

Development of an Artificial Intelligence-Based Marine Pipeline Corrosion Prediction and Detection Model for Offshore Platforms

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ABSTRACT

Corrosion in subsea and marine pipelines remains one of the most persistent threats to the structural integrity, environmental safety, and operational continuity of offshore oil and gas installations. Conventional monitoring practices, which rely on manual inspection, electrochemical testing, and periodic non-destructive evaluation, are reactive, labour-intensive, and poorly suited to the scale and hazard profile of modern offshore assets. This study develops and evaluates an artificial intelligence (AI)-based framework for the prediction, classification, and image-based detection of marine pipeline corrosion. Two complementary AI pathways were investigated. First, four supervised machine learning (ML) classifiers - Random Forest (RF), Decision Tree (DT), Support Vector Machine (SVM), and Multilayer Perceptron (MLP) - were trained on a simulated offshore sensor dataset comprising 2,500 samples described by wall thickness, temperature, pressure, humidity, pH, and vibration, and labelled into normal, minor, and severe corrosion classes. The Synthetic Minority Over-sampling Technique (SMOTE) was applied to correct class imbalance, and best-first attribute selection reduced the feature space to the three most informative predictors (wall thickness, humidity, and pH). Second, a hybrid convolutional neural network (CNN) coupled with the YOLOv8 detection architecture was trained on inspection imagery to localise and classify corroded pipeline surfaces. The RF and DT classifiers achieved the strongest performance, with a weighted-average accuracy, precision, recall, and F1-score of 99.8%, while the MLP and SVM attained 94.8% and 80.8% respectively. The CNN-YOLOv8 detector converged rapidly, reaching a test accuracy of 100% within three training epochs, with a final model loss of 0.060 and model accuracy of 97.4%. These results demonstrate that hybridising interpretable ensemble classifiers with deep image-based detection offers a promising, proof-of-concept route to proactive corrosion management on offshore platforms, reducing reliance on manual inspection while improving the timeliness and reliability of maintenance decisions. Because the sensor data are simulated and rule-labelled and the image set is small, the reported accuracies indicate separability within these datasets rather than field performance; robustness to sensor noise and explainability of predictions remain to be evaluated before safety-critical deployment.

Keywords: marine pipeline corrosion; artificial intelligence; machine learning; convolutional neural network; YOLOv8; offshore platforms; predictive maintenance

Nomenclature

Abbreviation	Meaning
AI	Artificial Intelligence
ML / DL	Machine Learning / Deep Learning
RF / DT	Random Forest / Decision Tree
SVM	Support Vector Machine

MLP	Multilayer Perceptron
CNN	Convolutional Neural Network
YOLOv8	You Only Look Once, version 8 (object detection architecture)
SMOTE	Synthetic Minority Over-sampling Technique
MAE / MSE / RMSE	Mean Absolute Error / Mean Squared Error / Root Mean Squared Error
mAP	mean Average Precision
ROV / AUV	Remotely Operated Vehicle / Autonomous Underwater Vehicle
IoT	Internet of Things
TP / FP / TN / FN	True Positive / False Positive / True Negative / False Negative

INTRODUCTION

Offshore platforms are multifaceted engineering systems built to support the extraction, processing, and transport of hydrocarbons from subsea reservoirs. Marine pipelines are among the most critical components of this infrastructure, channelling oil and gas from wellheads through processing facilities to export terminals (Ojie et al., 2026; Amiri et al., 2021). Other safety-critical offshore systems, such as the dynamic positioning of semisubmersible drilling units, likewise depend on measurement-driven strategies, which have been evaluated in simulation for power efficiency (Ojie et al., 2026). Laid on or buried beneath the seabed, these pipelines are continuously exposed to high salinity, fluctuating temperature, strong currents, biofouling, and microbial activity, all of which accelerate degradation through galvanic, pitting, crevice, and microbiologically influenced corrosion mechanisms (Kim et al., 2020). The consequences extend well beyond material loss: wall thinning and cracking can precipitate oil spills, gas leaks, and explosions, with severe economic and environmental repercussions (Ali et al., 2023).

Corrosion monitoring in the marine environment has historically depended on manual inspection, electrochemical impedance spectroscopy, ultrasonic and magnetic flux methods, and visual assessment by divers or remotely operated vehicles (ROVs). These techniques, while informative, are costly, hazardous, difficult to scale, and inherently reactive rather than predictive (Komary et al., 2023). The emergence of artificial intelligence - particularly machine learning, deep learning, and computer vision - has opened a data-driven alternative capable of exploiting heterogeneous sensor streams and inspection imagery to forecast corrosion rates, flag high-risk segments, and automate visual detection at scale (Imran et al., 2023; Yang et al., 2024). Deep learning-based image analysis frameworks, in particular, are increasingly used to automate the interpretation of imagery captured by drones, ROVs, and underwater cameras, enabling continuous, low-oversight surveillance of otherwise inaccessible assets (Zhou and Hou, 2025).

The intersection of AI and marine engineering can be conceptualised as three interacting layers, illustrated in Figure 1. The AI layer is the transformation zone in which intelligent solutions - CNN/YOLO-based analysis of mechanical properties, machine learning for predictive maintenance, and data analytics for structural decision-making - are developed and implemented (Zhou et al., 2025). The marine engineering layer comprises the physical infrastructure with which these solutions interact: crude oil and gas transport pipelines, subsea distribution networks, vessels, remotely operated and autonomous underwater vehicles, and shipboard sensor systems (Amaechi et al., 2022). The intersection core is the integration layer in which AI methods are applied directly to marine engineering surfaces - offshore wind farms, vessels, and pipelines - to deliver operational value.

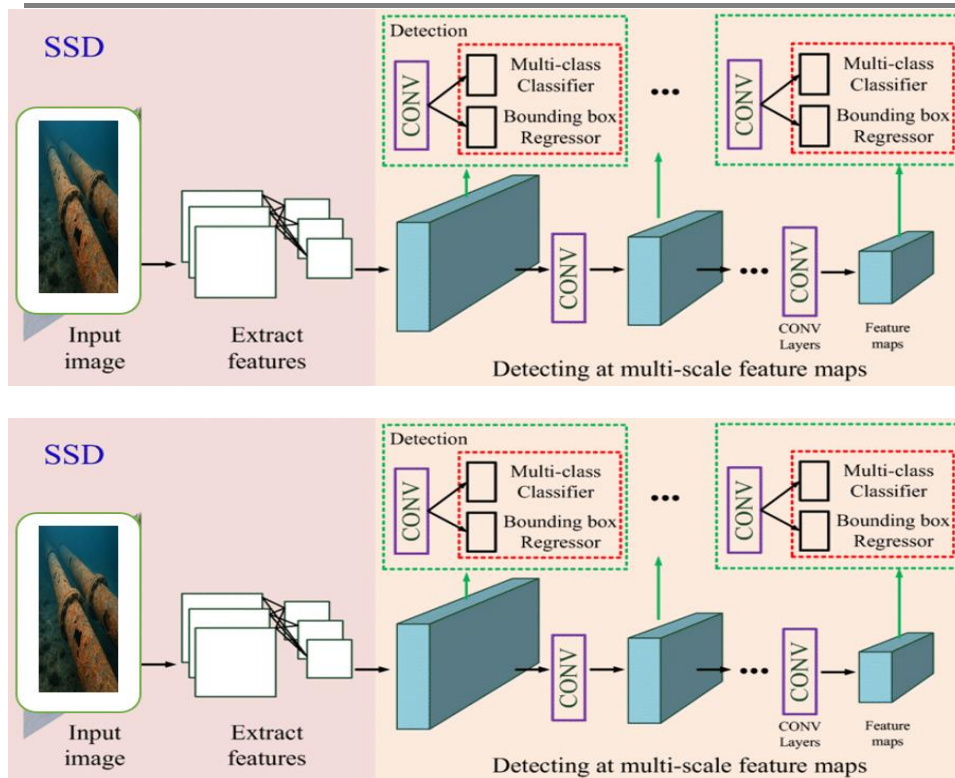


Figure 1: Conceptual architecture

linking artificial intelligence and marine engineering (adapted from Zhang and Hong, 2019)

Despite this progress, most reported systems address either sensor-based prediction or image-based detection in isolation, and comparatively few studies evaluate both pathways within a single integrity-management framework. This study addresses that gap by developing and jointly evaluating (i) a suite of supervised ML classifiers for multi-class corrosion severity prediction from environmental and structural sensor data, and (ii) a CNN-YOLOv8 deep learning detector for image-based identification of corroded pipeline surfaces, within a single offshore pipeline integrity management framework.

