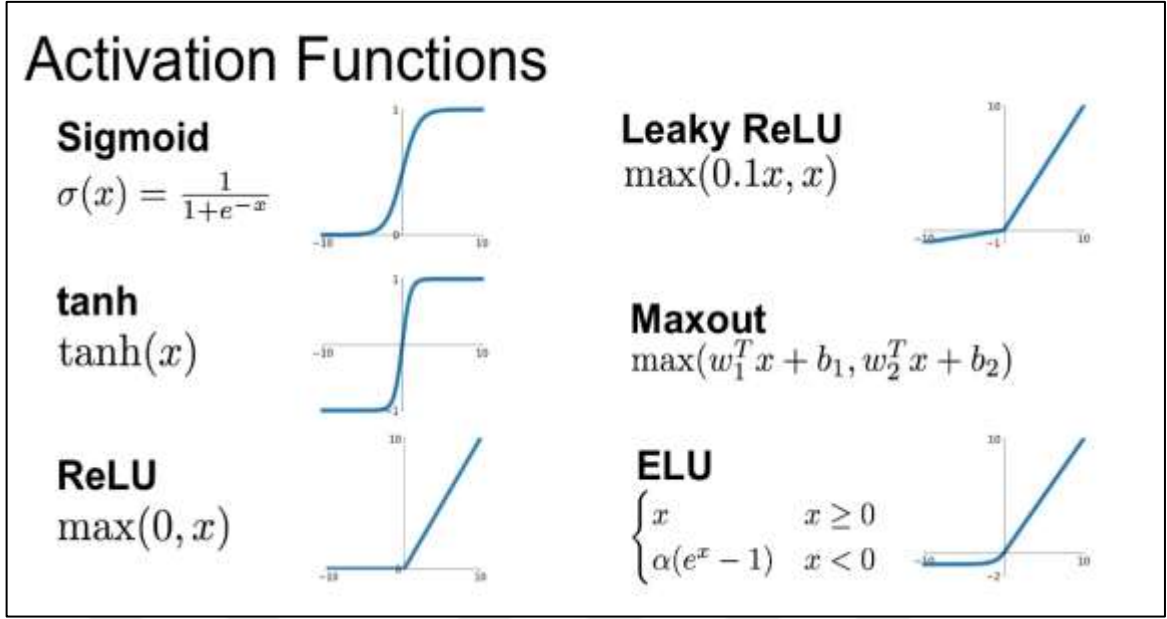


Figure 3.8: Main Activation Functions Used in ANNs.

which are generally used in pattern classification applications.

On the other hand, Fig. 3.7 shows a multi-layer feedforward architecture composed of one or more intermediate layers of neurons. The Multilayer Perceptron Network (MLP) is the most widely used multilayer architecture, as it can be applied to solve a greater variety of problems compared to single-layer architectures, such as pattern classification, universal function approximation, time series forecasting, system optimization, and process control [102]. This flexibility in solving different problems is mainly due to the more significant number of hidden layers and the MLP learning method, called the generalized Delta rule or backpropagation algorithm, introduced by [103]. which is used in the network training phase.

The backpropagation algorithm minimizes the error between the network output and expected values (Eq. 3.4) by adjusting synaptic weights and activation thresholds. In Eq.3.4, $DJ(k)$ refers to the desired output value, and $y_j(k)$ refers to the prediction of the network generated by the j -th neuron of the output layer (with n neurons) for a k -th data of training. In a training set that contains p data, the error backpropagation algorithm considers Eq. 3.5 represents the error mean square of Eq. 3.4.

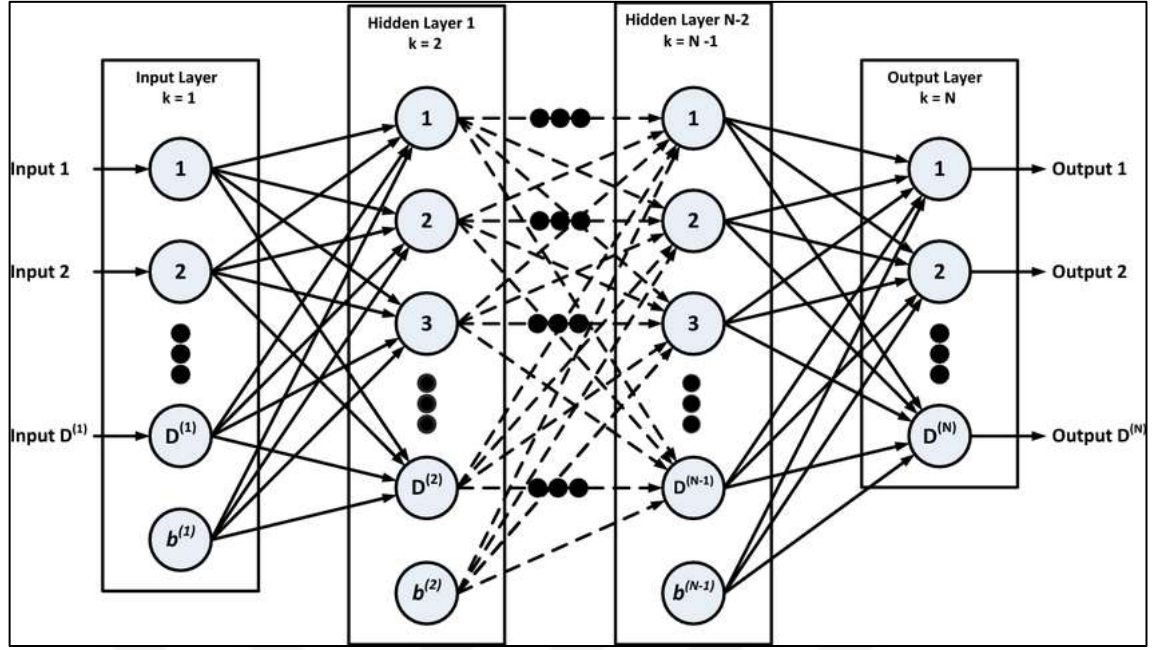


Figure 3.9: Illustration of the Multilayer Perceptron Network.

$$AND(k) = -\sum_j (d_j(k) - y_j(k))^2 \quad (3.4)$$

$$AND = NDE(k) = -\sum_j AND(k) \quad (3.5)$$

The input of the j -th neuron of the output layer and w_{ji} represent the vector of synaptic weights that correlates such output neuron to the i -th neuron of the previous layer.

Substituting the results of such equations into Eq. 3.6, one can rewrite the gradient expression according to 3.6.

$$\nabla AND = -\sum_{pk=1}^{1XP} (DJ(k) - y_j(k)) \cdot g(I_j) \cdot y_i \quad (3.6)$$

Knowing that the network's free parameters are adjusted to follow the opposite direction to the gradient vector, which points to the maximum of the EQM function, Eq. 3.7 describes the expression for updating the synaptic weights multiplied by a learning rate η . The weight adjustment expression can be reformulated in algorithm format to generate Eq. 3.8

$$\Delta w_{ji} = -\eta \nabla AND = \eta \cdot (DJ(k) - y_j(k)) \cdot g(I_j) \cdot y_i \quad (3.7)$$

$$w_{ji} \leftarrow w_{ji} + \eta \cdot \delta_j \cdot y_i \quad (3.8)$$

Having described the fundamentals of ML, the following section introduces the essential concepts in Deep Learning. Among these concepts, CNNs stand out as the primary tools for structuring the method of this and other works in the SIDE literature.

3.4.3 Deep Learning

According to, Deep Learning is an area of Artificial Intelligence, specifically Machine Learning, which aims to build complex neural network models to extract abstract representations of images from low levels to higher levels of abstraction through accumulation experiences with data. According to [105], Deep Learning networks use the generalized Delta rule to update their internal parameters, which are responsible for forming the hierarchy of representations.

The Venn Diagram in Fig. 3.8 shows that Deep Learning is a subdivision of the area of Representation Learning, consequently Machine Learning, which is characterized by techniques capable of computing representations of input data and applying them to tasks. Classification and detection. Therefore, it is concluded that Deep Learning networks are types of Representation Learning methods, but with more levels of representation referring to multiple neural layers of processing[106].

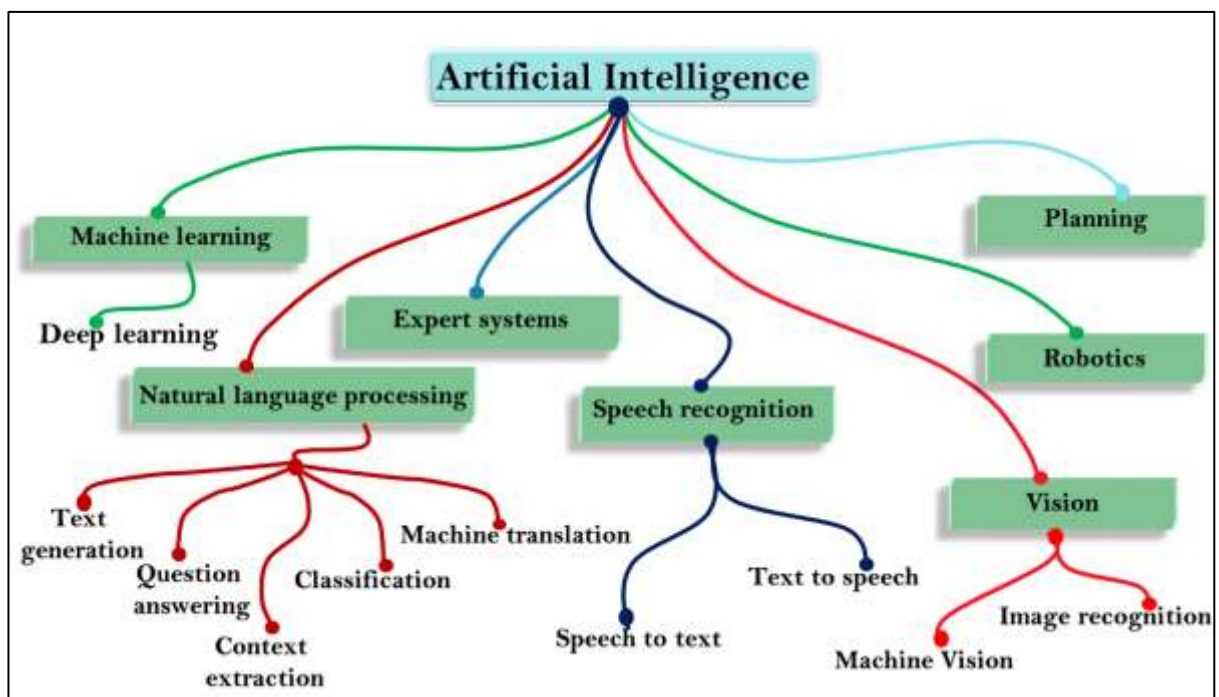


Figure 3.10: Subdivisions of the Field of Artificial Intelligence.

Due to the emergence of faster Central Processing Units (CPUs) and GPUs, in addition to the increase in data available in digital media, Deep Learning networks have been successful when applied to solving different problems previously solved by classical Vision methods. Computational and Machine Learning. Among such issues, it is possible to mention depth estimation[107].

3.5 CONVOLUTIONAL NEURAL NETWORK CNN

CNNs [108]. are adaptive deep-learning network architectures capable of automatically learning spatial characteristics of data in a standard grid format, such as images, videos, and time series. Such networks are inspired by the structure of the visual cortex [110], and they differ from classical neural networks by using the linear convolution operation in at least one of their layers [109].

The convolution operation, in the continuous plane, can be expressed by Eq. 3.9, whose reduced form is presented in Eq. 3.10. In convolutional neural network applications, the function $x(a)$ refers to the input of the convolution operation, the function $w(t - a)$ refers to the kernel and $s(t)$ is called the feature map. However, for the convolution operation to be used in CNNs, Eq. 3.11 and Eq. 3.12 must be expressed in the discrete plane. Thus, Eq. 3.13 represents the discrete convolution operation, in which, in Deep Learning, the input and the kernel have the format of a multidimensional vector (tensor). The tensor values relating to the convolution kernel are updated during the backpropagation algorithm execution process.

$$s(t) = \int x(a)w(t - a)da \quad (3.9)$$

$$s(t) = (x(a) * w(t - a))(t) \quad (3.10)$$

$$s(t) = (x(a) * w(t - a))(t) = \sum x(a)w(t - a) \quad (3.11)$$

Since CNNs receive data in grid format, it is considered that convolution operations are performed in a multidimensional manner and on a finite number of data, which correspond to the parts where there is information in the convolution input tensor (sparsity). Thus, a two-dimensional kernel K is used in the discrete convolution of Eq. 3.12 for an image I .

Benefiting from the commutative property of convolution, it is possible to determine the relationship in Eq. 3.13, which is most used in Deep Learning algorithms [111].

$$s(i, j) = (I * K)(i, j) = \sum_m \sum_n I(m, n) K(i - m, j - n) \quad (3.12)$$

$$s(i, j) = (I * K)(i, j) = \sum_m \sum_n I(i - m, j - n) K(m, n) \quad (3.13)$$

As discrete convolutions, in addition to being sparse, reuse the kernel parameters in more than one input region. It is possible to illustrate this operation through Fig 3.5. In this figure, it is observed that the values of the convolution kernel elements, gray 3×3 grid, are applied to all regions of the input image, blue 5×5 grid. The kernel follows a step with value 1. The green grids represent the feature maps obtained at the output of the discrete convolution, which are formed by multiplying the kernel elements by the image elements when the gray grid superimposes these. This way, the multiplication results are summed to form the output feature map. A kernel with the exact dimensions is used for an image with more than one dimension. In this case, discrete convolution operations are performed for each dimension separately[112].

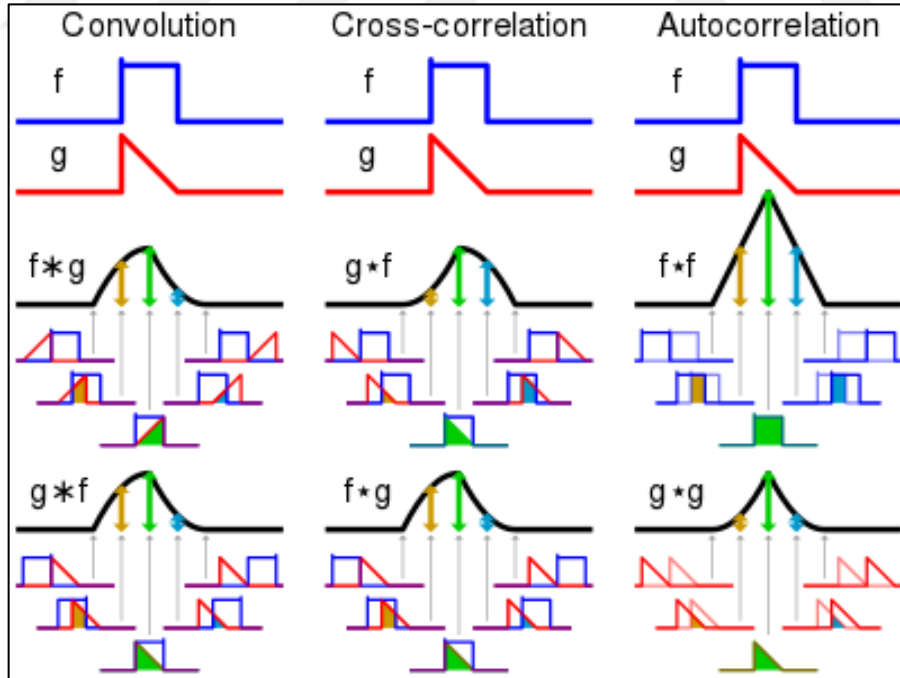


Figure 3.11: Discrete Convolution Operation.

3.5.1 CNN Topologies

Concerning structure, CNNs can be divided into an initial encoding step, followed by a decoding step. In the coding stage, feature maps of smaller sizes and with different levels of abstraction are extracted from the input image. Subsequently, the decoding stage is responsible for processing the feature maps produced during coding and generating the desired network output for different applications. Depending on the application, CNN topologies generally present structural modifications in the decoding stage to adjust the network output to return data in grid format in different ways. According to the topology, CNNs can be classified as fully convolutional (FCN) or containing fully connected layers (CNN-FC).

FCNs are composed only of convolutional layers in decoding. However, such layers are typically used in conjunction with over-sampling operations, such as bilinear and nearest neighbor operations, to increase the size of the image at the network output. The blocks consisting of convolution and over-sampling operations are called deconvolution. Fig. 3.11 illustrates an example of FCN topology [113], applied to the semantic segmentation task for autonomous navigation.

