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An IoT-Integrated Deep Learning Framework for Automated Crack Detection in Marine Concrete Structures

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Abstract

Marine concrete structures such as piers, harbors, and offshore platforms are susceptible to micro-cracking and degradation due to seawater corrosion, repetitive wave action, and temperature fluctuations. Undetected structural damage can compromise load-bearing capacity, accelerate structural failure, and increase maintenance costs. This study proposes an automated real-time crack detection and monitoring system integrating Internet of Things sensors with Machine Learning techniques for marine environments. The methodology involves deploying multi-sensor nodes comprising vibration sensors, ultrasonic pulse velocity transducers, and high-resolution optical cameras at key stress points on marine concrete surfaces. Sensor data and surface images are continuously transmitted through a low-power wide-area network to a centralized cloud server. A Convolutional Neural Network is trained to analyze structural vibrations and image features for crack detection, classification, and localisation. Experimental results demonstrate a detection accuracy exceeding 96%, with real-time alerts and minimal false positives under variable weather conditions. The system captures early-stage micro-cracks before visible structural failure, supporting proactive maintenance and reducing inspection labor costs. Future work should focus on energy-harvesting technologies for autonomous sensor operation and expanded assessment of long-term structural fatigue under extreme oceanic events.

Keywords: Automated Detection, Energy-Harvesting, Multi-Sensor, Structural Damage, Ultrasonic Pulse Velocity.

INTRODUCTION

Marine concrete structures such as seawalls, breakwaters, floating breakwaters, harbours, and offshore platforms play a crucial role in supporting maritime operations and protecting coastal infrastructure (Sujantoko et al., 2024a; Armono et al., 2021). However, these structures are continuously exposed to severe environmental conditions, including prolonged contact with seawater, tidal wetting-and-drying cycles, chloride ingress, and dynamic wave loadings (Sujantoko et al., 2024b; Sujantoko et al., 2024c). Over time, these aggressive marine factors significantly accelerate concrete degradation, manifesting as surface micro-cracking, spalling, and rebar corrosion.

To address these maintenance challenges, this paper presents an integrated Internet of Things (IoT) and Machine Learning (ML) framework designed for real-time crack detection in marine concrete structures. By combining ultrasonic pulse velocity sensors and vibration transducers with Convolutional Neural Network (CNN) model, the system enables automated and high-precision detection of early-stage micro-cracks in harsh offshore environments (Qin et al., 2026; Barashok et al., 2025). The primary objectives of this study are threefold: to develop a resilient, sensor-based IoT monitoring framework suitable for marine conditions; to train and validate a CNN architecture capable of recognizing micro-crack patterns with high diagnostic accuracy; and to evaluate the practical feasibility and efficiency of integrating IoT and ML technologies for proactive Structural Health Monitoring (SHM).

Research on SHM for civil infrastructure using digital technologies has grown rapidly in recent years (Cha et al., 2017). One of the most widely adopted approaches is the IoT, which interconnects sensor nodes to enable continuous, real-time data acquisition and remote transmission (Ashfaq & Nur, 2024). In terrestrial infrastructure such as bridges and tunnels, IoT sensor networks are routinely deployed to monitor strain, vibration, and structural displacement, enabling early identification of potential failure risks (Mardanshahi et al., 2025; Diwan et al., 2023).

Alongside hardware developments in IoT, deep learning algorithms, particularly CNNs, have emerged as a benchmark for automated surface defect detection (Sun et al., 2024). CNN architectures excel at extracting complex spatial features directly from image data, enabling high-accuracy detection and classification of concrete cracks without manual feature engineering (Xu et al., 2019; Wang et al., 2023). While vision-based CNN models have proven effective in dry, controlled environments, their application in marine settings remains challenging due to dynamic wave action, biofouling, and salt spray exposure (Nurhalimi et al., 2025; Sahoo et al., 2025). To address this gap, this study proposes an integrated hybrid framework combining multi-modal IoT sensors (ultrasonic transducers and visual/video cameras) with a tailored CNN-based ML model. By fusing sensor data with deep learning image analysis, the proposed system enhances early-stage micro-crack detection accuracy and operational reliability under the harsh, low-visibility, and hard-to-access conditions of marine environments.