Aim and Objectives

The aim of this study is to develop an artificial intelligence-based model for the prediction, classification, and detection of marine pipeline corrosion on offshore platforms. The specific objectives are to:

1. investigate the role of artificial intelligence in marine corrosion prediction and detection;
2. collect and pre-process a representative marine pipeline corrosion dataset for model training;
3. develop machine learning and deep learning models for the classification and image-based detection of pipeline corrosion; and
4. evaluate and benchmark the developed models using standard classification performance metrics.

Significance of the Study

The proposed framework is significant on five counts. First, by identifying early signs of deterioration such as wall thinning and cracking, it supports the prevention of catastrophic failures in safety-critical offshore infrastructure. Second, predictive detection reduces the risk of oil spills and gas leaks, safeguarding fragile marine ecosystems. Third, the shift from reactive to proactive maintenance reduces the substantial financial losses associated with emergency repair and unplanned production shutdowns. Fourth, the AI-based approach enables continuous, autonomous surveillance of hazardous or inaccessible underwater environments where manual inspection is difficult or unsafe. Fifth, the study contributes a proof-of-concept hybrid modelling

framework that advances the empirical basis for deep learning applications in marine pipeline integrity management.

Scope and Limitations

The study is limited to the development and offline validation of the prediction and detection framework using a simulated environmental sensor dataset and a publicly available pipeline-imagery dataset; live integration with an operational Internet of Things (IoT) sensor network is left for future work. The sensor dataset exhibited class imbalance, which was addressed using SMOTE, and the image dataset was comparatively modest in size (192 images), necessitating resizing and augmentation to support reliable training. Computational cost for the CNN-YOLOv8 pipeline was correspondingly higher than for the classical ML classifiers. Notwithstanding these constraints, the framework provides a proof of concept for AI-assisted corrosion management that is readily extensible to field-collected data.

LITERATURE REVIEW

Corrosion in Offshore Pipeline Systems

The marine oil and gas industry depends on onshore, offshore, nearshore, and ship-based structural systems that together support the full life cycle of petroleum production (Amaechi et al., 2022). Offshore and subsea pipelines are exposed to some of the most aggressive corrosive conditions on Earth, and the consequent risks to structural integrity, safety, and the environment have made corrosion detection and control an enduring priority for asset managers (Xia et al., 2025; Shojaei et al., 2025). Traditional inspection regimes - manual survey, ultrasonic thickness gauging, magnetic flux leakage, and acoustic emission monitoring - remain widely used but are constrained by accessibility, cost, and the difficulty of achieving continuous coverage in hazardous subsea environments (Zheng et al., 2020). Integrity management practice has consequently shifted from reactive repair toward proactive, predictive maintenance strategies that draw on real-time operational and environmental data such as pressure, temperature, flow rate, pH, and dissolved oxygen to anticipate the onset and progression of corrosion before critical thresholds are reached (Singh and Poblete, 2025; Ruiz et al., 2024).

Structural Context: Onshore, Offshore, Nearshore, and Ship-Based Systems

Marine oil and gas infrastructure is generally grouped into four categories. Onshore structures - drilling rigs, processing plants, storage tanks, and pipeline networks - are the most accessible and cost-effective to inspect and maintain. Offshore structures, including fixed and floating platforms and subsea pipeline networks, operate in the harshest and least accessible corrosive environments, where inspection and repair are constrained by water depth, pressure, and visibility. Nearshore structures - jetties, terminals, and coastal pipeline landfalls - experience the compounding effects of tidal cycling, wave action, and splash-zone corrosion, which is often more aggressive than fully submerged corrosion. Ship-based structures, including tankers and support vessels, add the further complication of a moving corrosion environment subject to ballast-tank and hull-specific degradation mechanisms (Amaechi et al., 2022; Kim et al., 2020). Marine pipelines - onshore, offshore, and nearshore alike - are the connective infrastructure across all four categories, transporting crude oil and gas from wellhead to processing and export facilities, which is why their structural integrity carries disproportionate operational and environmental weight (Bai and Bai, 2012; Palmer and King, 2008).

Environmental Exposure and Consequences of Corrosion

Marine pipelines are continuously exposed to saline water, biofouling, and wide temperature and pressure fluctuations, conditions that accelerate galvanic, pitting, crevice, and microbiologically influenced corrosion (Melchers and Jeffrey, 2008; Tansel and Zhang, 2022). Left undetected, these mechanisms progressively thin the pipe wall until structural failure occurs, with consequences that extend from localised leaks to catastrophic ruptures. Zardasti et al. (2015) modelled the consequences of gas-pipeline failure due to corrosion, highlighting cascading safety, environmental, and economic impacts, while Fayomi et al. (2019) estimated the substantial direct and indirect economic costs corrosion imposes on the oil and gas sector, including unplanned shutdowns, emergency repair, and regulatory penalties. DNV GL (2015) and Palmer and King (2008) both emphasise that

failure to detect corrosion at an early stage compounds these costs disproportionately, reinforcing the economic as well as safety case for predictive, AI-assisted monitoring over purely reactive inspection regimes.

Role of Artificial Intelligence in Corrosion Detection and Prediction

Artificial intelligence contributes to marine corrosion management across several complementary functions: materials and design optimisation, predictive maintenance scheduling, corrosion-rate forecasting, real-time sensor-data anomaly detection, and image-based defect detection (Saminathan et al., 2024). Ahuir-Torres et al. (2019) benchmarked remote electrochemical corrosion-detection parameters for offshore wind turbine structures, establishing sensing benchmarks that inform AI-based feature selection. Baba and Avadhani (2020) demonstrated wireless sensor network (WSN) data acquisition for subsea and marine exploration fields, illustrating the sensing infrastructure that increasingly feeds AI-based prediction models. Khalid (2019) applied geospatial reliability mapping to offshore wind assets, an approach conceptually related to the risk-zonation methods used in marine corrosion prediction. Collectively, this body of work establishes both the sensing infrastructure and the analytical techniques on which the present framework builds.

AI-Based Corrosion Prediction and Detection: Related Works

A growing body of work has applied machine learning and deep learning to marine and pipeline corrosion problems. Ali et al. (2023) reviewed computer vision and image processing approaches for corrosion detection, noting that CNN and genetic-algorithm-based methods increasingly complement classical thresholding and edge-detection techniques. Diao et al. (2021) combined random forest-based feature selection with gradient-boosted decision trees to optimise the inputs used for corrosion-rate prediction, reporting a coefficient of determination of 94% on training data and 92% on test data. Kim et al. (2020) developed a time-dependent corrosion wastage model using probability density functions to predict corrosion damage progression in ship ballast tank structures. May et al. (2021) coupled wavelet packet transform feature extraction with a linear support vector classifier to grade acoustic-emission corrosion severity, achieving 99% classification accuracy. Seghier et al. (2022) benchmarked ensemble learners - random forest, gradient boosting, and AdaBoost - for internal corrosion-rate prediction in gas pipelines, finding that extreme gradient boosting (XGBoost) delivered the lowest error and the greatest improvement over single-model baselines. Spahić et al. (2023) proposed a risk-informed, CNN-based image analysis pipeline for subsea pipeline damage detection, reporting 90% accuracy without synthetic training data and improved performance once synthetic augmentation was introduced. Das et al. (2024) applied YOLOv5 and ResNet architectures to steel-surface corrosion imagery, exceeding 90% detection accuracy, while Dang et al. (2025) used an ensemble of deep learning classifiers (CNNs, RNNs, and a voting classifier) on subsea pipeline inspection imagery, outperforming individual models at the cost of higher computational demand and larger annotated datasets. A condensed comparison of these studies is presented in Table 1.

Table 1: Summary of related AI-based corrosion prediction and detection studies

Study	Approach	Key Finding	Limitation
Ali et al. (2023)	Computer vision / image processing, CNN, GA	Improved detection accuracy from visual indicators	Sensitive to lighting variation and surface roughness
Diao et al. (2021)	RF-based feature selection + gradient-boosted trees	R ² = 94% (train), 92% (test); reduced overfitting	Limited generalisability across environments
Kim et al. (2020)	Time-dependent corrosion wastage model (probabilistic)	Predicted corrosion damage progression over time	Requires accurate material/environmental parameters
May et al. (2021)	Wavelet packet transform + linear SVC on acoustic emission	99% classification accuracy for severity levels	AE interpretation sensitive to environmental noise

Seghier et al. (2022)	Ensemble learning (RF, GBRT, AdaBoost, XGBoost)	XGBoost RMSE 0.031 mm/y; best overall accuracy	Performance sensitive to feature quality
Spahić et al. (2023)	Risk-informed CNN image analysis + segmentation	90% accuracy (baseline); improved with synthetic data	Some steps still require manual annotation
Das et al. (2024)	YOLOv5 and ResNet on steel-surface imagery	>90% detection accuracy; real-time capable	Trained mainly on lab imagery; limited field generalisation
Dang et al. (2025)	Ensemble deep learning (CNN, RNN, voting classifier)	Ensemble outperformed individual models	High computational cost; needs large annotated data

Taken together, the literature indicates clear progress in both sensor-based prediction and image-based detection of marine corrosion, yet three gaps persist. First, publicly available, large-scale marine corrosion datasets remain scarce, constraining model training and cross-study benchmarking. Second, many reported systems rely on a single data modality - either sensor readings or imagery - rather than integrating both within one framework. Third, relatively few studies report classical, interpretable ensemble classifiers and modern deep detection architectures side by side with a view to tiered deployment, which limits practical guidance on model selection for offshore deployment. The present study addresses these gaps by jointly developing and evaluating sensor-based ML classifiers and a CNN-YOLOv8 image detector within a single corrosion management framework.