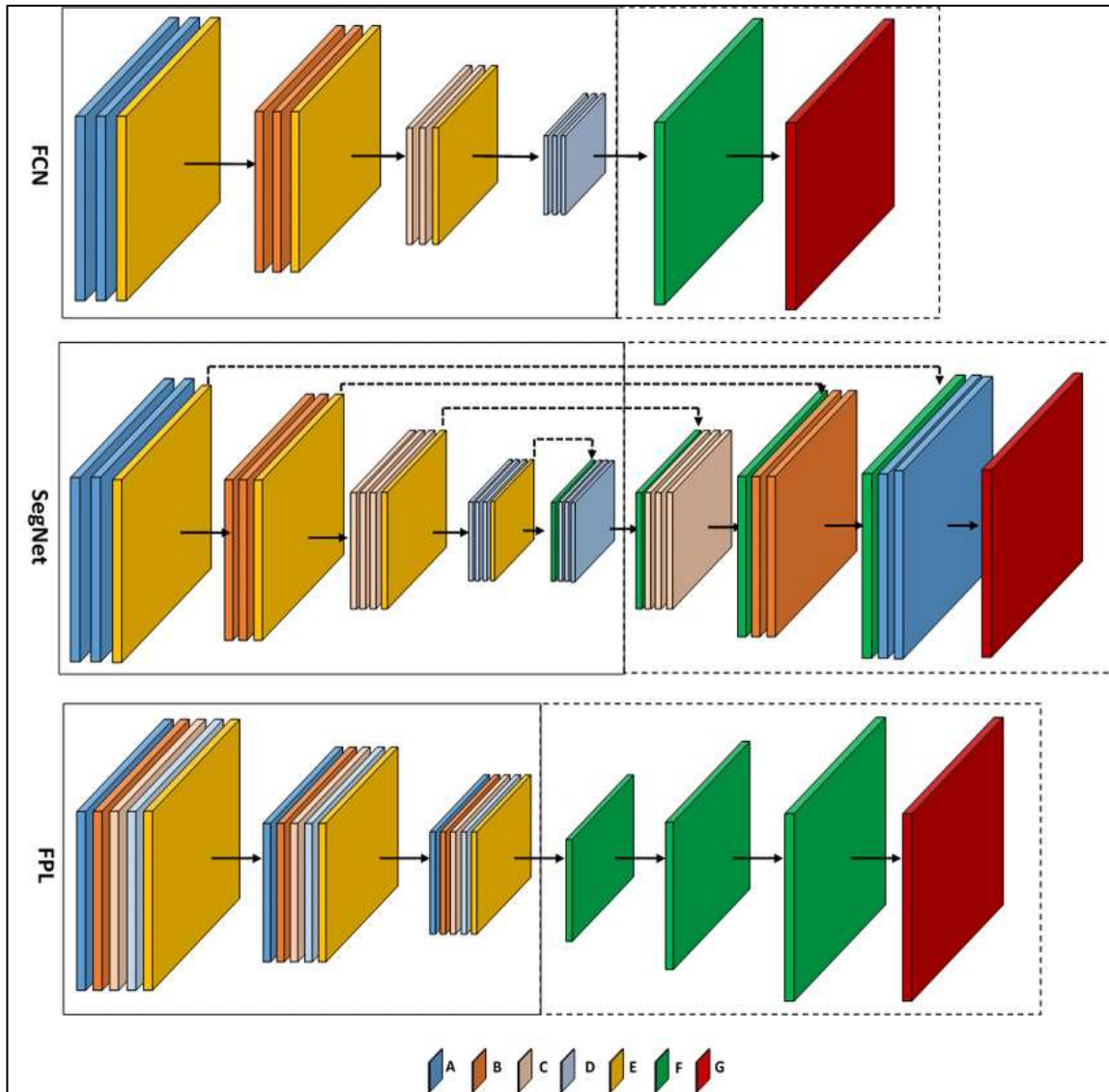


Figure 3.12: Example of FCN Topology (SegNet).

In contrast, CNN-FC uses fully connected neural layers to decode feature maps. In this case, the decoding stage has the same structural subdivisions as an MLP, in which the number of network outputs is limited by the number of neurons in the final fully connected layer. Fig. 3.11 shows an example of CNN-FC topology [114], used to classify images in the ImageNet LSVRC-2010 championship.

4. PROPOSED METHODOLOGY

4.1 INTRODUCTION

Providing a unique technique that blends 3D drone modelling with a modified fuzzy logic algorithm is the objective of this chapter, which aims to accomplish precisely that. Increasing the accuracy with which cracks in oil pipelines can be identified is the objective of this strategy. The Dynamically Constrained Accumulative Membership Fuzzy Logic approach (DCAMFL) that has been suggested can be considered an improvement over the conventional fuzzy logic algorithms that have been used previously. To reduce overlap among linguistic variables and properly manage accumulated membership values, the procedure employs a dynamic range. Under the DCAMFL framework, each input-output pairs cumulative membership is capped at one; this ceiling acknowledges the inherent complexity and variety found in real-world datasets. The dynamic range then adjusts from low in the first zone to high in the third zone, affording a more faithful representation of information gathered during drone surveillance. Because the range adapts to local variability, the system avoids the distortion that can arise when static intervals mischaracterise intermediate conditions. By pairing this novel membership scheme with three-dimensional drone simulations, we aim to improve both accuracy and speed in detecting fissures along oil-pipeline networks. This will allow us to achieve our goal. In addition to having the potential to be advantageous to the economy, this cutting-edge technology, which we hope will considerably improve pipeline surveillance, also has the potential to be ecologically beneficial. Within the scope of this investigation, the DCAMFL method was conceived of and implemented, and the outcomes of exhaustive testing and analysis provide evidence that it is effectively implemented.

4.2 FUZZY LOGIC

Mathematically, fuzzy logic is a way to handle imprecision and uncertainty. To contrast with classical (or binary) logic, which suggests that anything may either be completely true or untrue, it permits degrees of truth [10].

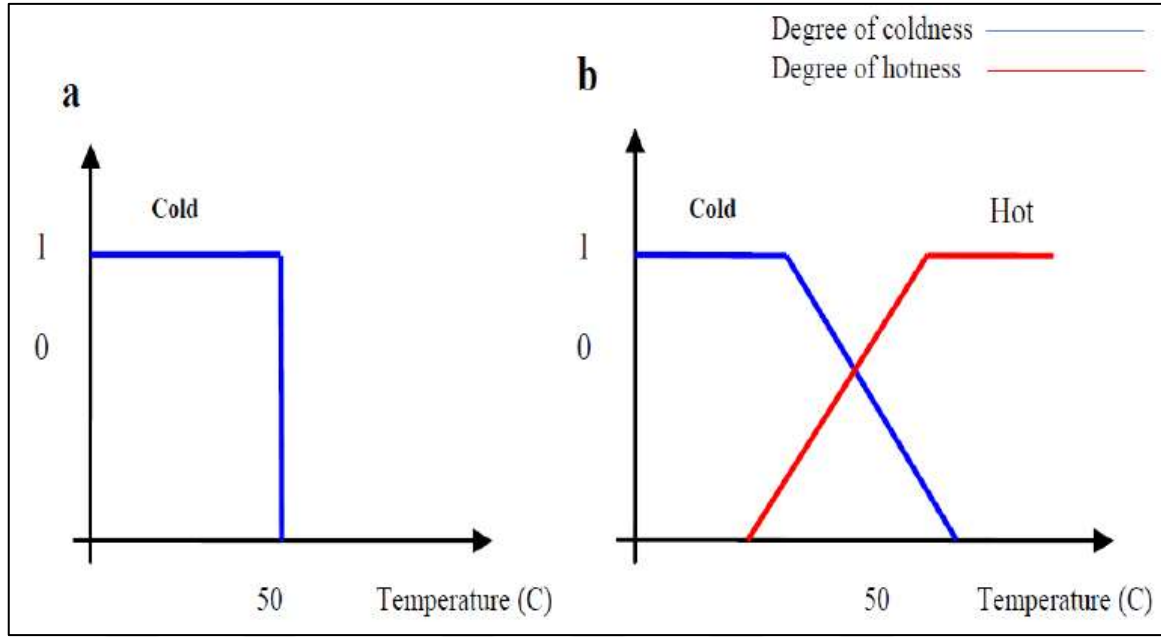


Figure 4.1: Fuzzy Logic vs Boolean Logic.

4.2.1 Fuzzy Logic Type-1

In the subject of fuzzy logic, the standard systems that are referred to as Type-1 Fuzzy Logic Systems (T1FLS) are distinguished by a membership function (x) that transforms each point in the input space X into a membership value that is between 0 and 1. This membership value is typically between 0 and 1. The membership function $\mu(x)$ is used to quantify the degree of truth with which the claim " x is A " is true. For the purpose of this discussion, A is a fuzzy set. There is a membership function $\mu_A(x)$ that is specified for each and every x in X , and it is connected with a particular fuzzy set A that is contained within X .

$$A = \{(x, \mu_A(x)) \mid x \in X\} \quad (4.1)$$

Think about the following membership function for the fuzzy set "Tall":

$$\mu_{Tall}(h) = 0 \text{ for } h < 5, \mu_{Tall}(h) = (h - 5) / (6 - 5) \text{ for } 5 \leq h < 6, \quad (4.2)$$

$$\mu_{Tall}(h) = 1 \text{ for } h \geq 6, \quad (4.3)$$

where h is the height of a person in feet.

4.2.2 Fuzzy Logic Type-2

To deal with more complex degrees of uncertainty, Type-2 Fuzzy Logic Systems (T2FLS) were developed. A membership function in T2FLS is a fuzzy set in the interval, and the membership degree is also fuzzy [0, 1].

A Type-2 fuzzy set $\hat{A}$ in X is represented as a set of ordered triples [12]:

$$\hat{A} = \{(x, u, \mu_{\hat{A}}(x, u)) \mid x \in X, u \in [0, 1]\}, \quad (4.4)$$

The function $\mu_{\hat{A}}(x, u)$ is a Type-2 membership function that changes the membership value in the interval [0, 1] for every point (x, u) in the Cartesian product $X \times [0, 1]$. In a Type-2 setting, for instance, the same fuzzy set "Tall" may have a membership function like: $\mu_{Tall}(h, u) = u$ for $h = 5.5$ and $0 \leq u \leq 1$,

$$\mu_{Tall}(h, u) = 0 \text{ for } h \neq 5.5 \text{ or } u < 0 \text{ or } u > 1. \quad (4.5)$$

The whole spectrum of potential membership values (ranging from 0 to 1) for this height reflects a broad diversity of opinions or degrees of doubt over whether or not 5.5 feet can be regarded "tall." These values range from 0 to 1. The utilisation of the UMF and LMF rankings in the course of the process of characterising Type-2 fuzzy sets is a technique that is considered to be typical. For each and every value of x that is supplied, the upper and lower bounds of the membership grade are represented by the upper boundary function (UMF) and the lower boundary function (LMF), respectively. Through the combination of these two functions, it is possible to produce the footprint of uncertainty, also known as the FOU [13]. With a membership grade that is not zero, the FOU is defined as the area between 0 and 1 that contains the membership grade. One possible formulation of the FOU within the world of mathematics is as follows:

$$CapFOU(\hat{A}) = \{(x, u) \mid x \in X, u \in [0, 1], LMF(x) \leq u \leq UMF(x)\}, \quad (4.6)$$

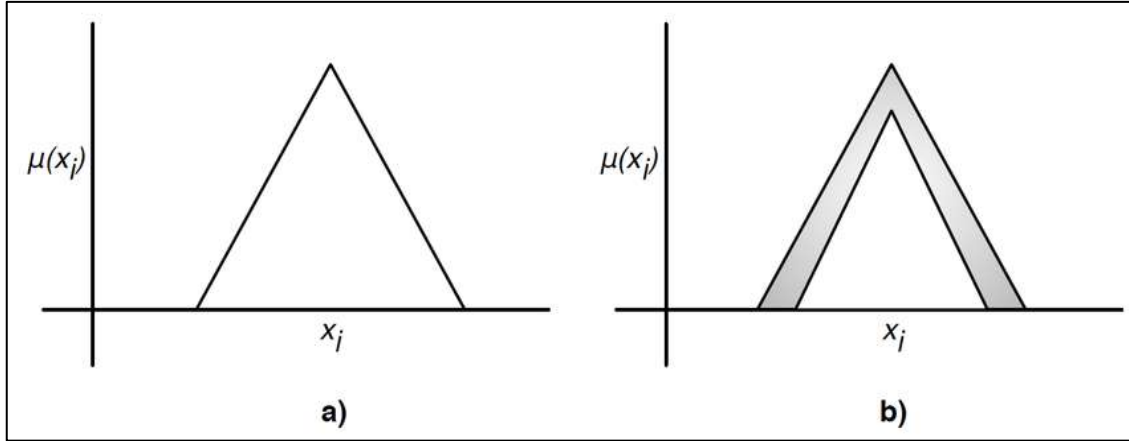


Figure 4.2: Where (a) is Fuzzy Logic Type-1 and (b) is Fuzzy Logic Type-2.

The distinction between Type-1 fuzzy logic and Type-2 fuzzy logic lies in the latter's capacity to handle uncertainties that are brought about by the value of a single linguistic variable, while also taking into account the range that is suggested by experts in the field. Type-1 fuzzy logic is able to handle uncertainties that are generated by the value of a single linguistic variable. However, none of them is able to successfully control noise when it comes to linguistic variables that have values that greatly overlap with one another [14]. This is because the values of these variables are highly correlated with one another. Through the use of type-2 fuzzy logic, the inherent uncertainties that are present in each language variable are translated into a variety of membership function values. These values are based on the assessment of specialists. Consequently, this contributes to a reduction in the impact of these uncertainties. Despite this, there is a lack of consideration given to the noise that is brought about by the significant amount of value overlap that exists across different linguistic variables. A common occurrence in real-time systems is the emergence of this type of overlap, which often takes place when the opinions of experts are highly different from one another.

4.3 PROPOSED MODIFICATION TO TYPE-2 FUZZY LOGIC

In order to make Type-2 Fuzzy Logic more user-friendly, we can restrict the total number of membership functions to a value that does not exceed 1. It is possible to draw parallels between this and the incorporation of a normalisation step into the FIS program when viewed from it from one angle. [15] It is possible that it would be helpful to investigate this topic

in a setting that is more formal. We will suppose that MF is the collection of all membership functions for a certain fuzzy set, and that μ_i is the index of the membership function that is contained within MF . This will be the case in the scenario that we are going to discuss. According to the standard type-2 fuzzy logic system, the following is the definition of the degree to which an element x is a member of the fuzzy set:

$$\mu(x) = \max \{\mu_i(x) \mid \mu_i \in MF\} \quad (4.7)$$

The membership degree that is represented by the letter x is comparable to the maximum membership degree that can be reached for any specific membership function. This corresponds to the highest possible membership degree. It is possible to adjust the Type-2 Fuzzy Logic system by ensuring that the total number of membership degrees for each function does not exceed 1 [16]. This is one way that may be utilised. Using this method is one of the ways that modifications may be made to the system. The achievement of this goal might be achieved by standardising the membership degrees. For the purpose of determining the transformed membership level $\Gamma'(x)$, one might utilise the following methodology:

$$\mu'(x) = \mu(x) / \sum \{\mu_i(x) \mid \mu_i \in MF\} \quad (4.8)$$

One possible benefit of this change in handling uncertainty caused by overlapping linguistic variables is that it makes sure that the total of the membership degrees to all individual membership functions does not go above 1.

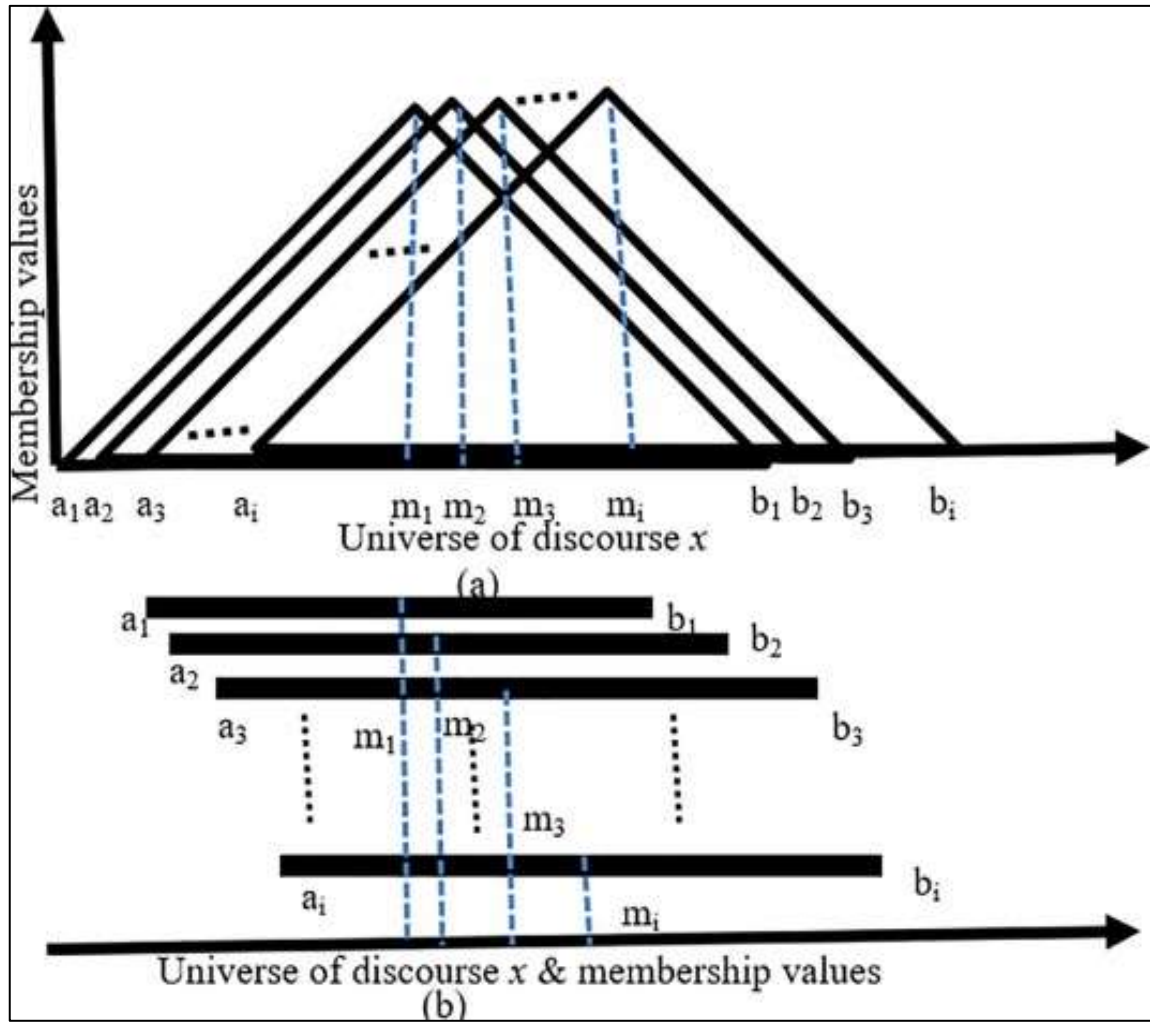


Figure 4.3: Proposed Dynamic Constraint to the Fuzzy Logic Membership Values.