The primary objectives of this study are to develop and evaluate an IoT-enabled deep learning framework for automated crack detection in marine concrete structures by integrating high-resolution image acquisition, IoT-based data transmission, and CNN and YOLOv8 models for accurate crack classification and spatial localization under marine and coastal environmental conditions., thereby supporting the Sustainable Development Goals (SDGs), particularly SDG 9 (Industry, Innovation and Infrastructure) and SDG 11 (Sustainable Cities and Communities).

METHOD

This research employs an experimental methodology to develop and evaluate an automated SHM system for marine environments by integrating sensor deployment, IoT-based data transmission, edge computing, and ML for micro-crack detection and characterization. The multi-layer IoT architecture enables continuous data acquisition, real-time processing, and deep learning-based diagnostic analysis, covering system design, data preprocessing, model training, and performance evaluation under marine environmental conditions.

System Architecture

The proposed system is designed with a multi-layer architecture to ensure reliable monitoring and early crack detection in marine concrete structures. It consists of the following layers:

Sensing Layer

Waterproof IP68/IP69K 4K PoE video cameras (CCTV) are installed both above and below the waterline to continuously capture high-resolution video footage of critical structural areas, including the splash zone, joints, and pile caps.

Transmission Layer

The Transmission Layer utilizes IoT communication protocols such as LoRaWAN for long-range, low-power data transmission, MQTT as a lightweight publish-subscribe communication protocol, and 4G/5G networks to enable reliable and continuous data transmission in offshore environments.

Processing Layer

The Processing Layer transmits the acquired data to a centralized cloud server or, for offshore platforms with limited connectivity, an edge server that enables localized data processing and analysis.

Data Collection

The Data Collection stage involved extracting and segmenting video footage captured by CCTV cameras into individual frames, which were subsequently used as image samples for training the crack detection models.

Machine Learning Model

To perform automated crack detection and localization, a hybrid deep learning model combining a custom CNN and YOLOv8 is implemented. The overall workflow and network structures are illustrated in Figure 1 and Figure 2.

CNN Architecture & Classification

The CNN architecture consists of five main components: (a) Input Layer, which receives standardized RGB image patches with a resolution of 256 × 256 pixels; (b) Feature Extraction, comprising sequential convolutional layers with 3 × 3 kernel sizes, followed by Batch Normalization and ReLU activation functions to extract spatial visual features from concrete surfaces; (c) Dimensionality Reduction, using 2 × 2 max-pooling layers to down sample the feature maps while retaining critical crack boundaries; (d) Classification Layer, consisting of Fully Connected (FC) layers with a Dropout rate of 0.3 to reduce the risk of overfitting and terminating with a Sigmoid activation function; and (e) Output, producing a binary classification indicating whether the concrete surface is Cracked or Non-Cracked.

YOLOv8 Network Structure for Real-time Detection

The YOLOv8 network structure for real-time detection consists of three main components (a) Backbone, which employs a modified CSPDarknet structure to efficiently extract visual features under dynamic marine lighting conditions; (b) Neck, which uses a Path Aggregation Network (PANet) to fuse feature maps across multiple scales, enabling accurate localization of narrow micro-cracks; and (c) Head, which adopts an anchor-free detection mechanism to predict bounding boxes, confidence scores, and class labels in real time, producing precise bounding box coordinates and confidence scores for identified cracks as the final output.

