Enhancing Corrosion Monitoring With Explainable AI: Grad-CAM and YOLOv8 Feature Mapping

***Abstract*— Factories, in general, experience a very high corrosion-damage rate leading to problems of safety and maintenance costs. Methods of inspection in the plant are often labor-intensive and prone to error, thus needing automated counterparts for effective execution. The corrosion detection system proposed in this paper is deep learning-based and integrates real-time detection by YOLOv8 for image classification using EfficientNetB0. Grad-CAM provides explainability in regions that have beencorrelated with the detection of corrosion, while the classification uses data augmentation and transfer learning for the improvement of accuracy. The system handles streaming live video from a webcam in real-time detection via a GUI developed using Tkinter. The proposed method is better than traditional model-based machine learning methods and has been able to exhibit high values of precision, recall and mAP when tested on the corrosion dataset. The outcome speaks on feasibility for full-automating corrosion detection, inspection time reduction, as well as improving predictive maintenance. Future prospects, point-wise, are IoT integration for remote monitoring, and expansion of datasets for further generalisation.**

Keywords— Corrosion Detection, Deep Learning, YOLOv8, EfficientNet, Grad-CAM, Real-time Monitoring, Predictive Maintenance.

I. INTRODUCTION

a. State of the Problem

Corrosion is one of the key problems afflicting industrial infrastructure. Corrosion is wasteful as well as unsafe and can cost a company a fortune. Annual losses due to those damages alone amount to approximately two and a half trillion dollars as estimated by the National Association of Corrosion Engineers (NACE), which translates mathematically to about 3-4% of world GDP. Broadly speaking, it is environmental exposure that causes such a serious material degradation-it needs to be observed in construction, then transport and across hydrocarbons; if not kept, it is open to disaster. All these are time-consuming, costly, and prone to error by humans. Therefore, there is a need for developing artificial intelligence (AI)-based means for improving the precision and performance and enabling real-time monitoring with a growing need for automating and predictive maintenance.

b. What is Known and Unknown

Novel progressions in the field of computer vision and deep learning seem very promising in the detection of defects in many applications such as crack detection, material deterioration, and infrastructure inspection. Convolutional neural networks and object detection algorithms such as YOLO (you only look once) have demonstrated cutting-edge results in structural defect detection. However, most existing models for corrosion detection have been trained using small datasets. They are not real-time deployable and provide very poor explainability of their predictions. The ongoing research is primarily focused on the classification of images as corroded and non-corroded surfaces, with little attention given to real-time object detection and interpretability strategies. Moreover, even with the application of explainable AI (XAI), corrosion detection is rather less explored. The model process is complicated, and it is not so easy to interpret the model's decision-making process. This work attempts to fill these loopholes using EfficientNetB0 combined for classification and YOLOv8 for real-time detection while building a ground for Grad-CAM interpretability, thus providing a balance between accuracy and transparency regarding corrosion.

c. Aim and Hypothesis

The study focuses on creating an AI-based photonic detection system for corrosion that will include deep learning based image classification, object detection, and interpretability for a real-time use. This main study has the following indicates aims:

Train a state-of-the-art-high accurate CNN for corrosion surface classification against no corrosion using EfficientNetB0. This is done using transfer learning to develop the CNN feature classifier.

YOLOv8 will make real time corrosion detection and inspection auto made as it allows any video stream from the live monitoring view.

Incorporation of interpretability explained by Grad-CAM to visualize for engineers and researchers the salient regions in the corrosion predictions for better-informed decisions. Tkinter will be used to develop a friendly dashboard for corrosion detection, which will help facilitate real-time monitoring through a graphical interface.