MATERIALS AND METHODS

The methodology comprises four stages: (i) formulation of the AI-assisted corrosion management workflow, (ii) collection and pre-processing of a marine pipeline corrosion dataset, (iii) development of machine learning and deep learning models for corrosion classification and detection, and (iv) performance evaluation against regression and classification metrics. The overall research workflow is shown in Figure 2.

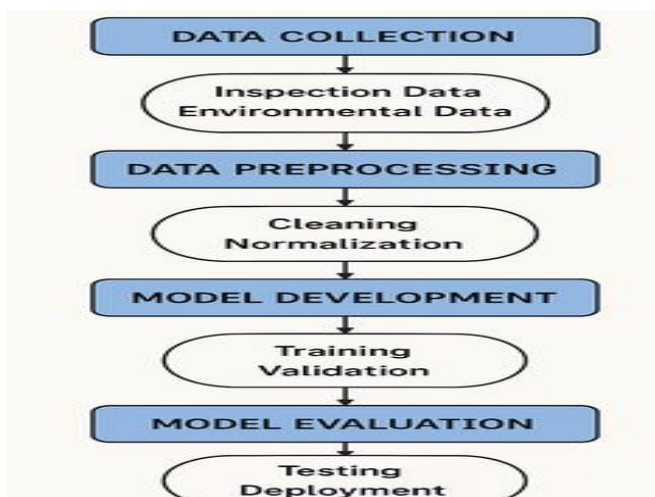


Figure 2: Research workflow for the AI-based corrosion prediction and detection framework

Corrosion Modelling Basis

Material selection and design analysis were informed by an electrochemical corrosion-current formulation. The instantaneous corrosion current density $i(\eta)$ was estimated from the Butler-Volmer relation:

$$i(\eta) = i_0 \left[\exp(\alpha_a F \eta / RT) - \exp(-\alpha_c F \eta / RT) \right] \quad (1)$$

where i_0 is the exchange current density (A/m²), η is the overpotential (V), F is the Faraday constant ($\approx 96,485$ C/mol), R is the gas constant, T is the absolute temperature (K), and α_a and α_c are the anodic and cathodic

charge-transfer coefficients. The corresponding mass loss Δm over time was obtained from Faraday's law, and the corrosion rate C_{rate} from the conversion of predicted current density to wall-thickness reduction:

$$\Delta m = (i_{avg} \cdot A \cdot t \cdot M) / (nF) \quad (2) \quad C_{rate} = (K \cdot i_{corr} \cdot M) / (n \cdot \rho \cdot F) \quad (3)$$

where A is the exposed area (m^2), M is the molar mass (kg/mol), n is the number of electrons per reaction, ρ is the material density (kg/m^3), and K is a unit-conversion constant. These relations underpin the physical interpretation of the sensor-derived features used in the subsequent machine learning models.

Dataset Collection and Description

Because real-time sensor readings from operational marine pipelines are rarely released for proprietary and liability reasons, a simulated environmental sensor dataset was adopted, following the practice reported by Salgueiro et al. (2024). The dataset comprises 2,500 samples described by six features - wall thickness (mm), temperature ($^{\circ}C$), pressure (bar), humidity (%), pH, and vibration (Hz) - and labelled into three corrosion classes: normal (0), minor (1), and severe (2), obtained by thresholding a continuous corrosion-risk indicator τ against a binary alarm rule. Because the labels were generated by a rule applied to simulated variables rather than by field inspection, the classification task is partly one of recovering that rule; high accuracy therefore shows that the models can reproduce the labelling logic, not that they have learned corrosion behaviour independently (see Section 4.5). A representative excerpt of the dataset is shown in Table 2.

Table 2: Representative excerpt of the simulated marine pipeline sensor dataset

Wall Thickness (mm)	Temperature ($^{\circ}C$)	Pressure (bar)	Humidity (%)	pH	Vibration (Hz)	Corrosion Class
4.497	68.56	10.73	97.36	8.13	8.13	2
3.862	74.52	10.64	52.88	4.40	4.40	1
4.648	55.03	6.61	71.00	6.43	6.43	1
5.523	50.82	11.01	84.16	2.98	2.98	2
3.766	43.72	14.20	73.41	3.95	3.95	2

The class distribution was imbalanced (111 normal, 915 minor, and 1,474 severe samples), so the Synthetic Minority Over-sampling Technique (SMOTE) was applied to balance the classes, yielding 1,474 samples per class (4,422 samples in total). Best-first attribute selection was then used to identify the most informative predictors, reducing the feature set to wall thickness, humidity, and pH alongside the corrosion class label, which reduced training complexity while preserving classification performance. The vibration column in the excerpt shown in Table 2 is identical to the pH column, which indicates a data-generation artefact; it carries no independent information and was not retained after attribute selection. The balanced dataset was split 90:10 and, in a separate experiment, 80:20 between training and testing to assess sensitivity to split ratio. The held-out partition summarised in Table 5 contains 500 instances (295 severe, 186 minor, 19 normal) and therefore retains the original class imbalance, so normal-class estimates rest on only 19 cases. The overall pre-processing and modelling architecture is shown in Figures 3 and 4.

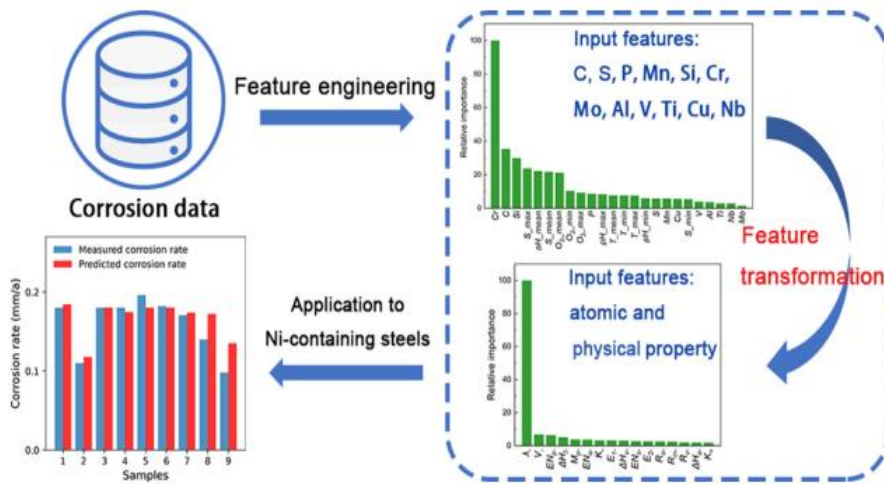


Figure 3: Data acquisition and pre-processing pipeline

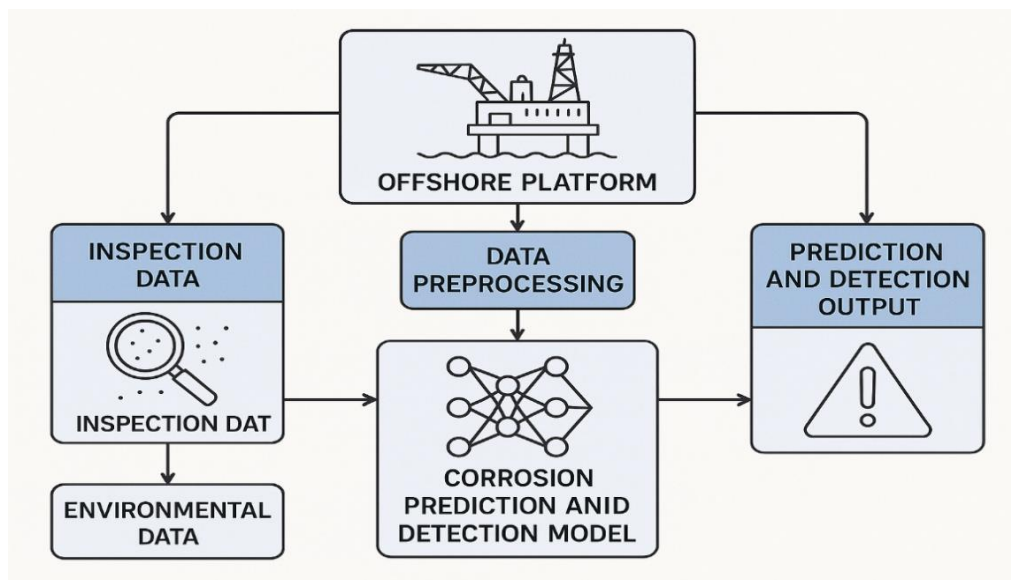


Figure 4: Architecture of the proposed AI-based corrosion prediction and detection model

