

AN AI-ENABLED DIGITAL TWIN FRAMEWORK FOR REAL-TIME STRUCTURAL HEALTH MONITORING AND PREDICTIVE MAINTENANCE OF MODULAR REINFORCED CONCRETE STRUCTURES

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ABSTRACT

Increasing complexity and progressive deterioration of modular reinforced concrete structures demand intelligent methods for monitoring structural conditions and conducting necessary maintenance activities on time. An artificial intelligence-based Digital Twin method, incorporating IoT sensors, data acquisition in real-time, Artificial Intelligence, and predictive maintenance, is proposed as a solution for conducting an accurate structural condition assessment in the paper. Strain, vibration, displacement, crack width, temperature, humidity, and load are defined as primary monitoring parameters within the scope of the framework. Random Forest, Support Vector Machine, Artificial Neural Network, and Gradient Boosting machine learning algorithms were tested for the accuracy, precision, recall, and F1-score criteria. The results indicated that Gradient Boosting produced the best performance with the accuracy of 94.1%, precision – 93.6%, recall – 93.0%, and F1-score – 93.3%. The crack width, strain, and vibration were defined as the main influencing factors. Predictive maintenance algorithm provided above 90% of accuracy for all types of maintenance categories.

Keywords: Artificial Intelligence, Digital Twin, Structural Health Monitoring, Predictive Maintenance, Reinforced Concrete Structures

1. INTRODUCTION

The construction industry is progressively embracing technologies such as smart and digital ones to ensure that the safety and efficiency of the structural systems as well as their life-cycle management are improved. Through the use of AI, IoT, sensor technologies, and Digital Twin systems, one can take advantage of the new possibilities in terms of the real-time monitoring of structures and predictive

maintenance. This chapter presents an introduction to the background of the study, structural health monitoring and Digital Twin technology, application of AI in predictive maintenance, research problem, aims and objectives.

1.1 Background of the Study

The construction industry is experiencing major transformations in terms of implementation of modern technologies like Artificial Intelligence (AI), Internet of Things (IoT), Building Information Modelling (BIM), automation, and Digital Twin technology. Such technologies are being employed to optimize construction efficiency, management of infrastructure, and structural safety. A Digital Twin refers to a real-time virtual representation of a physical asset that is fed with sensor data and always reflects the current state of the real-world object. Thus, it becomes highly relevant for structural health monitoring and management of infrastructure. Reinforced concrete structures undergo a lot of loadings, thermal stresses, humidity, corrosion, cracking, vibrations, and ageing during the service life. The lack of early identification of these factors leads to deterioration of structure and maintenance costs. Modular construction has received much popularity due to such benefits as accelerated construction process, better quality control, and minimized material waste. Nevertheless, the long-term behavior of modular reinforced concrete elements and joints needs constant monitoring. The inspection techniques currently used involve mainly visual inspections that are carried out periodically and are unable to identify any potential problems with the structure at an early stage. Thus, intelligent monitoring techniques are required that will constantly gather structural data and analyze them. Implementation of AI in Digital Twin technology allows carrying out constant structural assessment, damage detection, and predictive maintenance. Accordingly, the current paper presents an AI-enabled Digital Twin approach for real-time structural health monitoring and predictive maintenance of modular reinforced concrete structures.

1.2 Structural Health Monitoring

In Structural Health Monitoring (SHM), the assessment of the health status and performance of the structure is done by continuous or periodic measurements of structural parameters. SHM systems incorporate sensors and measurement technology that allow for monitoring the behavior of the structure. These include parameters such as strain, vibration, displacement, acceleration, crack width, temperature, humidity, and load applied. The variations in these parameters might show deterioration in the structure or unusual structural behavior. Increased crack width, for instance, might show signs of material

deterioration, whereas changes in vibration properties might show reduced stiffness. But analysis of large datasets from the sensors may prove to be challenging.

1.3 Digital Twin Technology

Definition: A Digital Twin is an interactive simulation of the physical asset which is kept updated by live data. As for the structural engineering, sensors are placed on the physical asset to gather relevant data on the state of the structure and transfer it to the Digital Twin platform.

The key elements of the Digital Twin system are:

1. Physical structural asset;
2. Sensors and data gathering system;
3. Communication and data storage system;
4. Virtual structural model;
5. Artificial Intelligence and machine learning; and
6. Decision-making system.