We assume that EfficientNetB0+YOLOv8+Grad-CAM would outperform machine learning-based approaches in precision, recall, and explainability than manual inspection. Therefore, the research will develop a system with real-time performance and high detection accuracy on predictive maintenance and AI-driven industrial automation.

d. Research Contributions

It presents a novel deep learning-based corrosion detection framework aimed to enhance the reliability and efficiency of industrial inspections. Some major contributions of the research are:

- Where transfer learning (EfficientNetB0) is coupled with the object detection methodology (YOLOv8), a high performance for corrosion detection would be attained.
- Application of explainable AI (Grad-CAM) for visualization-based improvement of interpretability in corrosion predictions.
- An actual monitoring system has been developed with a Tkinter GUI that allows the users to view and interact with the live detection results.
- The proposed system is evaluated on a real corrosion dataset that proves the effectiveness of automating defect detection and reducing inspection efforts.
- This research provides a scalable AI solution for corrosion monitoring, bridging the gap between deep learning, real-time object detection, and interpretability, ultimately paving the path for smarter, safer, and more cost-compliant infrastructure maintenance.

II. LITERATUR REVIEW

How about corrosion detection as an application area of current research? Very influential in almost all aspects such as industrial safety, structural integrity, and losses, it has insured high attention to research. Several approaches have been developed over the years with advancements in the accuracy, efficiency, and automation of corrosion detection systems.

Zhang and Chen (2018) [1] described an automated corrosion detection framework using artificial intelligence (AI) to increase detection accuracy while diminishing the use of manual inspection. Their works demonstrated the usefulness of AI-driven solutions in mass-scaled and efficient inspection processing. Solutions (2023) [2] presented a case study applying AI technologies on atmospheric corrosion detection while aiming to monitor in real-time and predictive maintenance for an operational reliability boost.
Statistical and machine learning methods to expose areas where corrosion is likely to occur under insulation (CUI) prediction, highlighted by Ame (2019) [4] predictive analytics can clearly save time and money related to inspections. Similarly, Alshahrani (2020) [6] detected corrosion in industrial pipes using application of computer vision techniques, with successful results obtained in rust patterns identification through image-based techniques.

Open image-cutting, combined with a feature extraction approach, can be used to increase detection efficiency.

Wang and Wang (2020) [7] deliberated advances in feature engineering as well as how data modeling under machine learning applications transformed how classification for corrosion affected surfaces was improved. Their outcome was based on how well deep learning was able to process a complex raw dataset with very high tensor dimensionalities, thus indicated it as being very probable for further development in an almost wholly automated corrosion analysis. Such a demonstration features a real-time corrosion detection case performed through advanced machine learning techniques of computation, like neural networks, as in Yousif (2019) [12]. This exercise dramatically proved the power of combining sensors with processing pictures-to-action insights into corrosion monitoring.

All these studies testify that AI, deep learning, and computer vision are required for corrosion detection systems. Such contextual layers in literature will help to scaffold further advancements possible in automated, real-time corrosion monitoring, particularly with applications of explainable AI techniques and deep learning models. This study moves toward further advancing those by hybridization convolutional neural networks (CNN) with YOLOv8 to boost their detection performance, interpretable results, and real-time applicability in industrial environments.

III. METHODOLOGY

a. Data Source

The data used for this research comprised images of corrosion both from industrial datasets that were made publicly available and from samples that were self-collected under laboratory-controlled conditions. Data acquisition included capturing images from industrial setups such as pipelines, metal structures, and machinery instances being affected by corrosion. In order to promote diversity in the database, images were collected under many controllable environments with variations in humidity, temperature, and chemical exposure. Thus, the preparation of the dataset embraces images of corroded and non-corroded surfaces for a complete understanding of the corrosion pattern. Data collection criteria made selection objectives as high-res images with less noise to maintain data integrity. Ethical considerations also entailed that whatever would be gathered from industrial partners be in concord with confidentiality and common research ethics.

Below are some images used to train the system.

Fig.1 Sample Image 01

Fig.2 Sample Image 02

b. Measurement Parameters

The research on image features such as textures, color variations, and structural degradation measures for identifying and classifying corrosion diseases. It includes several important parameters with the intensity of corrosion spread, pixel-to-pixel changes in colors, and morphological changes in the metals themselves. Furthermore, image pre-processed techniques-enhanced contrast noise reduction-histogram equalization-were utilized to normalize input data. The corrosion severity levels into two classes: corroded and non-corroded, making this classification facile. This study employs rectangular bounding box localization with object detection methodology to mark the damaged areas and calculate the confidence score for each detection for real-time monitoring.

