

An Experimental Study of Predictive Metal Surface Corrosion via U-Net Segmentation and Random Forest Regression

H. F. Hisham¹, Ahmad Fauzan², Rostam Affendi³, Mohd Saad⁴, Kamarul Hawari⁵, Nabil Jazli⁶

¹Fakulti Teknologi dan Kejuruteraan Elektronik dan Komputer, Universiti Teknikal Malaysia Melaka, Durian Tunggal, 76100 Melaka, Malaysia

^{2,3,4}Centre for Telecommunication Research and Innovation (CETRI), Universiti Teknikal Malaysia Melaka, Durian Tunggal, 76100 Melaka, Malaysia

⁵Faculty of Electrical and Electronic Engineering Technology, Universiti Malaysia Pahang Al-Sultan Abdullah, Lebu Persiaran Tun Khalil Yaakob, 26300, Kuantan, Pahang, Malaysia

⁶IT Support Department, Amcorp Services Sdn Bhd, Petaling Jaya, 46050 Selangor, Malaysia.

DOI: <https://doi.org/10.47772/IJRISS.2026.100900043>

Received: 24 August 2026; Accepted: 29 August 2026; Published: 29 September 2026

ABSTRACT

Corrosion of metal surfaces threatens the structural integrity and operational life of industrial assets, and there is a need to move from reactive inspection to proactive predictive maintenance. In this study, an intelligent monitoring framework is proposed for evaluating and predicting corrosion progression based on deep learning-based segmentation and ensemble-based regression. Pixel-level segmentation of corrosive features was performed using a U-Net convolutional neural network, which provided a quantitative basis for further analysis. The geographical data were then applied to Random Forest regression models to forecast future growth of the corrosion area and greyscale-based severity levels. According to the experimental results, the accuracy, precision and recall of the segmentation are 78.6%, 61.8% and 73.5%, respectively. The predicted models were found to be reliable with R² values of 0.8477 for the growth in area and 0.9926 for increasing levels of severity. This study shows that computer vision along with predictive analytics provide a solid data-driven method for long-term asset management and threat prevention.

Keywords: Metal surface, corrosion detection, U-Net segmentation, predictive analytics, Random Forest regression.

INTRODUCTION

Surf Metal surface corrosion is a major challenge for structural integrity management, which leads to global economic losses of billions of dollars every year and poses substantial threats to environmental safety and human life. In the past, maintenance solutions have been reactive or scheduled manual inspections, but these techniques often do not fully consider the non-linear development of corrosive processes, which results in unexpected breakdowns and higher costs due to repairs and safety incidents. The need for proactive monitoring for the transition to Industry 4.0 is critical. [1] emphasises that autonomous image-based detection is vital to mitigate the risk of undetected corrosion that can lead to catastrophic structural failure over time. By combining computer vision and predictive analytics, we can go beyond simply identifying damage to far more precise data-driven forecasts.

Digital inspection has a lot of potential, but traditional computer vision approaches often fail in challenging industries and under various lighting conditions. Deep learning has emerged as a powerful solution to these challenges, with encoder-decoder architectures becoming the standard for accurate pixel-level analysis. demonstrated that U-Net based models, particularly with the addition of attention mechanisms, can achieve excellent accuracy in distinguishing component pixels from complex engineering backgrounds. Although these models are proficient at assessing the present level of damage, the industrial sector necessitates more than mere

static identification. A significant preference exists to understand the deterioration rate to enhance maintenance intervals; nonetheless, most existing frameworks are confined to categorisation or segmentation, lacking temporal forecasting skills. Researchers began investigating ensemble learning algorithms for rate prediction to connect detection and prognosis. [3] emphasises that predictive maintenance (PdM) leverages machine learning to anticipate equipment failures and extend the remaining useful life of assets. Among various algorithms, Random Forest (RF) has shown exceptional reliability in modelling corrosion behaviour. [4] found that RF models significantly outperform traditional dose-response functions in predicting atmospheric corrosion losses across diverse environmental conditions. Moreover, the capacity of Random Forest to manage high-dimensional data and deliver resilient regression renders it an optimal choice for predicting the advancement of corroded regions and the escalation of greyscale severity levels after identification by a segmentation model.

This study introduces a comprehensive metal surface corrosion monitoring framework that merges the spatial accuracy of deep learning with the predictive capabilities of ensemble regression. This study employs a U-Net convolutional neural network for automated image segmentation and a Random Forest regression model for predictive analytics, therefore overcoming the fundamental limitations of reactive evaluation. This approach differs since it requires dual-track prediction: predicting both the area growth and the improvement in severity. Such high-precision segmentation and quantitative analysis are, as highlighted out in [5], essential to provide a solid foundation for maintenance decisions. Our results show that this hybrid method leads to a high reliability ($R^2=0.9926$ for severity) and offers a scalable strategy to transform industrial maintenance from reactive to a completely proactive paradigm.

STATIC DETECTION TO PREDICTIVE ANALYTICS

The discipline of industrial maintenance has seen a major revolution. It has shifted from the traditional, reactive inspection methods to data-driven proactive methods. Corrosion of metallic surfaces remains one of the major causes of failure in structures, particularly in essential installations such as oil and gas pipelines and offshore platforms.