Machine Learning Classification Models

Four supervised learning algorithms were trained on the pre-processed dataset: Random Forest (RF), Decision Tree (DT), Support Vector Machine (SVM), and Multilayer Perceptron (MLP). The RF and DT models provide interpretable, rule-based classification and are robust to noisy offshore data; the SVM separates corrosion classes via an optimal hyperplane in a kernel-transformed feature space; and the MLP models nonlinear interactions between environmental and structural features through interconnected neuron layers. The MLP was trained to minimise a cross-entropy loss between predicted and true class probabilities (the binary form is shown; for the three-class problem the loss is summed over classes using softmax outputs):

$$p(y = 1 | x) = \sigma(\omega Tx + b) = 1 / (1 + e^{-(\omega Tx + b)}) \quad (4)$$

$$LCE = -(1/N) \sum_i [y_i \log p_i + (1 - y_i) \log(1 - p_i)] \quad (5)$$

The four models were trained and compared individually (no voting or stacking ensemble was formed); RF and MLP are suited to capturing nonlinear interactions among features, while SVM and DT contribute robustness and interpretability, as illustrated schematically in Figures 5 and 6. Each model was trained on the labelled dataset and validated using the metrics defined in Section 3.5.

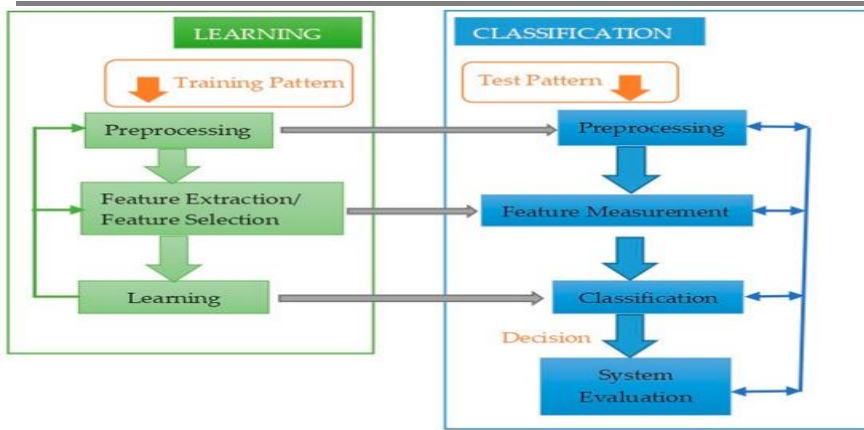


Figure 5: Flowchart of the learning and classification pipeline

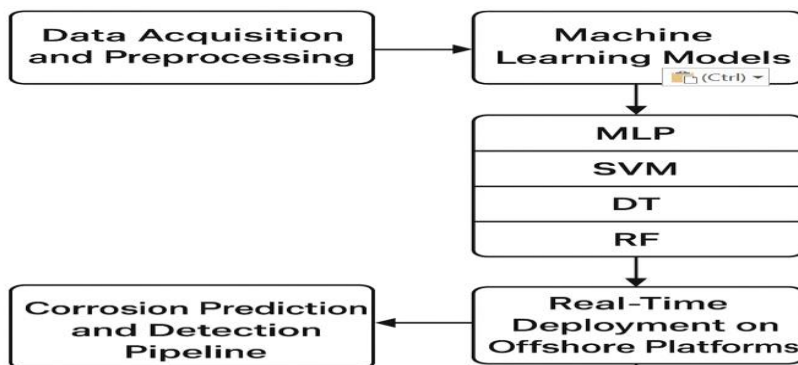


Figure 6: Conceptual framework of the machine learning classification model

CNN-YOLOv8 Image-Based Detection Model

For image-based detection, a hybrid convolutional neural network coupled with the YOLOv8 (You Only Look Once, version 8) architecture was developed. The CNN backbone performs feature extraction, transforming raw pixel data into hierarchical feature maps through successive convolutional and pooling layers, while the YOLOv8 framework provides multiscale feature fusion and bounding-box regression for localising corroded regions. A total of 192 labelled pipeline images (normal and corroded) sourced from a public repository were resized to 64×64 pixels, augmented to mitigate overfitting, and split into training and test sets. The labels are image-level (normal or corroded), and the accuracy values reported in Section 4.3 refer to image-level classification. The loss curves (Figures 10 and 11) and the F1, precision, recall, and mAP curves (Figures 13-16) are the training diagnostics produced by the YOLOv8 framework; no independent validation of localisation against annotated bounding boxes is reported. Training used a cross-entropy classification loss with stochastic gradient descent (learning rate 0.1) over three epochs, monitoring train/box_loss, train/obj_loss, and train/cls_loss throughout. The end-to-end detection procedure is illustrated in Figure 7.

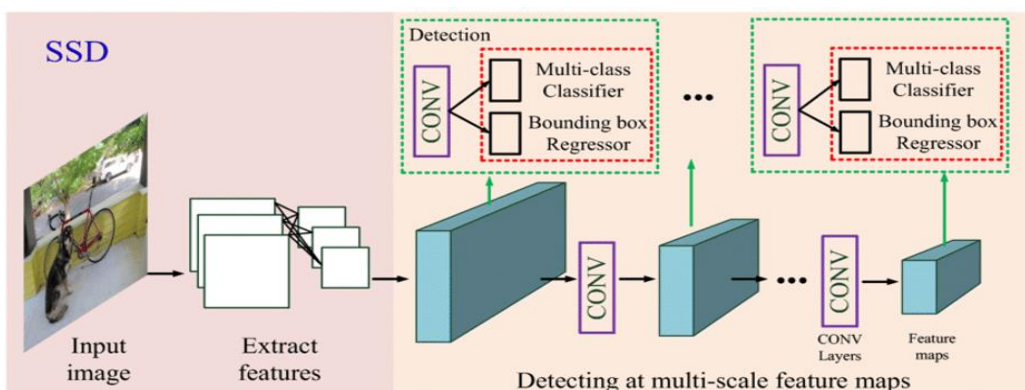


Figure 7: Procedure for pipeline corrosion detection in the CNN-YOLOv8 model

The CNN backbone was implemented as a compact VGG-style network comprising two convolutional blocks followed by a fully connected classifier. Each block contains two 3×3 convolutional layers with 40 hidden channels and GELU activation, followed by a max-pooling layer for spatial down-sampling; the classifier flattens the resulting feature maps and applies a single linear layer mapping to the two output classes (normal, corroded). This lightweight architecture was selected to keep training and inference cost low while retaining sufficient representational capacity for the binary corrosion-detection task on a modest image dataset, and is consistent with the efficiency motivation reported for compact CNN/YOLO backbones in prior corrosion-detection studies (Das et al., 2024).

Performance Evaluation Metrics

Model performance was assessed using complementary regression and classification metrics. Mean Absolute Error (MAE) and Mean Squared Error (MSE) quantify the average and squared deviation, respectively, between predicted and true corrosion measurements, while Root Mean Squared Error (RMSE) restores the original measurement units and is sensitive to large deviations. For classification, Accuracy measures the proportion of correctly classified segments; Precision quantifies the proportion of predicted corroded/high-risk segments that are truly corroded; Recall (Sensitivity) measures the proportion of actual corroded segments correctly identified; and the F1-score provides the harmonic mean of precision and recall. Together, these metrics validate both the numerical accuracy of corrosion-level estimation and the reliability of severity classification for real-time offshore monitoring. In the present study only the classification metrics are reported; MAE, MSE and RMSE are defined for completeness and apply to corrosion-rate regression, which was not performed.