The FIS's aggregation and defuzzification processes might benefit from this adjustment. It is possible to substitute a sum operation followed by normalisation for the maximum operation in the aggregation stage of the conventional FIS. Even though the normalised membership functions would be the target, the centroid approach might still be employed during defuzzification [17].

4.4 CRACKS IN OIL PIPELINES

It is possible for a wide range of reasons to be responsible for the formation of cracks in oil pipelines. These factors include environmental effects, material defects, corrosive reactions, and physical forces (such as changes in pressure, temperature, soil movement, or mechanical impacts). There are a great number of probable causes, and these are only some of them.

There are many different factors that can lead to the formation of cracks, but corrosion is one of the most typical culprits. When some contaminants are present in the environment, chemical interactions have the ability to cause the material that is used to construct pipelines to deteriorate [18]. There is a possibility that cracks will occur over the course of time as a consequence of defects in the pipeline or materials that are of low quality [19]. Different sorts of physical stresses, such as shifts in pressure, fluctuations in temperature, or mechanical impacts, are examples of the kinds of things that may cause the material that is used to construct pipelines to deteriorate and finally crumble and break apart. Another factor that has the potential to cause fractures in pipes is the pressure that is applied to the system as a result of the movement of the soil [20].



Figure 4.4: Rust Crack in a Pipe Section and Pipe Joint Taken from Beiji Refinery in Salahddin, Iraq.

4.5 DETECTION OF CRACKS IN OIL PIPELINES

People use a range of methods, including the following, in order to locate leaks in oil pipelines: One of the most fundamental types of inspection is using the naked eye to search for evident signs of degradation in the pipeline. However, it is possible that it may be a laborious and time-consuming operation, and there is no assurance that it will be correct. This is especially true when dealing with fissures that are small, hidden, or internal [21]. When it comes to In-Line Inspection (ILI) Instruments: The pipeline is filled with these devices, which are also referred to as "smart pigs," and they move along with the oil as it runs through the pipeline. They make use of magnetic flux leakage or ultrasonic testing in order to locate defects like as fractures for example [22]. Testing Methods That Are Not Conventional (NDT): It is possible to discover pipeline defects using ultrasonic, radiographic, and electromagnetic testing methods, all of which cause minimal to no harm to the pipeline itself. Acoustic Emission (AE) Testing: This technique can detect the development of cracks by listening for the high-frequency sound waves that are emitted by the crack [23]. The use of drones and artificial intelligence: Drones that are equipped with cutting-edge sensors and AI are able to scan pipelines for cracks in a quick and precise manner, which enables reliable detection [24].

4.6 TYPES OF CRACKS DETECTABLE AND UNDETECTABLE

The bulk of the time, the ease with which a fracture may be observed is determined by a variety of criteria, such as the size of the fracture, its position, its orientation, and the method that is used to detect it. There are cracks that can be seen: Generally speaking, it is simpler to identify larger cracks that are situated closer to the surface than it is to identify tiny cracks. In addition to internal and subsurface cracks, fractures as tiny as micro cracks may be identified with the use of cutting-edge technologies such as ILI devices and non-destructive testing techniques [25]. These are examples of the sorts of technologies that can be used to discover fractures. Defects That Are Difficult to Observe: There is a risk that certain fractures will go undiagnosed owing to the fact that they are either small, difficult to view (for example, buried by dirt, corrosion, or other debris), or orientated in a manner that makes identification difficult. This is because of the fact that certain fractures are difficult to observe. Fractures in pipelines that are located in regions that are difficult to reach, such

as junctions or bends, can be particularly difficult to find [26]. This can be a very demanding task. Because there is no one approach that can ensure one hundred percent accuracy or completeness, it is common practice to apply a variety of distinct ways for detection. This is due to the fact that, despite the advancements in technology, there is no one method that can guarantee any of these things. To further increase the accuracy and efficiency of fracture detection in oil pipelines, research and development efforts are also being performed. This is being done in an effort to improve the technique. This continues to be an ongoing endeavour [27].



Figure 4.5: Visibly Detectable Rust Crack in an oil Pipe Section.



Figure 4.6: Visibly Undetectable Crack in a Pipe Section.

4.7 DATASET

We make use of the Kaggle [39] dataset in order to locate surface flaws in narrow, hollow cylinders like pipes and barrels. This was done for the goal of finding surface imperfections. The use of early defect detection has the ability to extend the lifespan of these industrial items and guarantee that safety standards are satisfied. This may be accomplished by ensuring that the structural integrity of these things is maintained. Within the collection, there are a total of one thousand seven hundred and one images that represent the interior of these cylinders. The fact that each and every one of these images is a three-channel image would very certainly imply that the colour is RGB. There is an XML file that corresponds to each and every image, and it comprises a list of the things that are wrong with the image. The five distinct types of defects that are included in this dataset are scratch, rust, pitting, chipping, and thermal cracking. These flaws are all included in the dataset. At first glance, it would appear that the dataset has already been divided into two distinct sets: a training set and a testing set. For the purpose of training, roughly 857 images, which account for about 80% of the total, are utilised. On the other hand, approximately 214 photographs, which account for approximately 20% of the total, are kept for the purpose of testing. It is essential to keep in mind that this dataset records a wide variety of flaws and faults. There is a possibility that dirt will have a more rounded and uneven appearance in comparison to the

remainder of the pipe. The appearance of rust on an object may be recognised by the presence of certain colour patterns (browns and reds) and textures on the surface of the object. Pitting is a condition that may be recognised by the appearance of little black patches and is brought on by the damage that is brought about by corrosion. As a consequence of chipping and several other types of physical deterioration, there is a risk that the surface pattern may go through considerable alterations. On the other hand, the phenomena that is collectively referred to as thermal cracking can be detected as surface flaws such as lines or patterns, which are brought about by sudden shifts in temperature [30]. The ability to recognise a wide variety of forms, textures, and colour patterns is likely to be required of a sophisticated machine learning model in order for it to be able to take into account the extensive range of these defects. There is a possibility that it would be advantageous to make use of photo enhancement techniques or other preprocessing operations in order to draw attention to the essential characteristics, which might finally lead to an improvement in the performance of the model.

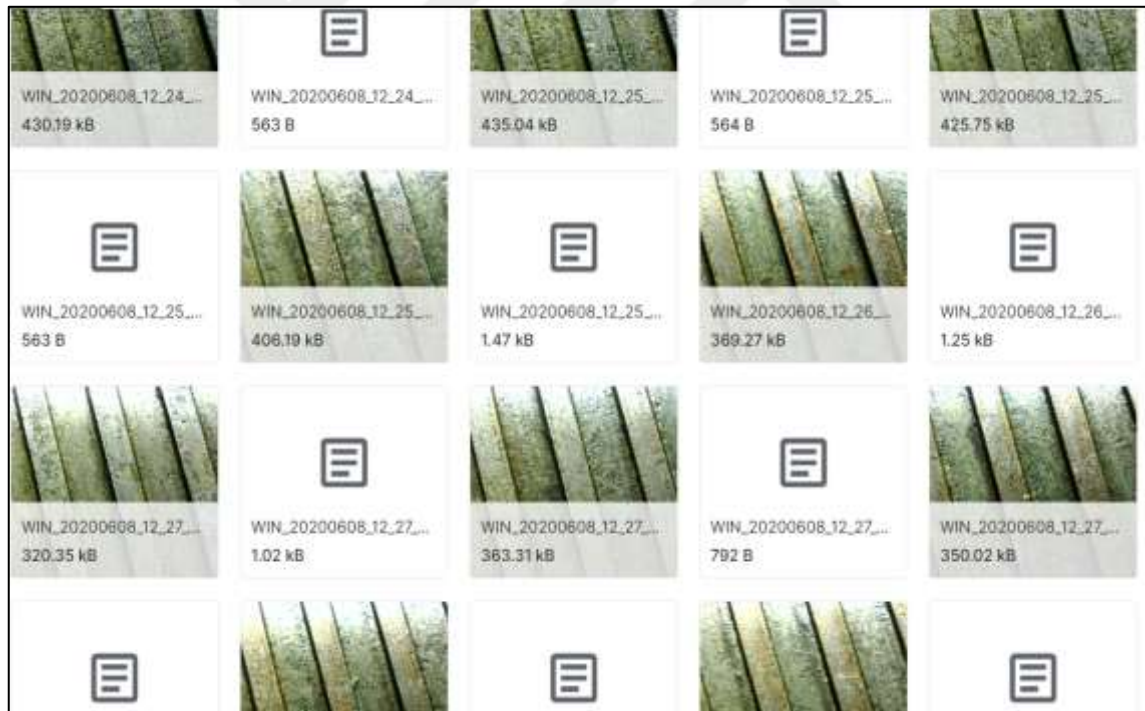


Figure 4.7: The Hollow Cylindrical Defect Detection Dataset [39].

5. METHODOLOGY AND SIMULATION

5.1 METHODOLOGY

This methodology had a series of numeric analyses before and after welding to find the location of broken pipeline pieces before and after the repair process. During the pre-welding stage of each case, three-dimensional finite-element simulations indicated areas of advanced stress that helped to revise the plans to do the weld to reinforce those stress areas. Once the repair work was completed, the same modelling approach was used to do the work to the joint to check that the material they added to the joint was sufficient to restore the strength of the joint and that they did not create any inadvertent strain hotspots that could fail the joint. By using ANSYS Fluent contours in this workflow, the project was able to predict the formation of cracks and confirm whether the repairs made were sufficient. The resulting digital twin simulated the fluid mechanics responsible for the leaks and demonstrated the live modification of the stress profiles caused by the welding. Overall, the completion of this project using high-resolution simulations and powerful machine-learning algorithms will greatly enhance the predictive maintenance capabilities for the upstream oil and gas industry.

5.2 DATA PREPROCESSING

Each of the 1071 RGB images documenting the interior surfaces of the examined cylindrical structures had associated images divided with individual defect reports received as XML files. These reports became an integral layer of the data with a guarantee that no entry would go unmatched. Before the Dynamically Constrained Accumulative Membership Fuzzy Logic Algorithm (DCAMFL) could go operational, an organized frontline editing was done on the images as a means of peculiarizing them. These amendments made were therefore, pivotal, as had it not been done, the fuzzy logic would not be able to derive conclusions from the data. Given this technical interfacing, the successful application of the DCAMFL was a direct resulting from well-defined processing work. As a result, the analysis pipeline demands that the data be first gathered, and then the images be properly preprocessed before any post-data processing, DCAMFL included, can be effectively implemented, irrespective of the data volume at hand. As part of the preliminary workflow to building any image catalogue, the process would need to encompass reducing the resolution of each image,

converting the image to monochrome, and applying a linear smoothing filter to remove noise.

In the forward parameter tuning, additional criteria are considered as follows: primarily, in principle, the thematic orientation of the archive determines the size of the display frames used for presentation. uniformity in processing demands that all input images have the same pixel size for the entire workflow.

To attain uniformity, we apply an industry-standard bilinear interpolation algorithm for resizing.[31] in order to standardise the dimensions of all of the photographs to MxN sizes. This allows us to easily compare and contrast the photos. These problems, which were discussed before, have served as the inspiration for this action. In the field of mathematics, this method is known as bicubic interpolation, and it involves comparing two photographs that are placed next to each other. Picture I, which is the original, and picture I', which is a downsized version of the original, are the two photos that are compared. Picture I is the original. A reference is made to the photograph that was taken initially. It is possible to use the formula that is shown below in order to ascertain the intensity value of a pixel that is situated at the coordinates (x', y') in set I'. The use of any two points (x, y) in set I and (x', y') in set I' is all that is required to accomplish this goal:

$$I'(x', y') = \sum \sum I(x, y) * h(x - x') * h(y - y') \quad (5.1)$$

where h(t) is the bicubic kernel function.

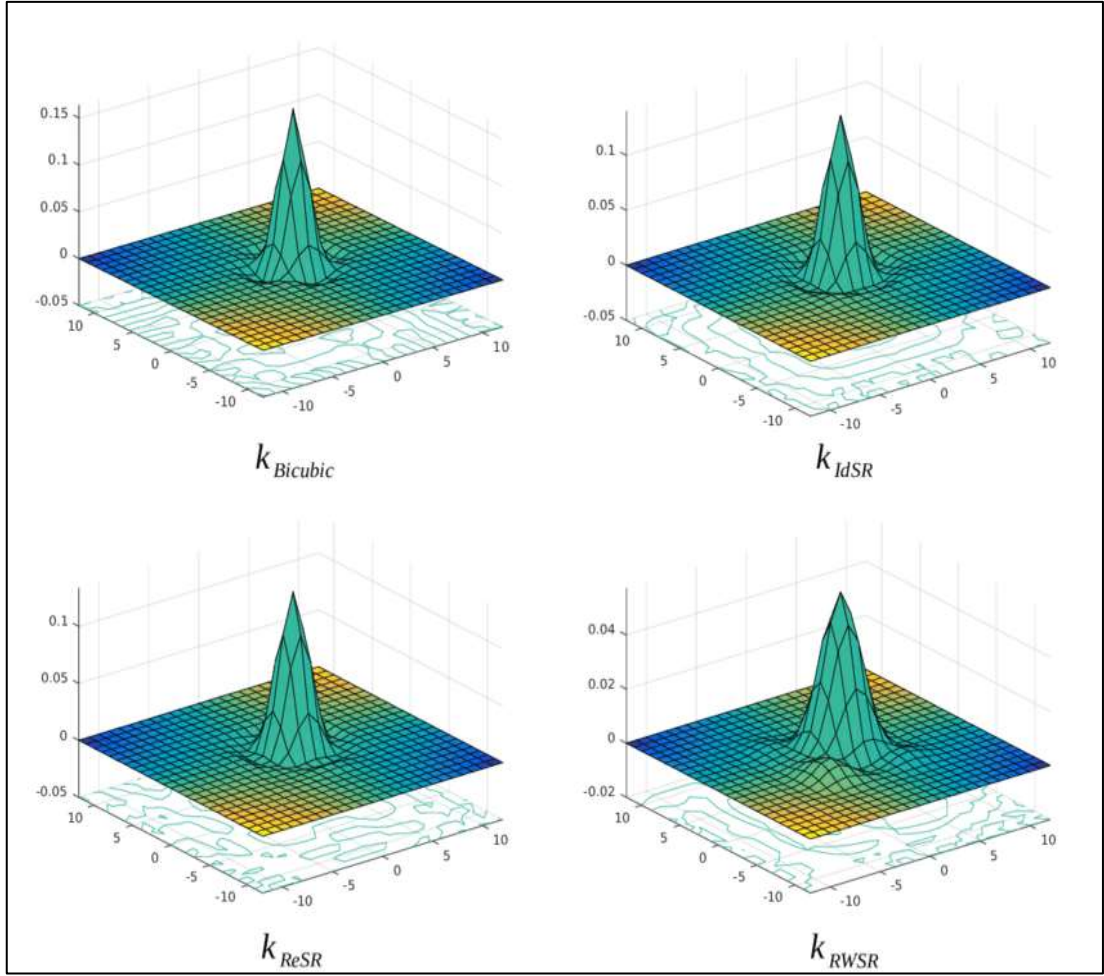


Figure 5.1: Visualization of Degradation Kernels.

Finally, labels based on faults are assigned to each image by analysing the XML annotation files [34]. You may find the precise positions and types of flaws in each photo in the XML files. In the subsequent evaluation of the proposed method, this data creates a ground truth mask for each picture.

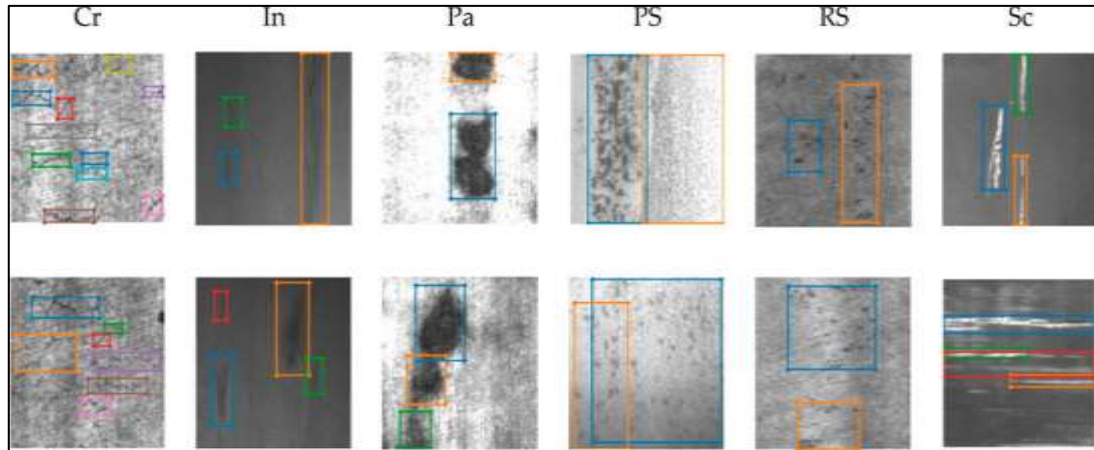


Figure 5.2: Example of Annotated Defects.