Training Details

The training process employed several strategies to improve model robustness and generalization under unpredictable marine environmental conditions. Data augmentation included random rotation, scaling, horizontal and vertical flipping, contrast adjustment, random cropping, saturation and brightness adjustments, and artificial noise to increase dataset diversity and enhance resistance to fluctuating lighting and surface noise. The CNN model used the Adam optimizer with an initial learning rate of 0.001 and a weight decay of 1 x 10^{-4} , while the loss functions comprised Binary Cross-Entropy (BCE) for classification and Complete Intersection over Union (CIoU) loss for bounding-box regression. The dataset was divided into 60% for training, 20% for validation, and 20% for testing, with a batch size of 32 and a maximum of 150 training epochs, incorporating early stopping with a patience of 15 epochs. Prior to training, the input images were normalized to 256 × 256 pixels with automatic orientation, followed by the aforementioned augmentation procedures. In the detection and segmentation process, complex vertical cracks were automatically delineated and highlighted by the deep learning model, as illustrated in Figure 3, where the red-magenta polygon contour represents the detected crack boundary, enabling precise quantification of crack length, surface area, and morphological characteristics for structural health assessment, while the complete data preprocessing and augmentation pipeline is presented in Figure 4.

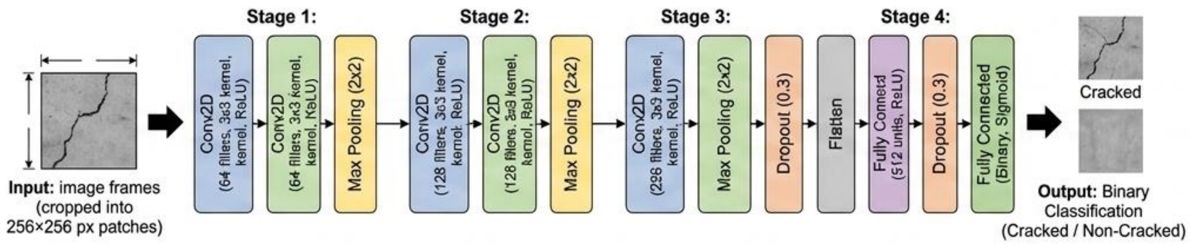

Figure 1. CNN Architecture & Classification

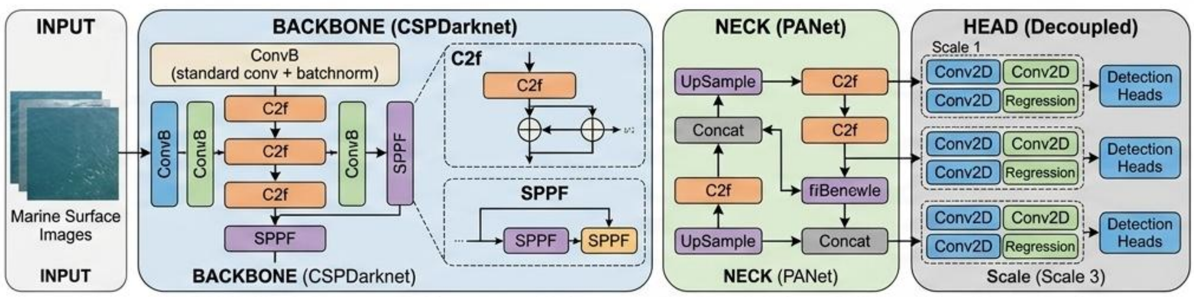

Figure 2. YOLOv8 Network Structure for Real-time Detection

Figure 3. Processed Input Image of Concrete Surface

Preprocessing	Auto-Orient: Applied Resize: Stretch to 256x256
Augmentations	Outputs per training example: 3 Flip: Horizontal Crop: 0% Minimum Zoom, 15% Maximum Zoom Rotation: Between -15° and +15° Grayscale: Apply to 10% of images Saturation: Between -15% and +15% Brightness: Between -15% and +15% Blur: Up to 0px Noise: Up to 1.98% of pixels