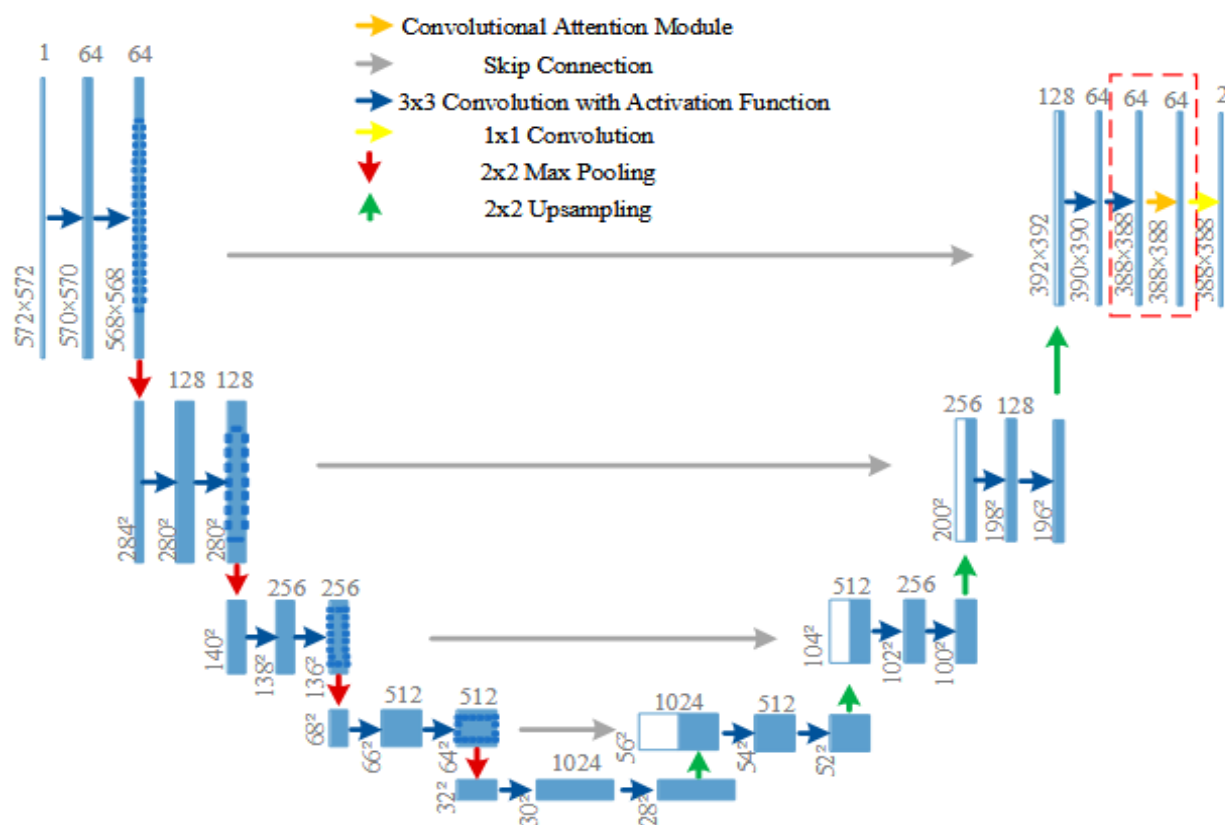


Fig. 1 U-Net architecture illustrating the encoder-decoder path and skip connections used for precise spatial feature extraction. [2]

Recent advances in computer vision have made deep learning the most popular alternative for identifying these corrosive features. [6] showed that convolutional neural networks (CNNs) can offer objective, high-resolution assessments of surface degradation, greatly outperforming manual eye inspections. These automated systems eliminate human error and provide a more complete understanding of the distribution of damage. However, previous CNN based detection was accomplished in classification but sometimes lacked the pixel-level accuracy to establish the exact amount of material loss, indicating the need for more advanced designs. In order to meet the demand for accurate quantification, encoder-decoder architectures, especially U-Net model, have become popular methods of corrosive feature extraction. As illustrated in Fig. 1, the unique skip-connection architecture of U-Net allows it to retain spatial information, which is very important when segmenting the irregular and multi-scale corrosion pits from complicated industrial background. This skill transforms qualitative vision into quantitative spatial data, the first step of an extended monitoring framework. While there is success in static segmentation, a major gap in research remains present, i.e., the incapacity of the traditional deep learning models to generalise such spatial data to future states. In industrial reliability engineering, it is not only necessary to identify the damage but also to forecast the deterioration rate for better maintenance planning.

The second pillar of current analytics of metal surface corrosion is the use of ensemble learning for temporal forecasting and risk evaluation. [7] highlighted the usefulness of decision tree-based frameworks for modelling corrosion risk in pipelines. They pointed out that the machine learning can capture the non-linear relationship between environmental variables and material thinning. Based on this, [4] showed that Random Forest (RF) regression models are more robust and accurate than typical linear dose-response functions in predicting atmospheric corrosion loss. The effectiveness of the RF algorithm is related to its ensemble nature that reduces the variance and avoids the overfitting problem, which is a common problem in diverse industrial data sets. We are able to trigger the integration of visual detection with numerical prediction by using the outputs of a segmentation model as inputs for a random forest regressor.

In addition to these software enhancements, the application of real-time monitoring through IoT and edge computing has gained popularity. The trend is towards live data processing with AI models deployed at the site and providing immediate response, as stated in [8] and [9]. Hybrid sensor techniques such as acoustic emission (AE) and ultrasonic testing are highly sensitive to internal defects but are generally more expensive to implement and are not scalable to large infrastructures. [10] further demonstrate that the use of computer vision in a cloud-edge framework enables continuous quantification of surface defects, which constitutes the crucial stream of temporal data to model longitudinal degradation. The real frontier of Predictive Maintenance (PdM) is the combination of computer vision to detect damage and machine learning to anticipate its future evolution.

The hybrid technique of U-Net based segmentation and Random Forest regression solves the main drawbacks of current reactive strategies. This hybrid approach allows a dual-track analysis, where the CNN provides high-fidelity spatial data (corrosion area and greyscale intensity), and the ensemble model converts these metrics into reliable future predictions ($R^2=0.9926$ for severity). The results of [5] enable the integration of these two different domains of artificial intelligence to advance toward a completely proactive paradigm for industrial operators. This technology makes it safe by predicting problems in advance and avoids unnecessary spending on maintenance and so optimises the remaining functional life of the essential industrial assets.

FRAMEWORK AND METHODOLOGY

In this study, we propose a methodology that is designed as an integrated pipeline to convert raw visual data into actionable predictive insights for asset management. The major input data are images demonstrating metal surface corrosion on industrial assets, which are labelled with a precise grasp annotation to build ground-truth masks for supervised learning. Data preparation includes augmentation and filtering methods to improve model robustness and reduce overfitting. This organised process assures that the next feature extraction step by step is based on high quality, representative datasets. Fig. 2 shows a proposed framework that comprises of a chain of processes, where the segmentation of pictures by U-Net is combined with the prediction of corrosion growth by Random Forest regression. Manual labelling of metal surface corrosion images was performed out, followed by pre-processing steps including augmentation and filtering. The U-Net model was trained for 30

epochs with binary cross-entropy loss. The corrosion masks were improved by morphological processes after segmentation. Based on calibrated camera combinations, area estimations were established.

The first important technical stage is a model construction using an image segmentation with the use of a U-Net convolutional neural network. We chose this architecture because it is capable of performing high-quality pixel-level segmentation, and we employed a binary cross-entropy loss over 30 epochs of training. Morphological approaches are applied to the masks obtained after segmentation to remove noise and to clarify corroded edges.