This technology allows engineers to conduct analysis of the structural state not being totally dependent on physical inspection. Digital Twin can be used to simulate modular reinforced concrete structures including individual modules and connections.

1.4 Artificial Intelligence and Predictive Maintenance

AI allows computers to carry out activities associated with learning, prediction, classification, and pattern recognition. Machine learning techniques may analyze connections between structural parameters and various damage states in structural health monitoring. Predictive maintenance analyzes existing and past data to make future estimates regarding maintenance. Instead of having a structural failure occur, the system will diagnose potential issues and recommend maintenance.

This can be illustrated by the following:

Sensor Data → Data Processing → AI Analysis → Structural Condition Assessment → Damage
Prediction → Maintenance Recommendation

This approach can improve structural safety, reduce unexpected failures, and support efficient maintenance planning.

1.5 Problem Statement

Modular reinforced concrete constructions are subjected to different kinds of loads and environmental impacts, which may influence the behavior of these structures over time. Though the technique of periodic monitoring is widely used, it does not ensure continuous monitoring of the real status of structural elements. The methods of traditional maintenance are usually reactive, meaning that the maintenance is provided after the occurrence of any deterioration and issues.

Despite the use of such technologies as Digital Twin, sensor monitoring and artificial intelligence in engineering, there is still a demand for an integrated system, especially for the real-time monitoring and predictive maintenance of modular reinforced concrete structures. Thus, this paper provides an AI-enabled Digital Twin framework that is able to collect real-time structural data, detect anomalies, assess structural status and predict maintenance needs.

1.6 Aim of the Study

The main aim of the study is:

To develop an AI-enabled Digital Twin framework for real-time structural health monitoring and predictive maintenance of modular reinforced concrete structures.

1.7 Objectives of the Study

The Research Objectives of the Study are:

- To determine the essential parameters to be monitored for such buildings which include structural parameters and environmental parameters.
- To build an AI-based digital twin model that will represent the building and its current status.
- To use AI algorithms for the assessment of structural status and anomaly detection.
- To establish a predictive maintenance framework through structural monitoring.
- To analyze the performance of the proposed AI-based digital twin model.

1.8 Research Questions

1. Which parameters are key to the real-time monitoring of modular reinforced concrete structures?
2. In what ways can Digital Twin technology be combined with structural monitoring?
3. How efficient are AI algorithms in categorizing the structural condition?
4. Can an AI model predict future maintenance needs?
5. How would an AI-based Digital Twin help structural maintenance management?

2. REVIEW OF LITERATURE

Ojanperä & Vuori (2021) explored the application of Artificial Intelligence, digital platforms, and human intelligence in transforming contemporary businesses and organisations. This research highlighted the increasing use of AI platforms to assist in making data-driven decisions, automation of tasks and integration of human intelligence with technological capabilities. The authors considered the trends in which companies had been implementing platforms that integrated data and intelligent technologies to increase efficiency and generate new value. The study is related to the present research because of the need to integrate AI technologies in digital platforms. However, Ojanperä & Vuori have primarily focused on business and organisational practices rather than structural health monitoring and Digital Twin applications in infrastructure management.

Porter & Dennis (2020) conducted a literature review on the testing and evaluation of AI-enabled and autonomous systems. In particular, the study has considered approaches adopted by researchers to assess the performance, reliability and effectiveness of AI-based systems operating in complicated environments. The authors noted that traditional approaches were not always enough for evaluating AI-enabled systems since those could learn from data and act differently under various conditions. They have emphasised the significance of systematic testing, validation, performance assessment and reliability estimation of the systems. The study provides important theoretical foundations for the evaluation of AI-based structural monitoring systems because of the need to validate and assess the performance of AI models in detecting structural abnormalities.

Ravache & Sartor (2018) examined transformational strategies for implementing state-of-the-art approaches in high-performance and energy-efficient buildings in India. The authors focused on the use of technological and design innovations to enhance building performance and apply energy-efficiency measures. The authors highlighted the necessity to adopt innovative methods capable of improving the performance of buildings while satisfying certain requirements. The study is related to the present

research because it highlights the role of technological innovation in improving the performance monitoring of buildings.

