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RESEARCH ARTICLE

Neuro Graph Temporal Fusion Network for predicting corrosion rate in marine-exposed reinforced concrete structures

Selvaprasanth PANNEERSELVAM[a*], **Malathy RAMALINGAM**[b]

[a] *Department of Civil Engineering, Velammal Engineering College, Tamil Nadu 600066, India*
[b] *Department of Civil Engineering, Sona College of Technology, Tamil Nadu 636005, India*
[*] *Corresponding author. E-mail: selvatamil50@gmail.com*

ABSTRACT Reinforced concrete (RC) structures exposed to marine environments are highly susceptible to chloride-induced corrosion, which can cause premature deterioration, cracking, spalling, reduced service life, and increased maintenance costs. While advances in sensor-based systems, non-destructive testing, imaging techniques, and probabilistic life-cycle models have improved early detection, most existing methods rely on single-modality measurements, simplified assumptions, or fail to capture the complex spatio-temporal dynamics of corrosion. To address these limitations, this study proposes the Neuro Graph Temporal Fusion Network (NGTFNet), a unified framework for corrosion prediction in marine RC structures. NGTFNet integrates multimodal sensing data, including optical, thermal, ultrasonic, and electrochemical inputs using Convolutional Neural Networks (CNN)-based feature extraction, graph-based modeling to capture spatial deterioration patterns, and temporal fusion for life-cycle forecasting. The proposed approach enables the accurate estimation of corrosion rates and service life under dynamic marine exposure, representing a significant step toward the resilient and sustainable monitoring of marine RC structures.

KEYWORDS marine environment, RC structures, CNN, NGTFNet, corrosion rate prediction, deterioration

1 Introduction

Reinforced concrete (RC) structures form the backbone of coastal and offshore infrastructure. However, their long-term durability is severely compromised in aggressive marine environments owing to chloride penetration, carbonation, and steel-reinforcement corrosion. These processes trigger cracking, spalling, and delamination of concrete, thereby reducing structural safety and significantly increasing maintenance costs. Therefore, the development of advanced monitoring and predictive frameworks for the corrosion of marine RC structures is a pressing research priority.

In recent years, considerable progress has been made in sensor-based corrosion monitoring technologies. Feasibility studies have demonstrated the potential of autonomous corrosion assessment systems for RC structures using embedded sensors [1], whereas piezoelectric-based approaches have been experimentally validated for detecting chloride-induced corrosion in concrete [2]. Ultrasonic guided wave techniques, in combination with embedded fiber Bragg grating sensors, have been effective for the early detection of rebar corrosion [3]. Novel electrochemical methods have also been explored, such as polyaniline–MnO_2 solid-state reference electrodes for in situ monitoring [4] and zinc sacrificial anodes for marine chloride exposure protection [5,6]. Additionally, array sensors for monitoring chloride profiles within RC have recently been proposed [7].

In parallel, non-destructive testing (NDT) and vision-based methods are employed for surface-level and subsurface corrosion detection. Ground-penetrating radar (GPR), enhanced by machine learning, enables the classification of corrosion states in concrete [8]. Thermal tracing has been used for monitoring spalling in submerged structures [9], whereas infrared thermography

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has been applied in durability studies of seawater and recycled aggregate concretes [10,11]. Machine vision techniques have further advanced the automated corrosion diagnosis of marine steel-concrete composites [12], with Convolutional Neural Networks (CNN)-based architectures supporting automated crack detection [13,14]. The integration of deep learning (DL) with ultrasonic, thermal, and image-based methods has also improved the diagnostic accuracy [15–17].

By complementing these approaches, probabilistic and reliability-based models provide insights into long-term structural degradation. Bayesian networks have been adopted for reliability assessments of RC under environmental actions [18], and ensemble learning (EL) frameworks have been developed for life-cycle performance prediction in marine environments [19]. The importance of spatial variability in corrosion initiation has been highlighted in risk-based maintenance [20]. Probabilistic approaches combining field exposure and numerical simulations have been demonstrated for corrosion initiation in marine bridge components [21]. Active learning-enhanced Bayesian neural networks have also emerged for predicting the life-cycle performance of prestressed concrete beams under coastal conditions [22].

In terms of materials and coatings, several studies have addressed the durability of marine concrete and its protective strategies. Seawater and sea-sand concrete-filled composite tubes have shown enhanced corrosion resistance [10], while seawater recycled aggregate concrete frames have been assessed under long-term marine exposure [11]. Coating-based approaches, such as silicone-infused polydimethylsiloxane, have demonstrated improvements in marine concrete durability [16]. Similarly, BN-TiO_2 multilayer coatings have shown improved corrosion performance for alloys in marine environments [23].

Beyond corrosion-specific studies, research in graph neural networks (GNNs) and advanced Artificial Intelligence (AI) frameworks presents new opportunities for modeling structural degradation. GNNs have been applied in distributed Internet of Things (IoT) services [24], material quantity estimation for RC [25], and routing optimization [26]. Surveys have confirmed their synergy with reinforcement learning for networking applications [27]. These advances highlight their capacity to represent spatial relationships within structural components, a feature that is highly relevant for corrosion propagation modeling. Similarly, hybrid frameworks that integrate DL, IoT-enabled sensing, and probabilistic reasoning have been applied to smart structural monitoring [28,29]. Studies on self-healing concrete [17] and structural health monitoring in nuclear facilities [30] also emphasize the importance of intelligent, sustainable approaches in durability research.

Despite this progress, significant gaps remain in the literature. Existing monitoring techniques are often limited to single-modality sensing (e.g., electrochemical, ultrasonic, or vision-based), which reduces the robustness under heterogeneous marine conditions. Probabilistic models, while useful for lifecycle assessment, rely on simplified assumptions and lack integration with real-time multimodal data [18–22]. Machine vision and CNN-based crack detection provide valuable surface diagnostics [13,14] but fail to incorporate spatio-temporal degradation dynamics. Moreover, durability studies on novel concretes and coatings [10,11,16,23] remain primarily experimental, with limited predictive modeling frameworks. Recent advances in graph-based and temporal fusion learning [22,24–27] suggest a pathway for integrating multimodal sensing with spatio-temporal modeling, such methods have not been fully realized for corrosion prediction in marine RC structures.

In this scenario, the Neuro Graph Temporal Fusion Network (NGTFNet) offers a promising unified framework. By fusing multimodal data (optical, thermal, ultrasonic, and electrochemical) through CNN-based feature extraction, constructing graph-based representations of deterioration, and applying temporal fusion, NGTFNet can predict both the corrosion rates (mm/year) and service life under dynamic marine conditions. This integration represents a crucial step toward real-time, multimodal, and spatio-temporal corrosion prediction, with the potential to significantly improve the durability, resilience, and sustainability of marine RC infrastructure.

With these contributions toward corrosion monitoring and detection, this research manuscript is structured with a brief introduction and contribution in Section 1. Section 2 A provides a brief introduction to show the literature review. A detailed illustration of the proposed model is presented in Section 3, and performance and comparative analyses are presented in Section 4. Section 5 presents details of case studies. Finally, Section 6 concludes the article, highlighting the advantages of the proposed research work along with insights into the future scope of enhancements.

2 Literature review

RC structures in marine environments are particularly susceptible to chloride-induced corrosion, which is a major cause of premature deterioration and structural failure. To mitigate these risks, extensive research has focused on developing effective monitoring and predictive methods. Existing studies span four main technological domains: sensor-based and electrochemical monitoring, NDT and imaging, probabilistic and reliability-based service-life models, and emerging artificial intelligence frameworks. Each domain offers specific advantages in detecting or forecasting corrosion;

however, none alone provides a complete solution for capturing the complex spatial and temporal behavior of marine degradation. By systematically reviewing these approaches, this study highlights their key contributions, identifies critical limitations, and establishes a foundation for advancing toward integrated multimodal frameworks such as NGTFNet.

Graph-based AI frameworks are increasingly applied to infrastructure durability prediction due to their potential to model relational dependencies and temporal variations. Distributed fog computing frameworks have been proposed to deploy GNNs for real-time IoT monitoring services with reduced latency [24], while knowledge-enhanced GNNs have demonstrated improved accuracy in estimating RC building material quantities [25]. Reviews of GNN applications in routing and network optimization highlight their potential in sustainable infrastructure [26] and their integration with deep reinforcement learning for adaptive decision-making [27]. Beyond GNNs, hybrid machine learning models such as swarm-optimized Extreme Learning Machines have shown effectiveness in underwater concrete strength prediction [15]. Probabilistic reasoning using Mixed Bayesian Networks (MBNs) has been applied for reliability assessment of RC under environmental loads [18], and EL approaches have enhanced lifecycle predictions of marine RC structures [19]. Bayesian neural networks combined with active learning further improve lifecycle performance modeling of prestressed concrete beams under marine exposure [22]. Together, these studies underline the adaptability of AI frameworks for predicting corrosion and degradation in RC infrastructure.

Smart sensing technologies are critical for the early detection and monitoring of corrosion in marine-exposed RC. IoT-enabled autonomous assessment frameworks have been explored to provide continuous monitoring without manual intervention [1], whereas piezoelectric sensors have been embedded to detect chloride-induced corrosion with strong experimental validation [2]. Advanced diagnostic methods that integrate ultrasonically guided waves with fiber Bragg grating sensors have improved sensitivity to early-stage deterioration [3]. Electrochemical innovations, such as Polyaniline–MnO_2 solid-state reference electrodes, provide stable in situ corrosion measurements [4]. Depth-dependent modeling of RC piles [31] and array sensors for mapping chloride profiles [7] have further refined our understanding of the corrosion mechanisms under varying marine conditions. More recently, IoT-integrated frameworks combining electrochemical and fiber-optic sensors have enabled real-time monitoring of both the strength and corrosion progression in concrete [28]. Collectively, these sensor-based approaches provide accurate, continuous, and multi-dimensional insights into the deterioration of RC.