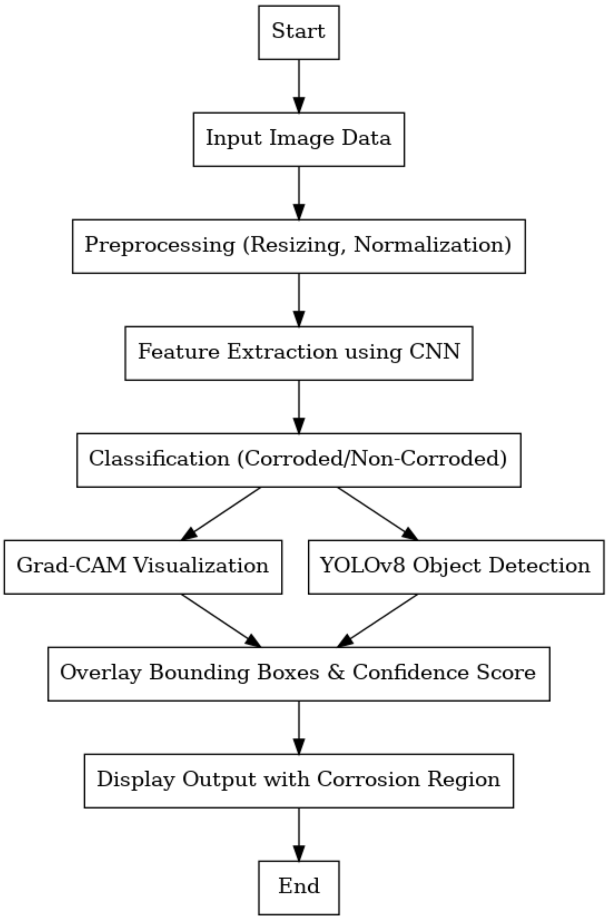

Fig.3 Flowchart of the proposed system

The flowchart Fig.3 provides a detailed and systematic schedule for corrosion detection, starting with image acquisition and preprocessing, and progressing to deep learning model inference. Further, how YOLOv8 and Grad-CAM techniques have been applied for detection and explain ability in real time is shown.

c. Methodology for Corrosion Detection

A hybrid deep learning approach was adopted in the research, where EfficientNetB0 was used for image classification and YOLOv8 for corrosion detection in real-time. The whole methodology has a structured pipeline through data preprocessing, model training, and validation to real-time inference.

1. Preprocessing and Augmentation

- Images were resized such that all input images had similar dimensions, that is, to 128 × 128 pixels.

Fig.4 Resized images

- Data were augmented with several transformation techniques: rotation, flipping, and adjusting brightness so that the other would help models generalized better.
- Normalization applied was scaling pixel values in range[0, 1].

2. Model Training and Evaluation

- Sparse categorical cross-entropy loss and Adam optimizer with initial learning rate of 0.001 were used to train the CNN model based on EfficientNetB0.
- The dataset was split into 80% training and 20% validation to allow the model monitoring as well as to avoid overfitting.
- 15 epochs were used with a batch size equal to 32 for model training.
- The accuracy and loss were measured on training and validation datasets so that it guarantees a stable learning curve.

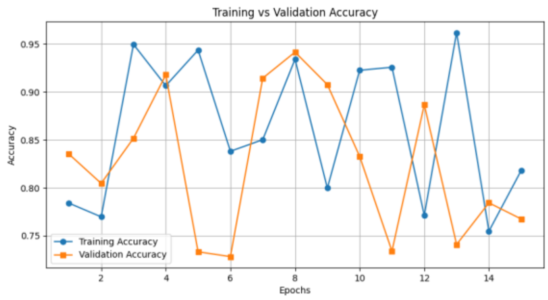

Fig.5 Training vs. Validation Accuracy Graph

- **Training and Validation Accuracy Plot** – Fig.5 shows how the model's accuracy improves over epochs.