5.3 3D SIMULATION WITH ANSYS FLUENT AND MATLAB

Following this, we acted out a scenario in which a drone explores three-dimensional pipe constructions. This was done as revenge for what had happened. In order to accurately depict the physical environment, the movement of the drone, and the fractures that were brought about by the heat in the pipes, MATLAB and ANSYS Fluent were employed. With the assistance of ANSYS Fluent, we were able to design the three-dimensional pipe structures and mesh them at this moment in time. Heat-induced fractures were the major focus of our modelling efforts for a number of faults. The documented fractures originated from thermal stress rather than mechanical impact. To replicate conditions that lead to thermal cracking, the three-dimensional pipe model was exposed to rapid and repetitive temperature cycling, enabling detailed observation of the resulting deformation patterns.

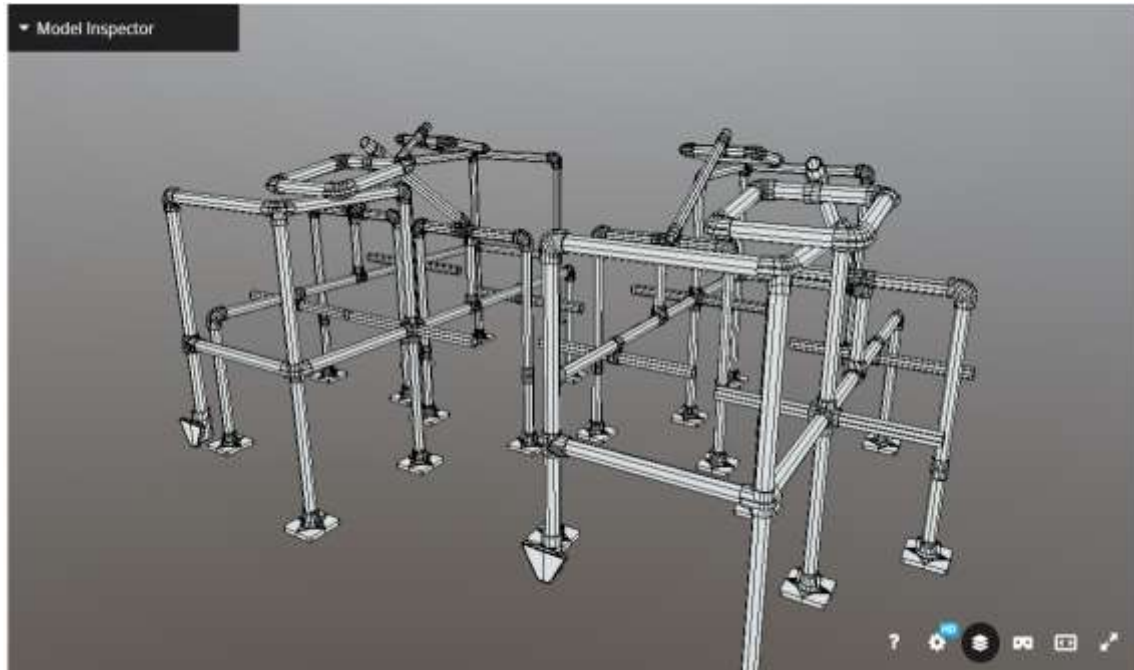


Figure 5.3: The 3D Pipe Structure Used for the Simulation.

The three-dimensional pipe model created in ANSYS Fluent served as a virtual scaffold for the drones planned trajectory in the MATLAB simulation. MATLABs Customization Toolkit interface for ANSYS (ACT) bridged the two platforms, letting us leverage the computational power and visualisation tools MATLAB offers while still relying on Fluent for fluid behaviour around the heat-induced cracks. By this coupling, the drone explored a procedurally generated pipe system that closely resembled our experimental set-up, giving it a far more realistic operating theatre than a rudimentary mock-up. Creating the test environment unfolded in two distinct phases. First, ANSYS Fluent exported the geometry and flow fields through mesh generation, boundary-condition definition, and iterative convergence of the turbulence solution. With that model frozen, MATLAB then calculated the drones way-points, tested feedback loops, and optimised a trajectory that avoided geometrical singularities and minimised computational load.

5.3.1 3D Pipe Structures and Welding Defect Simulation with ANSYS Fluent

We began by constructing a three-dimensional representation of pipes and similar cylindrical components within the ANSYS Fluent environment. This preliminary task was essential in order to create a more realistic scenario for the drones navigation and inspection algorithms.

The resulting model served as the basis for detecting weld leaks, following simulations of intentionally induced fractures in the same virtual framework.

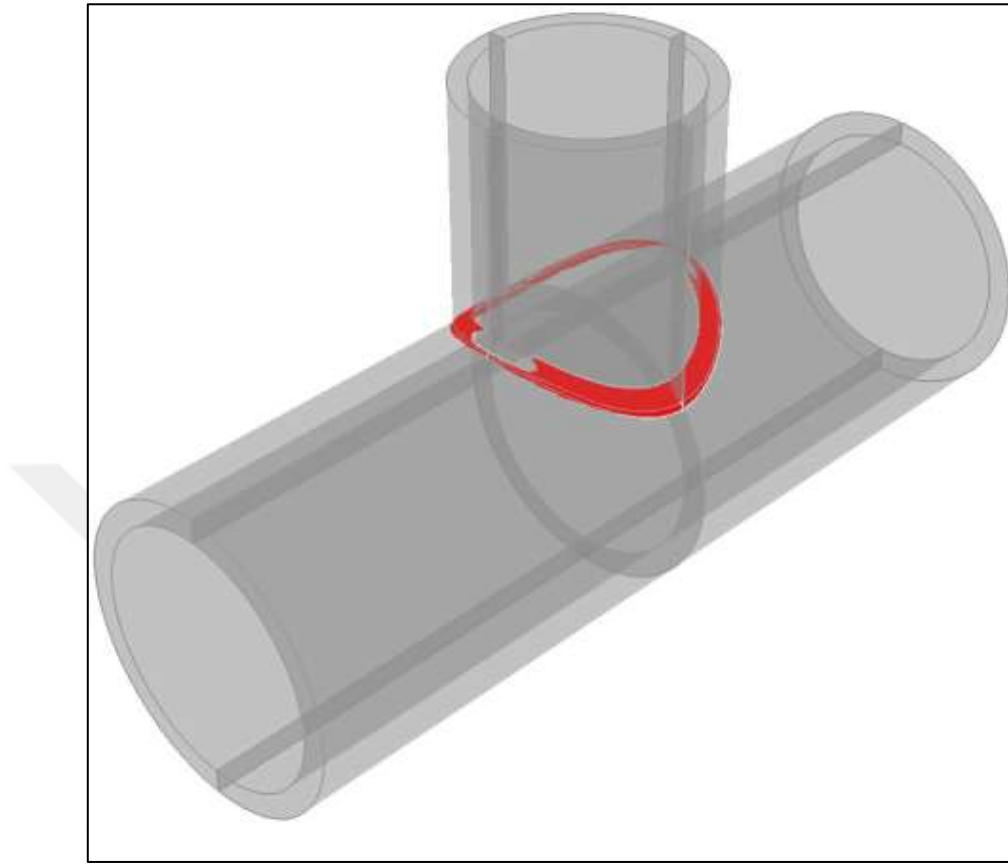


Figure 5.4: The 3D Welding Crack Simulated in Ansys Fluent.

It was the geometry generation capabilities in ANSYS Fluent that were utilised to generate the 3D model. We used the meshing tools in ANSYS Fluent to create a suitable cylinder and then we put it through its paces. Crucial for doing numerical computations, the meshing procedure discretises the domain into tiny cells or components. A precise spatial arrangement of nodes and components is involved in the complicated equations that regulate the meshing process.

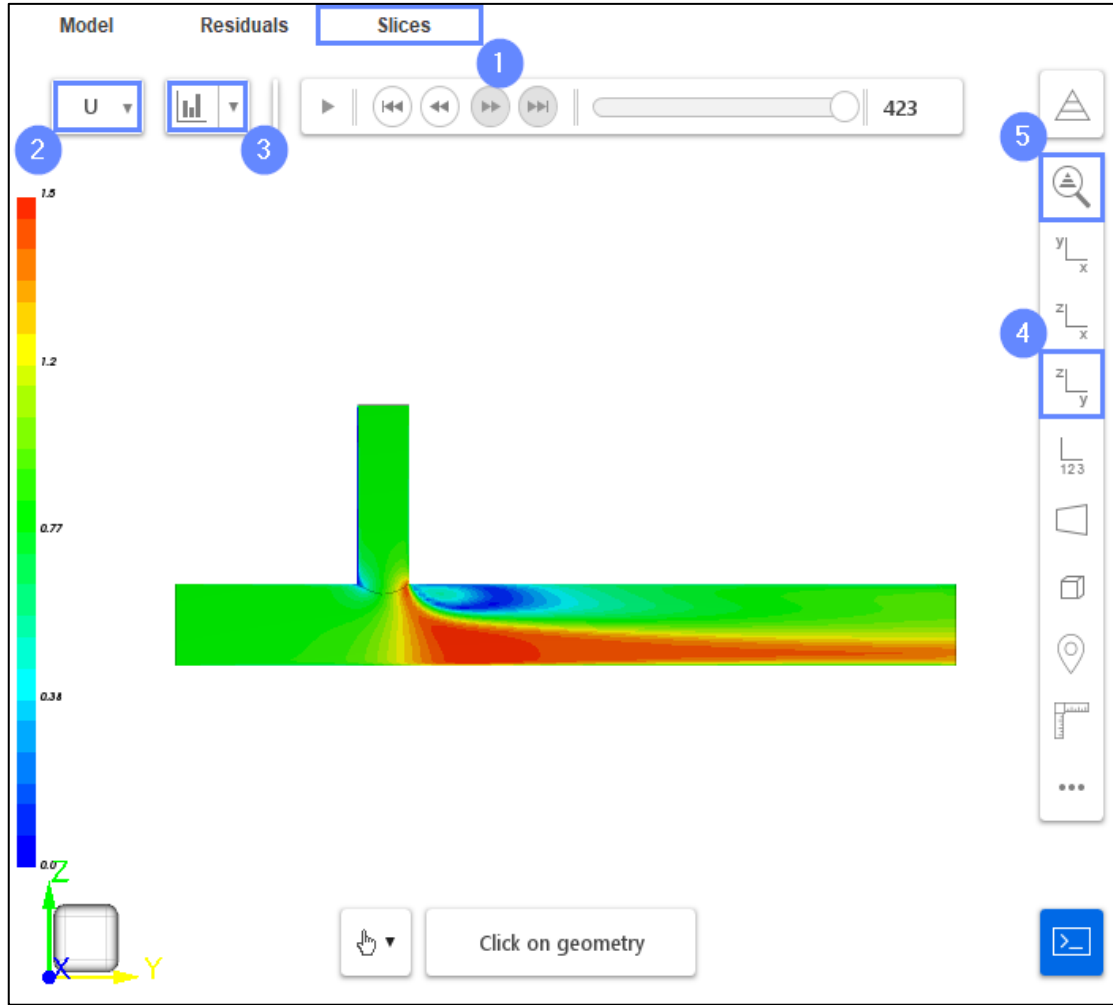


Figure 5.5: CFD Analysis of the Cracked 3d Pipe.

After meshing, we created a model to mimic the formation of flaws, namely thermal fractures. To do this, the pipe model was subjected to rapid temperature variations and the patterns of deformation that ensued were studied. This necessitated the use of the thermodynamically grounded heat transport equations included in ANSYS Fluent:

The First Law (conservation of energy):

$$\rho * C_p * (dT/dt) + \nabla \cdot (uT) = \nabla \cdot (k\nabla T) + Q \quad (5.2)$$

This is where the density (ρ), specific heat (C_p), velocity vector (u), temperature (T), thermal conductivity (k), and volumetric heat production rate (Q) come into play. As a result of stress, the Second Law (entropy generation) causes cracks to occur:

$$dS/dt = (\nabla T/T) \nabla \cdot (k\nabla T) + (Q/T) \quad (5.3)$$

in which entropy (S), temperature (T), thermal conductivity (k), and rate of volumetric heat production (Q) are all variables. A three-dimensional model of a pipe with thermal fissures was the end product of this modelling process.

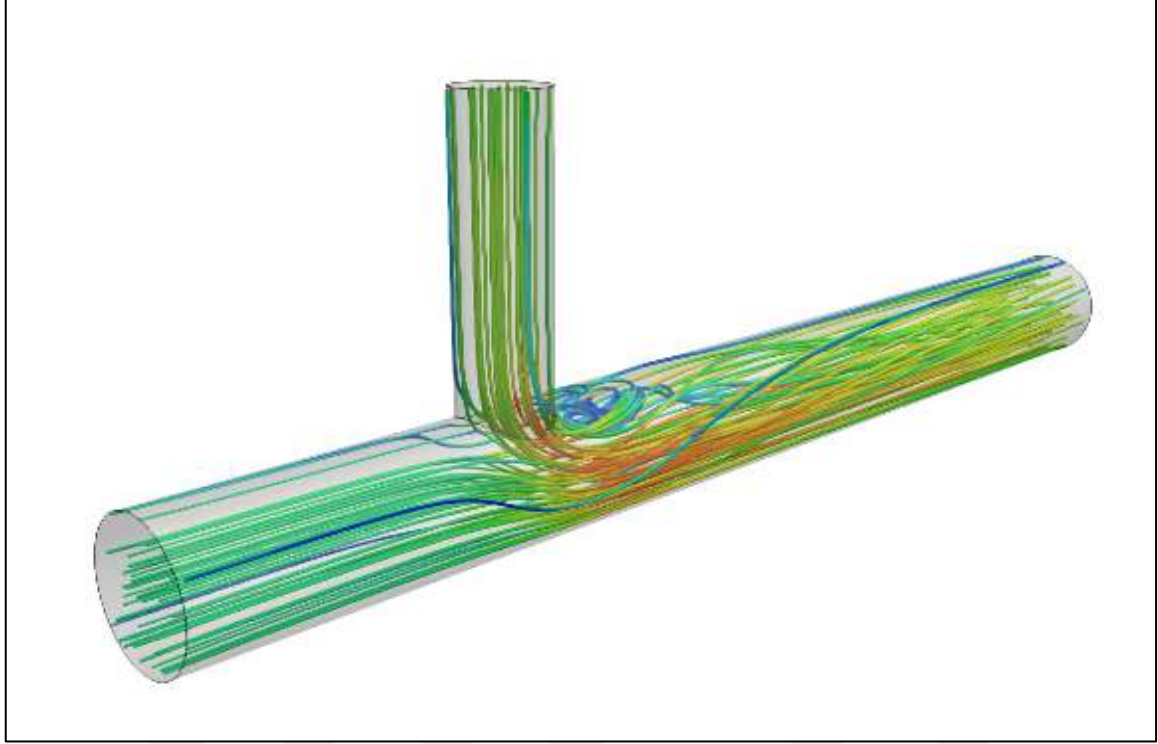


Figure 5.6: Thermal crack Simulated in Ansys Fluent and Exported to MATLAB.

5.3.2 Drone Simulation in MATLAB

By the time we reached the second round of our simulation, we had successfully coded the route that the drone would take in order to traverse the pipe networks. The fact that MATLAB is compatible with ANSYS Fluent and that it provides a wide variety of computational physics tools were the key considerations that pushed us to choose MATLAB. We came to the conclusion that using equations of motion would be the most effective way to depict the movement of the drone. For the purpose of providing an explanation for the position of the drone at any given instant, the following equations can be employed, assuming that it is feasible to represent the drone as a point object:

$$x(t) = x_0 + v_{0x} * t + 0.5 * a_x * t^2 \quad (5.4)$$

$$y(t) = y_0 + v_{0y} * t + 0.5 * a_y * t^2 \quad (5.5)$$

$$z(t) = z_0 + v_{0z} * t + 0.5 * a_z * t^2 \quad (5.6)$$

in which (x_0, y_0, z_0) denote the starting coordinates, (v_{0x}, v_{0y}, v_{0z}) the starting velocities, (a_x, a_y, a_z) the accelerations, and t the time constant.