Advances in imaging and NDT have enabled the detection and classification of structural deterioration with minimal intervention. Machine vision supported by DL has been used for automated corrosion recognition in marine concrete-filled steel tubular structures, thereby reducing reliance on manual inspection [12]. Similarly, GPR integrated with machine learning improves the classification of subsurface reinforcement corrosion states [8]. Thermal tracing techniques allow non-contact detection of surface spalling in submerged concrete [9]. CNNs have also been applied to crack detection, achieving high accuracy in pattern recognition [13], whereas DL algorithms enable automated severity classification of cracks in RC for predictive maintenance [14]. These combined imaging and AI approaches represent a shift toward autonomous, data-driven NDT in marine-exposed RC infrastructure.

Material innovations and protective coatings are increasingly being recognized as proactive measures to mitigate corrosion in marine-exposed RC. Studies on seawater and sea sand concrete-filled Basalt Fiber Reinforced Polymer–steel composite tube columns have shown strong durability against chloride ingress [10], whereas the use of seawater fully recycled aggregate concrete has demonstrated resilience and sustainability benefits under long-term exposure [11]. Coating technologies such as silicone-infused Polydimethylsiloxane formulations significantly enhance hydrophobicity and corrosion resistance [16], and BN–TiO_2 multilayer coatings provide improved anti-corrosion performance in aggressive environments [23]. Beyond coatings, nanomaterial-infused self-healing concrete has been developed to provide real-time monitoring and autonomous crack repair [17]. Zinc sacrificial anodes have also been validated as cost-effective cathodic protection systems against chloride intrusion [5]. Together, these material strategies extend the service life while reducing maintenance costs for marine infrastructure.

Probabilistic modeling approaches provide essential insights into the uncertainty associated with corrosion initiation and propagation in RC structures. The spatial variability in corrosion initiation parameters has been shown to significantly influence maintenance and inspection scheduling [20]. Probabilistic assessment methods have also been applied to RC bridge components by combining field exposure data with simulations for reliable service life prediction [21]. Comprehensive reviews of monitoring and characterization techniques emphasize the role of integrating sensors, modeling, and imaging to capture complex deterioration processes in marine concrete [32]. At the structural performance level, investigations into bond failure between corroded rebars and concrete have demonstrated how corrosion reduces the interface strength, directly impacting load transfer and durability [33]. These probabilistic approaches complement empirical studies and support risk-informed asset management.

Guo et al. [18] proposed a novel MBN framework to provide a comprehensive Bayesian Network framework for the life-cycle reliability assessment of RC structures in marine atmospheric environments. The MBN incorporates three main modules. It integrates various physical models, including a two-dimensional chloride transport model and analytical and finite element methods. The MBN aims to reduce the complexity of Bayesian Network modeling by establishing a new MBN that uses separate sub-Bayesian Networks for different modules, connected by 'pinch point variables' to transmit probabilistic information. This approach enables objective modeling and inference while simplifying the process and enhancing efficiency.

Guo et al. [19] proposed a robust and efficient framework for predicting and interpreting the life-cycle performance of RC structures in marine environments. Integrating interpretable EL with detailed physical modeling and real-world data validation provides valuable insights into the complex interplay of environmental, durability, and mechanical factors, facilitating more targeted design and maintenance strategies. LightGBM, a tree-based EL technique, was adopted to predict the life-cycle performance of coastal and marine RC structures because of its speed, minimal memory usage, high accuracy, and interpretability. The LightGBM surrogate model achieved outstanding precision across all target variables, with R-squared values exceeding 99.9% for the untrained test data set. It also significantly improved the prediction speed compared to the conventional numerical simulation method.

Several additional studies have provided a valuable context for understanding corrosion and durability challenges in diverse environments. Investigations into carbon steel corrosion in tropical waters have established baseline data on chloride, pH, and oxygen effects under Mauritian conditions [34]. Indirect monitoring approaches, such as analyzing tool wear at high temperatures, demonstrate transferable methodologies for assessing material degradation [35]. Hybrid AI frameworks combining statistical and DL techniques have improved the quality assessment of ceramic materials [36], and IoT-driven neural network models have been applied to real-time algae prediction, showing parallels for marine deterioration forecasting [29]. Long-term studies on reinforcement corrosion in nuclear concrete facilities underscore the durability challenges under radiation and extreme exposures [30]. Collectively, these studies broaden the knowledge base and inspire cross-disciplinary approaches for corrosion management.

Although recent advances in GNNs, Bayesian modeling, and sensor-based monitoring have enhanced our understanding of corrosion in RC exposed to marine environments, significant challenges remain in integrating multimodal data for accurate, long-term prediction. Current studies using machine learning for structural health monitoring largely rely on single-modality inputs, such as electrochemical data, ultrasonic signals, or optical imaging. Although effective within their scope, these methods fail to fully capture the spatio-temporal complexity of corrosion processes, which are influenced by chloride ingress, temperature, humidity, and structural loading conditions.

Jiang et al. [37] outlined a clear path for future work focusing on expanding the scope of the model to more diverse corrosion scenarios and environments, along with methodological advancements to improve predictive resolution and address data scarcity. This study itself fills critical gaps by offering a precise, GAN-based approach for predicting corrosion in paint-coated steel, an area where traditional methods and earlier DL applications have significant limitations.

Tran et al. [38] investigated the application of DL techniques to enhance the efficiency of crack detection and prediction of crack growth, which is crucial for the risk assessment of engineering structures. By utilizing SegNet and U-Net networks for crack identification on concrete surfaces and employing the Gated Recurrent Unit and Long Short-Term Memory algorithms for crack propagation forecasting, this study demonstrates the effectiveness of DL models for these tasks. The findings highlight the superiority of U-Net over SegNet for crack segmentation and validate the accuracy of GRU and LSTM in evaluating crack propagation, offering valuable insights for improving computational efficiency in structural risk assessment.

Moreover, most existing AI frameworks (e.g., Bayesian networks [18,21], EL [19], and CNN-based vision models [13,14] are limited to either spatial correlation or temporal trend analysis, but not both simultaneously. The integration of multimodal data, such as optical images, thermal profiles, and ultrasonic measurements for corrosion prediction, remains unexplored, despite evidence that each modality reveals different deterioration signatures [3,9,12]. Additionally, although GNNs have shown promise in material quantity estimation [25] and network optimization [26], their application to graph-structured corrosion features in marine RC is still lacking. A critical review of the previous studies is presented in Table 1.

NGTFNet provides a unique opportunity to bridge this gap by combining CNN-based feature extraction, graph construction for spatial correlation, and temporal fusion for dynamic prediction. However, no published work has yet applied NGTFNet for predicting corrosion rate (mm/year) in RC under real marine exposure. Addressing these gaps through the implementation of NGTFNet would represent a substantial advancement in structural health monitoring by enabling robust, multimodal, and time-aware corrosion prediction, thereby supporting

Table 1 Critical review of existing corrosion prediction technologies

Technology/ Approach	Key contributions	Limitations	Research gap	Potential for marine RC corrosion prediction	Refs.
Sensor-based and electrochemical monitoring	Provides real-time measurements of chloride ingress, half-cell potential, and corrosion rate; widely used in laboratory and field applications.	Sensor durability issues in harsh marine conditions; localized measurements are not representative of global behavior.	Lack of scalable, long-term autonomous sensor networks capable of capturing both spatial and temporal variations.	Useful for short-term monitoring but needs integration with predictive models.	[1–6]
NDT and imaging	Detects hidden deterioration through infrared thermography, GPR, ultrasonic testing, and vision-based systems; machine learning enhances interpretation.	Environmental sensitivity; accuracy depends on calibration and expert interpretation.	Limited ability to fuse multimodal imaging data into unified corrosion progression models.	Strong for condition assessment, particularly when fused with other techniques.	[7–13]
Probabilistic and reliability-based models	Quantifies service life and structural reliability under uncertainty; supports risk-based maintenance planning.	Relies on assumed probability distributions and simplified corrosion kinetics.	Insufficient integration of real-time monitoring data and spatial heterogeneity into models.	Valuable for lifecycle prediction when coupled with sensor inputs.	[14–19]
AI and machine learning	DL (CNNs, GNNs, hybrid models) captures spatial-temporal patterns; applied successfully for defect recognition and forecasting.	Requires large labeled data sets; often restricted to a single data type; interpretability challenges.	Lack of integrated multimodal frameworks that combine sensing, imaging, and temporal prediction for marine RC corrosion.	High potential for accurate multimodal corrosion forecasting.	[20–28]
Advanced materials and protective coatings	Corrosion-resistant steel, FRP wraps, and protective coatings extend durability under chloride exposure.	Expensive; performance validation under aggressive marine conditions is limited.	Need for complementary predictive systems to monitor and forecast performance degradation over time.	Preventive measure, but requires coupling with monitoring and predictive technologies.	[29–38]

sustainable lifecycle management of marine RC infrastructure.