RESULTS AND DISCUSSION

Feature Analysis of the Sensor Dataset

Exploratory analysis of the 2,500-sample sensor dataset confirmed that wall thickness, humidity, and pH carried the strongest discriminatory power for corrosion class, consistent with the attribute-selection results summarised in Figure 8. Wall thickness showed a clear inverse relationship with corrosion severity, thinner sections being systematically associated with the severe class, while elevated humidity and lower pH were both associated with an increased likelihood of minor and severe corrosion, consistent with the accelerating effect of moisture and acidity on electrochemical corrosion mechanisms.

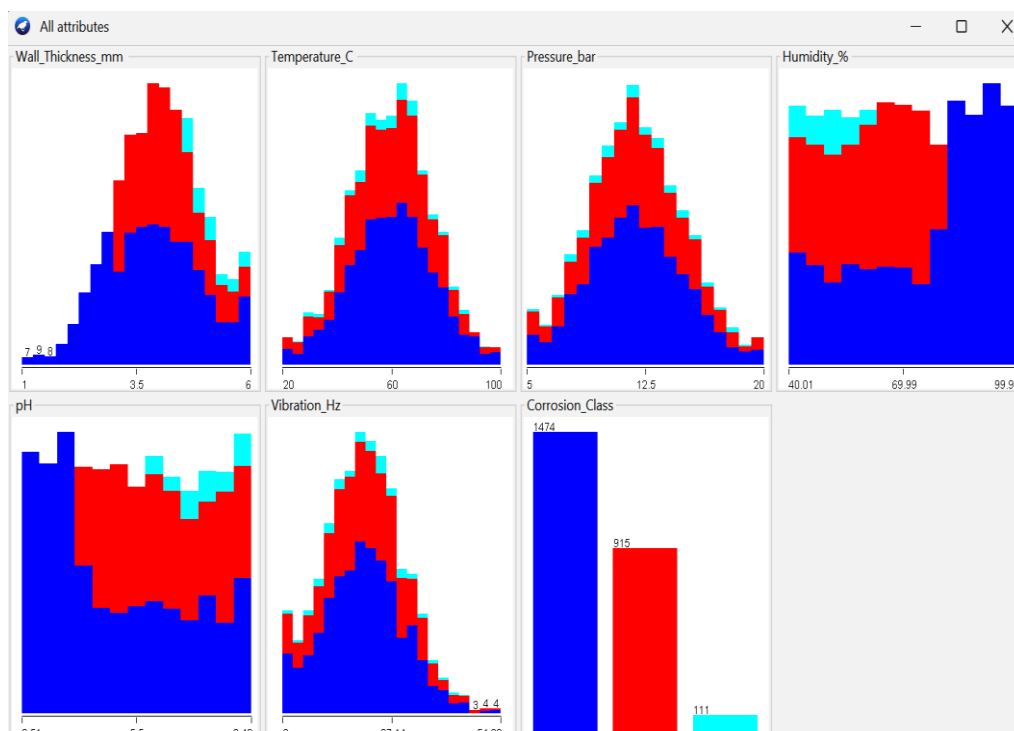


Figure 8: Attribute selection analysis of the marine pipeline corrosion dataset

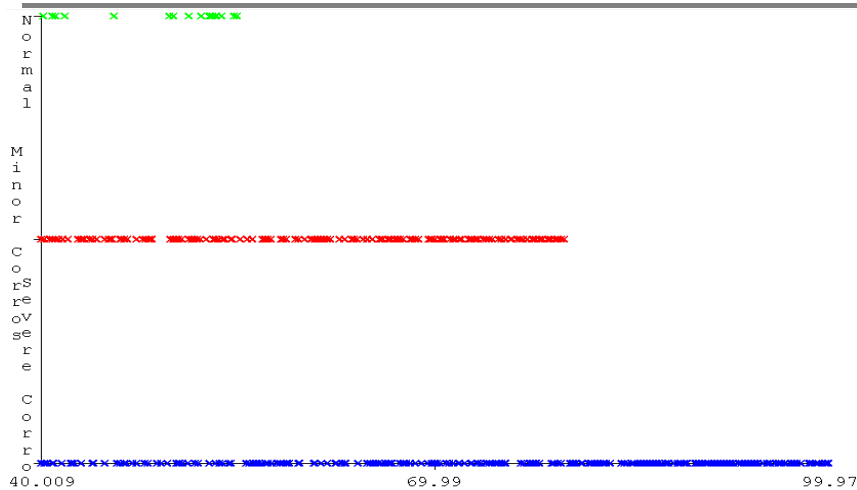


Figure 9(a): Humidity versus corrosion class

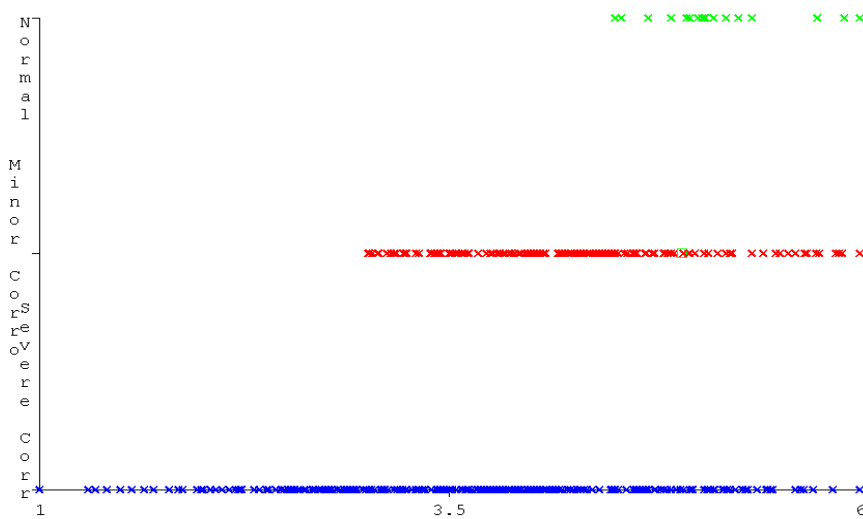


Figure 9(b): Wall thickness versus corrosion class

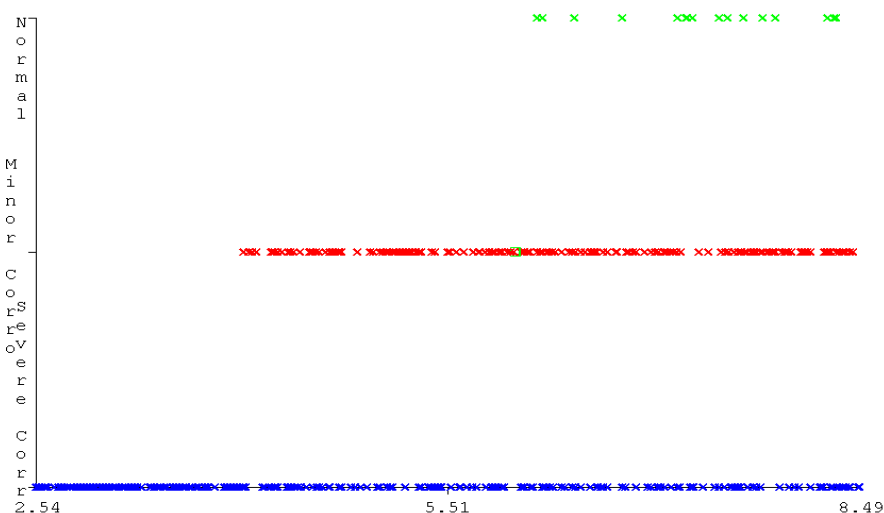


Figure 9(c): pH versus corrosion class

The class-wise distributions confirm the expected physical relationships: severe-corrosion samples cluster at lower wall thickness and pH and higher humidity, while normal samples cluster at higher wall thickness, higher pH, and lower humidity, with minor-corrosion samples occupying the intermediate range. This separability explains why tree-based models, which partition the feature space along threshold boundaries, were able to achieve near-perfect classification performance (Section 4.2).

Machine Learning Classification Results

Table 3 summarises the weighted-average classification performance of the four ML models on the held-out test partition. Random Forest and Decision Tree achieved the strongest and near-identical performance, with a weighted-average accuracy, precision, recall, and F1-score of 99.8%. The Multilayer Perceptron achieved a weighted accuracy and recall of 94.8%, while the Support Vector Machine recorded the lowest weighted performance, at 80.8% accuracy, 80.9% precision, 80.8% recall, and an F1-score of 80.6%. Training time for the RF and DT models was under 0.03 seconds on the 90:10 split and under 0.01 seconds on the 80:20 split, underscoring the computational efficiency of tree-based ensembles for this feature set. Precision and F1-score are not reported for the MLP because its precision for the normal class is undefined (no instance was predicted as normal), so the weighted averages cannot be computed.