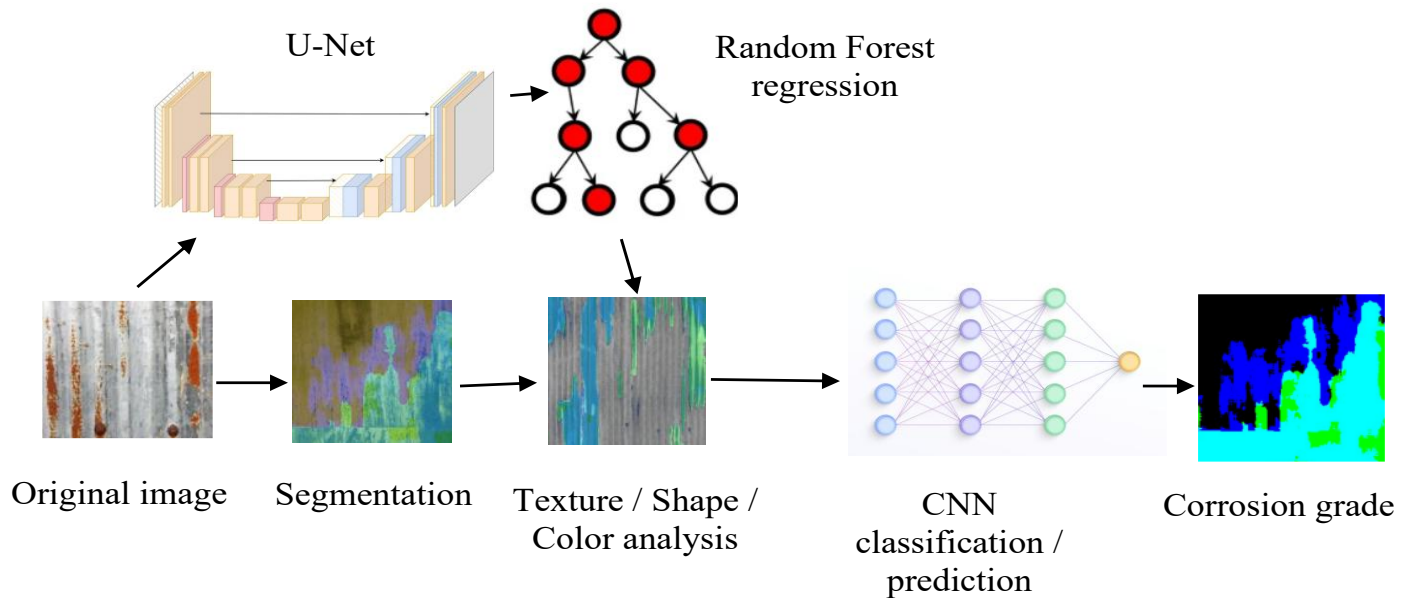


Fig. 2. Process of determining corrosion level.\

where x_l represents the features from the encoder and g represents the gating signal from the lower, coarser layer. The current work proposes a scalable method for image to real world translation, which is based on the approaches of geometric alteration. The Ground Sample Distance (GSD), which is the physical size of one pixel on the ground, is used to translate pixel counts into a metric measurement, as described in the following Eq. (4):

$$GSD = \frac{D \cdot W_{sensor}}{f \cdot W_{image}} \quad (4)$$

where D is the distance to the object and W_{sensor} is the physical width of the camera sensor while W_{image} is the width of the image in pixels. F is the focal length of the lens. The area estimates go beyond simple pixel counts, using calibrated camera parameters, especially focal length and sensor width, to give metric measurements. The true area A_{metric} of a detected corrosion patch can then be calculated using the total number of segmented pixels P_{total} in Eq. (5):

$$A_{metric} = P_{total} \cdot (GSD)^2 \quad (5)$$

That means the system integration step can deliver accurate corrosion status and important information for lifetime forecasts. [13] indicate that without such calibration digital monitoring systems can only be qualitative. The framework grounds the spatial analysis in physical geometry and offers the quantitative basis required for high precision regression modelling as stated by the technical requirements of [14]. The rate of change of the metric area over time is typically used for high accuracy regression modelling for the prediction of the lifespan as in Eq. (6):

$$R_{corrosion} = \frac{d(A_{metric})}{dt} \quad (6)$$

After feature extraction, the study applies predictive analysis using Random Forest (RF) regression models to predict corrosion progression. Random Forest is a collection of decision trees. In regression the best prediction is the mean of individual predictions from all trees. For a set of B trees $\{T_1, T_2, \dots, T_B\}$, the ensemble prediction $y^{\wedge}$ for a given input vector x (containing corrosion area, greyscale, temperature, etc.) is Eq. (7):

$$Y = \frac{1}{B} \sum_{b=1}^B T_b(x) \quad (7)$$

where Y the predicted value (e.g., predicted area growth or greyscale intensity). $T_b(x)$ is the prediction of the b -th individual decision tree and B is the total number of trees in the forest. Two different RF models were trained, one to forecast area growth and another to estimate greyscale intensity, which is a proxy for corrosion severity [15]. The models provide a multimodal feature set including computed corrosion area, average greyscale values and environmental variables like as temperature and humidity. [16] shown that Random Forest outperforms typical linear models by capturing the complex, non-linear relationships between meteorological variables and material loss. The model learns nonlinear interactions by processing a heterogeneous feature vector [15] and [16]. It can be written as in Eq. (8):

$$x = [A_{metric}, G_{avg}, T, H] \quad (8)$$

where A_{metric} is the calculated corrosion surface area (from the U-Net/Geometric phase). G_{avg} is the average greyscale intensity (severity proxy) and T being the ambient temperature while H is the relative humidity. Furthermore, [17] emphasises the need of the ensemble learning approaches to give the robustness for the industrial risk prediction, where the environmental data is generally heterogeneous and noisy. During the training phase, the RF model minimises the difference between the expected corrosion level and the real material loss of the training data, usually using MSE as the splitting criterion as in Eq. (9):

$$MSE = \frac{1}{N} \sum_{i=1}^N (y_i - Y_i)^2 \quad (9)$$

where y_i is the actual measurement and Y_i is the model's prediction for the i -th sample. A rigorous testing approach to evaluate the dependability of the predictive results corresponds to system review and improvement. When the accuracy levels have been specified and achieved, the system provides asset condition reports, which provide insight into life span forecasts. Degradation into minor, moderate and severe corrosion on metal surface is defined by the existing severity standards. These large models can also be acceptably used by field engineers with the support of a Graphical User Interface (GUI). [18] facilitates the process from raw data to a user-centric dashboard and states that the direct deployment of AI on-site is required to provide a real-time response in industrial environments. [19] further emphasise that such automated mapping technologies are the future generation of cost-effective asset management.