3 Proposed work

The proposed model for the early prediction of corrosion in an RC structure in a marine environment using NGTFNet is composed of five phases: multi-modal image acquisition, feature extraction, graph construction, temporal fusion with the NGTFNet, followed by corrosion classification and prediction, and output and interpolation for the detection of corrosion. The architecture of the proposed method using the NGTFNet model is illustrated in Fig. 1.

The proposed framework predicts the corrosion rate of RC structures in marine environments by integrating multi-modal imaging data into the NGTFNet.

3.1 Multi-modal image acquisition

The original optical image of the RC structure was enhanced by generating simulated ultrasound and thermal modalities using the Jupiter notebook. Together, these three modalities provide surface-level, subsurface, and thermal anomalies, respectively.

$$D = \{I_{\text{Opt}}, I_{\text{Ultra}}, I_{\text{Therm}}\}, \tag{1}$$

where I_{Opt} = optical image; I_{Ultra} = simulated ultrasound image; I_{Therm} = simulated thermal image.

In this study, simulated ultrasound and thermal

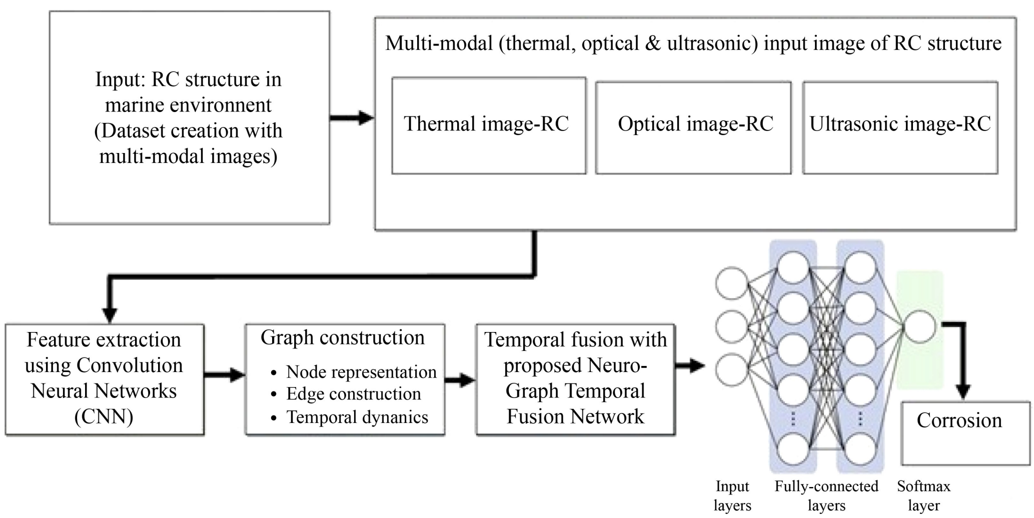


Fig. 1 Architecture of the proposed research.

modalities were generated from original optical images of RC structures using a physics-informed image transformation process implemented in the Jupyter Notebook. The simulation aims to emulate the behavior of real NDT techniques applied to RC structures exposed to marine environments. Initially, the optical images were preprocessed through contrast enhancement and noise reduction to highlight surface defects such as cracks and rust stains. Subsequently, a thermal simulation was performed by modeling the heat flow distribution and surface emissivity characteristics and capturing the temperature gradients associated with corrosion-induced deterioration. Similarly, the ultrasound modality was synthesized by simulating acoustic wave propagation through a concrete matrix, accounting for the signal attenuation and reflection caused by internal voids and corrosion zones.

To ensure realism, the simulation parameters were calibrated using experimentally obtained data, including Linear Polarization Resistance (LPR) corrosion measurements and field-based NDT readings. This approach enabled the simulated modalities to closely match the real-time field data, providing a reliable multimodal data set for training the proposed NGTFNet model for corrosion rate prediction.

3.2 Feature extraction using CNN

Each modality is passed through a CNN to extract high-dimensional feature representations:

$$F_m = CNN(I_m),\ m \in \{\text{Opt}, \text{Ultra}, \text{Therm}\}, \tag{2}$$

where $F_{\text{Opt}}, F_{\text{Ultra}}, F_{\text{Therm}}$ represent feature vectors from respective modalities.

The CNN architecture shown in Fig. 2 comprises three convolutional layers, each followed by Rectified Linear Unit (ReLU) activation and max-pooling operations to progressively capture corrosion-related spatial hierarchies. The first convolutional layer (Conv1) extracts low-level surface features such as rust color and texture gradients. The second layer (Conv2) identifies fine cracks and corrosion pits, while the third layer (Conv3) focuses on deep texture irregularities and non-uniform corrosion spread. Following the convolutional stages, the extracted feature maps are flattened and passed through a fully connected dense layer that produces a 64-dimensional embedding vector. This embedding encodes the essential corrosion-related attributes and serves as the node descriptor in the Graph Construction module of the NGTFNet. ReLU activations after each convolution and dense layer introduce nonlinearity, while max-pooling minimizes spatial redundancy and computational load.

The CNN design was intentionally kept lightweight to align with the limited data set size (~1500 samples) and to mitigate overfitting risks commonly associated with deeper architectures such as ResNet-50 or VGGNet. Despite its compactness, the network demonstrated strong capability in capturing critical corrosion indicators, including color variations, crack propagation, and surface roughness.

Finally, the feature embeddings from all three modalities were concatenated and normalized to form the fused multimodal feature representation, which was subsequently utilized in the graph construction phase of the NGTFNet framework, as shown in Table 2.

3.3 Graph construction

The extracted multimodal features are employed to construct a heterogeneous graph, denoted as $G = (V,E,A)$, which effectively represents both the spatial and cross-modal relationships among the image regions.

Each node (V) corresponds to a region of interest (ROI) or feature embedding derived from optical, thermal, and ultrasound modalities, encapsulating localized corrosion-related information.

Edges (E) define the connectivity between nodes based

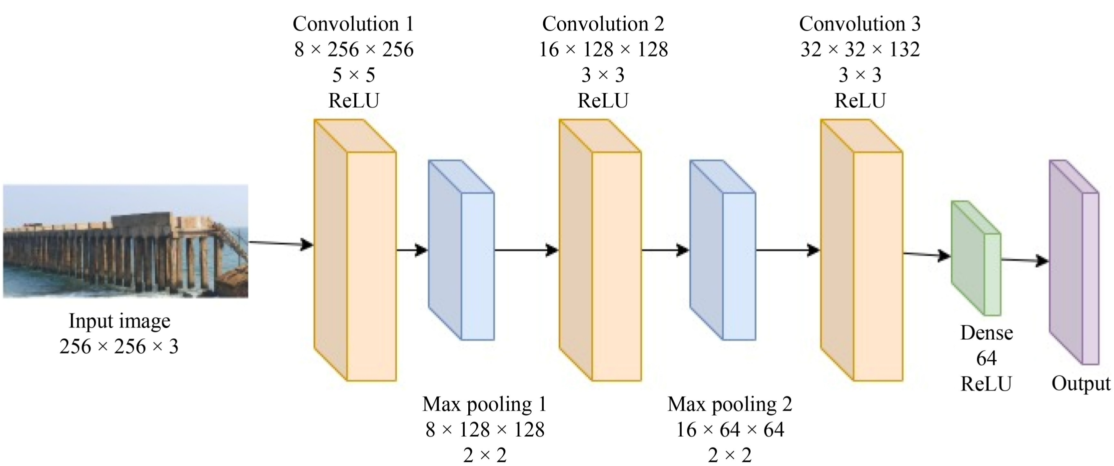


Fig. 2 CNN architecture for NGTFNet.

Table 2 CNN layer configuration for NGTFNet feature extraction

Depth (Count)	Height (pixels)	Width (pixels)	Filter size	Operation	Activation	Description
3	256	256	–	Input image	–	Red-Green-Blue image of RC surface (corrosion patch), normalized between 0 and 1
8	256	256	5 × 5	Convolution (Conv1)	ReLU	extracts low-level corrosion features such as rust color and texture
8	128	128	2 × 2	Max-Pooling (Pool1)	–	reduces spatial dimensions and minimizes noise
16	128	128	3 × 3	Convolution (Conv2)	ReLU	detects fine cracks and localized corrosion pits
16	64	64	2 × 2	Max-Pooling (Pool2)	–	down samples feature maps while preserving key patterns
32	32	32	3 × 3	Convolution (Conv3)	ReLU	captures deeper corrosion gradients and high-level spatial cues
64	1	1	–	Dense (Fully Connected)	ReLU	converts flattened feature maps into compact embedding
–	–	–	–	Output feature vector (64-D)	–	passed to the Graph Construction module in NGTFNet for node creation

on either spatial adjacency or feature similarity, thereby allowing the integration of complementary information across modalities.

The adjacency matrix ($A \in R^{n \times n}$) quantifies the pairwise similarity between node and is defined as

$$A_{ij} = sim(F_i, F_j), \tag{3}$$

where F_i, F_j denote the feature vectors of nodes i and j, respectively, and $sim\ (\cdot)$ denotes the similarity function. In this study, similarity is computed using either cosine similarity or a Gaussian radial basis function kernel, expressed as

$$sim(F_i, F_j) = \begin{cases} \dfrac{F_i.F_j}{\|F_i\| \|F_j\|}, & \text{(Cosine Similrity)}, \\ \exp\left(-\dfrac{\|F_i - F_j\|^2}{2\sigma^2}\right), & \text{(Gaussian Kernel)}. \end{cases} \tag{4}$$

This similarity-based graph representation enables NGTFNet to capture non-local spatial dependencies and inter-modal feature correlations. Consequently, the model learns a unified and robust representation, enhancing the accuracy of corrosion rate prediction in RC structures exposed to marine environments

3.4 Temporal fusion with NGTFNet

Since corrosion progresses over time, NGTFNet fuses spatial and temporal information.