Sharma et al. (2021) conducted a review of modern progress in the field of artificial intelligence-enabled smart electronics packaging for structural health monitoring purposes. The researchers studied the development of intelligent electronic systems and sensing technologies that could be used in structural health monitoring. It has been noted by the authors that AI and smart sensing systems were increasingly being used in order to collect and analyze structural information. The study shows that AI-enabled sensing technologies were providing possibilities for improved monitoring, damage detection, and condition assessment. Thus, the paper is relevant to the present research since it underlines the importance of using intelligent sensors along with the AI-based technology. However, the research did not develop an integrated approach for the Digital Twin system for predictive maintenance of modular reinforced concrete structures.

Van Dyck (2022) studied emergence, development, and governance of innovation ecosystems. The research described the process of technological innovation in terms of interaction of different organizations, technologies, stakeholders, and knowledge systems. It has been shown that successful technological innovation was determined not only by technologies themselves but also by their integration. This is relevant to the case of Digital Twin technology for structural health monitoring since this system should include integration of sensors, data platform, AI model, digital twin of the structure, and other stakeholders such as engineers and people responsible for making decisions about maintenance of the structure. However, the research was focused on innovation ecosystems in general.

3. RESEARCH METHODOLOGY

The methodology outlined a structured way of creating and analyzing the proposed framework of an AI-empowered Digital Twin. This involved aspects such as the research design, data collection, pre-processing, creation of Digital Twins, AI models, predictive maintenance, and performance analysis of models. Overall, the entire method was aimed at integrating real-time data of structures with intelligent structural assessment and maintenance.

3.1 Research Design

The study employed an experimental research methodology with a quantitative orientation. Quantitative methodology was appropriate to employ in the study because the study relied on structural and environmental parameters that were quantifiable. The experimental element involved the development and testing of machine learning models for condition classification and predictive maintenance.

3.2 Research Framework

The research followed the sequence:

Data Collection → Data Pre-processing → Feature Selection → Digital Twin Development → AI Model Training → Structural Condition Assessment → Predictive Maintenance → Performance Evaluation

This framework established a continuous connection between the physical modular structure and its digital representation.

3.3 Data Collection

Data on structure and environment were taken from sensing, experiments, simulations, and appropriate structural databases. The primary data types were strain, vibrations, displacements, crack widths, temperature, humidity, and load.

Table 1: Parameters Considered

Parameter	Purpose
Strain	Identifying stress-related changes
Vibration	Detecting abnormal structural behaviour
Displacement	Assessing deformation
Crack Width	Identifying structural deterioration
Temperature	Assessing thermal effects
Humidity	Evaluating environmental exposure
Load	Analysing structural response

3.4 Data Preprocessing

The collected data were cleaned before AI model development. Duplicate records and missing values were treated, measurement noise was reduced, outliers were examined, and relevant features were selected. Data normalization was also performed to place variables on a comparable scale.

The Min-Max normalization method was expressed as:

Here is the correctly formatted min-max normalization formula:

$$X' = \frac{X - X_{\min}}{X_{\max} - X_{\min}}$$

where X' is the normalized value.

3.5 Digital Twin Development

A Digital Twin was developed as a virtual representation of the modular reinforced concrete structure. It incorporated structural geometry, individual modules, connections, sensor locations, material information, and real-time monitoring data. New sensor information was used to update the virtual model and represent the current structural condition.

3.6 AI Model Development

Four machine learning algorithms were considered:

1. Random Forest;
2. Support Vector Machine;
3. Artificial Neural Network; and
4. Gradient Boosting.

The dataset was divided into 80% training data and 20% testing data. Structural parameters were used as input variables, while structural health condition was used as the output. The conditions were classified as Normal, Moderate Risk, High Risk, and Critical.

3.7 Predictive Maintenance

The predictive maintenance model used current and historical structural data to identify future maintenance requirements. The process followed:

Real-Time Data → AI Analysis → Risk Prediction → Maintenance Category → Recommendation

Maintenance requirements were classified as no immediate maintenance, routine inspection, preventive maintenance, or immediate intervention.