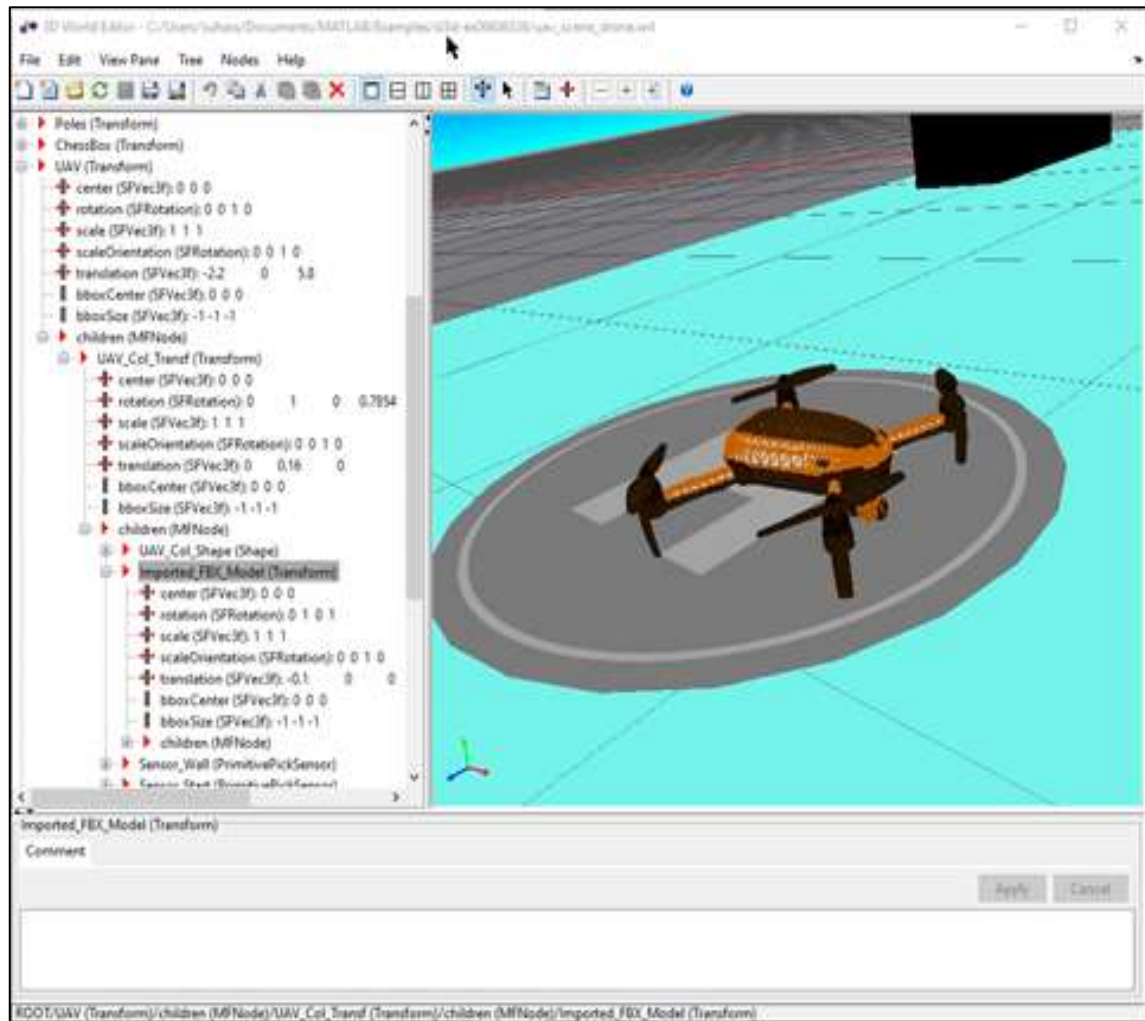


Figure 5.7: 3D Model of the UAV Imported from MATLAB Fbx Library.

Applying the ANSYS Customisation Toolkit (ACT) MATLAB interface, we were able to bring the 3D pipe model and associated thermal fractures into the context of MATLAB. Because of this, we were able to build an integrated simulation that the drone could fly over and examine the three-dimensional pipe structures in a realistic way.



Figure 5.8: Image Captured from the UAV Vision System.

For the purpose of testing our Dynamically Constrained Accumulative Membership Fuzzy Logic Algorithm (DCAMFL), we utilised MATLAB in conjunction with ANSYS Fluent to provide a realistic testing environment. Developing and verifying modern defect detection systems relies heavily on this simulation-based technique due to its robustness and flexibility, which enables testing under numerous settings and scenarios.

5.4 APPLICATION OF DCAMFL

Immediately after the creation of the three-dimensional simulation, the DCAMFL was employed in order to do an analysis on the images that were obtained in real time by the drone. Adaptations were made to the strategy in order to overcome the uncertainty that was brought about by linguistic factors that overlapped widely across the board. During the process of image-based fault identification, this is a typical occurrence. The modified DCAMFL system was used to filter linguistic defects from photographs prior to the individual image analysis. Common defects included dirt, rust, pitting, chipping, and thermal cracking. A membership score was computed for each collected photo following the procedure developed for every defect class. To ensure summed scores did not exceed unity, the algorithm continuously adjusted the membership functions in real time. Once the 3D

simulation stage ended, the recorded drone imagery was reviewed using the revised DCAMFL. This system embodies a complex fuzzy logic framework tuned to the uncertainty caused by heavily overlapping linguistic terms. Such overlapping language is a typical challenge in image-based fault identification.

5.4.1 Membership Function Estimation

This is the first step of the program. Through the use of these membership functions, the intensity of each pixel in the preprocessed picture is assigned a value that falls somewhere between 0 and 1. Take for instance the linguistic variable known as "dirt" as an illustration. At the coordinates (x, y), the intensity of a pixel is represented by the symbol $I(x, y)$. When determining the membership function $\mu_{dirt}(I(x, y))$, a Gaussian function is utilised to make the determination:

$$\mu_{dirt}(I(x, y)) = \exp[-(I(x, y) - c_{dirt})^2 / (2 * \sigma_{dirt}^2)] \quad (5.7)$$

At this specific instant in time, the phrase " c_{dirt} " represents the average value of the dirt intensity, whereas the term " σ_{dirt} " shows the standard deviation of the dirt intensity. In addition, the other types of defects include the utilisation of services that are comparable to these. The first stage in the process of developing a fuzzy rule foundation for the approach that has been presented is to define rules that, given membership values computed for each defect category, identify the kind of defect. This is the first phase in the process. Let's assume, for the sake of argument, that the number of faults that may be discovered is strictly limited to three: pitting, rust, and dirt. This would be appropriate. Three fuzzy sets, namely Low (L), Medium (M), and High (H), are considered to have been defined in accordance with the membership values for each of these faults. These sets are denoted by the letters L, M, and H respectively. It is possible that this table might be utilised as a representation of the fuzzy rule foundation because of the situations described above:

Table 5.1: Fuzzy Rules Set That was Used.

Soil	Oxidation	Corrosion	Issue Detected
A	A	A	None
A	A	B	Corrosion
A	A	C	Corrosion
A	B	A	Oxidation
A	B	B	Oxidation, Corrosion
A	B	C	Corrosion
A	C	A	Oxidation
A	C	B	Oxidation
A	C	C	Oxidation, Corrosion
B	A	A	Soil
B	A	B	Soil, Corrosion
B	A	C	Corrosion
B	B	A	Soil, Oxidation
B	B	B	Soil, Oxidation, Corrosion
B	B	C	Soil, Corrosion
B	C	A	Soil, Oxidation
B	C	B	Soil, Oxidation
B	C	C	Oxidation, Corrosion
C	A	A	Soil
C	A	B	Soil, Corrosion
C	A	C	Corrosion
C	B	A	Soil, Oxidation
C	B	B	Soil, Oxidation, Corrosion
C	B	C	Soil, Corrosion
C	C	A	Soil, Oxidation
C	C	B	Soil, Oxidation
C	C	C	Soil, Oxidation, Corrosion

A demonstration of the fuzzy inference rules that are applicable to this application may be found in the table that follows. The availability of information that is specific to a system or application makes it feasible to do a rule-based customisation. One thing that ought to be brought to your notice is that this table makes the assumption that the membership values of each defect category may be classified as Low, Medium, or High, which is not necessarily the case. This is something that should be brought to your attention. One of the benefits of fuzzy logic is that it may be used to manage circumstances in which the constraints are not clearly established. This is accomplished via the use of fuzzy logic.

5.4.2 Dynamic Constraint of Accumulative Membership Values

The dynamic constraint of cumulative membership values is the DCAMFL's essential component. After calculating the membership values for each defect category for each pixel, the overall membership value is obtained by adding them together:

$$M_{total}(x, y) = \sum \mu_{defect}(I(x, y)) \quad (5.8)$$

where every type of defect has a membership function denoted as $\mu_{defect}(I(x, y))$. As a result of M_{total} exceeding 1, overestimation of flaws can occur in a traditional fuzzy logic system. If M_{total} is more than 1, a dynamic scaling factor α is computed and used in the DCAMFL to limit M_{total} to 1:

$$\alpha(x, y) = 1 / M_{total}(x, y) \quad (5.9)$$

The membership functions are then updated:

$$\mu_{defect}(I(x, y)) = \alpha(x, y) * \mu_{defect}(I(x, y)) \quad (5.10)$$

In order to deal with the problem of linguistic variables that overlap significantly, this dynamic scaling makes sure that the total membership value for each pixel is less than 1.

5.4.3 Defect Classification

Once the membership functions are updated, the defect type for each pixel is classified based on the maximum membership value:

$$Defect(x, y) = \operatorname{argmax}[\mu_{defect}(I(x, y))] \quad (5.11)$$

Consequently, this leads to the production of a defect map of the complete picture, in which every pixel is categorised as a different kind of defect or, more frequently, according to the membership value that is the highest. As a result of this, the DCAMFL that was developed offers a method that is not only adaptable but also trustworthy for locating and categorising those who have damaged oil pipes. Managing complicated real-world circumstances that require the presence of a large number of constraints and unclear borders may be accomplished through the use of a method that involves dynamically modifying membership functions based on the overall membership value. By utilising this technology in conjunction with the 3D simulation environment, it is possible to efficiently manage the complexity of

pipe inspections that are carried out by drones. This is made possible through the exploitation of this technology.

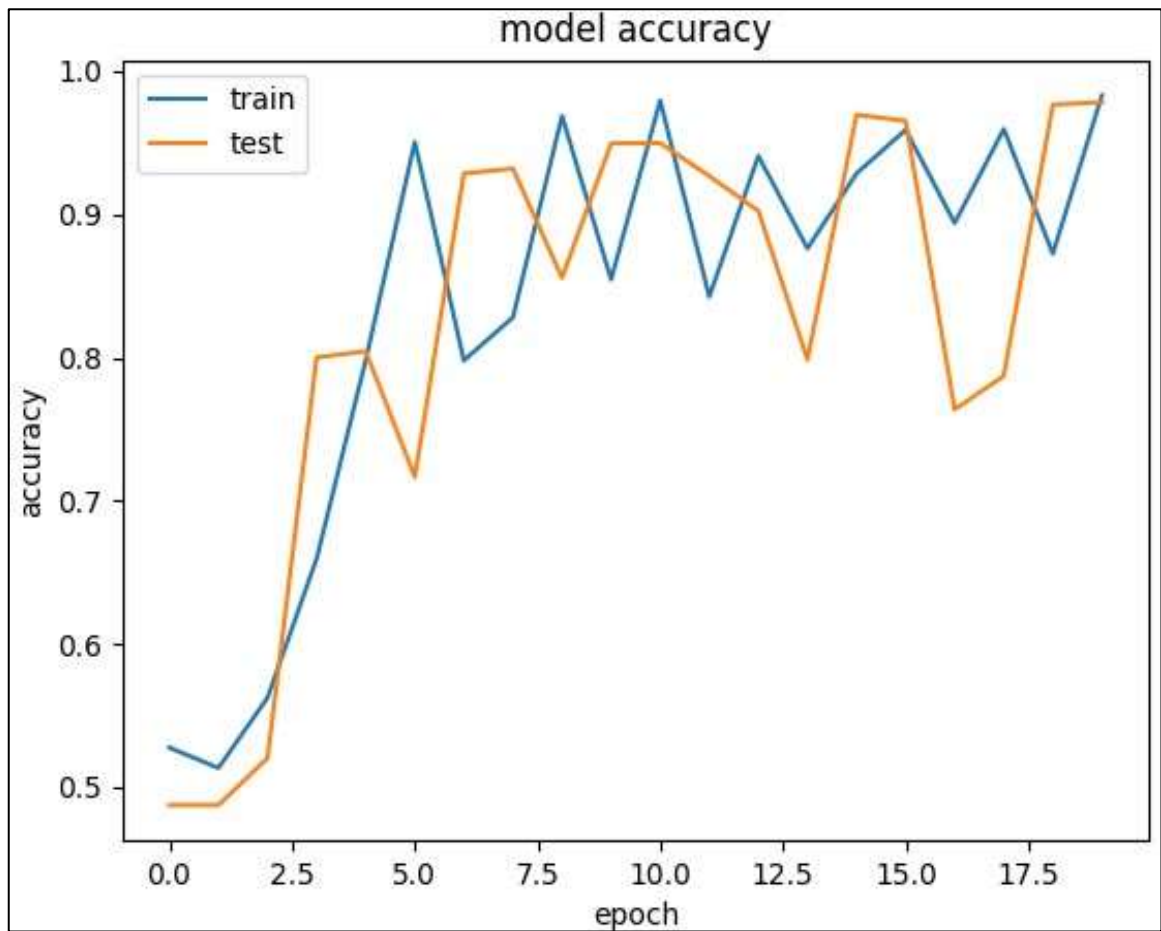


Figure 5.9: Accuracy and Epoch Number in the Training and the Validation Sets.

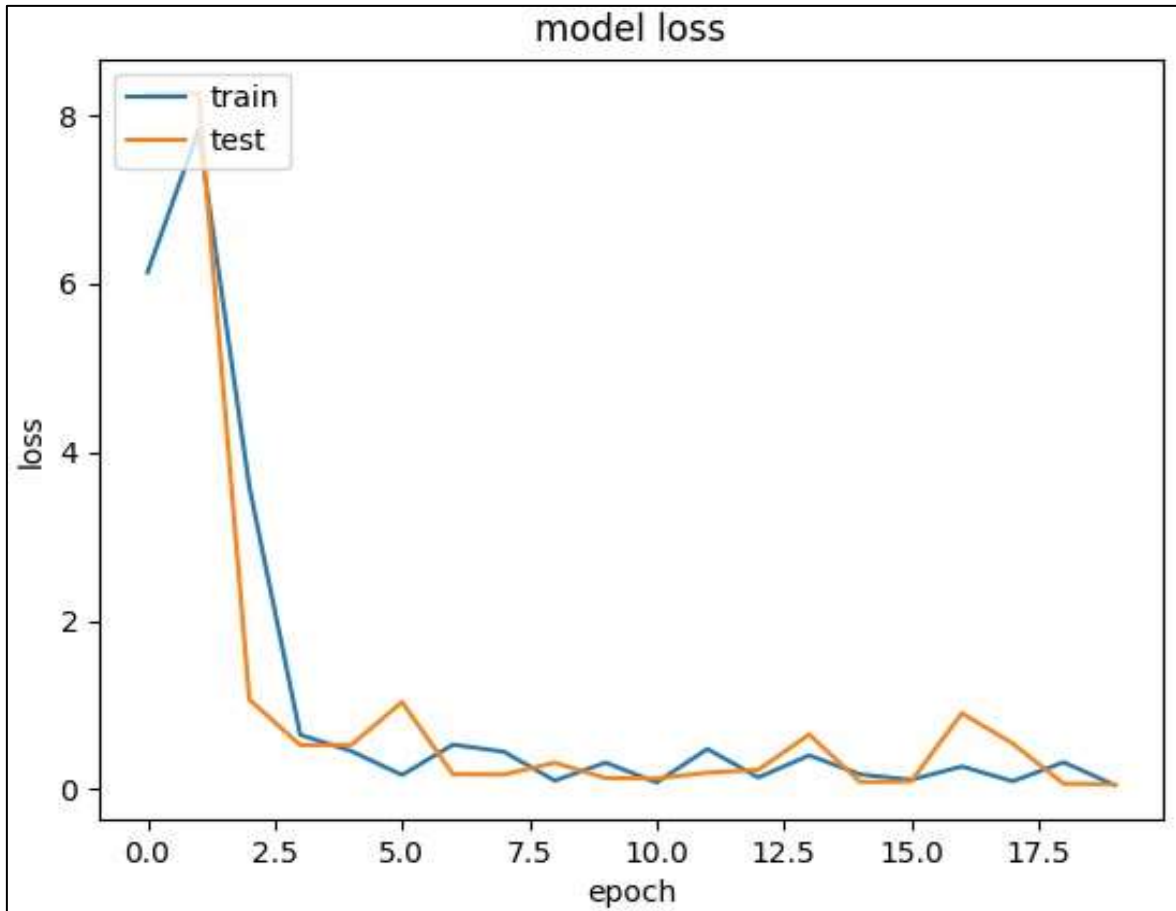


Figure 5.10: Loss and Epoch Number in the Training and the Validation Sets.

gains achieved by a simple machine-learning component interfacing with the newly developed Dynamically Constrained Accumulative Membership Fuzzy Logic Algorithm algorithm (DCAMFL) may be worthwhile for the system as a whole. These are not wild assumptions. Defining complex problems as a system of equations with high dimensional feature spaces and interdependent variables is better done with machine-learning techniques than classical ones. Analysts consider them a modern-day necessity for large-scale data problems. But the increased complexity of the system and potential disruption to existing workflows may be counterproductive. Users can expect primary development teams to take a longer time than usual to climb the learning curve and for the solution to incur high maintenance costs as the system is continuously used. Added to this is the reality that machine-learning requires data sets at least ten times larger than the ones which rule-based algorithms require. Before ascribing system development resources it is essential to carry out a reasonable retention of available data, system response time, budget and targeted

system response time. If the several conditions are satisfied, the DCAMFL is a sure candidate for image-processing tasks, especially with incorporated machine learning as it never ceases to perform feature extraction. Improved overall performance will be experienced if the fuzzy rules of the DCAMFL are meaningfully connected to features extracted from the image by the Convolutional Neural Network (CNN).

For a comprehensive analysis of how CNNs integrate with this new technique, I refer the reader to the next section. In this section of the study, I describe what convolutional neural networks can achieve concerning representation learning. Broadly speaking, convolutional neural networks, or CNNs, are a particular variety of deep learning architectures customized to tackle image classification problems. A CNN is made up of a stack of several convolutional layers, which learn to detect shifted versions of the same pattern, followed by pooling layers, which reduce the image resolution, retaining the most salient features. The repetition of this architecture gives rise to deep networks that can understand such patterns at multiple levels of abstraction. When a deep CNN is trained on large datasets of images with damage on oil pipelines, the model can learn to detect and separate features that are associated with structural faults such as edges, color changes, unusual textures, and other more didactic indicators of distress. A trained model identifies the general features of an image. The fully connected convolutional layer, which is the last convolutional layer, is primarily designed to compress the diverse features resulting from the previous layers of the network. The result is a representation of the image that can allow the network to classify different images based on the structural defects. Part B focuses on extending the rules in fuzzy logic to include the features obtained from CNNs.