1) GNN learns structural relationships from the graph.

2) Temporal Fusion Network (TFN) integrates sequential corrosion patterns across monitoring intervals.

The fused representation is

$$H_t = NGTFNet(F_{\text{Opt,}} F_{\text{Ultra}}, F_{\text{Therm}}, A, t), \tag{5}$$

where H_t is the latent fused feature at time t.

3.5 Corrosion rate prediction

Finally, the fused representation was mapped to the corrosion rate (mm/year) using a regression layer

$$\widehat{y_t} = WH_t + b, \tag{6}$$

where $\widehat{y_t}$ is the predicted corrosion rate at time t, W and b are learnable parameters.

The multimodal features from optical, thermal, and ultrasound images are used to build a heterogeneous graph, where nodes represent feature regions and edges represent their similarities. The Temporal Fusion Transformer module captures time-based changes in corrosion patterns. Finally, fused spatial and temporal features were used to predict the corrosion rate of RC structures exposed to marine environments.

3.6 Algorithm: NGTFNet-based corrosion rate prediction

The flowchart illustrates the algorithmic workflow of the NGTFNet designed for corrosion rate prediction using multimodal imaging data. The process integrates spatial, temporal, and cross-modal features from optical, thermal, and ultrasonic modalities.

Step 1: Start process.

The algorithm begins with initializing model parameters and setting the monitoring time steps for corrosion analysis.

Step 2: Multimodal image data acquisition.

Three types of input images such as optical, thermal, and ultrasonic are acquired or simulated to represent surface-level, thermal, and subsurface characteristics of RC structures exposed to marine environments.

Step 3: Image pre-processing.

Each image is pre-processed through normalization, noise reduction, and alignment to ensure that all modalities are spatially and radiometrically consistent. This step enhances data quality and reduces redundancy.

Step 4: Multimodal data fusion.

The pre-processed images are fused using weighted or attention-based fusion techniques. This integration enhances the representation of corrosion-induced features by combining complementary information from different modalities into a unified feature space.

Step 5: CNN-based feature extraction.

A CNN extracts high-dimensional spatial features from the fused image. These features encode patterns related to crack propagation, rust formation, and material degradation within the RC structure.

Step 6: Graph construction.

A heterogeneous graph is constructed where nodes represent feature regions (ROIs), and edges represent spatial or similarity-based correlations among features. The adjacency matrix quantifies pairwise relationships, enabling the model to capture non-local dependencies across modalities.

Step 7: Temporal feature extraction.

Temporal features are extracted using the NGTFNet. This module fuses spatial graph features across multiple time steps to learn corrosion evolution patterns, effectively capturing spatio-temporal dependencies.

Step 8: Iterative update.

The process iterates for each time step t. If $t < T - 1$, the system updates the input graph with new temporal data and continues feature fusion until the final monitoring step.

Step 9: Corrosion rate prediction.

Once the final time step is reached ($t = T - 1$), the fused features are passed through a regression layer to predict the corrosion rate in mm/year. The model also provides a severity mapping for localized degradation assessment.

Step 10: End process.

The process terminates after outputting the predicted corrosion rate and severity level for the structure.

Figure 3 illustrates the algorithmic workflow of the proposed NGTFNet for predicting the corrosion rate of RC structures exposed to marine environments.

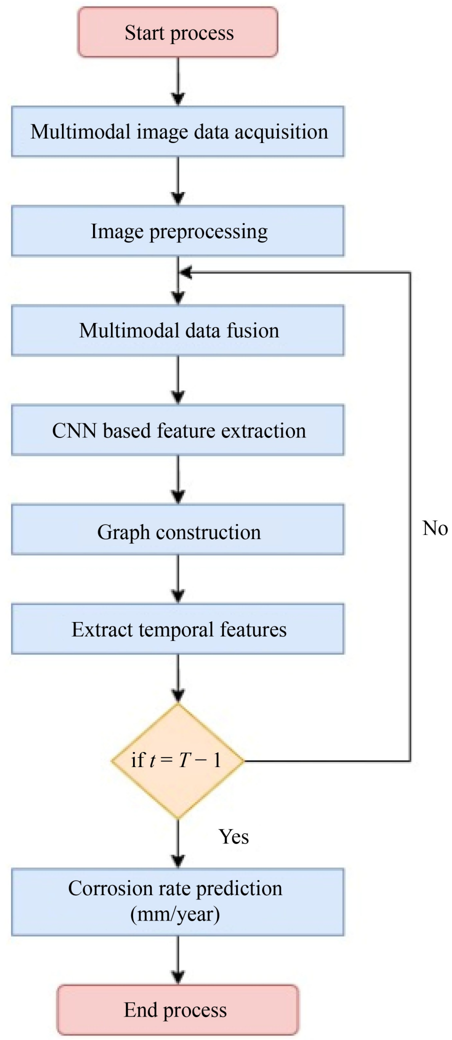


Fig. 3 Algorithmic workflow for NGTFNet-based corrosion rate prediction.

4 Results and discussion

The proposed NGTFNet-based corrosion detection system for RC structures is a combined hardware and software model. It includes sensors that monitor and transmit data such as humidity, temperature, moisture, and salinity, along with three types of images: thermal, ultrasonic, and optical of the RC structures. A Jupiter notebook was used for the simulation. The received images were processed, and NGTFNet was implemented using a Python simulation tool. The NGTFNet model was trained using a data set that was specifically created for this study. The data set employed in this study was compiled from a combination of field-acquired and simulated multimodal images representing the corrosion progression of RC structures located along the south-east coastal region of India. Data were collected from 12 distinct RC structures, including eight bridge piers, three jetty platforms, and one retaining wall, all of which were exposed to marine environments characterized by varying chloride concentrations and humidity levels. Each structure was monitored for 18 months, covering approximately ten corrosion exposure cycles, each lasting 60 d. Multimodal data acquisition was conducted at the end of each cycle using optical imaging, infrared thermography, and ultrasonic pulse-echo techniques. This acquisition frequency ensured an adequate temporal resolution to capture both the initiation and propagation phases of corrosion. The final data set comprised 1500 labeled multimodal image samples, categorized as follows: 500 optical images (RGB, 256 × 256 pixels), 500 thermal images (8-bit grayscale, 256 × 256 pixels), and 500 ultrasonic intensity maps (grayscale, 256 × 256 pixels). Of these, 1200 samples (80%) were used for model training, and the remaining 300 samples (20%) were reserved for validation and testing. The data set spans a total duration of 1.5 years, enabling the NGTFNet model to effectively learn both short-term degradation patterns and long-term corrosion dynamics. The accuracy of the NGTFNet model in detecting corrosion in RC structures was evaluated using a sample input image, and the results are presented in Tables 3 and 4.

From the accuracy analysis performed in Table 2, a sample of 7 images was fed to the proposed system, and the employed Softmax function produced a binary output of corrosion rate. A Sample of seven images was fed into the proposed system, which detected the corrosion status to the maximum level of accuracy. The term accuracy in detecting corrosion in RC structures in the marine environment is commonly referred to as the correctly identified cases (corrosion present and absent), with respect to the total number of evaluations performed by the model. Accuracy is the critical performance metric for the corrosion detection model, and it relies on four factors, namely, True Positive (TP), which is the correct detection of corrosion. The True Negative (TN) occurs when the non-corrosion status is identified correctly. The alternate parameters are the False Positive (FP) and False Negatives (FN), which mistakenly determine non-corrosion as corrosion, and corrosion mistakenly detected as no corrosion. The mathematical background used to determine the accuracy of the proposed model using these

Table 3 Accuracy analysis of the proposed NGTFNet with sample input images

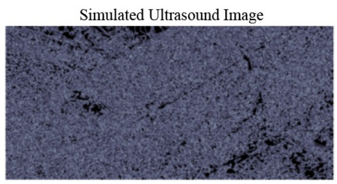
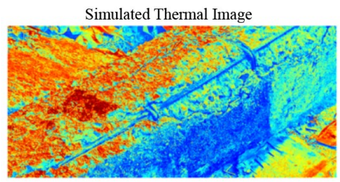
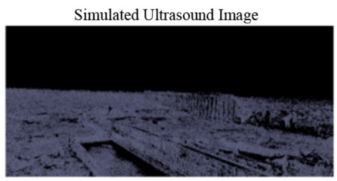
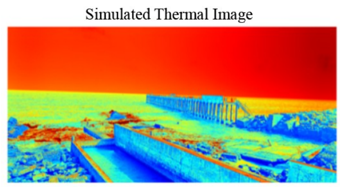
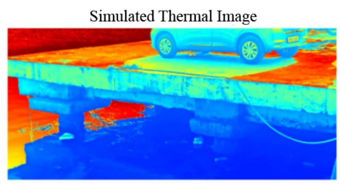
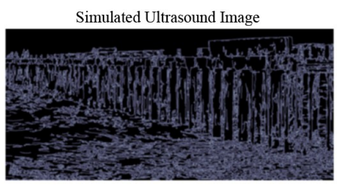
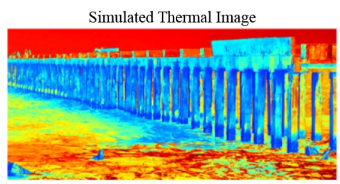
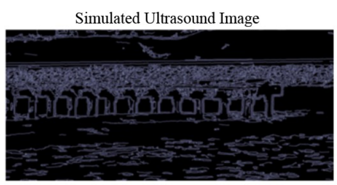
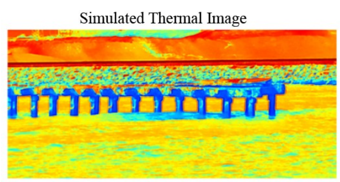
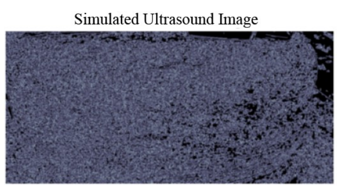
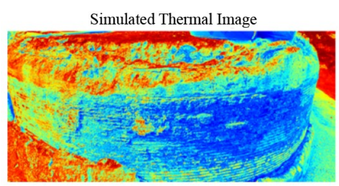
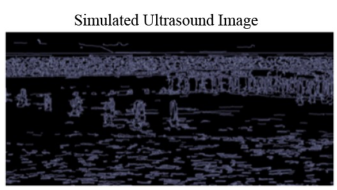
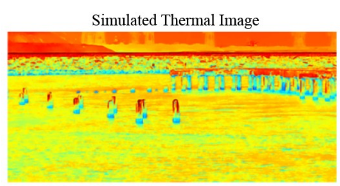
Serial No.	Optical image	Ultrasound image	Thermal image
1			
2			
3			
4			
5			
6			
7			