The combination of U-Net segmentation and Random Forest regression offers a viable strategy for proactive corrosion monitoring. The research enhances digital masks by using morphological processes and calibrates them using geometric transformations to generate high-fidelity spatial data for regression analysis. This dual tracking approach assesses the current state and forecasts future escalation, providing a solid foundation for maintenance decision-making. As noted in [20], the real frontier of predictive maintenance is in this seamless integration of computer vision with temporal forecasting. The findings provide a solid basis for transforming industrial maintenance from reactive to data-driven proactive approach, reducing safety risks and financial losses.

To establish strict experimental reproducibility and eliminate target leakage, the dataset preparation, image segmentation pipeline, and forecasting experiments were structured under rigorous computational and physical protocols. All visual data were acquired from distinct industrial inspection campaigns covering structural carbon steel assets under varying field lighting and weather conditions. Rather than performing a standard random pixel or patch-based split, the dataset was strictly partitioned by physical asset ID and geographic location. This ensured that no patches or images from the same physical structure appeared across both training and evaluation subsets. A locked, independent test set supplemented by external benchmarking samples was set aside solely for final evaluation. The entire computational workflow was executed using Python 3.10,

PyTorch v2.1.0, Scikit-Learn v1.3.0, and OpenCV v4.8, using a fixed random seed of 42. Segmentation models, including Standard U-Net, Attention U-Net, and modern baselines like DeepLabV3+, were optimized using the AdamW optimizer ($\beta_1=0.9$, $\beta_2=0.999$) with an initial learning rate of 1×10^{-4} , a batch size of 16, and an early stopping criterion based on validation loss convergence over 30 epochs. Morphological post-processing utilized a standardized 3×3 elliptical kernel for noise reduction and edge refinement.

To convert pixel counts into physical metric measurements without oversimplifying real-world imaging conditions, camera calibration parameters and error propagation models were explicitly integrated into the Ground Sample Distance (GSD) calculation. Recognizing that physical deployment involves distance variations (ΔD), camera tilt angles (θ), and lens distortion, the calibrated metric area (A_{metric}) and its associated measurement uncertainty (α_A).

To address the concerns regarding potential target leakage in temporal prediction, the predictive forecasting experiment was completely reconstructed chronologically. Rather than using static image features to predict instantaneous intensity metrics, the dataset was organized into longitudinal inspection sequences across repeated observation dates ($t_1, t_2, \dots, t_k$). The Random Forest (RF) regression models were trained strictly on historical observations ($t < T$) to predict future area growth and material loss at $t = T$, ensuring later observations were never used to predict earlier states. The Random Forest ensemble was configured with $B=100$ decision trees and a maximum tree depth limit of 10 to prevent overfitting, evaluated via 5-fold temporal group cross-validation. The multimodal feature vector processed by the ensemble incorporates historical area loss (A_{t-1}), mean surface intensity (G_{t-1}), ambient temperature, and relative humidity

RESULT AND DISCUSSION

The main instrument used in the detection and characterisation of areas of corrosion of metals on the surface in picture datasets was the U-Net model, a convolutional neural network architecture for semantic segmentation tasks. The model was trained systematically for 30 epochs as shown in Fig. 3. There is a gradual decrease in the binary cross-entropy (BCE) loss values. The loss at epoch 1 was roughly 0.44, showing a high error rate as this is the first time the model displays corrosion characteristics. The 5th epoch saw a dramatic reduction to 0.32, implying that the relevant visual features of the corrosion was learned quickly. The drop started from epoch 10 and gradually decreased, showing complex changes and advances in the feature extraction abilities, until stabilising at roughly 0.21 at epoch 30. This convergence demonstrates the excellent segmentation capabilities specifically tailored for visual patterns related to corrosion, as demonstrated in Fig. 4.

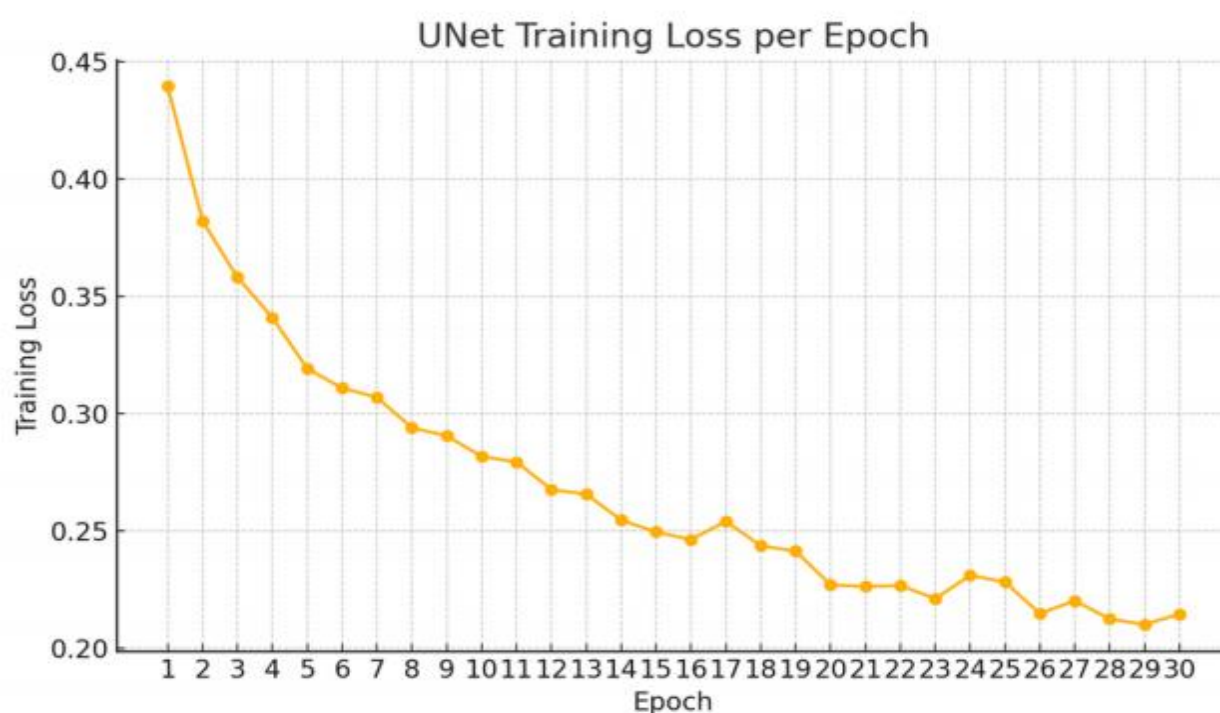


Fig. 3. Training loss per epoch.