Table 3: Weighted-average performance of the machine learning classifiers

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
Random Forest (RF)	99.8	99.8	99.8	99.8
Decision Tree (DT)	99.8	99.8	99.8	99.8
Multilayer Perceptron (MLP)	94.8	-	94.8	-
Support Vector Machine (SVM)	80.8	80.9	80.8	80.6

Table 4 presents the detailed, class-wise accuracy obtained for each classifier, and Table 5 the corresponding confusion matrices.

Table 4: Detailed class-wise accuracy of the RF, DT, SVM, and MLP classifiers

Model	Class	TP Rate	FP Rate	Precision	Recall	F-Measure	ROC Area
RF	Severe	1.000	0.000	1.000	1.000	1.000	1.000
RF	Minor	1.000	0.003	0.995	1.000	0.997	1.000
RF	Normal	0.947	0.000	1.000	0.947	0.973	1.000
DT	Severe	1.000	0.000	1.000	1.000	1.000	1.000
DT	Minor	1.000	0.003	0.995	1.000	0.997	1.000
DT	Normal	0.947	0.000	1.000	0.947	0.973	0.986
SVM	Severe	0.868	0.224	0.848	0.868	0.858	0.837
SVM	Minor	0.747	0.156	0.739	0.747	0.743	0.796
SVM	Normal	0.474	0.002	0.900	0.474	0.621	0.984
MLP	Severe	0.980	0.005	0.997	0.980	0.988	1.000
MLP	Minor	0.995	0.080	0.881	0.995	0.934	0.995
MLP	Normal	0.000	0.000	-	0.000	-	1.000

Table 5: Confusion matrices for the RF, DT, SVM, and MLP classifiers (test partition)

Model	Predicted Severe	Predicted Minor	Predicted Normal	Actual Class
RF	295	0	0	Severe
RF	0	186	0	Minor
RF	0	1	18	Normal
DT	295	0	0	Severe
DT	0	186	0	Minor
DT	0	1	18	Normal
SVM	256	39	0	Severe
SVM	46	139	1	Minor
SVM	0	10	9	Normal
MLP	289	6	0	Severe
MLP	1	185	0	Minor
MLP	0	19	0	Normal

RF and DT correctly classified all 295 severe-corrosion and 186 minor-corrosion instances, with only a single normal-class instance misclassified as minor corrosion out of 19. The MLP performed similarly well on the severe and minor classes but failed to correctly identify any of the 19 normal-class instances, misclassifying all of them as minor corrosion, which depressed its normal-class precision and recall to effectively zero despite strong overall weighted accuracy. The SVM confusion matrix showed the greatest cross-class confusion, particularly between severe and minor corrosion (39 severe instances misclassified as minor, and 46 minor instances misclassified as severe), consistent with its comparatively lower weighted performance. These results indicate that tree-based ensembles are best suited to this feature set, likely because the underlying corrosion-class boundaries are governed by threshold-like interactions between wall thickness, humidity, and pH that align naturally with recursive partitioning, whereas the SVM's kernel-based hyperplane separation and the MLP's continuous decision surface are comparatively less well matched to these interactions without further tuning or additional minority-class data.

CNN-YOLOv8 Image-Based Detection Results

A pipeline-image dataset of 192 normal and corroded samples was resized to 64 x 64 pixels and split into training and test sets. Representative samples are shown in Figure 9(d): corroded samples display visible surface pitting, discoloration, and localised material loss relative to the smooth, uniform surface of normal pipeline sections, providing a visually separable basis for classification.



Figure 9(d): Representative normal and corroded marine pipeline image samples used for CNN-YOLOv8 training

The CNN-YOLOv8 model was trained on the resized (64×64) pipeline image dataset over three epochs. At epoch 0, the model recorded a train loss of 0.700, test loss of 0.675, and test accuracy of 44.6%. By epoch 1, train loss had risen transiently to 0.963 while test loss fell to 0.661 and test accuracy improved to 55.4%. By epoch 2, the train loss fell sharply to 0.445, the test loss to 0.011, and the test accuracy reached 100.0% at a training time of 22.75 seconds. Evaluated over the full dataset after training, the model achieved a model loss of 0.0596 and a model accuracy of 97.4%. The training and validation loss curves are shown in Figures 10 and 11. The confusion matrix is shown in Figure 12. The 44.6% test accuracy at epoch 0 is close to chance for a balanced two-class task, and the 100% test accuracy at epoch 2 was obtained on a small test partition after only three epochs; these figures should be read as evidence that the classes are visually separable in this laboratory-style image set, not as evidence of field performance.

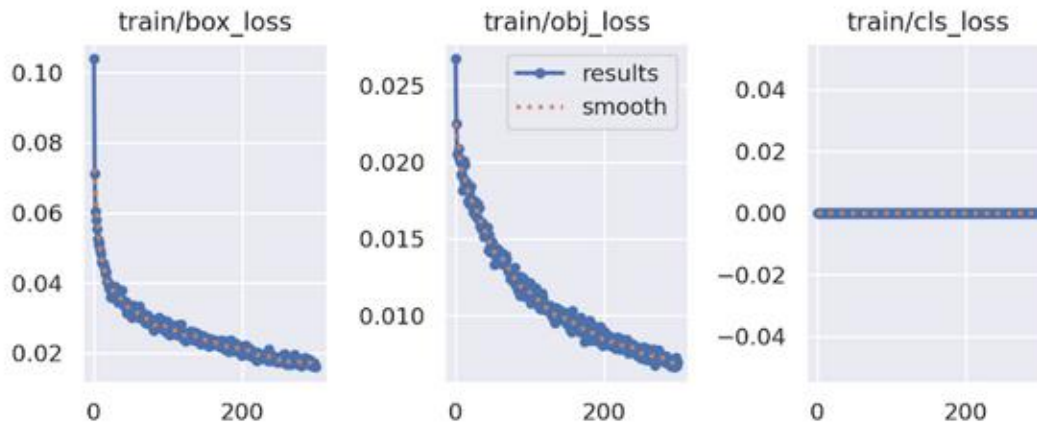


Figure 10: Training loss curves (box loss, object loss, and classification loss) for the CNN-YOLOv8 model

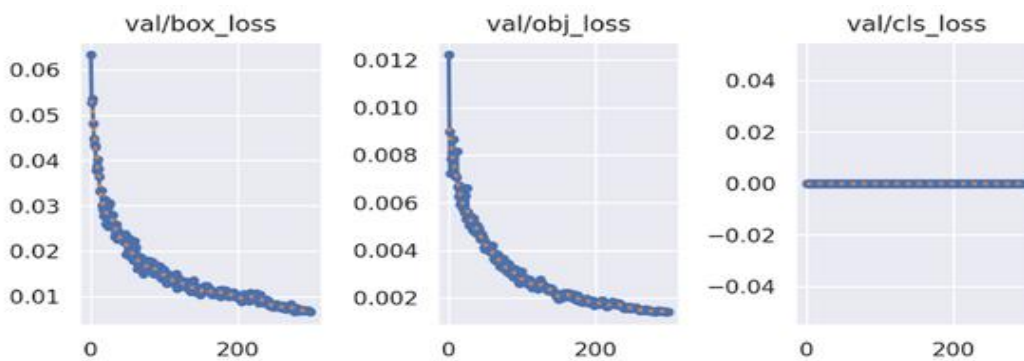


Figure 11: Validation object-loss curve for the CNN-YOLOv8 model

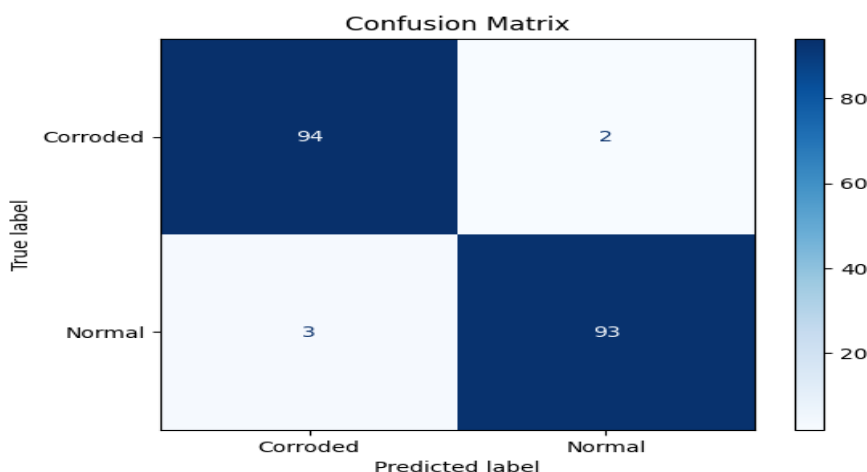


Figure 12: Confusion matrix of the CNN-YOLOv8 corrosion detection model

The decreasing box, object, and classification loss curves are consistent with improving fit during training, but because no held-out localisation benchmark is reported they do not establish localisation accuracy. The F1-confidence curve (Figure 13) identifies the confidence threshold at which precision and recall are jointly optimised, providing an operating point for further evaluation. The precision-confidence, precision-recall, and recall-confidence curves (Figures 14-15) further characterise the detector's operating behaviour, while the combined precision, recall, and mean Average Precision (mAP@0.5-0.95) curve (Figure 16) summarises overall detection quality across the training run.