Table 4 Predicted corrosion rate

Serial No.	Exposure zone (condition)	Corrosion rate (mm/year)
1	Splash/Tidal zone pier column	0.35
2	Marine atmospheric (beam above splash)	0.20
3	Submerged footing/pile	0.12
4	Coastal atmospheric (deck element)	0.08
5	Jetty piles (splash zone)	0.30
6	Exposed reinforcement (spalled cover)	0.45
7	Pile group (tidal/submerged)	0.18

four factors is defined by Eq. (7).

$$Accu_y = \frac{TP+TN}{TP+TN+FP+FN}. \quad (7)$$

In the marine environment, the factors influencing the accuracy of the proposed model are the high salinity, humidity, surface degradation, and noise in the environment. Consequently, to determine the accuracy, the other supporting parameters that determine the efficiency of the proposed model are the precision. Precision in the context of detecting corrosion in RC structures in marine environments refers to the proportion of correctly identified corrosion instances (TPs) among all instances predicted as corrosion (TPs + FPs). It measures the accuracy of positive predictions. The mathematical expression for determining precision is represented by Eq. (8).

$$Prec_n = \frac{TP}{TP+FP}. \quad (8)$$

The high precision value indicates that low rate of FPs, which means that the model is reliable when predicting corrosion in the RC structure. In turn, the low precision value suggests that the model misidentifies frequently with false detections, namely non-corroded as corroded or vice versa.

The term recall in the context of detecting corrosion in RC structures in a marine environment is a performance metric that evaluates how effectively the detection model identifies all actual instances of corrosion. It is also known as the True Positive Rate or Sensitivity. Recall measures the proportion of true corrosion cases that are correctly identified by the model out of all actual corrosion cases present in the data set. The mathematical expression for the recall is presented in Eq. (9).

$$Reca_l = \frac{TP}{TP+FN}. \quad (9)$$

In the proposed model, recall reflects the percentage of corroded regions (as annotated in the ground truth) that were successfully identified by the detection system. Finally, the $F1$ score is a vital parameter and a key evaluation metric used in classification problems, especially in contexts such as detecting corrosion in RC structures in marine environments. It balances precision and recall to provide a single performance metric. The mathematical expression for determining the recall is presented in Eq. (10).

$$F1 = 2 \times \frac{Prec_n \times Reca_l}{Prec_n + Reca_l}. \quad (10)$$

The $F1$ Score is the harmonic mean of precision and recall, ensuring a balance between the two metrics. An $F1$ score close to 1 indicates excellent model performance, while a score closer to 0 indicates poor performance. The observed values of the accuracy, precision, recall, and $F1$ score of the proposed model and the state-of-the-art methodologies are listed in Table 5.

The same multimodal data set was employed to re-implement the baseline methods [39–44] to enable a fair comparative analysis. The comparative analysis of the proposed method exhibited 92.16% accuracy, 91.48% precision, 91.15% recall, and 91.31% $F1$ score. The performance exhibited by the proposed work stands superior to the performance of the state of art methods with 83% accuracy, 81% precision, 78% recall and 81% $F1$ score [39]; 85.71% accuracy, 80.15% precision, 81.24% recall and 80.69% $F1$ score [40]; 88.21% accuracy, 86.15% precision, 85.97% recall and 86.05% of $F1$ score [41]. The same multimodal data set was reimplemented for the baseline methods [39–44] for comparative analysis. The graphical representation of the performance of the proposed method is shown in Fig. 4.

The proposed NGTFNet model exhibits a better level of accuracy when compared with other state-of-the-art methodologies, owing to its potential to integrate the processing of multi-modal images. The fusion of images enables the proposed NGTFNet model to access complementary information from various modalities of input images, enhancing the distinguishing ability of the model. Additionally, the graph-based representation of the models, along with the spatial and structural relationships among the RC structures, enables the model to provide a deeper understanding of the interconnected features. Therefore, the proposed model was classified at a higher rate of accuracy and with minimal misclassi-

Table 5 Performance comparison-proposed model vs state-of-the-art of art methodologies

Method	Accuracy	Precision	Recall	*F*1
Putranto et al. [39] (DL-SVM)	83%	81%	78%	81%
Abubakr et al. [40] (DL-DT)	85.71%	80.15%	81.24%	80.69%
Yeganehfallah et al. [41] (DL-Based Predictive Assessment of Early Deterioration)	88.21%	86.15%	85.97%	86.05%
Mukhti et al. [42] (AI-CNN)	84%	72%	71%	73%
Xin et al. [43] (ML-X Ray)	81.02%	79.18%	80.56%	79.86%
Murthy et al. [44] (ML-LGBM)	82.16%	81.57%	80.49%	81.02%
Proposed model (NGTFNet)	92.16%	91.48%	91.15%	91.31%

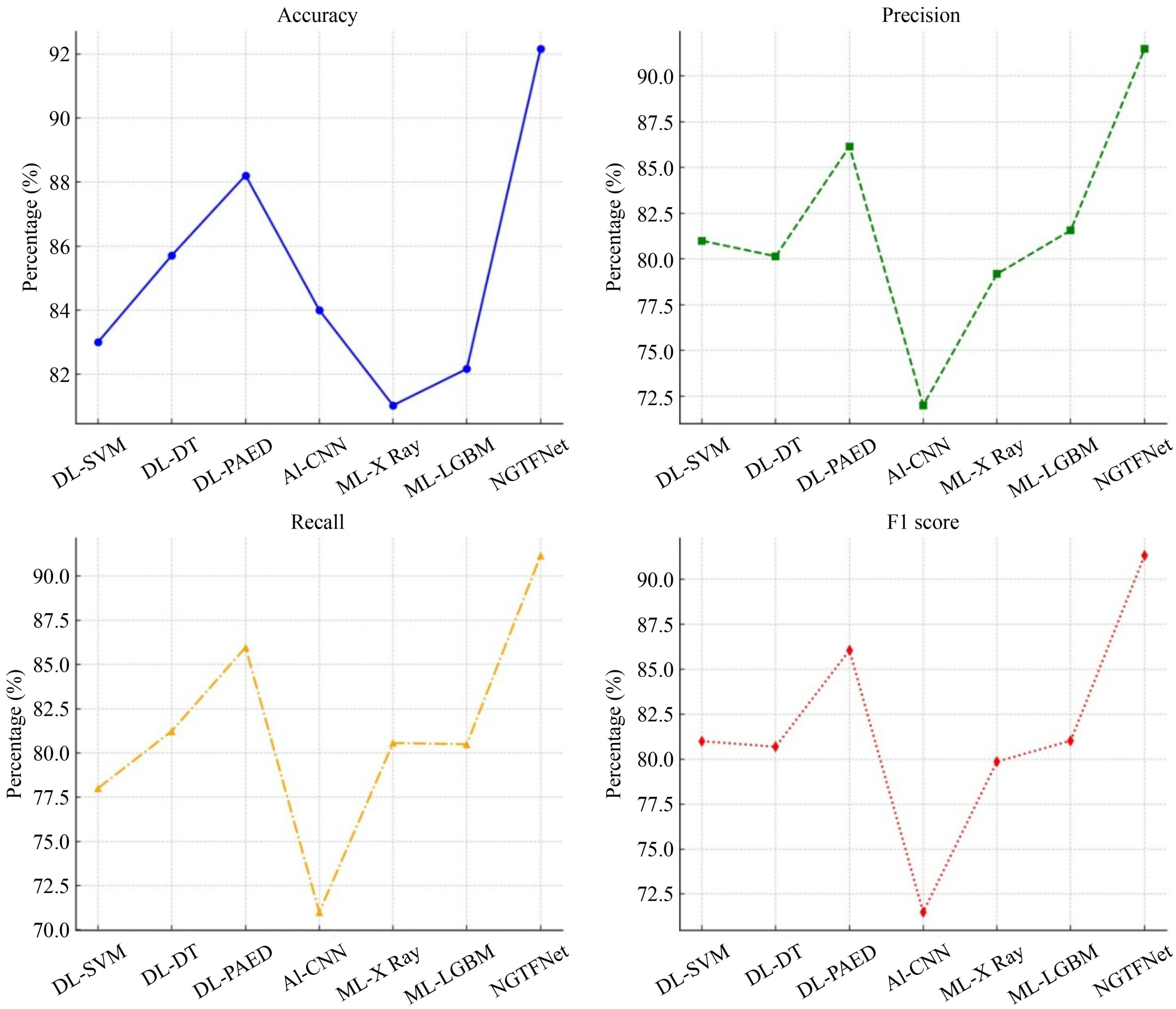


Fig. 4 Performance comparison of the proposed model in corrosion detection.

fication, thus producing 92.16% of accuracy. Similarly, the precision and the recall of the proposed NGTFNet model in detecting corrosion in RC structures in the marine environment are superior when compared with the existing methodologies. This is due to the employment of an attention mechanism in the spatial and temporal attention process. This mechanism assists the proposed model in reducing the false positive prediction, thus enhancing the precision to 91.48% and the recall to 91.15%. Finally, the better precision and recall of the proposed method enhance the *F*1 score by offering a proper, balanced performance between the precision and recall. This minimizes the FP and FN predictions through the attention mechanism in spatial and temporal relationships.