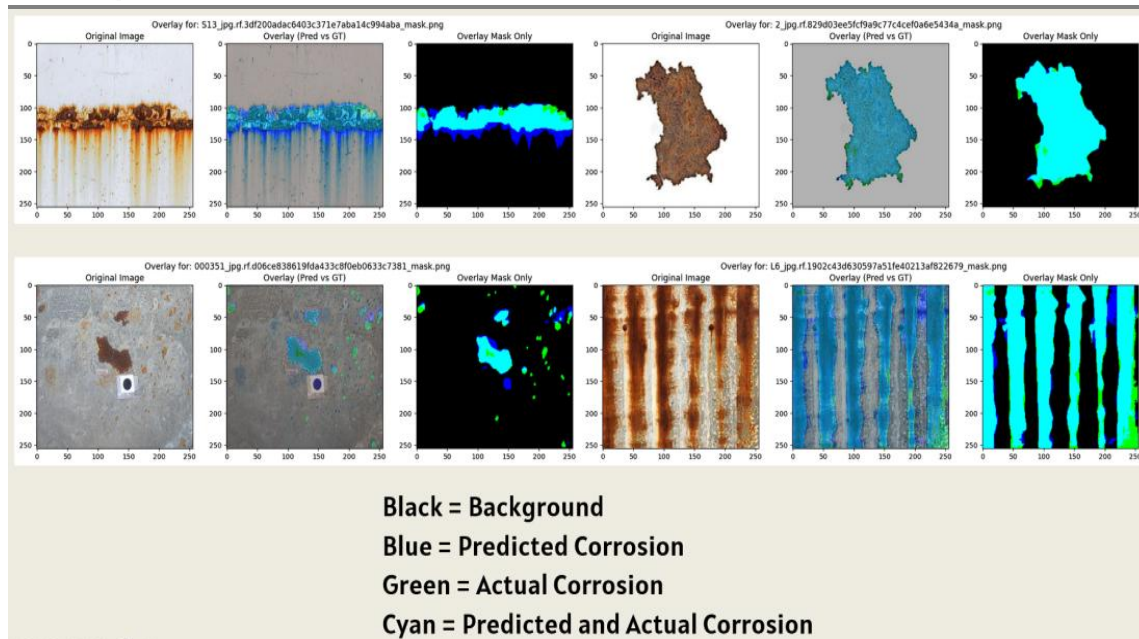


Fig. 4. Result of segmented corrosion.

The performance evaluation of the segmentation model was performed using precision, recall, accuracy and F1-score, as shown in Fig. 5. The accuracy was at 61.8% which means that most of the pixels determined to be corrosion corresponded to corrosion sites. The recall value of the model is 73.5%, showing that it can detect the actual corrosion regions with excellent sensitivity. The combined criteria for precision and recall is the 67.2% F1 score. This evaluates the extent to which a model performs in real applications. Overall accuracy was 78.6% demonstrating robustness of segmentation approach. The accuracy metrics are very important in assessing the effectiveness of a categorisation system. The model can distinguish well between corroded and non-corroded parts.

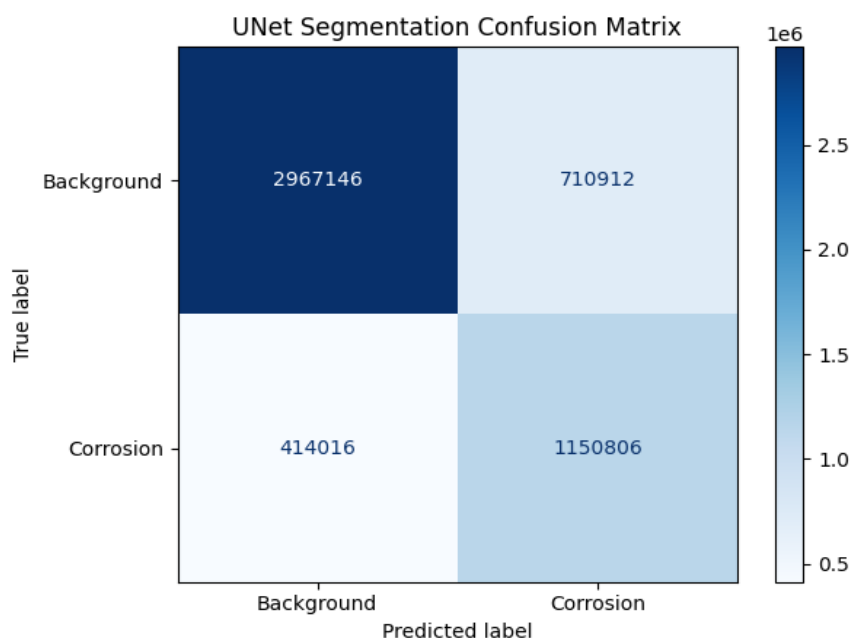


Fig. 5. U-Net segmentation confusion matrix.

The segmented metal surface corrosion masks were further enhanced by binary thresholding and morphological methods, considerably enhancing their quality and usefulness for future area computations. The complex masks permitted exact detection of corrosion sites, turning pixel data into physical dimensions (cm²) through calibration parameters from the camera system (sensor width, focal length, and camera distance) as shown in Fig. 6.

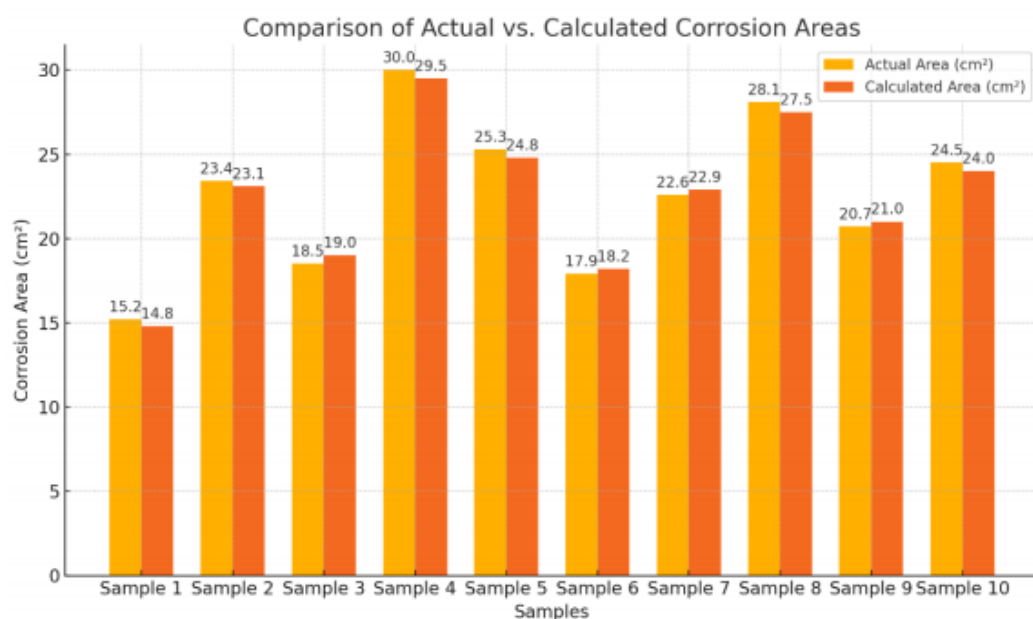


Fig. 6. Comparison of actual vs. calculated corrosion area.