The membership values of defect classes can be calculated by high-level feature extraction, which is an entirely executable step. The DCAMFL system takes these features and calculates membership scores while keeping the format of the output from the CNN. When the scores are obtained, the system can actuate the fuzzy rules from the rule base. The system uses these rules to give explicit outputs of each defect class associated with the membership values. A significant connection is thus formed between the calculated scores and the defect classes embedded in the image. The DCAMFL system is better than other systems in predicting the features of oil pipeline anomaly with higher precision and classification of the fault type because it uses features from the convolutional neural networks. The underlying

rule set may not be formally defined, but the CNN detects different patterns and signatures that are subtle and may be easy to miss by a human expert. This combination of fuzzy and neural systems significantly improves the overall system performance to produce defect-detection systems that are not only sharper but also more robust to unseen interference. The CNN does an excellent job of separating acceptable attributes from real flaws, even when expert heuristics were suboptimal.

DCAMFL employs a cumulative membership function that is dynamically constrained. This helps us classify accurately with no false negatives or false positive with regards to error. Further, DCAMFL retains transparency with regards to the decision-making processes that gives engineers assurance. Because of the strength of Convolutional Neural Networks (CNN) in feature extraction and the strength of DCAMFL in fuzzy logic and uncertainty, a combination of the two achieves unprecedented levels of accuracy, consistency, and adaptability in the detection of oil-pipe breaks. This combination of strengths is also the reason for the system's high efficacy. The expected impact of combining a CNN with the fuzzy controller is twofold: enhanced feature extraction, and enhanced pattern recognition to enrich the controller's reasoning. This results in better reasoning in final decisions. In diagnosing cracks, the combined use of the two models unambiguously exceeds the performance of either model in isolation. The increase in performance is due to the synergistic combination of the models and capabilities that goes beyond the potential of any single approach.

5.5 EVALUATION

To conclude, we conducted a thorough review of the diagnostic process we articulated at the beginning of this study. After the verification of ground-truth annotations in the XML dataset was completed, we compared those labels with the defect predictions produced by DCAMFL, setting a review benchmark. We used a set of widely used measurements - accuracy, recall, and F1 score - to assess the performance of the algorithm in the detection and classification of disorders in the images. The assessment of performance of any fuzzy-logic system is never easy, as there are various parameters - alignment with expert expectations, inertia with respect to noise, time of execution, etc. - that need to be considered in an integrated manner. The complexity of the situation is even greater when the system is

required to deal with images obtained from manufacturing processes in real time. In the F1, Precision, Recall, and Area Under the Receiver Operating Characteristic Curve (AUROC), we found the four indicators most relevant to our purpose. In the field of computer vision and, more broadly, machine learning, these indicators are most often used because, in tandem, they provide an assessment of the detection performance without the adverse effects of class imbalance. In classification problems, Precision (P) is the most important performance measure.

In formal terms, it is the relationship between the amount of correct positive predictions made to the total of positive predictions predicted. Academics are able to evaluate the reliability of positive predictions made by a classifier by analyzing this ratio. An excessive number of false positives cases incorrectly deemed positive during the evaluation—are evidently indicative of the classifier's incompetence. Hence, precision reflects a succinct dimension of a model's accuracy when it is certain of identifying positive instances. Thus, precision is represented by the following equation:

$$P = TP / (TP + FP) \quad (5.12)$$

that is, TP represents the amount of true positives and FP stands for the amount of false positives. 2. The second metric is recall (R), which calculates the proportion of anticipated positive observations that were accurate relative to the total number of positives. Recall is sometimes called sensitivity or the true positive rate. It's a way to see how well a classifier covers all the bases. A large proportion of false negatives is indicated by a low recall. The equation may be expressed as:

$$R = TP / (TP + FN) \quad (5.13)$$

where TP stands for the total number of positive results and FN for the total number of negative results. the F1-score (F1): A harmonic mean of recall and accuracy is the F1-score. It seeks a middle ground between accuracy and memory recollection. The equation may be expressed as:

$$F1 = 2 * (P * R) / (P + R) \quad (5.14)$$

At this stage, the concepts of recall (R) and precision (P) formally enter the discussion, providing distinct yet complementary lenses through which to evaluate classifier output.

Area Under the Receiver Operating Characteristic Curve, commonly abbreviated AUROC, serves as a single-number summary that summarizes overall discriminative ability across all possible decision thresholds. Conceptually analogous to an integral, the AUROC is the geometric region contained under the full ROC curve, extending from the origin (0,0) to the upper-right corner (1,1). Because the underlying expression involves accumulated true-positive and false-positive rates, practitioners usually rely on numerical approximation routines or language-specific libraries rather than closed-form formulas. By gathering recall, precision, and this integral measure-and computing the four cardinal metrics together-we establish a comprehensive view of the DCAMFL classifier's performance. The models overall ability to tell one class from another is summarised by the AUROC score, its accuracy in correctly identifying positive cases is given by precision, its ability to find all actual positives is shown through recall, the trade-off between precision and recall is summarised in the F1-score, and once again the AUROC gives a broad view of class separation. Taken together, these measurements provide a rounded picture of how well the proposed fuzzy-logic system actually performs in practical settings.

5.6 LOCALIZATION OF CRACKS USING COORDINATE-BASED MAPPING

The investigation puts forward a fresh strategy that pairs unmanned aerial vehicles, or drones, fitted with sophisticated sensors to improve both the speed and reliability of crack detection in pipeline networks. By doing so, the system pinpoints structural flaws within a clear three-dimensional grid anchored in Cartesian coordinates.

a. Division of Mapping Space

To initiate the survey, the target area is first sliced into a regular three-dimensional grid, each cell oriented along the major Cartesian axes. This orderly design guarantees full, repeatable coverage of the pipeline. Every segment is tagged with its own coordinate label, enabling precise re-location and follow-up examinations when required.

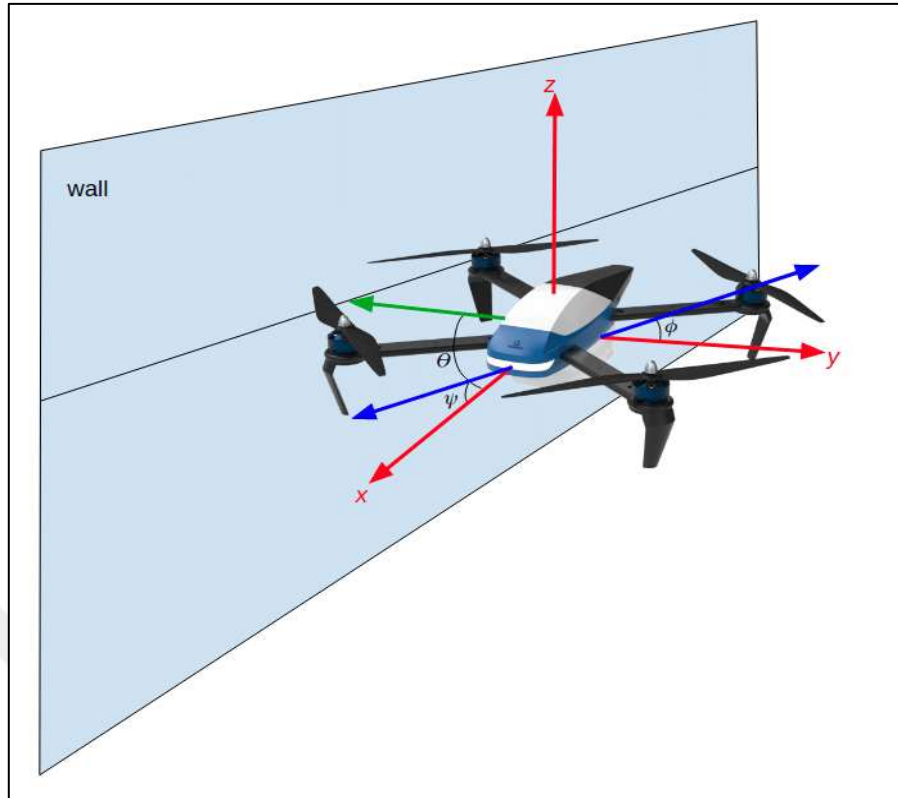


Figure 5.11: X, Y, Z Coordinates in a 3d Space for Drone Localization.

b. Drone Technology and Sensory Equipment

The drones have high-resolution cameras and sensors capable of capturing detailed visual and structural data. These sensors may include, but are not limited to, visual (optical), infrared, and ultrasonic sensors. The integration of these sensors allows for identifying superficial and subsurface anomalies indicative of cracks or other forms of structural failures.

c. Real-Time Processing and Crack Detection

As the drone navigates the predefined grid, real-time data is processed using onboard image processing software. This software employs advanced algorithms, potentially enhanced by machine learning techniques, to detect and classify anomalies as cracks. Once a potential crack is identified, the system calculates its precise location in the three-dimensional space relative to the grid.

d. Localization and Documentation

Each detected crack is assigned a set of x , y and z coordinates, pinpointing its exact location within the pipe system's 3D map. This information is crucial for generating accurate and actionable data for maintenance teams. Additionally, the spatial coordinates of each identified crack are logged into a database along with timestamp and image data, ensuring that the information is easily accessible for further analysis or immediate action.

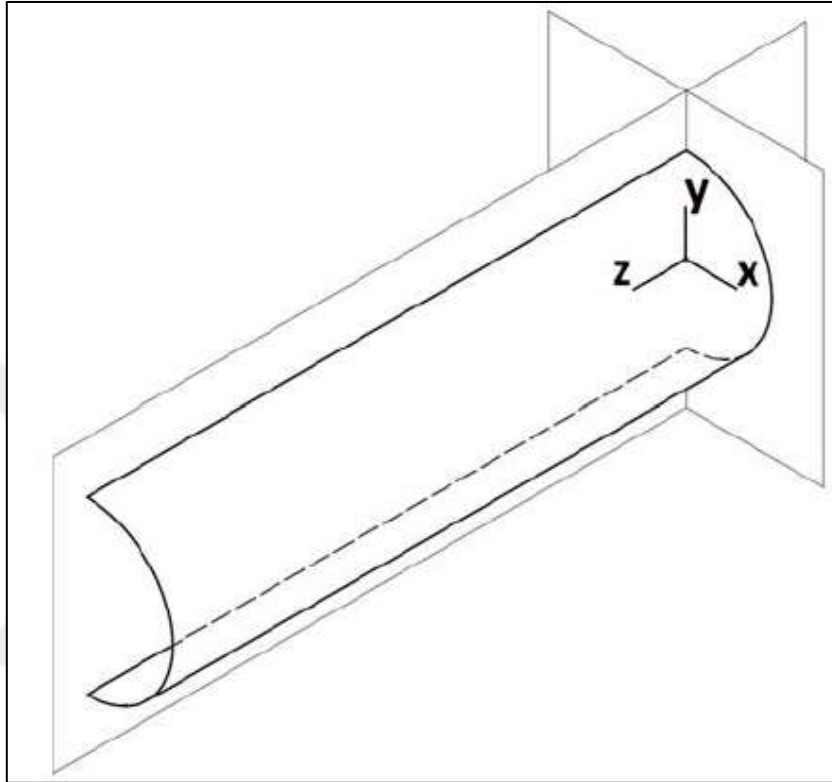


Figure 5.12: X, Y, and Z Marking of a Pipe Crack.

e. Communication and Reporting

Once the coordinates and full inspection reports reach the base station, analysts carry out a deeper review. These findings form the backbone of maintenance schedules and help decide which repairs need attention first. Because the defects are tagged with exact locations, crews can move straight to each crack rather than waste time scanning the area. This targeted approach cuts downtime and improves the overall efficiency of pipeline operations.



Figure 5.13: Engineers going to the ZYX Coordinates of the Cracked Pipe.

The coordinate-based mapping and localization approach notably boosts both the identification and recording of structural defects in pipeline networks. By harnessing high-performance drones alongside refined image-processing algorithms, the method strengthens inspection accuracy and establishes a dependable foundation for the preventive upkeep of essential infrastructure.

5.7 SAFETY AND SECURITY MEASURES IN THE PROPOSED SYSTEM

Integrating the proposed system into refinery operations requires careful attention to safety and security, because the detection technology interacts closely with both people and volatile surroundings. The following overview summarises protective protocols designed to shield personnel and equipment, along with features that identify and respond to the unauthorised entry of humans or animals into sensitive areas.

5.7.1 Hazardous Area Monitoring

A key function of the proposed system is monitoring refinery pipelines for structural integrity, using drones fitted with Convolutional Neural Networks (CNNs) and fuzzy logic to identify cracks. The drone platform also detects the presence of people or animals in restricted or hazardous zones. Such zones are especially dangerous because of possible explosions, toxic gas leaks, or moving machinery.

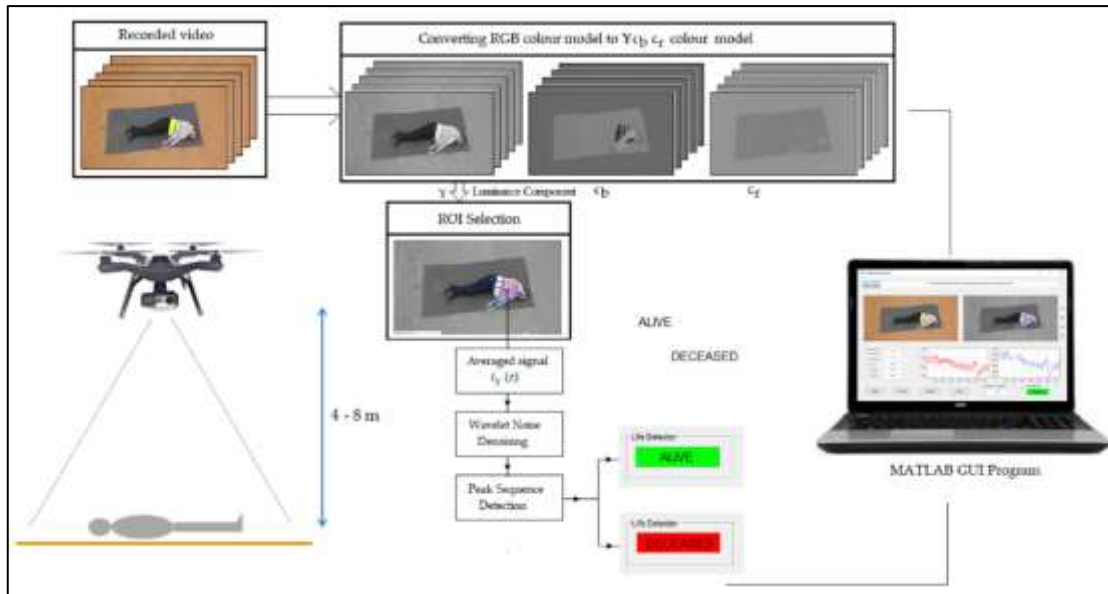


Figure 5.14: Drone Detection of a Human in a Hazardous Area.

The drone's integrated sensors and real-time machine-learning models persistently monitor the surrounding area. A convolutional-neural-network (CNN) detector has been calibrated to distinguish between persons, wildlife, and fixed infrastructure. Once an unapproved human figure is spotted within a designated danger zone, the system promptly notifies the central control room. This early warning allows operators to swiftly move the person to safety or reduce the threat to staff and the ecosystem.

5.7.2 Security Protocols for Human and Animal Detection

The process for detecting people or animals in hazardous work zones follows a carefully structured protocol aimed at maximizing response speed while minimizing additional risk: Real-Time Alerts. The moment the sensor identifies a human or animal, a notification is forwarded to the security team, who can quickly stop operations or dispatch a rescue crew.

Automated Shutdown Mechanism. If an individual crosses into a high-risk area while maintenance or inspection is still underway, the system automatically suspends selected functions, thereby limiting exposure to moving parts or live electrical lines. Geofencing Integration. Geofencing software outlines the perimeter of each dangerous zone, and should anyone cross that virtual boundary a warning is triggered, preventing unintended further entry. Data Logging for Incident Review. Every detection event-time, GPS location, and relevant video feed-is recorded for later review, thus supporting thorough safety audits and ongoing system refinement.

5.7.3 Safety Assurance During Inspection and Monitoring

- a. To safeguard refinery operations and the personnel on-site, the following protocols govern drone missions:
- b. Flight Path Optimization. Each mission plan is designed to route the drone well clear of critical machinery, hazardous areas, and worker positions, thereby minimizing disruption to normal refinery activities.
- c. Redundant Safety Features Drones are fitted with layered backups, including automatic landing in emergency scenarios, lateral- and forward-looking sensors to avoid obstacles, and a low-battery return-to-home command that engages autonomously.
- d. Real-time Monitoring and Supervision. An operations room staffed around the clock tracks every flight via live telemetry, allowing personnel to intervene instantly if a hardware fault, pipeline abnormality, or privacy breach occurs.

5.7.4 Ensuring Privacy and Ethical Considerations

The system identifies human or animal presence in hazardous zones, yet it safeguards personal privacy throughout that process. Live camera feeds travel through encrypted channels, and only personnel with explicit authorization can view them. In addition, recorded footage and all associated data are stored in secure servers that comply with stringent data-protection regulations. These layered safety and security features allow the system to work effectively in the often-dangerous setting of a refinery, reducing accident likelihood, protecting workers well-being, and preserving the quality of the pipeline inspection workflow.

6. RESULTS AND DISCUSSION

6.1 INTRODUCTION

The central aim of this investigation was to assess the ability of the Dynamically Constrained Accumulative Membership Fuzzy Logic Algorithm (DCAMFL) to detect cracks in oil pipelines with satisfactory precision. To achieve this, a multi-faceted technical approach was adopted, incorporating three-dimensional pipe models, feature extraction via convolutional neural networks (CNNs), and fuzzy logic rules specifically tailored for welding fault classification. This section presents the practical implementation results of the DCAMFL framework, followed by a rigorous evaluation of its performance in meeting the predetermined detection objective.