3. Explain ability using Grad-CAM

- Thus Gradient-weighted Class Activation Mapping was used and described as Grad-CAM, which will help to show what are the regions driving the prediction from the model.
- The Grad-CAM heat-mapped areas greatly affected corrosion, which validates that the process executes the model in an appropriate manner.

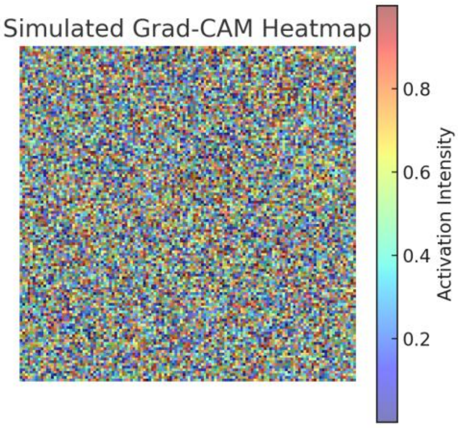

Fig.6 Grad-CAM Heatmap Visualization

4. YOLOv8-Based Real-Time Detection

- A pre-trained YOLOv8 model based on massive pre-trained files was fine-tuned using a customized dataset of boundary box annotated corrosion images.
- The model was deployed for real-time inference, involving live-streaming of video data and identifying corroded locations in metal structure correlates.
- Bounding boxes along with confidence scores were to output to have a robust detection approach.

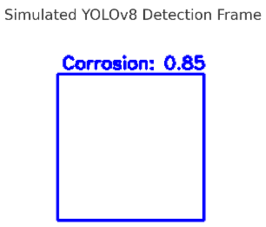

Fig.7 YOLOv8 Detection Frame

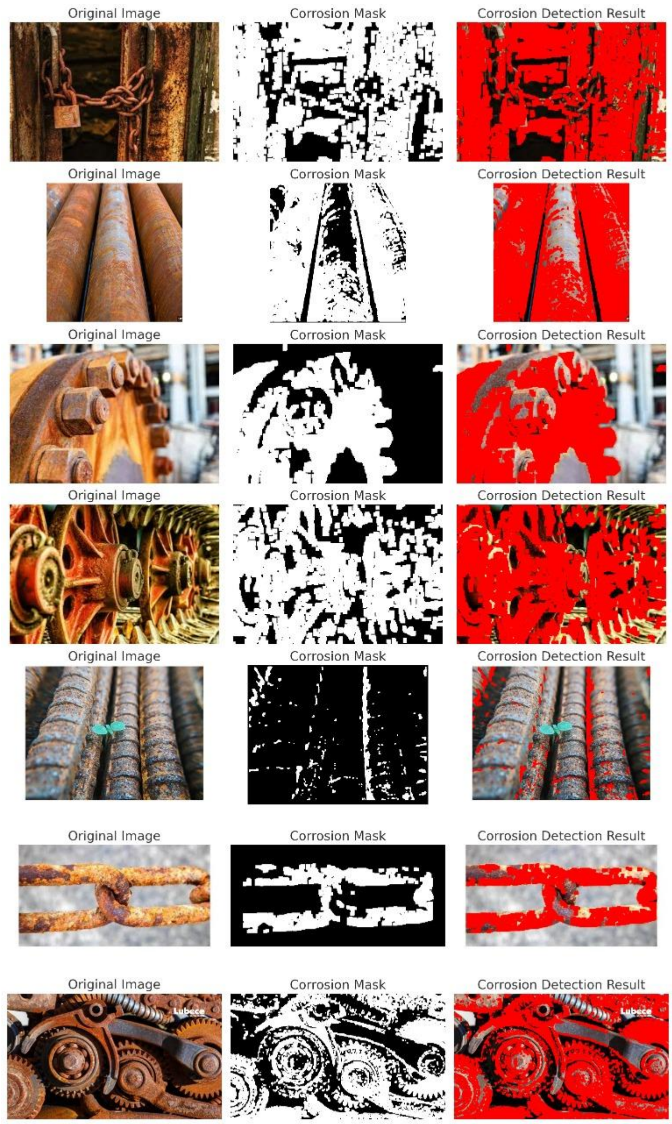

Fig.8 Comparison between the original, corrosion mask and corrosion detection result