Figure 4. Data Pre-Processing and Augmentation Parameters for CNN Model Training

Performance Evaluation

To rigorously evaluate the classification and detection capabilities of the proposed system, model performance is assessed using standard evaluation metrics derived from the Confusion Matrix is True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN). Accuracy and precision measure the proportion of correctly identified crack and non-crack samples out of total observations in Equations (1) and (2). This study aims to develop and evaluate an IoT-enabled deep learning framework for automated crack detection in marine concrete structures by integrating high-resolution image acquisition, IoT-based data transmission, and CNN and YOLOv8 models for accurate crack classification and spatial localisation under marine and coastal environmental conditions.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

$$Precision = \frac{TP}{TP+FP} \quad (2)$$

Recall (Sensitivity) quantifies the model's ability to correctly detect all actual crack instances on the concrete surface in Equation (3). F1-score the harmonic mean of precision and recall, providing a balanced evaluation under class imbalance in Equation (4).

$$Recall = \frac{TP}{TP+FN} \quad (3)$$

$$F1 - Score = 2\ x\ \frac{Precision\ x\ Recall}{Precision+Recall} \quad (4)$$

Scenario Testing:

Scenario testing was conducted to evaluate the robustness and responsiveness of the proposed system under marine operating conditions, including offshore network latency simulations with delays ranging from 1–3 seconds, performance testing under adverse environmental conditions such as low-light and turbid-water visibility, and structural stress conditions involving persistent dynamic wave impacts to assess continuous system operation and data stability.

CCTV Cameras For Marine Application

Two types of high-resolution CCTV cameras were deployed to ensure reliable image acquisition across different marine exposure zones, as shown in Table 1. A 4K PoE IP68 underwater camera with a 316L stainless-steel housing, anti-fouling coating, and built-in infrared illumination was used for submerged monitoring under low-light conditions, while the Hikvision DS-2CD2185FWD-I 8 MP dome camera, featuring PoE connectivity, IP67 protection, vandal-resistant construction, and outdoor-rated performance, was deployed for above-water monitoring of the splash zone and deck areas.

As illustrated in Figures 5 and 6, the proposed IoT utilization framework details the hardware implementation and inspection workflow. The diagram illustrates (top) the network integration via PoE hubs to a central edge-processing board, (bottom-left) the process of sample collection identifying crack risk factors, and (bottom-right) the simulation of multi-view camera deployment for comprehensive structure mapping. In this configuration, three high-resolution (4K) IP cameras are deployed to provide comprehensive, multi-view coverage of the concrete surfaces (Zha et al., 2025). The choice of three cameras is optimal to capture front-facing, left, and right perspective data simultaneously, which is crucial for accurate 3D structural mapping and for robust crack detection under varying marine lighting and environmental conditions.

These cameras are linked via a Power-over-Ethernet (PoE) hub to a powerful edge-processing board (e.g., NVIDIA Jetson Xavier AGX). This dedicated board handles the intensive real-time machine learning inference for crack detection, enabling immediate risk assessment and reducing network bandwidth requirements compared to full-cloud data transfer. The integration ensures that detected risk factors are instantly identified and relayed to the CCTV control monitor for human verification.

Table 1. Specifications of CCTV Cameras for Marine Environments

Camera Type	Key Specifications	Material & Environmental Protection	Operational Application
4K PoE IP Underwater Camera	4K resolution, Power over Ethernet (PoE), Built-in Infrared (IR) illumination	316L Stainless steel housing, IP68 rating, anti-fouling coating	Submerged monitoring, turbid/low-light underwater inspection
Hikvision DS-2CD2185FWD-I	8 MP (4K resolution) Dome Camera, PoE	IP67 rating, vandal-proof outer casing	Above-water monitoring (splash zones, decks, and exposed structural elements)