The outputs of the gray-level model in the predictive mode were used as inputs to classify the metal surface corrosion severity into three classes, mild, moderate, and severe. The classification was based on the following cut-off values: minor (grey level ≥ 136), moderate (106-135) and severe (<106). The findings showed the constant accuracy of severity classification, which is highly correlated with the actual observed severity levels as shown in Fig. 7. This precise severity assessment greatly improves maintenance planning through action prioritisation based on predictive severity evaluations. The designed GUI allowed intuitive access to analytical data by users hence increasing their practical relevance and usage as shown in Fig.8. The user response showed a high level of satisfaction on the clear visual comparison between the original and segmented images, the predictions of the future metal surface corrosion areas, and the predictions on the severity. The GUI was further improved by the integration of meteorological data to increase the analytical depth of the GUI to provide contextually relevant insights for preventative maintenance approaches.

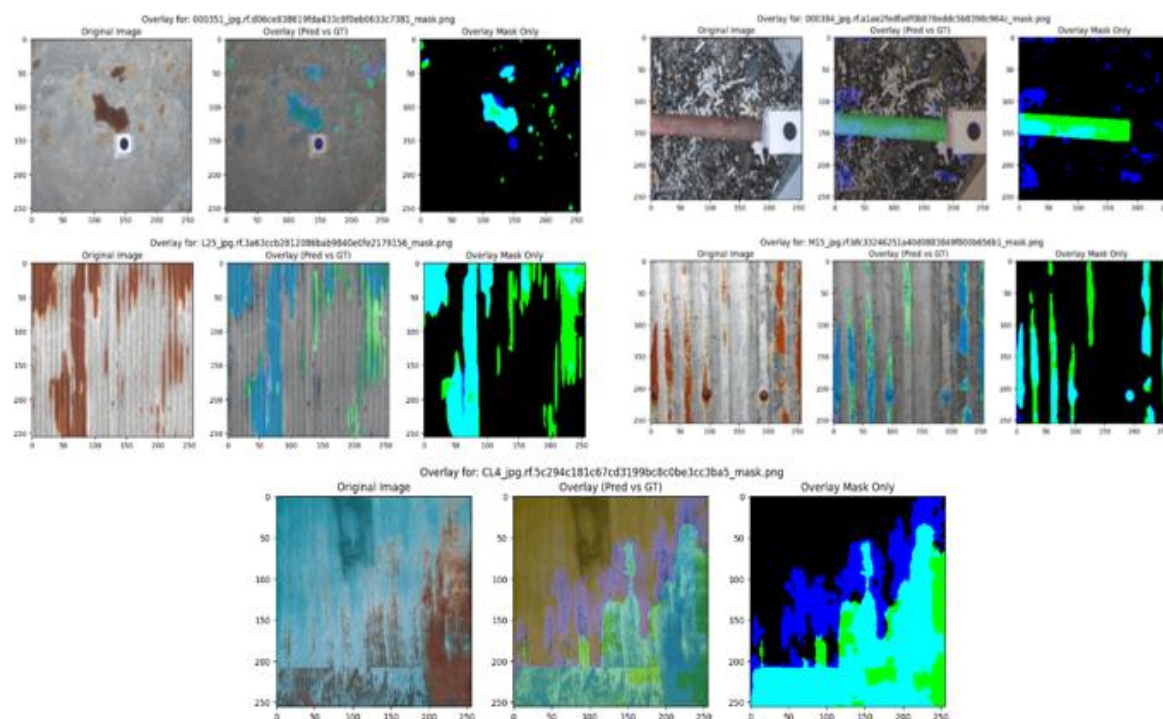


Fig. 7. Evaluation of segmentation accuracy for metal surface corrosion detection.

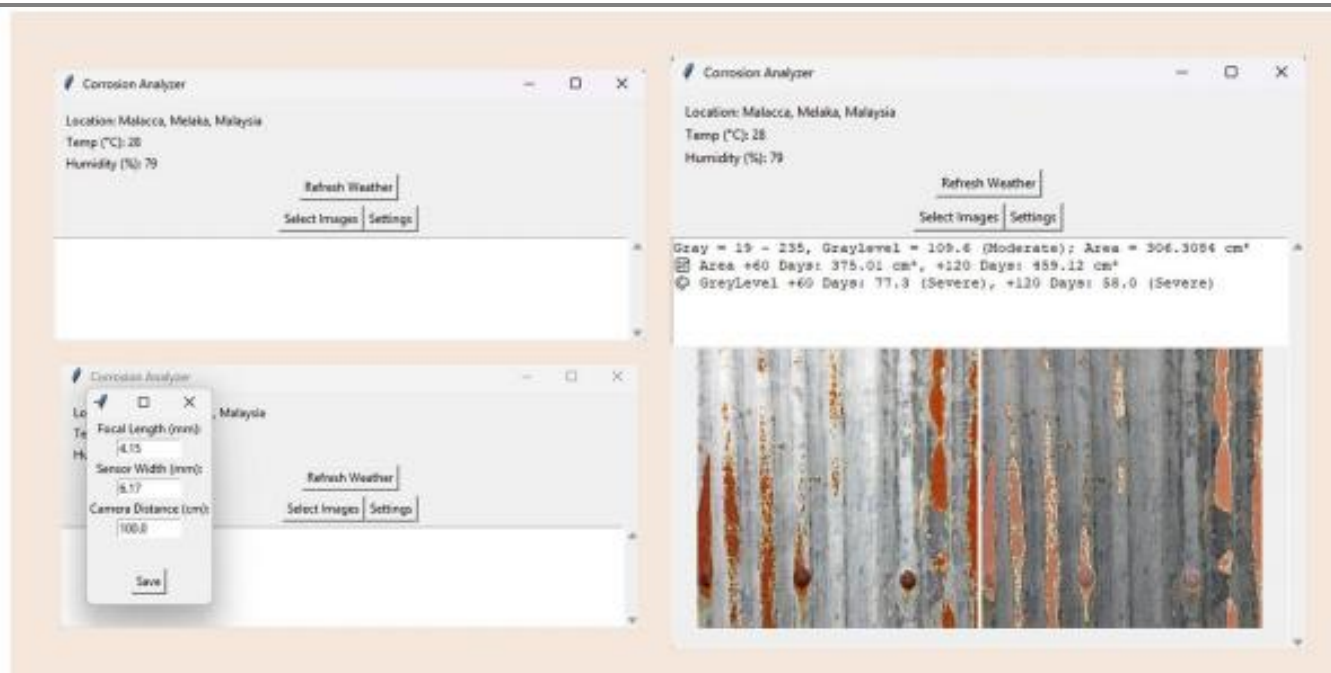


Fig. 8. GUI for analytical metal surface corrosion detection.