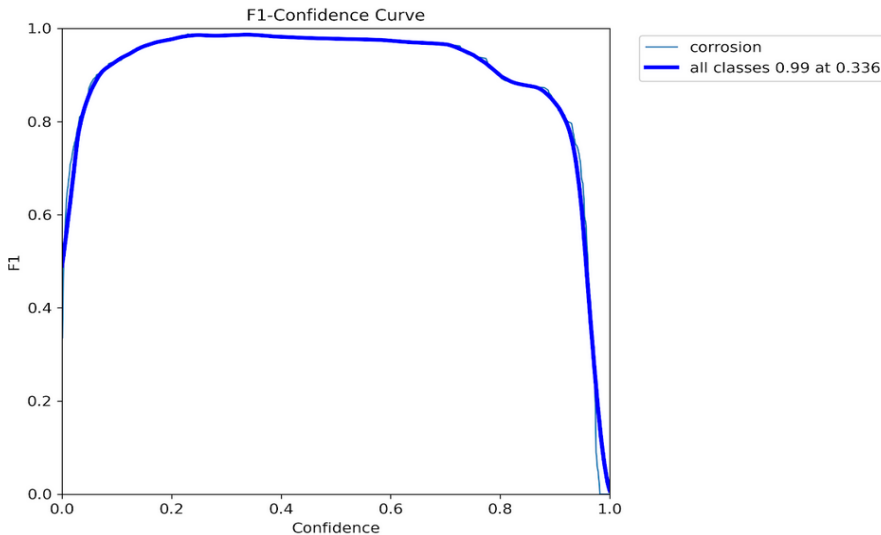


Figure 13: F1-confidence curve for the CNN-YOLOv8 corrosion detection model

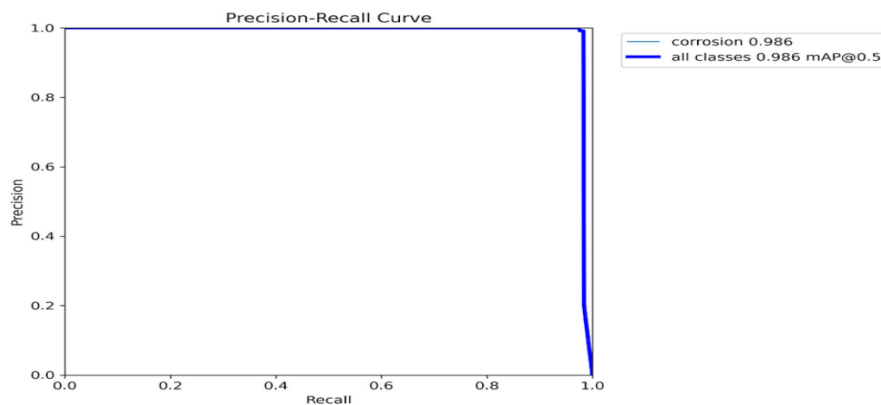


Figure 14: Precision-recall curve for the CNN-YOLOv8 corrosion detection model

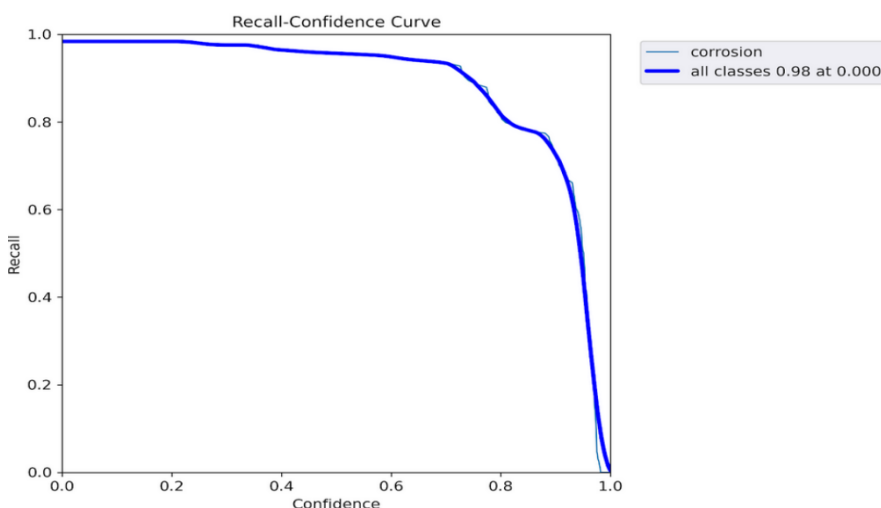


Figure 15: Recall-confidence curve for the CNN-YOLOv8 corrosion detection model

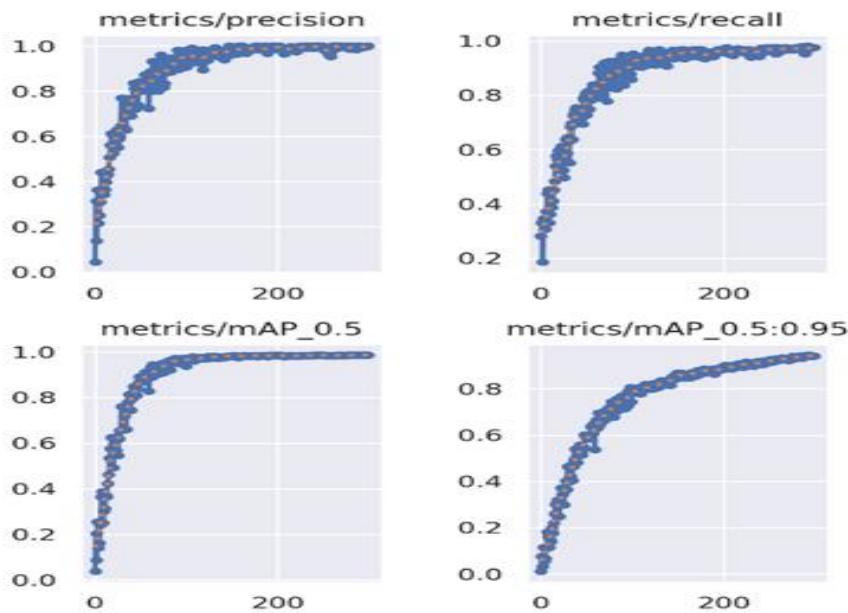


Figure 16: Combined precision, recall, and mAP (0.5-0.95) metric curves for the CNN-YOLOv8 model

DISCUSSION

The comparative results demonstrate that classical ensemble classifiers (RF, DT) and a deep image-based detector (CNN-YOLOv8) are complementary rather than competing tools within a single corrosion management framework. RF and DT delivered near-perfect, computationally inexpensive classification of the simulated severity labels from sensor readings, which suggests they are worth testing for to continuous, low-latency monitoring. The CNN-YOLOv8 model, while more computationally demanding to train, adds the capability to localise and visually confirm corrosion directly from inspection imagery, which sensor-only models cannot provide. These findings are consistent with, and extend, prior work reporting strong ensemble-learning performance for sensor-based corrosion-rate prediction (Seghier et al., 2022) and strong deep-learning performance for image-based corrosion detection (Das et al., 2024; Spahić et al., 2023), while providing a within-study evaluation of both pathways, albeit on different data modalities and therefore not as a like-for-like comparison.

Table 6 places the present results alongside comparable figures reported in the literature reviewed in Section 2.5. The figures in Table 6 are not directly comparable. Seghier et al. (2022) report regression error (RMSE) for corrosion-rate prediction, whereas the present RF/DT figure is classification accuracy on a simulated, rule-labelled dataset. Likewise, the CNN-YOLOv8 results (97.4% overall; 100% at epoch 2) come from a 192-image set and cannot be said to exceed the greater-than-90% accuracy reported for YOLOv5/ResNet-based detection by Das et al. (2024) or the 90% baseline accuracy reported by Spahić et al. (2023), which were obtained on larger and more varied imagery. Table 6 is therefore a qualitative context, not a performance ranking.