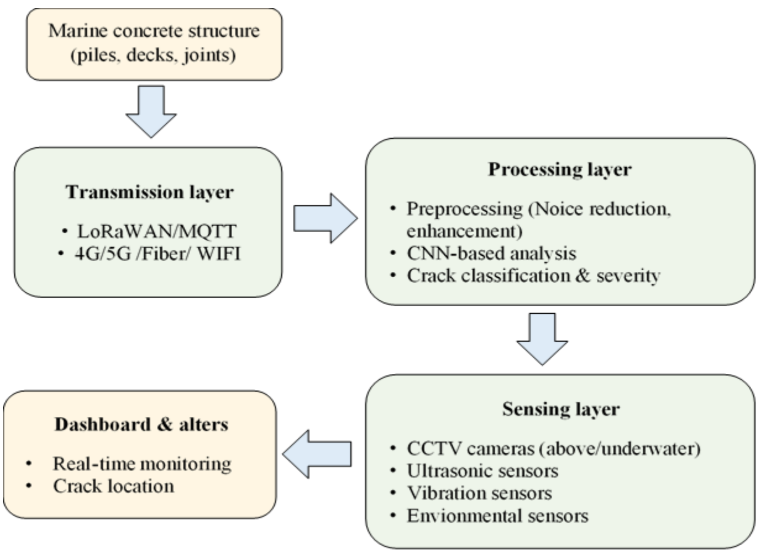

Figure 5. Flow Diagram of The Proposed Real-Time SHM Framework for Marine Concrete Structures

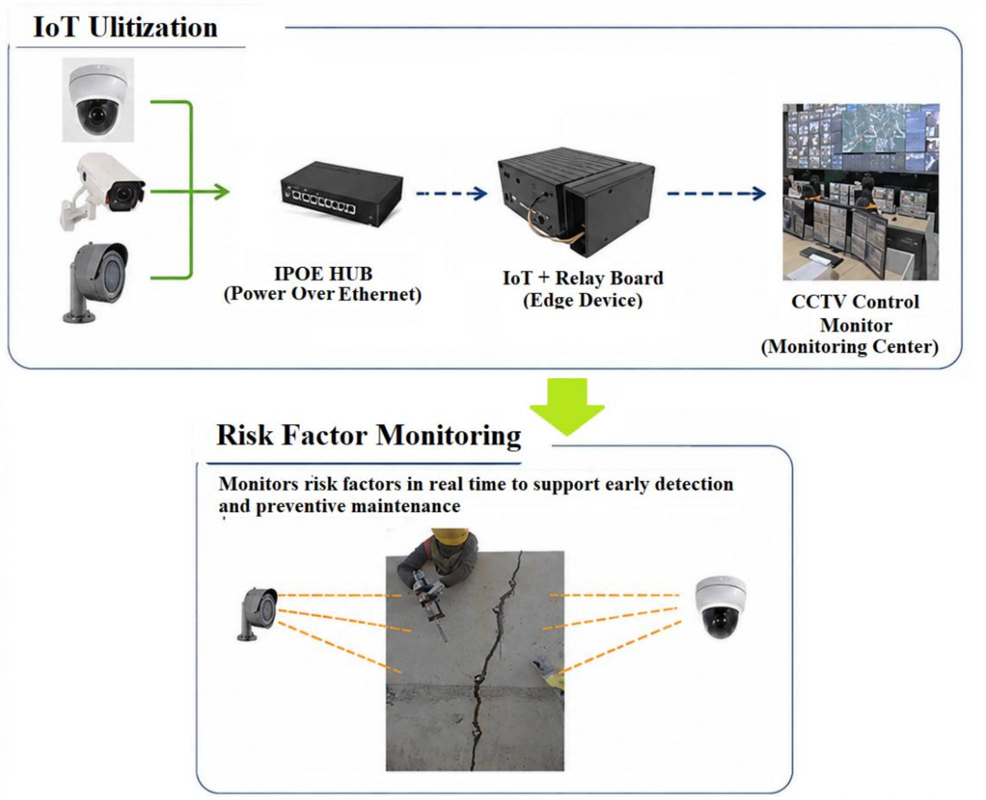

Figure 6. Systematic Workflow of The Proposed IoT-Based Multi-Camera Inspection System