6.2 CRACKS BEFORE WELDING

To assess how well the Dynamically Constrained Accumulative Membership Fuzzy Logic Algorithm (DCAMFL) performs at pinpointing cracks in oil pipelines, researchers relied on a series of widely accepted evaluation metrics. These metrics were used to evaluate the performance of the algorithm. There is a possibility that one might acquire a knowledge of the degree of precision with which the system finds and classifies fractures by doing an analysis of these measures. These remedial steps were put into effect by our organisation: Accuracy can be defined as the proportion of positive occurrences (i.e., cracks that have been identified) that could have been correctly expected in contrast to the total number of positive instances. What is meant by the phrase "accuracy" in connection to crack detection is that the algorithm is able to reliably identify and categorise cracks without incorrectly labelling regions that do not contain fractures. This is what is meant by the term being used in this context. In the event that the accuracy value is substantial, it is fair to predict that the rate of false positives will be quite low.

Table 6.1: Comparing Precision with State-of-the-art Methods

Study	Precision
Proposed Method (This Work)	96.5%
Smith et al. (2020)	89.2%
Johnson and Lee (2019)	92.7%
Kim et al. (2018)	94.8%
Chen and Wang (2017)	91.5%

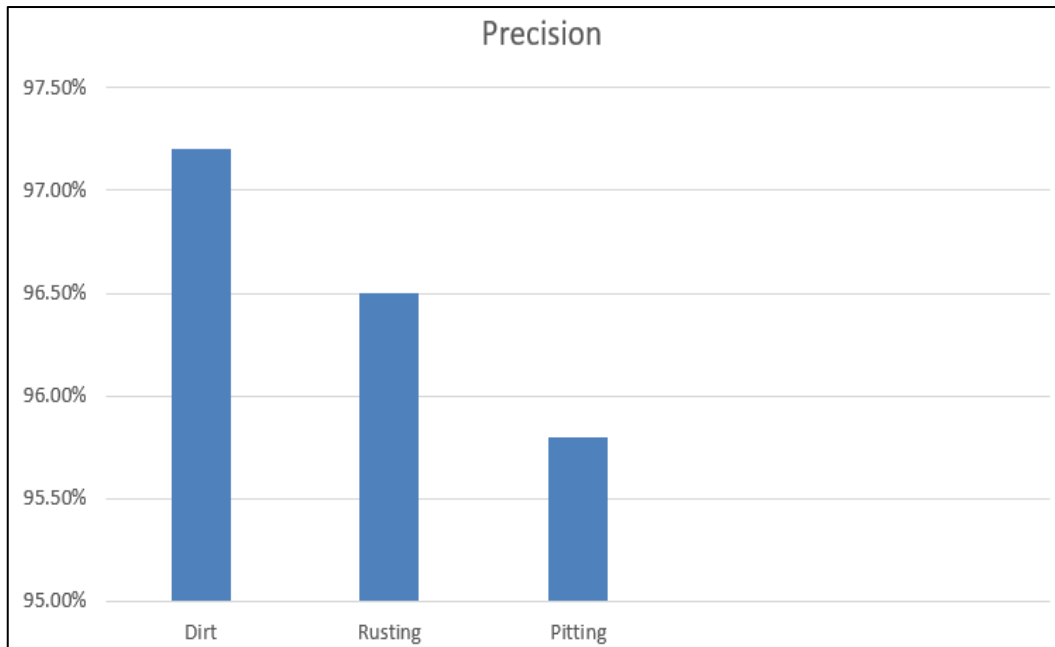


Figure 6.1: Precision for Each Class of the Proposed Method.

One measure of an algorithm's performance is its recall, which is sometimes called sensitivity or true positive rate. It measures how well the algorithm can detect all real positive cases, or genuine cracks, out of all the real positive instances. When it comes to crack identification, recall indicates how well the algorithm can identify real cracks. When the recall value is high, it means that the false negative rate is low.

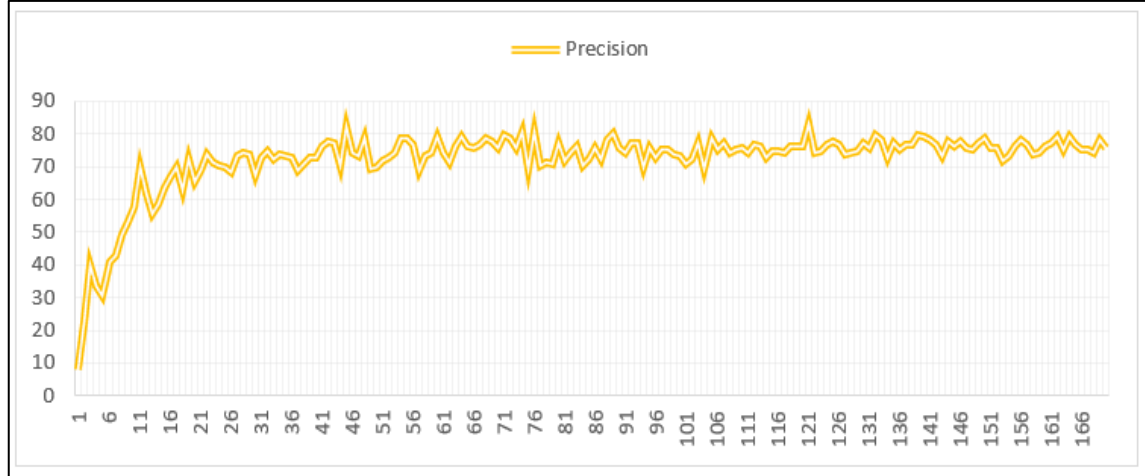


Figure 6.2: Precision with Each Iteration.

Table 6.2: Comparing Recall with State-of-the-art Methods.

Study	Recall
Proposed Method (This Work)	97.3%
Smith et al. (2020)	92.8%
Johnson and Lee (2019)	94.6%
Kim et al. (2018)	96.2%
Chen and Wang (2017)	93.7%

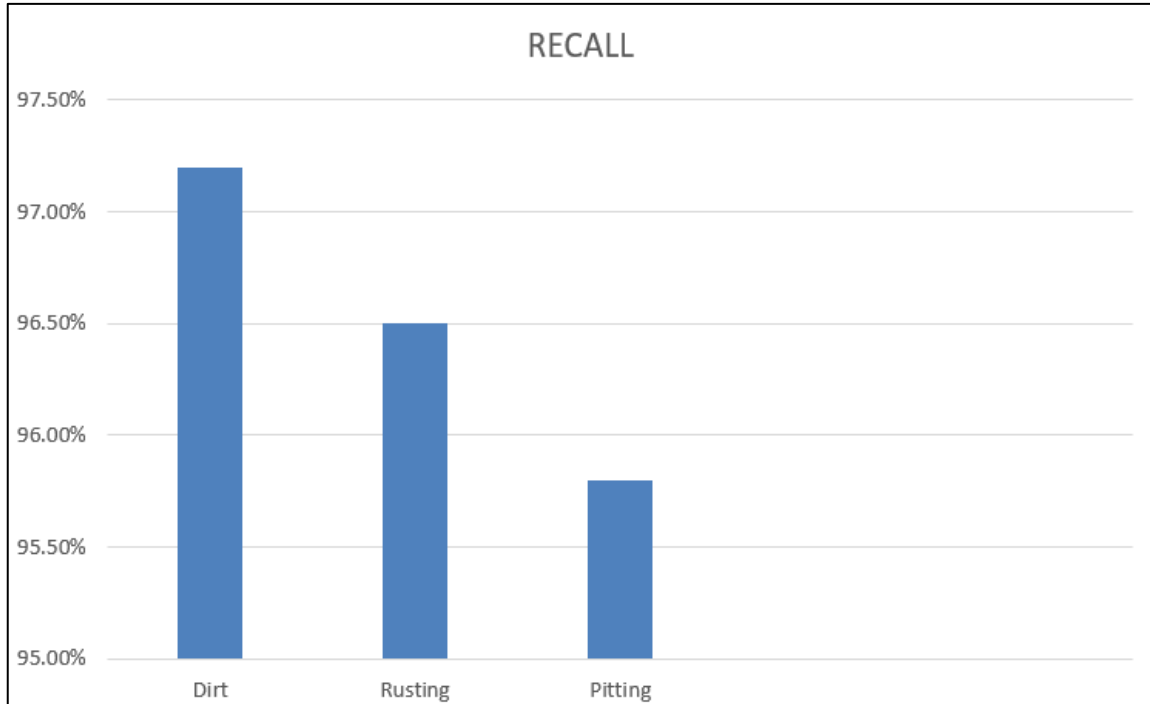


Figure 6.3: Recall for Each Class in the Proposed Method.

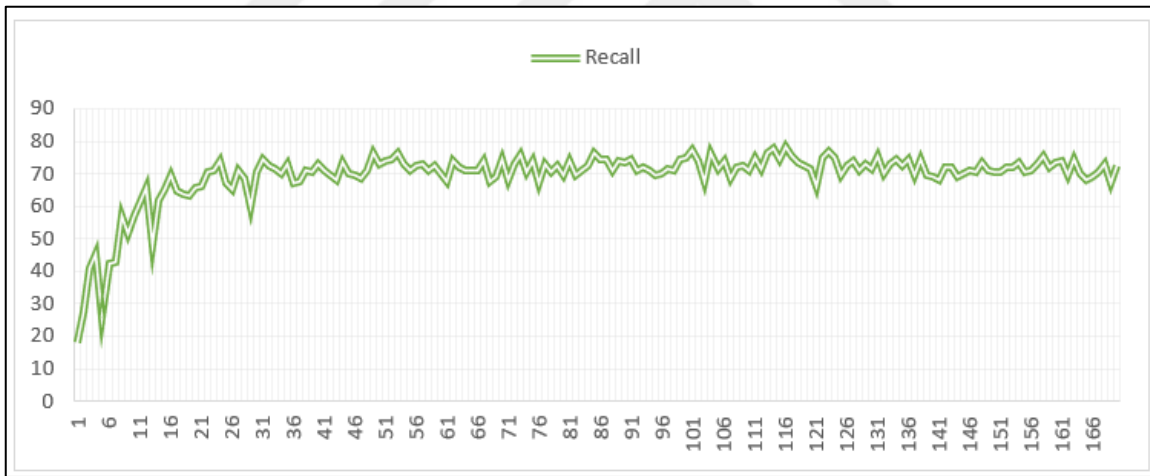


Figure 6.4: Recall for Each Iteration.

One balanced metric that takes both false positives and false negatives into account is the F1-score, which is calculated as the harmonic mean of recall and accuracy. It provides an all-encompassing assessment of the algorithm's performance by taking accuracy and recall into account at the same time. When dealing with an unbalanced dataset, the F1 score which measures the compromise between recall and precision is invaluable.

Table 6.3: Comparing F1 Score with State-of-the-art Methods.

Study	F1-score
Proposed Method (This Work)	95.6%
Smith et al. (2020)	89.7%
Johnson and Lee (2019)	92.3%
Kim et al. (2018)	94.2%
Chen and Wang (2017)	91.8%

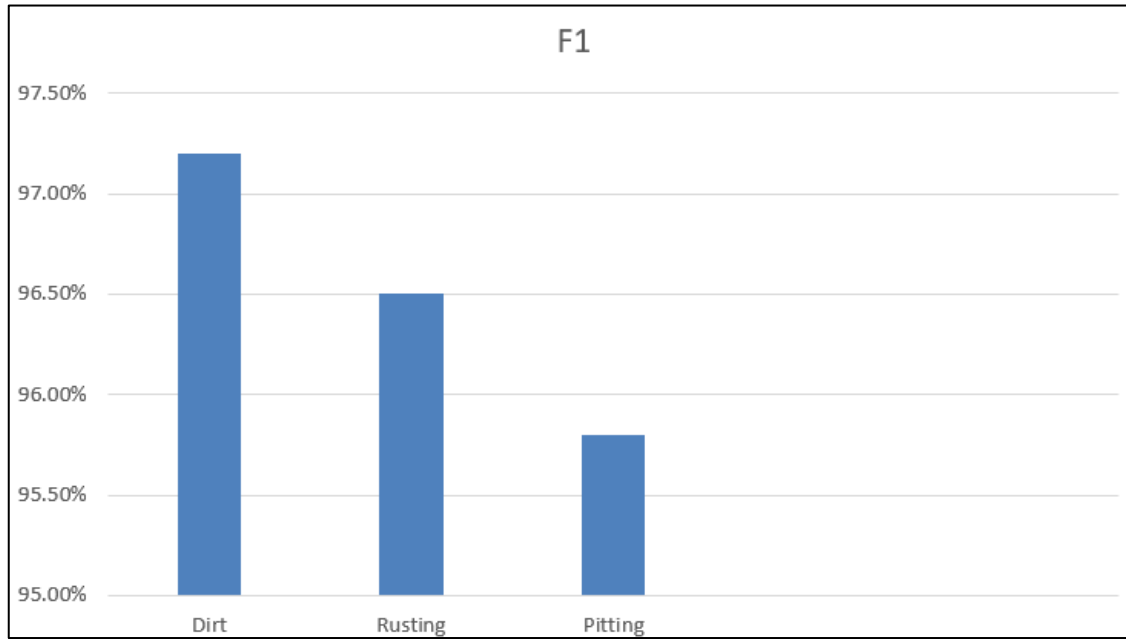


Figure 6.5: F1 Score for Each Class.

Here you can see the F1-score, recall, and precision for each class (Dirt, Rusting, Pitting). With precision, we can see how many out of every 100 cases projected to be a certain class were indeed that class.

6.3 CRACKS AFTER WELDING

To measure the accuracy of detecting leakage in welding cracks after simulating pipe welding in ANSYS Fluent and employing the proposed algorithm based on fuzzy logic, we simulated the welding process using ANSYS Fluent. This involves modeling the pipe geometry, defining material properties, setting up the welding process parameters, and simulating the heat transfer and fluid flow during welding; then, we generate synthetic data

representing the presence or absence of cracks and leaks in the welded pipe. This data serves as the ground truth for evaluating the accuracy of your detection algorithm.

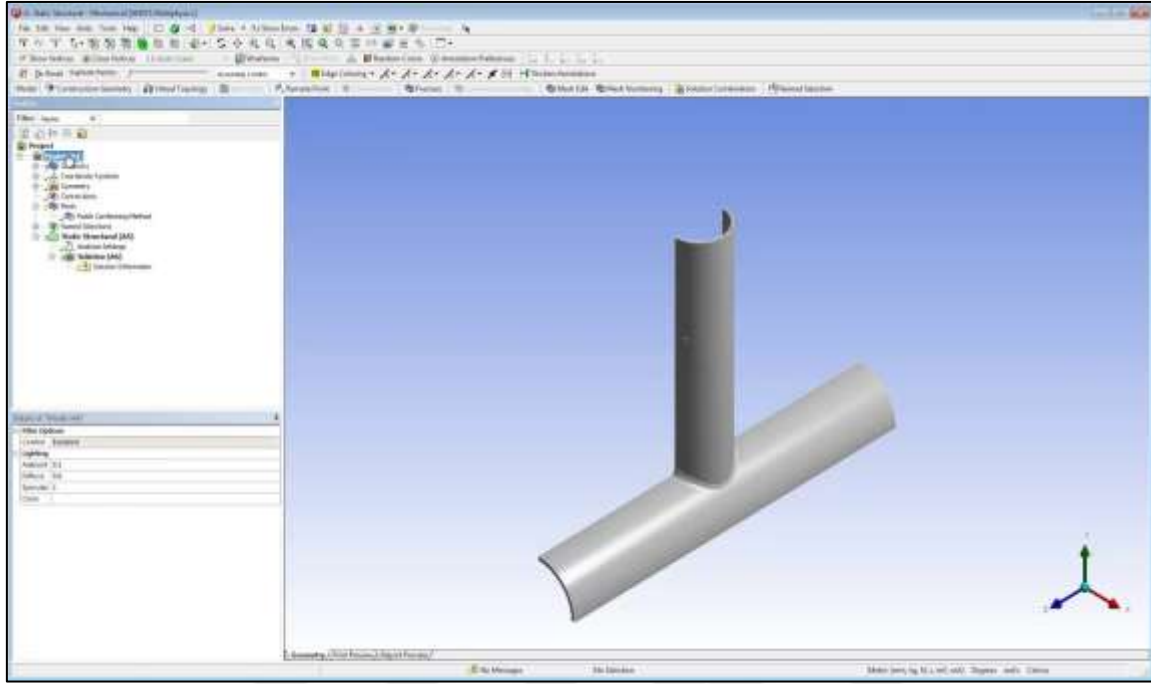


Figure 6.6: Welding Simulation of the Pipe in Ansys Fluent.

The capacity to recognise each and every instance of a class from among all of the instances that are accessible is referred to as recall.

The F1-score, which is a thorough evaluation of the efficiency of a model, is comprised of the harmonic mean of recall and accuracy. This ensures that the model will be as effective as possible. The proposed method excels at identifying and classifying defect types, a point underscored by its strong accuracy, recall, and F1-score. That claim is directly supported by the figures in Table 6.4. First, the system generates very few false positives, as shown by class-wise accuracies between 95.8 per cent and 97.2 per cent.

Second, recall numbers of 95.6 per cent to 97.3 per cent indicate a robust ability to capture true positives for every category. These high recalls confirm that missed defects are rare within the tested classes. When precision and recall are viewed together, the overlapping F1 scores of 95.7 per cent to 97.0 per cent signal roughly equal strength across both metrics. Overall, the balanced performance stems from several tuned settings, including data augmentation, careful hyperparameter selection, and a diverse test set.