The computational efficiency of the NGTFNet model, when processing large-scale real-time data, can be better understood by comparing it with the existing approaches. Methods such as DL-SVM and DL-DT offer acceptable accuracy on static data sets but face significant computational overhead when retraining is required for evolving data streams, making them less efficient for real-time monitoring. Ensemble-based techniques such as DL-PAED improve robustness through probabilistic detection but increase computational complexity as the ensemble size increases. Similarly, AI-CNN approaches perform well in extracting spatial features from corrosion imagery but lack efficient temporal modeling, which reduces their scalability under continuous data inflow. Machine learning strategies using X-ray data (ML-X Ray) provide valuable insights into internal defects but are not computationally feasible for large-scale real-time deployment, while ML-LGBM offers higher computational efficiency in tabular data sets but struggles with multimodal and spatiotemporal dependencies. In contrast, the proposed NGTFNet achieves a balance by combining CNN-based multimodal compression, graph-based spatial correlation, and attention-driven temporal fusion. Although graph construction and attention mechanisms demand higher computational resources, optimization strategies such as Graphics Processing Unit acceleration, sparse graph sampling, and quantization allow NGTFNet to sustain near real-time inference. This makes NGTFNet computationally more efficient and scalable for large-scale monitoring than traditional models, while ensuring superior predictive stability under dynamic environmental conditions. Table 6 lists the computational efficiency of the models used in this study.

Static models such as SVM demonstrate high accuracy on fixed data sets but require frequent retraining when environmental conditions evolve, limiting their long-term adaptability. Similarly, Decision Trees offer interpretability but are prone to overfitting and perform poorly under data drift, while Random Forests improve generalization yet still demand periodic updates to remain stable over extended monitoring periods. CNN-based approaches are effective at extracting features from corrosion imagery, however their lack of explicit temporal modeling reduces predictive stability when conditions change over time. Machine learning techniques applied with X-ray data provide insights into internal deterioration but are not scalable for continuous real-time monitoring, and boosting-based methods such as LGBM handle tabular data sets efficiently but fail to capture complex spatiotemporal dependencies inherent in corrosion processes. In contrast, the NGTFNet model integrates multimodal feature extraction with graph-based spatial correlation and attention-driven temporal fusion, allowing it to adapt dynamically to evolving environmental conditions and degradation patterns. This enables NGTFNet to maintain stable long-term predictive performance, addressing the limitations of static models and making it highly suitable for real-time corrosion monitoring of RC structures.

5 Case study

From the accuracy analysis performed in Table 7, a sample location in India is considered as a case study, namely, the Sea Bridge located in Muttukadu, Indira Gandhi Road Bridge, Pamban, Cuddalore O.T Harbour Structures, Atal Sethu Sea Bridge, Navi Mumbai, and Pamban New Vertical Lift Bridge were fed into the proposed system. The employed softmax function produces a binary output of “Corrosion Rate”.

The accuracy of the proposed NGTFNet model was analyzed using real-time case images to assess corrosion rates of various structures in India. The findings highlight the condition of several critical infrastructures, as outlined below.

Overall, the ability of NGTFNet’s to evaluate corrosion and predict future performance significantly emphasizes the importance of regular maintenance and monitoring of aging infrastructures. The diverse outcomes across different structures highlight that while some are relatively stable, others may soon require urgent intervention to prevent catastrophic failures. This analysis emphasizes the need for robust maintenance and monitoring practices for aging infrastructure.

Corrosion rate prediction, expressed in mm/year, provides a quantitative understanding of the degradation

Table 6 Computational efficiency of the models

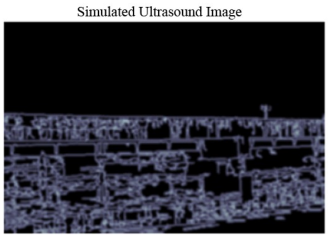
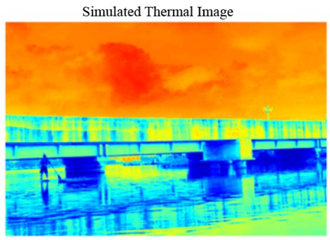
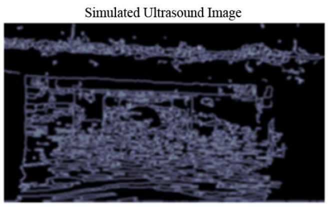
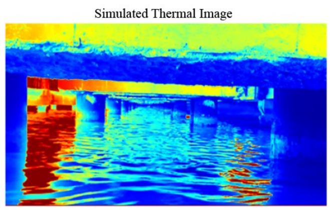
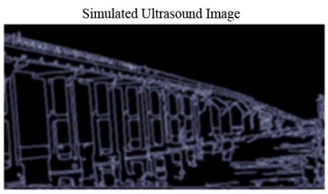
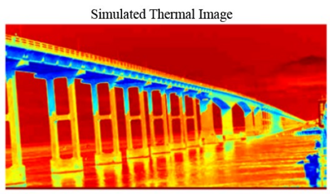
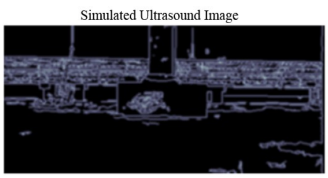
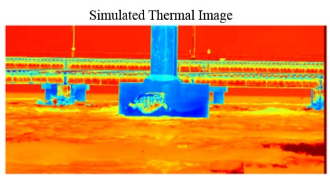
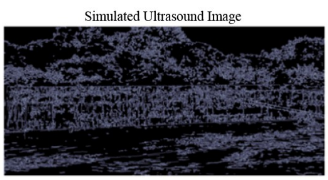
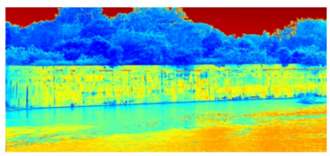
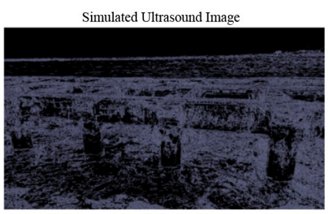
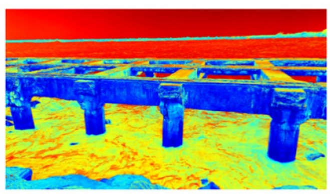
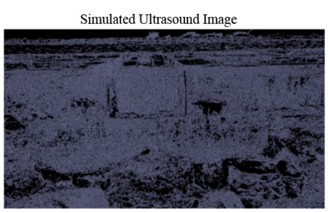
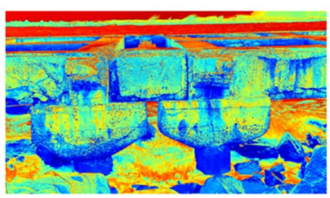
Model	Computational efficiency	Limitations for real-time use
DL-SVM	good accuracy on static data sets; moderate computational load for small data sets	requires frequent retraining for evolving data, increasing computational overhead
DL-DT	simple and interpretable; low initial computational cost	prone to overfitting; retraining with new data reduces efficiency
DL-PAED	robust through EL; captures uncertainty	computationally expensive as the ensemble size grows; slow for large-scale, continuous monitoring
AI-CNN	strong feature extraction from images; efficient on medium data sets	lacks explicit temporal modeling; reduced scalability for long sequences
ML-X Ray	effective for internal defect detection; moderate efficiency in controlled laboratory-scale settings	not scalable or computationally feasible for continuous large-scale field monitoring
ML-LGBM	highly efficient on tabular data; fast inference and low memory usage	cannot fully capture multimodal or spatiotemporal dependencies; limited adaptability to evolving data
NGTFNet	integrates multimodal compression (CNN), spatial correlation (GNN), and temporal fusion (attention); scalable with optimization	higher computational demand in graph construction and attention; mitigated by GPU, sparse sampling, and quantization

process in RC structures [45]. The calculated ranges (< 0.00116 mm/year to > 2.32 mm/year) align with internationally recognized guidelines such as ISO 9223 [46] and ASTM G1 [47], which classify corrosion intensity from negligible to critical. Based on the summary data provided from the analysis of corrosion rates, a risk map can be organized into categories. Table 8 presents the proposed risk map.