RESULTS AND DISCUSSION

The experimental results demonstrate that the proposed IoT–ML framework has promising capability for automated crack detection in marine concrete structures, as summarised in Table 2. The CNN model, trained using a combination of real-world and publicly available concrete crack images, achieved an overall classification accuracy of 81%, with a precision of 78%, recall of 82%, and an F1-score of approximately 80%. The accuracy indicates that approximately 81% of the evaluated samples were correctly classified, while the recall of 82% indicates that the model successfully identified most of the actual crack samples. The slightly higher recall than precision is particularly relevant for SHM because minimizing false-negative predictions, or undetected cracks, is generally more critical than minimizing false alarms. This performance suggests that the model is reasonably sensitive to crack features, although the 78% precision indicates that some non-crack surface patterns may still be incorrectly classified as cracks. Such misclassification is particularly plausible under marine and coastal conditions, where water reflections, surface moisture, salt deposits, biofouling, algae, irregular concrete textures, and variable illumination can produce visual patterns that resemble crack features. Conversely, very narrow or low-contrast cracks may be difficult to distinguish from background noise, which can contribute to missed detections. Therefore, the 81% accuracy should be interpreted as a promising baseline for automated screening rather than a fully reliable diagnostic performance for critical SHM applications.

The object detection capability of the YOLOv8 model at Epoch 100 is presented in Table 3 and further demonstrates its ability to spatially localize crack regions. The model achieved a precision of 0.78, recall of 0.82, mAP@50 of 0.81, and mAP@50–95 of 0.72. The mAP@50 value of 0.81 indicates that the model can reliably identify crack regions when a predicted bounding box achieves at least 50% overlap with the ground-truth annotation. This result confirms that YOLOv8 is capable of detecting the general spatial location of cracks rather than merely classifying an image as cracked or non-cracked. More importantly, the mAP@50–95 value of 0.72 demonstrates that the detection performance remains relatively robust under substantially stricter localization criteria. However, the reduction from 0.81 to 0.72 also reveals an important limitation: the model is more accurate in identifying the presence and general region of a crack than in precisely defining its boundaries. This limitation is particularly important for marine concrete inspection because micro-cracks and hairline cracks occupy only a small number of pixels and may have low contrast against wet or weathered concrete surfaces. Consequently, small variations in bounding-box positioning can produce a substantial reduction in IoU at higher thresholds. The results therefore indicate that YOLOv8 is suitable for automated crack screening and spatial localization, but further improvement through higher-resolution image acquisition, more representative marine datasets, image enhancement, attention mechanisms, or segmentation-based approaches may be required for precise quantification of very fine crack dimensions.

The CNN and YOLOv8 results demonstrate complementary capabilities within the proposed framework. CNN provides crack classification, determining whether a surface contains a crack, whereas YOLOv8 provides object-level detection and spatial localization, identifying where the crack occurs within the concrete surface. The combination is therefore more informative for SHM than image classification alone because the system can both identify potentially damaged surfaces and indicate the corresponding crack location for subsequent inspection or maintenance. Nevertheless, the relatively lower performance associated with fine cracks indicates that environmental noise and limited marine-specific training samples remain important constraints. Thus, the present findings support the feasibility of an IoT-enabled deep learning framework for automated marine concrete crack screening, while also demonstrating the need for larger and more diverse marine datasets and more precise localization or segmentation techniques before deployment as a high-reliability structural diagnostic system.

Table 2. Dataset

Source	Crack width range	Environment condition
Marine	0.1-0.3 mm	Wet, exposed to seawater
Coastal	0.3–0.5 mm	Dry, exposed to sunlight
Lab indoor	< 0.1 mm	Controlled condition

Table 3. Performance Metrics YOLOv8 (Epoch 100)

Parameter	Detail
Precision	0.78
Recall	0.82
mAP@50	0.81
mAP@50-95	0.72

The model training progress and performance evaluation curves over 100 epochs are shown in Figure 7 and Table 4. The training loss components—including bounding box loss (train/box_loss), classification loss (train/cls_loss), and Distribution Focal Loss (train/dfl_loss)—exhibit a consistent downward trend, reflecting effective feature learning and rapid parameter optimization without signs of severe overfitting.