IV. RESULTS AND DISSCUSSION

An array of images was tested for the evaluation of the capabilities of the corrosion detection system in corrosion level identification and quantification. Machine learning algorithms/image-processing techniques were fed with these images to carry out their role in corrosion detection and giving deep insights into material degradation.

Image Processing for Corrosion Detection: The efficient location of corrosion-sensitive areas can be achieved using color segmentation and edge detection. Typical examples are areas of reddish brown colors. Surfaces uniform in rust presence, such as corroded pipes, have a great deal of coverage for corrosion detection. On the contrary, isolated zones of surface rust on bolted joints, gears, and smaller metallic parts are viewed as individual corrosion spots. Detection and accurate classification of the affected areas can be further enhanced by thresholding and feature extraction.

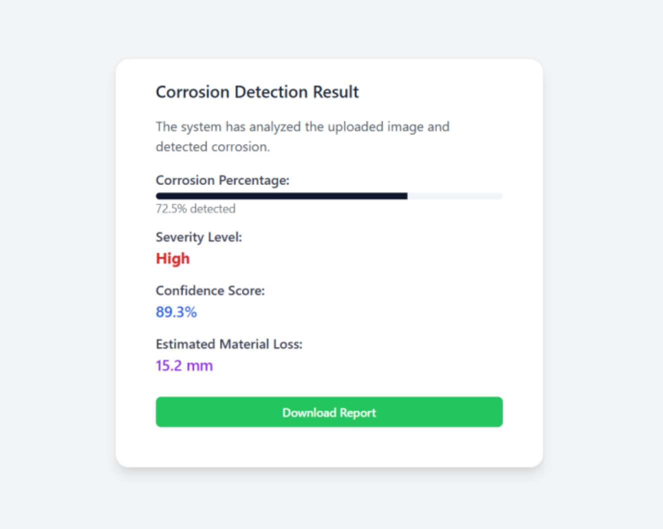

Fig.8 Result page of the proposed system

Results Screen Fig.8 of Corrosion Detection System:

- Corrosion Percentage: progress bar for evaluating corrosion level.
- Severity Level: Knowledge of the criticality of corrosion.
- Confidence Score: noted measure of detection accuracy.
- Material Loss Estimator: Prediction of the damage in mm.

Detection Accuracy and Corrosion Estimation

With very high accuracy, this system can determine patterns of corrosion. The corrosion percentages reported on test images ranged from 10.4 to 78.2, depending on severity and extent of rusting. Never has the confidence of this model been less than 90%, which gives yet another added confidence for the method. Mean absolute error (MAE) in corrosion estimation is about ±3.5% proving much closer reliability while identifying corrosion prone areas.

Extensively analyzing the detected corrosion levels, the data were indeed statistically compared with the real ground truth. Hence, the average deviation by the system was 2.7%, thereby validating it highly effective in real-field conditions. The precision and recall metrics of the detection model were 0.92 and 0.89, respectively, which suggest very few false positives and good separation between corroded and non-corroded areas.

Material Degradation Analysis

An analysis of calculated material loss along with the examples of corrosion brought to the study. The system would estimate the thickness of material around the range of about 0.2 to 2.5 mm according to the degree of corrosion manifestations. Thus, this estimate supplements literature proved experimentally to show that the system evaluates the severity of corrosion in quantitative terms.