1) Integration of NGTFNet in corrosion prediction

The integration of NGTFNet into corrosion studies substantially enhances the accuracy of the corrosion rate prediction and risk mapping compared with conventional electrochemical methods. While laboratory-based techniques such as LPR and Tafel plots provide point-based

Table 7 Multi-modal images and predicted corrosion rate of Indian coastal line structures

Optical image	Ultrasound image	Thermal image	Predicted corrosionrate (mm/year)
			0.15
			0.38
			0.28
			0.070
			0.023
			0.006
			0.05

(*Continued*)

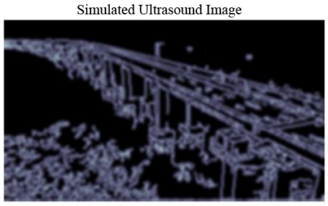
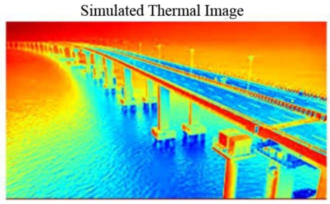
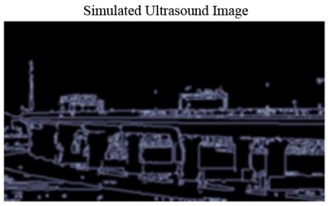
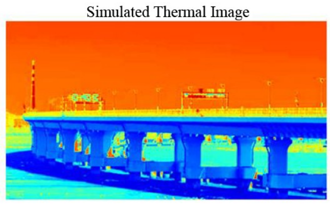
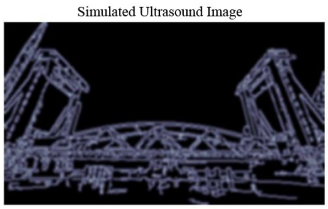
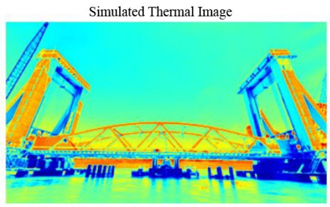
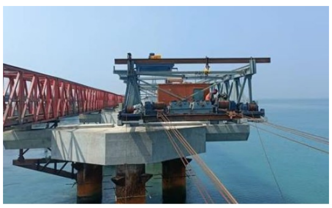
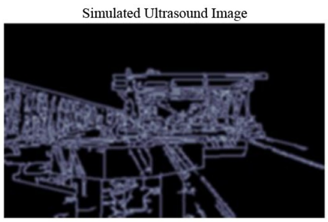
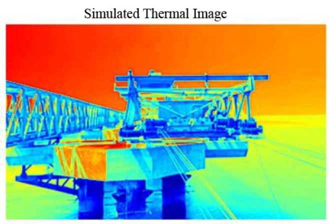
Optical image	Ultrasound image	Thermal image	Predicted corrosionrate (mm/year)
			0.02
			0.006
			0.03
			0.04

Table 8 Risk mapping based on corrosion rate

Serial No.	Corrosion rate (mm/year)	Risk level	Suggested remedial measures
1	< 0.00116	passive/negligible	normal monitoring, no intervention needed
2	0.00116–0.0058	very low	surface coating/sealants
3	0.0058–0.0116	low	periodic monitoring, apply inhibitors if required
4	0.0116–0.0232	moderate	local patch repair, crack sealing
5	0.0232–0.058	moderate–high	cathodic protection (incipient), protective coatings
6	0.058–0.116	high	electrochemical realkalization, surface treatments
7	0.116–0.232	severe	cathodic protection, corrosion inhibitors, and concrete repair
8	0.232–0.58	very severe	electrochemical chloride extraction, extensive patch repair
9	0.58–1.16	critical	full-scale cathodic protection, rehabilitation
10	1.16–2.32	extremely critical	major strengthening, section replacement
11	> 2.32	failure stage	demolition/reconstruction

measurements, NGTFNet captures both surface and subsurface deterioration signatures through multimodal inputs combining optical, thermal, and ultrasonic imaging with time–series laboratory data. This enabled the model to detect early signs of depassivation in the passive zone (< 0.00116 mm/year), predict accelerating corrosion in the moderate zone (0.0116–0.232 mm/year), and spatially highlight severe clusters in the critical zone (> 0.232 mm/year).

The graph-based architecture of NGTFNet further supports dynamic risk mapping by representing the environmental and electrochemical parameters (including chloride concentration, pH, corrosion current density, humidity, and temperature) as nodes, with their interdependencies captured as edges derived from the correlation measures. By embedding risk classification into the output layer, the predicted corrosion rates were translated into actionable categories ranging from negligible to critical, enabling automated alerts, maintenance scheduling, and cost–benefit optimization. This approach bridges the gap between laboratory observations and real-world performance, supporting localized, risk-prioritized rehabilitation strategies and promoting structural sustainability and extended service life.

2) Cost-effectiveness and practical implications

Compared with traditional corrosion monitoring methods, NGTFNet offers long-term cost advantages. Laboratory tests and field inspections require specialized equipment, repeated sampling, and skilled personnel, which increase lifecycle costs. Emergency repairs arising from late detection exacerbate expenses. By predicting future corrosion trends, NGTFNet allows interventions to be scheduled at optimal times, reducing maintenance costs and extending the service life of structures. Although initial investments in data acquisition, computational infrastructure, and model training may be high, they are offset by reduced emergency repairs, optimized resource allocation, and an extended structural lifespan.

The model's predictive capability, holistic integration of diverse data sources, and risk-based outputs enable preventive maintenance and enhance decision-making. The graph-based architecture facilitates the mapping of interdependencies among critical parameters, thereby providing a scientific basis for targeted interventions. By classifying the corrosion severity directly into risk categories, NGTFNet generates interpretable outputs for engineers and asset managers, thereby improving structural reliability, sustainability, and lifecycle cost optimization.

3) Limitations and implementation challenges

Despite its advantages, NGTFNet has several limitations. The model requires large, high-quality multimodal data sets for training, which may not be readily available for all structures or exposure environments. Data acquisition via thermal or ultrasonic imaging can be expensive and technically challenging under field conditions. NGTFNet is computationally demanding and necessitates advanced hardware, skilled operators, and robust validation protocols. Furthermore, the black-box nature of DL models complicates interpretability, potentially hindering adoption by practitioners who require transparent justification for maintenance decisions.

Challenges that extend beyond technical considerations. The standardization of input features and graph construction across laboratories and field sites remains unresolved, limiting the transferability of the trained models. Environmental variability, including fluctuations in temperature, humidity, and chloride exposure, adds further complexity to predictions. Integration with existing infrastructure management systems may be difficult because organizations may be reluctant to replace established methods with AI-driven frameworks. Finally, convincing policymakers and industry stakeholders to adopt NGTFNet remains a challenge, particularly when issues of interpretability and transparency persist.

6 Conclusions

Corrosion of RC structures exposed to marine environments poses a significant threat to structural integrity, public safety, and maintenance costs. Early detection of corrosion is critical; however, existing methodologies often struggle to identify corrosion during its initial stage. To address this challenge, the present study proposes an NGTFNet model that integrates GNNs with TFN to capture both spatial and temporal relationships among multi-modal images. The model processes diverse data types, including thermal, ultrasonic, and optical images, along with environmental parameters such as chloride diffusion, humidity, and temperature. Unlike traditional approaches, which rarely integrate such heterogeneous data, NGTFNet leverages multi-modal data fusion and graph-based learning to enhance corrosion detection accuracy.

The proposed model demonstrated superior performance with an accuracy of 92.16%, precision of 91.48%, recall of 91.15%, and $F1$ score of 91.31%. Its high predictive performance enables timely insights into corrosion risks, supports proactive maintenance, and potentially reduces repair costs. By facilitating continuous monitoring and reducing the need for frequent manual inspections, NGTFNet contributes to extending the lifespan of RC structures while optimizing maintenance resources. The model's integration with simulation platforms such as MATLAB and Python further validates its technical viability and comparability with state-of-the-art methods.

Despite these advances, some limitations remain. The model relies heavily on historical and real-time environmental data, which may restrict its applicability in scenarios with limited or non-representative data. The dynamic nature of marine environments, with variable chloride concentrations and humidity levels, may further affect the predictive accuracy. Additionally, while NGTFNet exhibits high recall, some trade-offs in precision suggest occasional misclassification of non-corroded elements, highlighting areas for improvement.

In future research, advanced imaging techniques and sensors will be explored to provide higher-resolution and more detailed assessments of RC structural integrity. Real-time integration of NGTFNet with IoT sensors is expected to enable the continuous monitoring of environmental and electrochemical parameters. The expansion and standardization of large-scale multi-modal data sets will enhance model generalization across diverse field conditions, while benchmarking against publicly available data sets will improve reproducibility and comparability. Research in explainable AI will be pursued to address the black-box nature of the model and build trust among practitioners. Hybrid approaches, combining NGTFNet with mechanistic corrosion models, are expected to enhance both predictive accuracy and interpretability. Furthermore, embedding NGTFNet outputs into Building Information Modelling and digital twin platforms will facilitate automated lifecycle management. Physical equations will also be incorporated into the framework to reduce data dependency, with AI-for-Partial Differential Equations techniques explored to further improve predictive capabilities and computational efficiency. Finally, economic optimization and sustainability impacts will be investigated to support practical adoption and cost-effective maintenance strategies.

Competing interests The authors declare that they have no competing interests.