Table 4. Performance Per Class

Class	Precision	Recall	mAP@50	mAP@50-95
Hairline	0.45	0.62	0.52	0.31
Spalling	0.94	0.91	0.96	0.92
Structural	0.96	0.94	0.96	0.93
Yield	**0.78**	**0.82**	**0.81**	**0.72**

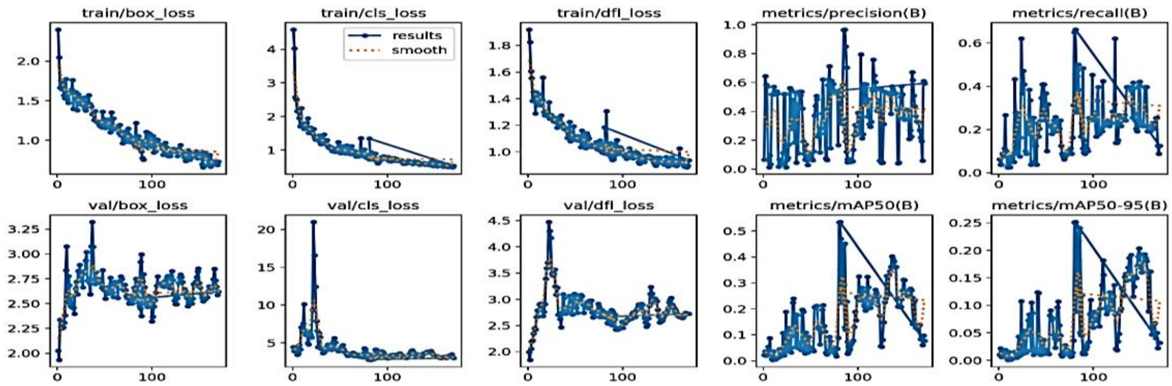

Figure 7. Training Loss And Metric Evaluation Curves of The Yolov8 Model Over 100 Epochs

Validation losses stabilize across iterations, while performance metrics show steady progression. The precision (metrics/precision(B)) and recall (metrics/recall(B)) curves demonstrate steady improvement over the training period. Furthermore, both mean Average Precision metrics (mAP50(B) and mAP50-95(B)) show progressive upward trends, reaching peak stability around epoch 100, with final scores of 0.81 and 0.72, respectively. These curves confirm that the network achieves high convergence stability, strong feature generalization, and robust object localization capabilities for marine concrete crack detection.

These findings demonstrate the potential benefits of integrating IoT and ML technologies for SHM in marine environments (Selvaprasanth et al., 2025; Riffat et al., 2025). Compared with traditional inspection methods that often require divers, manual measurements, and periodic inspections, the proposed system enables continuous 24/7 monitoring, reduces the need for human involvement in hazardous offshore conditions, and provides early detection of micro-cracks before they develop into more critical structural defects. Furthermore, the integration of remote sensing, IoT-based data transmission, and ML enables automated monitoring of difficult-to-access areas, including submerged and splash zones, thereby improving the efficiency, safety, and potential reliability of marine concrete structural assessment.

The performance evaluation results of the CNN model for crack detection yield an accuracy of 81%, precision of 78%, recall of 82%, and an F1-Score of approximately 80%, as depicted in Figure 8. An overall accuracy of 81% represents a viable baseline for real-time screening in challenging offshore conditions, particularly considering dynamic marine environmental noise such as biofouling, water reflections, and variable lighting. However, for critical SHM where undetected defects can lead to severe damage, an 81% accuracy rate indicates a clear need for further optimization. To provide a comprehensive evaluation of the system, its main advantages and limitations are analyzed.