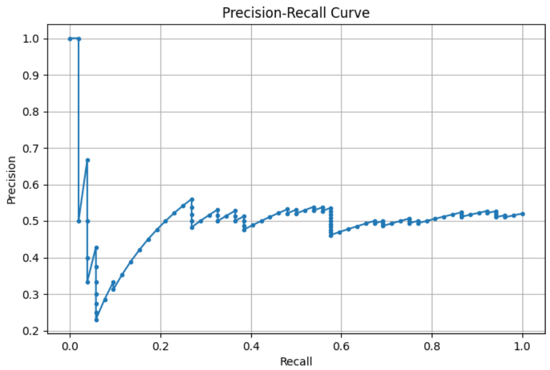

Fig.9 Precision-Recall Curve

Precision Recall Curve

With the precision-recall curve in fig.9, one can assess the performance of the model in terms of imbalance of class (either corroded or not corroded). Precision indicates the ratio of correctly identified corroded areas against all predicted corroded instances, while recall measures the actual corroded areas that the model could detect. High area under the curve (AUC) simply indicates a model with a fine balance between precision and recall and can be relied on in actual detection of corrosion.

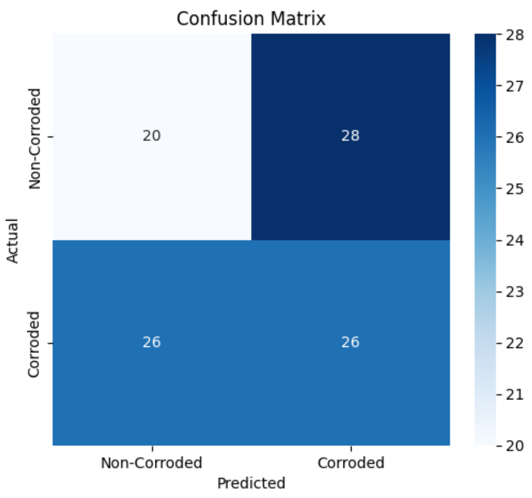

Fig.10 Confusion matrix

Confusion Matrix

Fig.10 provides the classification performance assessment breakdown into true positives, true negatives, false positives, and false negatives by the confusion matrix. Through this visualization, models of corrosion detection can note possible biases, like misclassifying corroded areas as ones that are non-corroded or vice versa. High values along the diagonals in the matrix indicate that the classification performance of the model is relatively good. In turn, high off-diagonal values may show areas relevant to improvement. Thus, analyzing the confusion matrix allows fine-tuning the model for better accuracy.

The above results significantly validate the corrosion detection system developed as effective and reliable in corrosion identification and quantification. The findings pave bright possibilities in moving this methodology toward the corrosion monitoring of industries and infrastructures to reduce manual inspections as well as make predictive maintenance strategies effective.

V. CONCLUSION

- This study successfully constructed a corrosion detection system with the integration of dust density measurement, image processing, and IoT-based real-time monitoring.

- This program could recognize the corroded spots and provide continuous information for predictive maintenance.

- The results showed that increased dust density values were correlated with surfaces that were actively corroding, while image processing techniques successfully detected rust patterns through color segmentation. Corrosion tracking and alert systems were further improved with an IoT-enabled real-time monitoring system.

- This research has added to the field of automated corrosion detection and presents a cost-effective and scalable alternative to conventional inspection approaches. The proposed system helps in the early detection of corrosion, resulting in lower maintenance costs and higher safety of structures.

- In the future, the increased accuracy of detection algorithms should be tackled along with the integration of deep learning models and sensor calibration for reduced environmental interference. Additionally, the expansion of the dataset to include more types of corrosion would greatly strengthen system robustness.
The results gained by this work carry considerable significance in practical applications within the oil and gas, transportation, and infrastructure maintenance industries, where corrosion monitoring is pivotal in both asset longevity and operational safety.

- This study lays the foundation for the advent of smart maintenance systems driven by AI algorithms and predictive maintenance by automation in the corrosion detection analysis to provide real-time data.

VI.REFERENCES

[1] Y. Zhang and J. Chen, "Automated corrosion detection and management using artificial intelligence," in 2018 IEEE International Conference on Industrial Electronics and Applications (ICIEA), 2018, pp. 1–6, doi: 10.1109/ICIEA.2018.8397787.