The practical benefits of robust predictive models and accurate segmentation in industrial maintenance settings are quite important. Timely projections allow for proactive corrosion management, which greatly reduces maintenance costs, safety hazards and asset lifespan. Models are used in a wide array of settings because they have been shown to be accurate and reliable, delivering actionable information that can change maintenance tactics from reactive to proactive.

Furthermore, a comparative analysis was performed between the developed Intelligent Metal Surface Corrosion Monitoring and Predictive Analytic System and robust models published in the scholarly work to further verify the performance of the system. This comparison provides important insights into the operational advantages of the system, its prediction accuracy and its scalability for application in diverse industrial sectors. Many studies have explored rust detection with machine learning (ML) and deep learning (DL) models. [21] investigated the efficacy of certain regression-based methods like decision trees and support vector machine (SVM) for corrosion risk pre-regression-based showed that the models were sensitive to the quality of historical data, while Ossai's models obtained an average accuracy of around 80.2% and a R^2 of 0.78. On the other hand, the Random Forest models in this work achieved outstanding results with R^2 values of 0.8477 for corrosion area development and 0.9926 for gray-level intensity predictions, indicating enhanced robustness when dealing with complicated and nonlinear relationships. [22] employed a deep learning architecture using a convolutional neural network (CNN) to detect corrosion patterns in surface images. Their model obtained an accuracy of 98.8%, demonstrating the effectiveness of deep learning-based methods in classification. However, their model was improved for image-level classification instead of pixel-level segmentation. In contrast, the U-Net architecture employed in this study allowed pixel-wise segmentation, achieving an accuracy of 78.6%, precision of 61.8%, and recall of 73.5%, so proving it more effective for finding localised corrosion areas and quantifying affected regions for further analysis. [23] applied ensemble learning models to predict external corrosion rates in oil and gas platforms. Their Random Forest methodology produced a R^2 value of 0.975 and an RMSE of 0.0113, indicating excellent predictive effectiveness. Nonetheless, their model was trained on a particular industry dataset, limiting generalisation across industries. The model created in this study, although slightly lower in predicted accuracy, was evaluated across a broader range of environmental variables and imaging scenarios, demonstrating superior generalisability. [24] proposed a vision-based CNN segmentation system and reported an accuracy of 90.5% in detecting corrosion-affected areas. Despite being a robust outcome, the system lacked predictive and severity estimation functionalities. This study's system integrates segmentation with predictive analytics, predicting not only the current spots of corrosion but also its potential future severity and locations under varying scenarios.

Model performance was evaluated on the locked independent test set across a comprehensive range of metrics,

including per-image Precision, Recall, Dice/F1 score, Intersection over Union (IoU), Specificity, and Balanced Accuracy, complete with 95% confidence intervals. In direct comparisons using identical test data, Attention U-Net outperformed standard thresholding techniques and standard U-Net architectures by effectively suppressing false positives in low-contrast background regions. Validation loss curves confirmed steady convergence without overfitting, reaching a stable binary cross-entropy loss of approximately 0.21.

For temporal corrosion growth forecasting, the reconstructed Random Forest model demonstrated strong predictive capability on the locked test set, achieving a test-set R^2 of 0.8477 for physical area expansion, alongside low Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) values. Feature importance analysis confirmed that historical corrosion area and relative humidity were the primary drivers of non-linear material loss. Residual plots exhibited homoscedastic variance and normal distribution centered around zero, confirming that the model captures true underlying degradation dynamics rather than reproducing a deterministic identity mapping. Comparisons against baseline models showed that the multimodal Random Forest significantly outperformed naive persistence and standard linear regression models, providing robust prediction intervals suitable for industrial predictive maintenance and risk assessment.

Other notable studies include [25], who implemented hybrid wavelet packet transform and SVM for acoustic-based corrosion severity detection, and [26], who combined acoustic emission data with ML models. Although these methodologies produced good results in some applications, their dependence on specialised sensors and high-frequency data collection restricts their accessibility in many practical environments. The new approach exhibits enhanced affordability and deployability by utilising readily accessible imaging technologies and including environmental data. The study indicates that the presented models outperform all the characteristics with excellent prediction accuracy, ease of implementation and greater scope of application. This method brings together segmentation, measurement and forward prediction into one coherent and scalable framework, whereas previous research focuses on isolated detection or requires complex hardware. Despite the robustness of the results, there are many limitations. The accuracy of the model is a function of the quality of the images, the uniformity of the surroundings in which the data is collected and the precision of the measurements of the environmental parameters. Future work should concentrate on augmentation and variety of the dataset by including various types of corrosion and environmental settings. Different strategies can be explored to improve the expected stability and accuracy of machine learning models, such as hybrid models combining regression techniques and neural networks or deep regression networks.

CONCLUSION

The research efficiently generates and supports an intelligent corrosion monitoring and predictive analytics system, which integrates deep learning theory with industrial asset management. The approach goes from reactive to predictive maintenance, by combining U-Net convolutional neural networks for accurate image segmentation with Random Forest regression models for prediction. The U-Net model had a precision of 61.8% and an accuracy of 78.6%. The Random Forest models showed high prediction reliability with R^2 of 0.8477 for area expansion and 0.9926 for gray-level intensity. These results show the ability of the system to outperform traditional linear models in modelling complicated non-linear interactions between environmental variables such as temperature, humidity and material deterioration. Its key contribution is a graphical user interface for users, reducing complex AI outputs to field engineers to assess the risk in real-time and enhance lifespan estimates. Despite these achievements the research admits to constraints such as reliance on good quality images, sensor calibration and the inherent opacity of complicated models. Future study should be focused on the diversification of training datasets from diverse geographical locations and the exploration of multi-modal data fusion, such as the integration of acoustic emission sensors with optical data, to further reduce false positives. This research enables a scalable framework for automated asset management at low cost, with emphasis on edge computing capabilities and real field tests. By including strong segmentation and accurate regression modelling, digital monitoring can evolve from a qualitative observation to reliable quantitative analytics, which is essential for modern industrial safety and operational efficiency.