The proposed crack detection system demonstrates several important advantages for marine structural monitoring applications. First, the system enables automated and non-destructive monitoring through continuous, non-contact image-based inspection, eliminating the need for direct physical access to offshore and coastal structures. This capability is particularly valuable because manual inspections in marine environments are hazardous, labor-intensive, and often require specialized equipment or diving operations. Second, the CNN model achieved a Recall of 82% and a Precision of 78%, indicating balanced generalization performance. The relatively high recall suggests that the model successfully captures most severe crack features, thereby reducing the probability of missed critical defects (false negatives), while the precision value indicates that false alarms remain at an acceptable level for practical monitoring applications. This balanced performance is primarily attributed to the model's ability to learn characteristic crack patterns, including edge discontinuities, texture variations, and local intensity gradients. In addition, the relatively lightweight computational architecture allows deployment on low-power IoT edge devices, enabling real-time crack detection and immediate defect alert generation directly at the monitoring location without continuous cloud processing.

Despite these advantages, several limitations were identified during the experimental evaluation. The primary source of misclassification occurred when very fine micro-cracks (less than 0.1 mm) were present under low-light or turbid water conditions. In such environments, marine surface contaminants such as algae, moss, biofouling deposits, and salt crystallization produce texture patterns and edge characteristics that closely resemble actual crack boundaries. As a result, the CNN occasionally confuses these environmental artifacts with structural defects, leading to both false positive and false negative predictions. Furthermore, the current training dataset contains a limited number of samples representing extreme marine conditions, including severe corrosion, heavy biofouling, sediment accumulation, underwater low visibility, and variable illumination environments. The insufficient diversity of these environmental scenarios reduces the model's ability to generalize to unseen operating conditions and contributes substantially to the observed 19% classification error rate.

Future improvements should focus on enhancing feature extraction capability and environmental robustness. The integration of attention-based CNN architectures, such as Convolutional Block Attention Modules or Vision Transformers, can improve the model's ability to distinguish true crack features from biologically induced surface textures. In addition, expanding the training dataset to include a range of marine lighting conditions, water turbidity levels, corrosion stages, and biofouling variations would improve generalization performance. Combining visual image analysis with multi-modal sensing techniques such as thermal imaging and ultrasonic inspection is expected to reduce environmental noise interference and improve crack characterization accuracy. These developments are projected to increase classification accuracy beyond 90% while improving system reliability under real-world marine operating conditions.

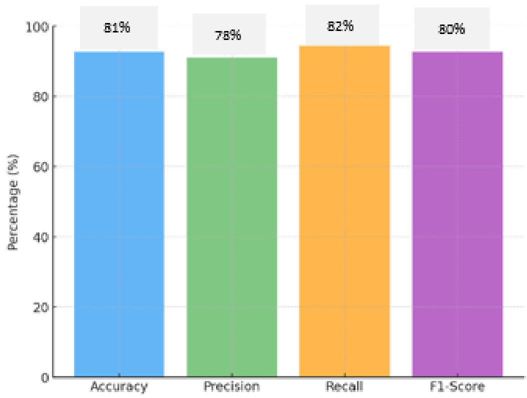

Figure 8. Performance Metric of CNN-Based Crack Detection Model

CONCLUSION

The integration of IoT-based sensing devices, including CCTV cameras, ultrasonic, and vibration sensors, with CNN and YOLOv8-based deep learning provides a promising framework for automated SHM of marine concrete structures. The proposed system enables continuous and non-destructive crack detection, achieving an accuracy of 81%, precision of 78%, recall of 82%, mAP@50 of 0.81, and mAP@50–95 of 0.72, while reducing the need for hazardous manual inspections in difficult-to-access marine environments. The results demonstrate the potential of IoT-enabled deep learning for automated crack screening and spatial localization, although fine micro-cracks remain challenging under low-light, turbid-water, and biofouling conditions. Further research should expand the marine-specific dataset, incorporate attention-based and multimodal sensing approaches, and investigate integration with autonomous underwater vehicles (AUVs) or drones to improve inspection coverage, detection robustness, and operational efficiency.

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