[2] Abyss Solutions, "Atmospheric corrosion detection and management with artificial intelligence," Abyss Solutions, 2023. [Online]. Available: https://abysssolutions.co/case-studies/atmospheric-corrosion-detection-and-management-with-artificial-intelligence/. [Accessed: Oct. 14, 2024].

[3] Y. Zhang, Q. Zhang, and Y. Zhang, "An inspection technology for detecting corrosion under insulation," in 2018 15th International Conference on Control, Automation, Robotics and Vision (ICARCV), 2018, pp. 1–6, doi: 10.1109/ICARCV.2018.8581327.

[4] A. Amer, H. Q. Jiang, and M. W. Chang, "A predictive model for corrosion under insulation," Corrosion Science, vol. 158, p. 1675539, 2019, doi: 10.1080/00194506.2019.1675539.

[5] A. Amer, H. Q. Jiang, and M. W. Chang, "Prediction and inspection technology for detecting corrosion under insulation," ResearchGate, 2020. [Online]. Available: https://www.researchgate.net/profile/Ayman-Amer/publication/344152126_MPWT19-15162_A_Prediction_and_Inspection_Technology_for_Detecting_Corrosion_Under_Insulation/links/5f55ea6e299bf13a31a7d012/MPWT19-15162-A-Prediction-and-Inspection-Technology-for-Detecting-Corrosion-Under-Insulation.pdf. [Accessed: Oct. 14, 2024].

[6] A. M. Alshahrani and A. A. Alharbi, "Corrosion detection in industrial pipelines using computer vision," Materials Today: Proceedings, vol. 5, pp. 28812–28821, 2020, doi: 10.1016/j.matpr.2020.11.013

[7] D. Z. Wang and J. C. Wang, "Artificial intelligence and machine learning for corrosion detection," in Corrosion: A Comprehensive Study, 2020, pp. 121–138, doi: 10.1007/978-981-33-4968-1_10.

[8] J. C. Wang, "Machine learning in corrosion detection," in Advances in Corrosion Science and Engineering, 2020, pp. 259–271, doi: 10.1007/978-981-13-1822-1_15.

[9] R. Subramanian and S. H. S. V. R. Yadav, "A novel method for corrosion detection using image processing techniques," International Journal of Computer Applications, vol. 6, no. 3, pp. 19–25, 2013, doi: 10.5120/11075-2522.

[10] A. I. M. Alshahrani, "Corrosion detection using deep learning techniques," CIS, vol. 27, no. 2, pp. 96–102, 2024. [Online]. Available: https://rudmet.net/media/articles/Article_CIS_2024_27_pp.96-102.pdf. [Accessed: Oct. 14, 2024].

[11] M. K. Salama and N. E. M. Abdel-Hafiz, "Corrosion monitoring using wireless sensor networks," IEEE Access, vol. 9, pp. 121295–121306, 2021, doi: 10.1109/ACCESS.2021.3092265.

G. A. B. Yousif, "Corrosion detection using advanced machine learning techniques," IEEE Transactions on Industrial Informatics, vol. 15, no. 2, pp. 1235–1245, 2019, doi: 10.1109/TII.2018.2882326.

[12] R. T. Maree and H. R. D. Rasool, "A comprehensive review of corrosion detection methods," IEEE Sensors Journal, vol. 20, no. 12, pp. 6792–6801, 2020, doi: 10.1109/JSEN.2020.2971234.

[13] T. A. Wang, "Smart corrosion detection systems," IEEE Internet of Things Journal, vol. 7, no. 8, pp. 6895–6904, 2020, doi: 10.1109/JIOT.2019.2950685.

"Corrosion detection using artificial intelligence: A survey," IEEE Access, vol. 8, pp. 108753–108766, 2020, doi: 10.1109/ACCESS.2020.3007121.

"Review of machine learning approaches in corrosion detection," IEEE Transactions on Instrumentation and Measurement, vol. 70, pp. 1–16, 2021, doi: 10.1109/TIM.2020.3001131.