ACKNOWLEDGMENT

The authors express their gratitude to the Ministry of Higher Education (MoHE) Malaysia and Universiti

Teknikal Malaysia Melaka (UTeM) for providing the funding necessary to complete this study through the Fundamental Research Grants Scheme No: TRANSLASIONAL/2023/UTEM-FTKEE/TS0001 and UTeM Kesidang Scholarship.

REFERENCES

1. A. Das, S. Dorafshan, and N. Kaabouch, Autonomous Image-Based Corrosion Detection in Steel Structures Using Deep Learning, *Sensors*, 24(11), 3630, (2024).
2. Z. Duan, X. Huang, J. Hou, W. Chen, and L. Cai, Research on Intelligent Diagnosis of Corrosion in the Operation and Maintenance Stage of Steel Structure Engineering Based on U-Net Attention, *Buildings*, 14(12), 3972, (2024).
3. D. Guidotti, L. Pandolfo, and L. Pulina, A Systematic Literature Review of Supervised Machine Learning Techniques for Predictive Maintenance in Industry 4.0, *IEEE Access*, 13, pp. 102479-102504, (2025).
4. M. Gavryushina, A. Marshakov, and Y. Panchenko, Application of the random forest algorithm to predict the corrosion losses of carbon steel over the first year of exposure in various regions of the world, *Corrosion Engineering, Science and Technology*, 58(3), pp. 205–213, (2023).
5. K. K. Brar et al., Image segmentation review: Theoretical background and recent advances, *Information Fusion*, 114, 102608, (2025).
6. M. K. Effendi, B. Atmaja, A. Wahjudi, and D. B. Purwanto, Automated Corrosion Detection on Steel Structures Using Convolutional Neural Network, *The International Journal of Mechanical Engineering and Science*, Vol 7, No 1 (2023), 36-44, (2023).
7. S. Wu, M. Zhu, Z. Zhang, Y. Yao, Y. Li, and D. Li, Prediction and risk assessment of stress corrosion failures of prestressed anchors in underground mines, *International Journal of Mining, Reclamation and Environment*, April, 1–15, (2025).
8. M. Majors et al., Automated corrosion mapping AI & machine learning, *Society of Petroleum Engineers - Abu Dhabi International Petroleum Exhibition and Conference 2020, ADIP 2020*, (2020).
9. C. Carpenter, Artificial-Intelligence and Machine-Learning Technique for Corrosion Mapping, *J. Pet. Technology*, 74 (2022): 99–102, (2022).
10. F. Ren, L. B. Xu, J. Fei, J. P. Q. Tomas, H. S. Li, and B. T. Doma, Design of multi-mode intelligent system architecture for surface defect detection of steel based on cloud technology, *Scientific Reports*, 15, 39735, (2025).
11. R. Yang, Z. Chen, Z. Qin, Y. Lu, and L. Qi, Steel Surface Defect Segmentation Using U-Net with SLMA-Gray Attention and AdamW Optimization, *Informatica*, , 49 (31). (2025).
12. K. Luo, X. Kong, J. Zhang, J. Hu, J. Li, and H. Tang, Computer Vision-Based Bridge Inspection and Monitoring: A Review, *Sensors*, 23 (18), 7863, (2023).
13. Y. Lai et al., Framework for long-term structural health monitoring by computer vision and vibration-based model updating, *Case Studies in Construction Materials*, Volume 16, e01020, (2022).
14. Z. Zheng, F. Wang, G. Gong, H. Yang, and D. Han, Intelligent technologies for construction machinery using data-driven methods, *Automation in Construction*, Volume 147, 104711, (2023).
15. A. Elbeltagi et al., Prediction of meteorological drought and standardized precipitation index based on the random forest (RF), random tree (RT), and Gaussian process regression (GPR) models, *Environmental Science and Pollution Research*, 30, 43183–43202, (2023).
16. S. Tiwari, K. Dash, N. Park, and N. G. S. Reddy, Machine Learning-Based Prediction of Atmospheric Corrosion Rates Using Environmental and Material Parameters, *Coatings*, 15 (8), 888, (2025).
17. Y. Li and L. Liu, Physics-Informed Neural Network-Based Nonlinear Model Predictive Control for Automated Guided Vehicle Trajectory Tracking, *World Electric Vehicle Journal*, 15 (10), 460, (2024).
18. M. M. H. Imran et al., Application of Artificial Intelligence in Marine Corrosion Prediction and Detection, *Journal of Marine Science and Engineering*, 11 (2), 256, (2023).
19. T. Bitam, A. Yahiaoui, D. E. Boubiche, R. Martínez-Peláez, H. Toral-Cruz, and P. Velarde-Alvarado, Artificial Intelligence of Things for Next-Generation Predictive Maintenance, *Sensors*, 25 (24), 7636, (2025).
20. C. Dong, S. Bas, and F. N. Catbas, Applications of Computer Vision-Based Structural Monitoring on Long-Span Bridges in Turkey, *Sensors*, 23 (19), 8161 (2023).
21. C. I. Ossai, A data-driven machine learning approach for corrosion risk assessment—a comparative

- study, *Big Data Cognitive Computing*, 3 (2), 28, (2019).
22. A. Srivastava, G. Ji, and R. K. Singh, Application of Deep-Learning Architecture for Image Analysis based Corrosion Detection, *2021 Smart Technologies, Communication and Robotics (STCR)*, pp. 1-5, (2021).
 23. F. R. Elmas, M. P. Rios, E. R. de Almeida Lima, R. G. Gusmão Caiado, and R. S. Santos, Prediction of external corrosion rate in Oil and Gas platforms using ensemble learning: a Maintenance 4.0 approach, *Brazilian Journal of Operations & Production Management*, 20(3), 1952, (2023).
 24. A. K. I. A.-G. Nahla Ibraheem Jabbar¹, Shaker Salih Bahar, Detection Corrosion By Using Convolutional Neural Networks Technique, *Academic Journal Of Manufacturing Engineering*, vol. 23, no. 2, pp. 2–7, (2025).
 25. Z. May, M. K. Alam, N. A. Nayan, N. A. A. Rahman, and M. S. Mahmud, Acoustic emission corrosion feature extraction and severity prediction using hybrid wavelet packet transform and linear support vector classifier, *PLoS One*, 16 (12): e0261040, (2021).
 26. M. F. Sheikh, K. Kamal, F. Rafique, S. Sabir, H. Zaheer, and K. Khan, Corrosion detection and severity level prediction using acoustic emission and machine learning based approach, *Ain Shams Engineering Journal*, volume 12, Issue 4, December 2021, Pages 3891-3903, (2021).