Table 6: Benchmark comparison of the present results with related studies

Study	AI Approach	Reported Performance	Comparable Metric in This Study
This study	RF / DT (sensor-based)	99.8% weighted accuracy	-
This study	CNN-YOLOv8 (image-based)	97.4% model accuracy; 100% test accuracy at epoch 2	-
Seghier et al. (2022)	XGBoost ensemble	RMSE 0.031 mm/y; 0.99 accuracy index	RF/DT: 99.8% weighted accuracy

Das et al. (2024)	YOLOv5 / ResNet	>90% detection accuracy	CNN-YOLOv8: 97.4% model accuracy
Spahić et al. (2023)	CNN + semantic segmentation	90% accuracy (baseline, no synthetic data)	CNN-YOLOv8: 100% test accuracy (epoch 2)
May et al. (2021)	Wavelet packet transform + linear SVC	99% classification accuracy	RF/DT: 99.8% weighted accuracy

The principal caveat is that both pathways were validated on simulated or comparatively small benchmark data; field validation on live IoT sensor streams and larger, operationally sourced imagery remains an important next step before full-scale deployment. It should also be noted that the reported studies differ in dataset composition, corrosion mechanism, and evaluation protocol, so the comparison in Table 6 should be read as indicative of relative performance trends rather than a strictly controlled benchmark.

Limitations

Several limitations qualify the present findings. First, the sensor dataset was simulated rather than field-collected, reflecting the general scarcity of publicly released, real-time marine pipeline corrosion sensor data noted in Section 3.2; results should therefore be interpreted as a proof of concept pending validation against operational data. Second, the image dataset (192 samples) is modest by deep-learning standards, and while resizing and augmentation mitigated overfitting risk, a larger and more diverse image corpus - spanning different pipeline materials, coatings, and inspection viewpoints - would likely improve generalisation. Third, the MLP's complete failure on the normal class (Table 5) illustrates a broader risk of residual class imbalance even after SMOTE resampling, which future work should address through stratified cross-validation and, where feasible, collection of additional minority-class samples from field inspections.

Four further limitations affect interpretation. First, because the class labels were produced by a rule applied to simulated variables, near-perfect RF/DT accuracy is expected, since tree models readily recover threshold rules; Table 3 should not be read as predictive skill on real corrosion. Second, the test partition in Table 5 contains only 19 normal-class instances (295 severe, 186 minor), so normal-class metrics carry wide uncertainty, and SMOTE should be applied to the training partition only so that synthetic samples cannot leak into evaluation. Third, the vibration variable duplicates pH in the excerpt shown (Table 2) and so provided no independent information. Fourth, the image model was trained and tested on 192 images for three epochs, and its 100% test accuracy at epoch 2 on a small test partition cannot be generalised.

From a practical standpoint, the results suggest a two-tier deployment strategy for offshore operators: lightweight, low-latency RF or DT classifiers embedded within existing sensor-monitoring infrastructure for continuous severity screening, escalating to CNN-YOLOv8 image-based inspection - via ROV or drone footage - for visual confirmation and precise localisation of flagged segments. This tiered approach would concentrate the computational cost of deep image analysis on the subset of pipeline segments already flagged as high-risk by the sensor-based classifiers, rather than requiring continuous image-based monitoring of the entire asset, offering a pragmatic balance between coverage, cost, and detection reliability for large offshore pipeline networks.

Sensor Noise and Deep-Sea Telemetry

The sensor dataset is clean by construction: the variables are simulated without measurement error, drift, missing values, or timing misalignment, so it does not reproduce the conditions of deep-sea telemetry. In subsea service, ultrasonic wall-thickness readings are affected by coupling quality, marine growth, and temperature (Salgueiro et al., 2024); acoustic-emission signals are sensitive to ambient noise (May et al., 2021); chemical sensors such as pH probes drift with fouling and need recalibration; and low-bandwidth acoustic or cabled links introduce dropouts, latency, and quantisation (Baba and Avadhani, 2020; Komary et al., 2023). Imagery is likewise degraded by turbidity, backscatter, uneven illumination, and biofouling, none of which the laboratory-style images used here represent (Ali et al., 2023; Das et al., 2024). Because the tree-based classifiers split on sharp

thresholds of wall thickness, humidity, and pH, modest measurement error near a class boundary could change the predicted class, and the accuracy in Table 3 should be treated as an upper bound on field performance.

None of these effects was tested in the present study. Future evaluation should (i) inject graded Gaussian measurement noise, sensor drift, and random dropout into the test data and report accuracy degradation per class; (ii) train with noise augmentation and compare against the noise-free baseline; (iii) output calibrated probabilities or prediction intervals, with a rule to escalate low-confidence segments to inspection; (iv) validate on field-collected or physics-based simulated data; and (v) for imagery, augment and test with underwater degradations (turbidity, colour cast, low light) and ROV footage. Online recalibration of model parameters against measured performance, as applied in simulation to thruster-efficiency drift in dynamic-positioning thrust allocation (Ojje et al., 2026b), is an analogous strategy that could be explored for sensor drift.

Explainability and Safety-Critical Deployment

No post-hoc explainability analysis was performed in this study. The Decision Tree is inherently inspectable because it exposes explicit threshold rules, and the Random Forest provides feature-importance rankings consistent with the attribute-selection result (Figure 8); however, global importance does not explain individual predictions, which is what an auditable integrity decision requires. The MLP and CNN-YOLOv8 models are opaque. For safety-critical offshore use we recommend (i) SHAP or LIME attributions for individual sensor-based predictions, checked against physical expectation (thinner wall, lower pH, and higher humidity should push towards higher severity); (ii) Grad-CAM or equivalent saliency maps for the image model, to confirm that detections rest on corrosion features rather than background or lighting artefacts; (iii) confidence calibration and human review of flagged segments within an integrity-management process such as DNV-RP-F116 (DNV GL, 2015), with the models serving as decision support rather than a replacement for inspection; and (iv) logging of inputs, model version, and outputs to support audit.

CONCLUSION AND RECOMMENDATIONS

Conclusion

This study developed and evaluated an artificial intelligence-based framework for the prediction, classification, and image-based detection of marine pipeline corrosion on offshore platforms, combining four supervised machine learning classifiers with a hybrid CNN-YOLOv8 deep learning detector. Random Forest and Decision Tree classifiers achieved the strongest sensor-based classification performance, with a weighted-average accuracy, precision, recall, and F1-score of 99.8%, outperforming the Multilayer Perceptron (94.8%) and Support Vector Machine (80.8%). The CNN-YOLOv8 detector achieved a test accuracy of 100% by the third training epoch and an overall model accuracy of 97.4%, indicating its promise for automated, image-based corrosion detection on this dataset. Collectively, these results confirm that hybridising interpretable ensemble classifiers with deep image-based detection offers a promising pathway toward proactive corrosion management on offshore platforms, subject to validation on field data, robustness testing under sensor noise, and explainability analysis.

Recommendations

1. Develop and field-test an edge-computing implementation of the framework to validate performance under real offshore environmental conditions.
2. Integrate the framework with an Internet of Things (IoT) sensor network to enable continuous, real-time data acquisition and inference.
3. Incorporate explainability techniques (e.g., SHAP, LIME, or Grad-CAM) into future prediction and detection systems to improve transparency and support auditable decision-making in safety-critical offshore operations.
4. Test robustness to realistic subsea measurement noise, drift, dropout, and underwater image degradation, and report performance degradation before any operational use.

5. Replace the rule-labelled simulated data with field-collected or physics-based labelled data, apply SMOTE within training folds only, and use stratified cross-validation with a larger normal-class sample.

Contribution to Knowledge

1. Development of an AI-based pipeline corrosion prediction and detection framework using DT, RF, SVM, and MLP, showing that RF and DT performed best on the simulated dataset used here, with 99.8% weighted-average performance.
2. Demonstration that multi-model benchmarking of ML classifiers for multi-class corrosion severity (severe, minor, normal) offers practical value for offshore maintenance planning and resource allocation.
3. Development and preliminary evaluation of a CNN-YOLOv8 image-based model for identifying corroded pipeline surfaces, evaluated alongside classical ML classifiers within a single framework (on different data modalities, so not a like-for-like comparison).

Author Contributions

Conceptualisation, methodology, software, formal analysis, investigation, data curation, and writing - original draft: W.J. Supervision, validation, and writing - review and editing: S.N. and K.N.W. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement

The simulated sensor dataset and the pipeline-image dataset used in this study are derived from a publicly accessible Kaggle repository. Processed data and model outputs supporting the findings of this study are available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare no conflict of interest.

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