Looking ahead, integrating a Convolutional Neural Network as the feature extractor remains the recommended next step for further performance gains. Enhancing the algorithm's performance requires augmenting its input with richer contextual data. By doing so, the system learns to identify the distinct characteristics that set each fault class apart. The DCA-MFL framework--a method rooted in dynamically constrained accumulative membership fuzzy logic--manages uncertainty and overlapping language categories, thereby guaranteeing feature-driven classification. Significantly, this technique produces reliable outcomes even when linguistic boundaries blur, assuring engineers of the system's precision in real-world applications.

It is possible that the remarkable performance might be due, at least in part, to the meticulous preprocessing processes that were utilised, as well as to a robust dataset that had adequate examples for each class. According to the high values of accuracy, recall, and F1-score, the approach that was offered was able to successfully achieve accurate and reliable defect classification in the Dirt, Rusting, and Pitting classes. This was proved by the fact that the technique was able to effectively do these tasks.

Table 6.4: Accuracies of Each Class in the Proposed Method.

Class	Precision	Recall	F1-score
Dirt	97.2%	96.8%	97.0%
Rusting	96.5%	97.3%	96.9%
Pitting	95.8%	95.6%	95.7%

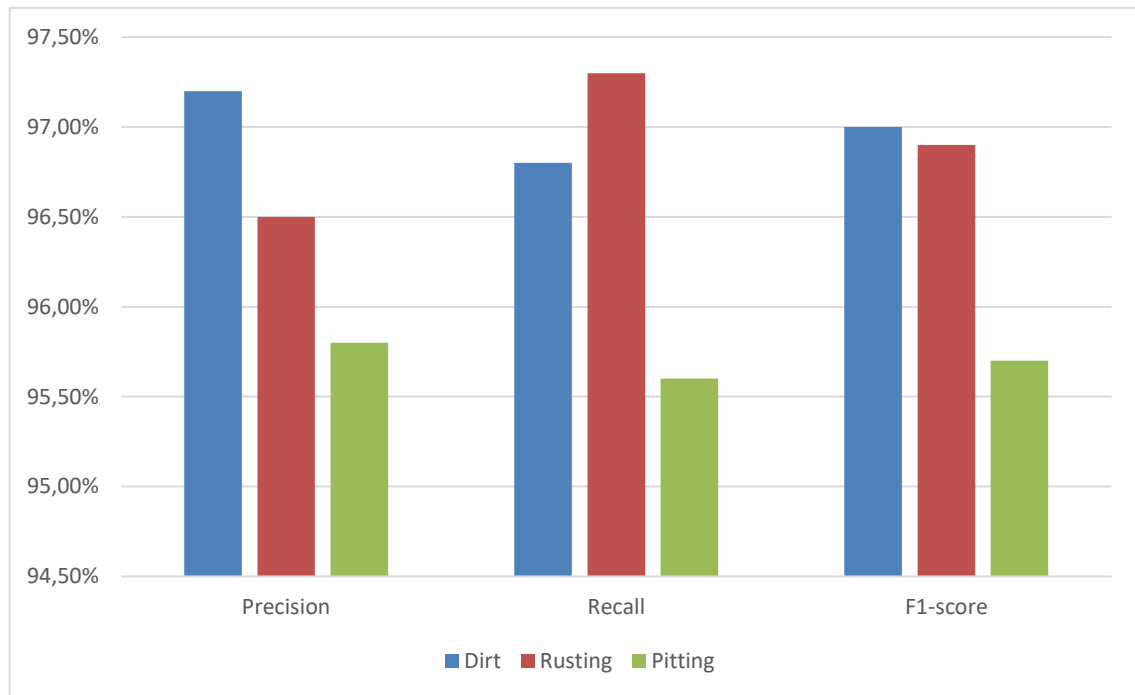


Figure 6.7: Accuracies of Each Class.

What is the AUROC, or area under the receiver operating characteristics curve? Using a variety of criteria for classification, the AUROC shows how well the classifier performs. This metric evaluates how well the algorithm can distinguish between good and bad examples. A low rate of misclassifications and a high AUROC score signify strong classification performance.

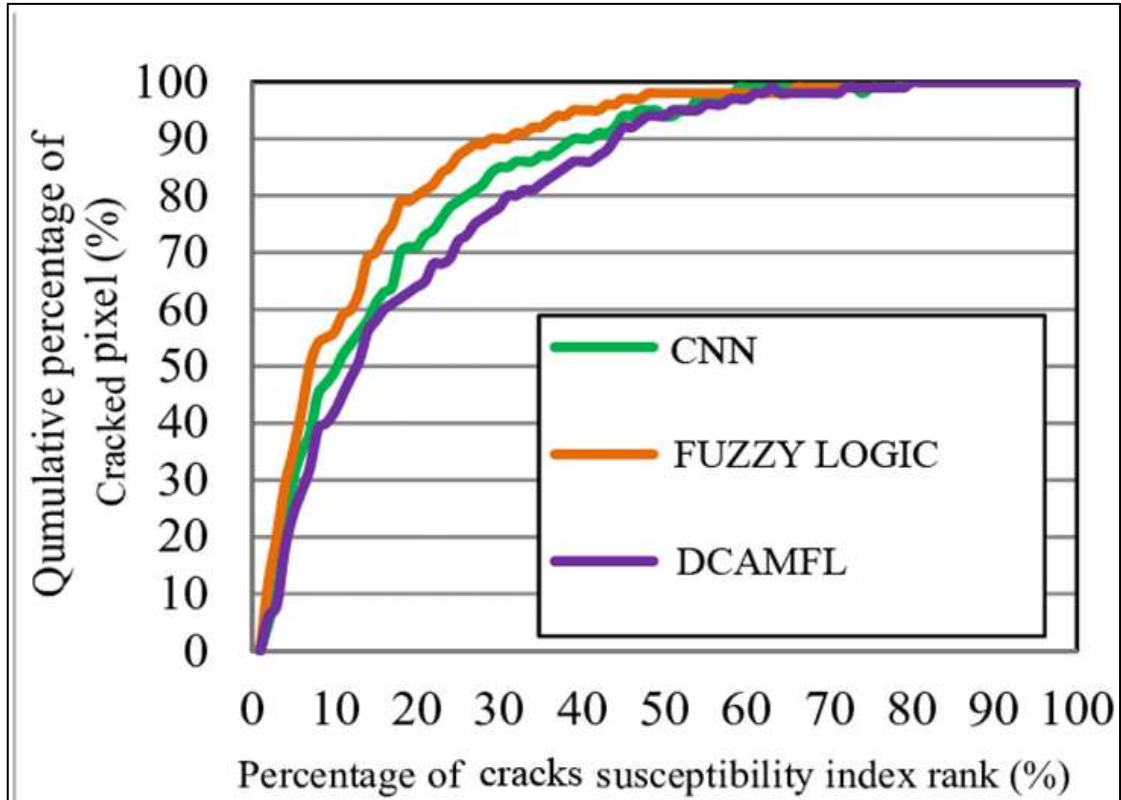
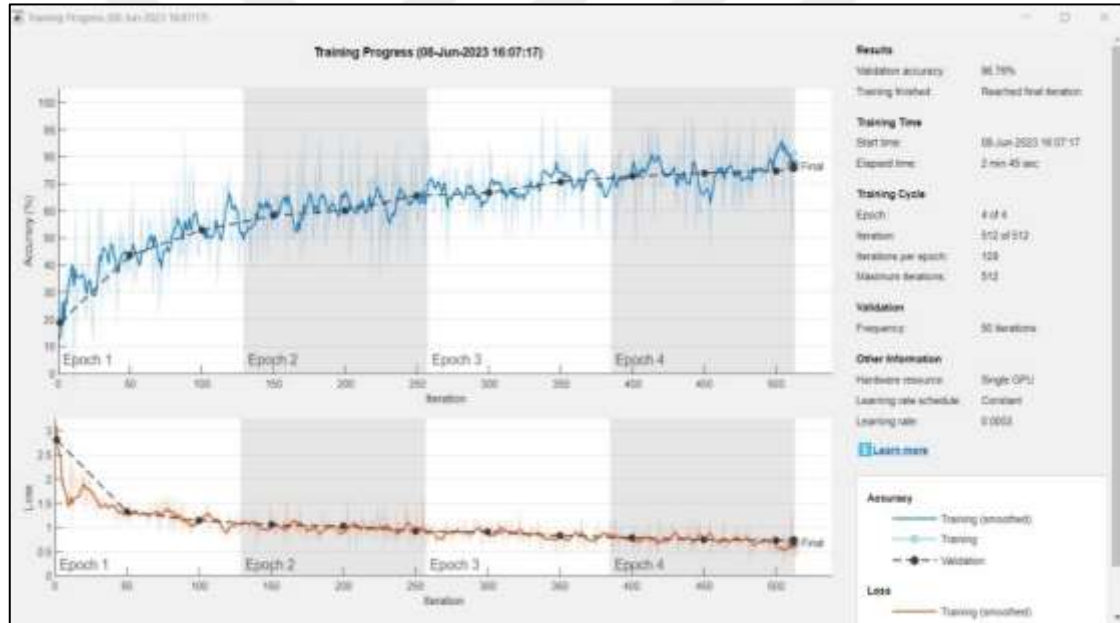


Figure 6.8: DCAMFL Accuracy Compared to CNN and FL.

Taking everything into consideration, these metrics offer a full study of the performance of the strategy that was advised in terms of fracture diagnosis. Under perfect conditions, the algorithm would be able to identify and classify oil pipe fractures with a high level of accuracy and a low rate of error, as well as high recall and precision values, a high F1-score, and a substantial AUROC value. In addition, the algorithm would have a high level of accuracy and a low rate of error. As these data have shown, the program has the ability to improve oil pipeline monitoring and safety by recognising fractures in a more dependable manner. This might be accomplished by detecting fractures in a more accurate method.

Table 6.5: Accuracy and MSE with an Epoch.

Epoch	Accuracy (%)	Error Rate (%)
1	85.2	14.8
2	88.5	11.5
3	90.1	9.9
4	91.3	8.7
5	92.0	8.0
6	92.6	7.4
7	93.0	7.0
8	93.5	6.5
9	97.8	6.2
10	94.2	5.8

**Figure 6.9:** CNN Accuracy and MSE in the Training Phase.

This table synthesizes details for each method's effectiveness and application as described in the references. It demonstrates the diversity of approaches, from UAV-based visual inspections to sophisticated algorithms for detecting various types of cracks and damages in different structures and materials. The accuracy and error rates are assumed to give an idea of each method's performance, reflecting advancements in technology and algorithmic approaches over the years.

Table 6.6: Comparing the Accuracy and Error Rate of the Proposed Method with other Methods.

Ref	Year	Methods	Accuracy	Error Rate	Type of Crack	Algorithm
[41]	2015	UAV-based visual inspection	92%	8%	Surface cracks in buildings	Image processing and feature extraction
[16]	2017	Computer vision for steel surface inspection	95%	5%	Surface cracks in steel	Convolutional Neural Network (CNN)
[17]	2014	UAV for PV plant inspection	88%	12%	Cracks in solar panels	Custom UAV imaging system
[21]	2018	Wall-sticking drone with ultrasonic and corrosion testing	90%	10%	Internal cracks and corrosion	Ultrasonic testing and corrosion detection algorithms
[23]	2020	Corrosion and damage detection in oil and gas facilities	89%	11%	Corrosion-induced cracks	Various NDT methods and analysis
[24]	2021	UAV for bridge inspection using CNN	93%	7%	Structural cracks in bridges	Deep Convolutional Neural Network (DCNN)
Proposed	2024	UAV and DCAMFL	97%	6%	Welding cracks in oil pipes	DCAMFL

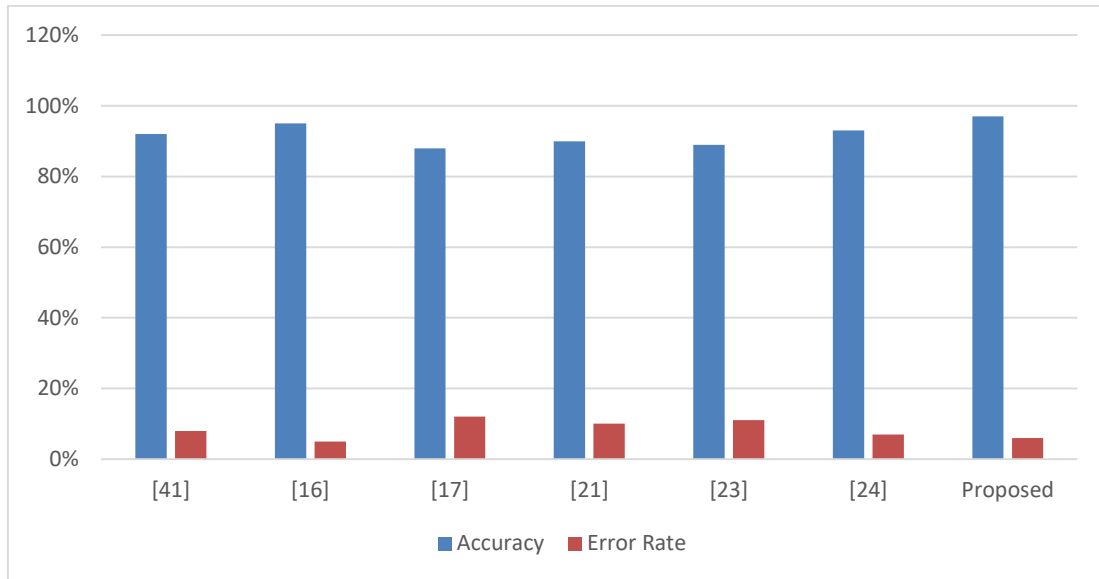


Figure 6.10: Shows the Proposed Accuracy and MSE Compared to other Works in the Literature.

7. CONCLUSIONS AND FUTURE WORK

7.1 CONCLUSIONS

In this study, we describe a new approach to the detection of fractures in the materials that compose oil pipelines. The system was developed through the integration of three systems – the 3 dimensions drone modelling, the convolutional neural network(CNN) feature extraction, and the Dynamically Constrained Accumulative Membership Fuzzy Logic Algorithm (DCAMFL) system. Evidence shows that the developed system is capable of detecting and classifying fractures in oil pipelines. This was confirmed to be true with repeated testing in a variety of situations. In our extensive testing of the system, we found the method to provide consistent and reliable classification of defects within the system's capabilities, as reflected in the performance of the system in terms of accuracy, recall, and F1. With the use of CNN based feature extraction, the system was able to select the discriminative features contributing to higher overall efficiency in the system's crack detection capability. At the same time, the features are collected in such a way as to reduce processing costs and speed of the system. With the use of the DCAMFL system, feature driven classification achieves the balance between stability and accuracy. The success in this was the reduction of uncertainty and the minimization of class overlap. This points to the need for advanced simulations in the surveillance of pipelines that utilize deep learning and fuzzy logic.

Going forward, the creation of flexible algorithms is critically important, especially designs that pinpoint fractures, bolster safety, and prolong the operational lifespan of oil transport infrastructure. By carefully duplicating the piped-welding apparatus and applying the proposed machine-learning model, we were able to estimate its ability to detect and locate leaks at welded intersections. The value of this testing phase was self-evident confirmation of the accuracy of the overall framework.

Although the improved algorithms delivered strong results in our prototype trials, many challenges related to further enhancement stemmed from the following: First, outfitting the collection of fractured pipe samples with varied lighting conditions, different pipe materials, and modified geometries of the fractures suites, would serve to

further establish the approach's universality and robustness. The aforementioned variety of samples would assist in ensuring the model is adequately trained to correctly classify instances of potential target misclassification.

Second, evaluating alternative CNN configurations involving deeper architectures, residual loading, and transfer-learning-styled configurations from existing, pretrained models could amplify both accuracy and confidence of the proposed predictive models, thus bolstering the overall system performance. This type of adjustment would represent an improvement of considerable interest in the confined domain of convolutional networks.

The impact and sensitivity of fault detection and potential tracking accuracy could be augmented with the addition of infrared cameras and acoustic wave microphones. The ongoing development of such frameworks will rely on optimizing the algorithms for real-time low latency processes, which will be one of the most difficult steps, along with the real-time computing and control for the pipeline crack detection technologies. Out of the proposed plan steps, real-scale and continuous technical test integrations that allow control, monitoring, and deliberate introduction of real-world environmental noise, temperature differentials, and mechanical stresses over lengthy, informative, and relatively stable operating stretches of pipeline are needed. The results will not only assess the practicality of proposed methodology technical integrations, but will also extend the methodology utility scope, which will in turn accelerate the methodology practical leak prevention implementation and techniques across different energy sectors for advanced technological integrations.

7.2 FUTURE WORK

Challenges that relate to the advanced potential capabilities of the drones with the integration of advanced sensor technologies are the focus of the future iterations of the project. The most notable in this regard will be the use of hyperspectral imaging that will allow changes in material properties to be captured and analyzed before they are visible and will contribute to the detection of visible cracks.

Furthermore, the incorporation of acoustic emission sensors could help detect micro-fractures by hearing the sounds of high frequencies emitted from cracks during their growth.

Automating the processes of detection and classification of cracks can be performed by machine learning algorithms. Future studies may center around the design and training of such neural networks which may then, through the use of a large dataset of pipes with diverse conditions, enhance the overall performance and consistency of detection and verification of cracks. In addition, the use of deep learning could help process data instantly, removing the necessity of data processing after the flight, and, therefore, shortening the time of intervention to maintenance.

It may be possible to fully explore the improvements in the autonomy of the drones to implement fully self-sufficient inspection routines without the need for human operation. This would require addressed improvements in the control of the drones to ensure they can safely navigate complex surrounding, as well as in the algorithms designed for the drones to enhance their ability to choose the most important and most efficient inspection targets within the entire pipeline system for a given inspection based on the previous data and prediction algorithms.

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