References

1. Taffese W Z, Nigussie E. Autonomous corrosion assessment of reinforced concrete structures: Feasibility study. Sensors, 2020, 20(23): 6825
2. Morwal T, Bansal T, Azam A, Talakokula V, Jothi Saravanan T. Exploring chloride-induced corrosion in reinforced concrete structures through embedded piezo sensor technology: An experimental and numerical study. Smart Materials and Structures, 2024, 33(3): 035039
3. Habbaba N, Mustapha S, Lu Y. Early detection of corrosion in reinforced concrete using ultrasonic guided wave technique correlated with embedded fiber Bragg grating strain sensors. Ultrasonics, 2025, 154: 107701
4. Subbiah K, Lgaz H, Annamalai S, MinGu J, Lee H S, Park T J. A comprehensive study on PANI–MnO_2 solid-state reference electrodes for *in-situ* corrosion assessment in concrete infrastructure. Construction and Building Materials, 2025, 468: 140438
5. Karthikeyan A, Muthusamy S. Performance of zinc sacrificial anode in reinforced cement concrete members under chloride intrusion and marine environment exposure. Matéria, 2024, 29(4): e20240561
6. Selvaprasanth P, Malathy R. Revolutionizing structural health monitoring in marine environment with the Internet of Things: A comprehensive review. Innovative Infrastructure Solutions, 2025, 10(2): 62
7. Xiao T, Feng X, Qu Z, Lu X, Zhang J, Zhu R, Zhou Q, He A, Zhang H, Chen S. An array sensor for monitoring the chloride concentration profile in concrete. Construction and Building Materials, 2025, 478: 141419
8. Wong P T W, Lai W W L, Poon C S. Classification of concrete corrosion states by GPR with machine learning. Construction & Building Materials, 2023, 402: 132855
9. Cheng F, Chen J, Wei X. Thermal tracing method for surface spalling monitoring in underwater concrete structures. Construction and Building Materials, 2025, 489: 142445
10. Ren C, Li S, Zhang Y, Wei X, Wei Y, Li G. Durability of seawater and sea sand concrete (SSC)-filled BFRP-steel composite tube columns in simulated marine environment. Engineering Structures, 2025, 343: 121010
11. Chen B, Wang Y, Peng L, Zhao Y. Durability performance of a seawater fully recycled aggregate concrete (SFRAC) frame structure under four-year marine exposure. Engineering Structures, 2025, 343: 121132
12. Zhou X G, Hou C. Automated corrosion diagnosis of marine concrete-filled steel tubular structures using deep learning-based machine vision. Automation in Construction, 2025, 178: 106403
13. Padmapoorani P, Senthilkumar S. Application of machine learning for crack detection on concrete structures using CNN architecture. Matéria, 2023, 28(1): e20230010
14. Shi T, Luo H. Deep learning for automated detection and classification of crack severity level in concrete structures. Construction and Building Materials, 2025, 472: 140793
15. Wang S, Jiang S, Xu Q, Li P, Wang W. Prediction of underwater concrete compressive strength using deep ELM optimized by rime optimization algorithm. Measurement, 2026, 257: 118648
16. Wang W, Xing Q, Bao J, Xue S. Silicone lubricant-infused polydimethylsiloxane-based coating with enhanced stability for improving the durability of marine concrete. Construction and Building Materials, 2025, 482: 141707
17. Mohan A M A, Kaliappan S, Natrayan L, Maranan R. Smart self-healing concrete infused with nanomaterials for sustainable construction and real-time structural monitoring. Matéria, 2025, 30: e20240969
18. Guo H, Dong Y, Bastidas-Arteaga E. Mixed Bayesian network for reliability assessment of RC structures subjected to environmental actions. Structural Safety, 2024, 106: 102392
19. Guo H, Dong Y, Bastidas-Arteaga E, Lei X. Life-cycle performance prediction and interpretation for coastal and marine RC structures: An ensemble learning framework. Structural Safety, 2024, 110: 102496
20. Clerc R, El-Soueidy C P, Schoefs F. Evaluating the importance of spatial variability of corrosion initiation parameters for the risk-based maintenance of reinforced concrete marine structures. Structural Safety, 2025, 114: 102568
21. Yuan Y, Wang X, Yi T H, Long G, Zheng X, Wang J. Probabilistic corrosion initiation assessment of marine concrete bridge components via exposure tests and numerical simulations. Case Studies in Construction Materials, 2025, 22: e04533
22. Lei X, Guo H, Dong Y, Bastidas-Arteaga E. Life-cycle performance prediction and interpretation for coastal and marine prestressed concrete beams using active learning-enhanced Bayesian neural networks. Reliability Engineering and System

Safety, 2026, 265: 111557

23. Meletlioğlu E, Çomakli O. BN–TiO_2 multilayer coating on AZ91 for enhanced corrosion performance in marine environments. Matéria, 2024, 29(3): e20240374
24. Zeng L, Chen X, Huang P, Luo K, Zhang X, Zhou Z. Serving graph neural networks with distributed fog servers for smart IoT services. IEEE/ACM Transactions on Networking, 2024, 32(1): 550–565
25. Fei Y, Liao W, Lu X, Guan H. Knowledge-enhanced graph neural networks for construction material quantity estimation of reinforced concrete buildings. Computer-Aided Civil and Infrastructure Engineering, 2024, 39(4): 518–538
26. Jiang W, Han H, Zhang Y, Wang J, He M, Gu W, Mu J, Cheng X. Graph neural networks for routing optimization: Challenges and opportunities. Sustainability, 2024, 16(21): 9239
27. Tam P, Ros S, Song I, Kang S, Kim S. A survey of intelligent end-to-end networking solutions: Integrating graph neural networks and deep reinforcement learning approaches. Electronics, 2024, 13(5): 994
28. Govindaraju S, Basha G T M N A. Real-time concrete strength monitoring: An IoT-enabled framework integrating electrochemical and fiber optic sensors for structural integrity assessment. Matéria, 2025, 30: e20240784
29. Balasubramaniam P, Jayaprahasam S K, Yuvaraj S, Vijayakumar M. Smart IoT sensors revolutionize water quality: Predicting algae growth with advanced neural networks for making concrete. Matéria, 2024, 29(3): e20240344
30. Vázquez D, Duffó G. Monitoring reinforcement corrosion of concretes designed for nuclear facilities. Matéria, 2018, 23(2): e12047
31. Annamalaisamy Sannasiraj R D, Shi S, Liu X, Gryllias K, Vandepitte D, Chronopoulos D, Zhang L. A fully coupled depth-dependent corrosion model for reinforced concrete piles under marine environmental conditions. Construction and Building Materials, 2025, 472: 140795
32. Li Q, Lan J, Shen L, Yang J, Chen C, Jiang Z, Wang C. A state-of-the-art review on monitoring technology and characterization of reinforcement corrosion in concrete. Case Studies in Construction Materials, 2025, 22: e04780
33. Hwang W, Ann K Y. Bond failure of steel rebar corrosion in concrete with different degrees of steel. Structures, 2025, 80: 109727
34. Seechurn Y, Chuttoo L S. Corrosion of carbon steel in Mauritian water bodies. Matéria, 2022, 27(2): e13166
35. Sousa e Silva F C, Gomes do Nascimento C, Vaughan L L T, Cangue F J R. Gomes de Sousa J A Monitoring coated carbide tool wear via chip analysis in high-temperature machining. Matéria, 2025, 30: e20250114
36. Mullainathan S, Natarajan R. An SPSS and CNN modelling-based quality assessment using ceramic materials and membrane filtration techniques. Matéria, 2025, 30: e20240721
37. Jiang F, Hirohata M, Hamada A. Predicting deterioration in paint-coated steel due to defects using a generative adversarial network approach. Frontiers of Structural and Civil Engineering, 2025, 19(5): 837–848
38. Tran T V, Nguyen-Xuan H, Zhuang X. Investigation of crack segmentation and fast evaluation of crack propagation, based on deep learning. Frontiers of Structural and Civil Engineering, 2024, 18(4): 516–535
39. Putranto A, Lin T H, Huang B X. Deep learning-integrated electromagnetic imaging for evaluating reinforced concrete structures in water-contact scenarios. Automation in Construction, 2024, 164: 105459
40. Abubakr M, Rady M, Badran K, Mahfouz S Y. Application of deep learning in damage classification of reinforced concrete bridges. Ain Shams Engineering Journal, 2024, 15(1): 102297
41. Yeganehfallah A, Avizzano C A, Caprili S. Automated crack identification to ease maintenance of reinforced concrete bridges. Procedia Structural Integrity, 2024, 62: 201–208
42. Mukhti J A, Gucunski N, Kee S H. AI-assisted ultrasonic wave analysis for automated classification of steel corrosion-induced concrete damage. Automation in Construction, 2024, 167: 105704
43. Xin J, Akiyama M, Frangopol D M. Autonomous detection of steel corrosion spatial variability in reinforced concrete using X-ray technology and deep learning-based semantic segmentation. Automation in Construction, 2024, 158: 105252
44. Murthy Y I, Meena K B, Patel N. Machine learning for predicting the half-cell potential of cathodically protected reinforced cement concrete slabs subjected to chloride ingress. Engineering Applications of Artificial Intelligence, 2024, 137: 109090
45. Selvaprasanth P, Malathy R. Priyadharshini R. Machine Learning based corrosion prediction in reinforced concrete structures exposed to the marine environment. Journal of Structural Engineering, 2025, 52(2): 89–112
46. ISO 9223-2012. Corrosion of Metals and Alloys—Corrosivity of Atmospheres—Classification, Determination and Estimation. Geneva: International Organization for Standardization, 2012
47. ASTM G59-23. Standard Test Method for Conducting Potentiodynamic Polarization Resistance Measurements. West Conshohocken, PA: ASTM, 2023