3.8 Performance Evaluation

The AI models were evaluated using accuracy, precision, recall, and F1-score.

$$\text{Precision} = \frac{TP}{TP + FP}$$

$$\text{Recall} = \frac{TP}{TP + FN}$$

$$F1 = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

These measures were used to compare the AI models and identify the most effective model for structural condition assessment and predictive maintenance.

4. DATA ANALYSIS AND INTERPRETATION

The data analysis focused on examining structural and environmental parameters, classifying structural health conditions, comparing the performance of selected AI models, identifying important structural features, and evaluating the predictive maintenance capability of the proposed framework. The analysis

was designed to determine whether the integration of Artificial Intelligence and Digital Twin technology could support accurate and timely structural condition assessment.

4.1 Descriptive Analysis of Structural Parameters

The initial analysis examined the descriptive characteristics of the selected structural and environmental parameters. The variables included strain, vibration, displacement, crack width, temperature, humidity, and load. These parameters were considered important indicators of structural behaviour and environmental exposure.

Table 2: Descriptive Statistics of Structural Monitoring Parameters

Parameter	Mean	Standard Deviation	Minimum	Maximum
Strain	0.48	0.16	0.12	0.89
Vibration	0.56	0.18	0.15	0.95
Displacement	0.42	0.14	0.10	0.82
Crack Width	0.38	0.17	0.05	0.88
Temperature	0.51	0.20	0.18	0.91
Humidity	0.58	0.19	0.20	0.94
Load	0.62	0.15	0.25	0.97

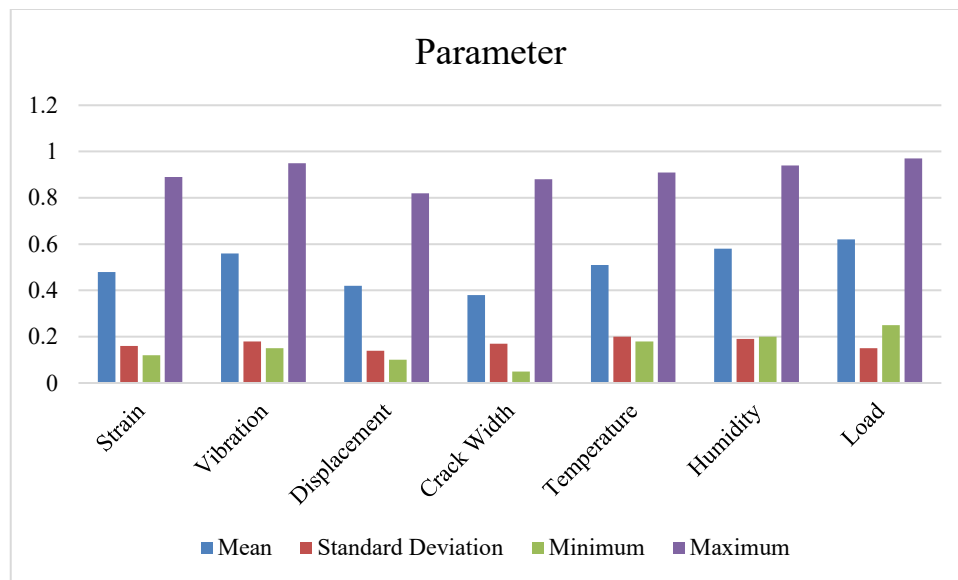


Figure 1: Graphical Representation of Descriptive Statistics of Structural Monitoring Parameters

There was observable variation in the measured parameters. The load parameter had the maximum mean value of 0.62, followed by humidity (0.58) and vibration (0.56). The mean value of crack width was 0.38, whereas that for displacement was 0.42. Standard deviation variation implied that the parameters related to the structure were not consistent depending on the changes in loading and environment.

It was concluded from the study that structural health assessment could not be conducted with respect to one parameter only. Several structural and environmental factors had to be studied at a time, which made the use of AI techniques possible.

4.2 Distribution of Structural Health Conditions

The structural assessments were grouped into four groups, namely Normal, Moderate Risk, High Risk, and Critical. The grouping helped in indicating different structural states and maintenance requirements.

Table 3: Distribution of Structural Health Conditions

Structural Condition	Frequency	Percentage (%)
Normal	420	42.0

Moderate Risk	280	28.0
High Risk	190	19.0
Critical	110	11.0
Total	1000	100.0

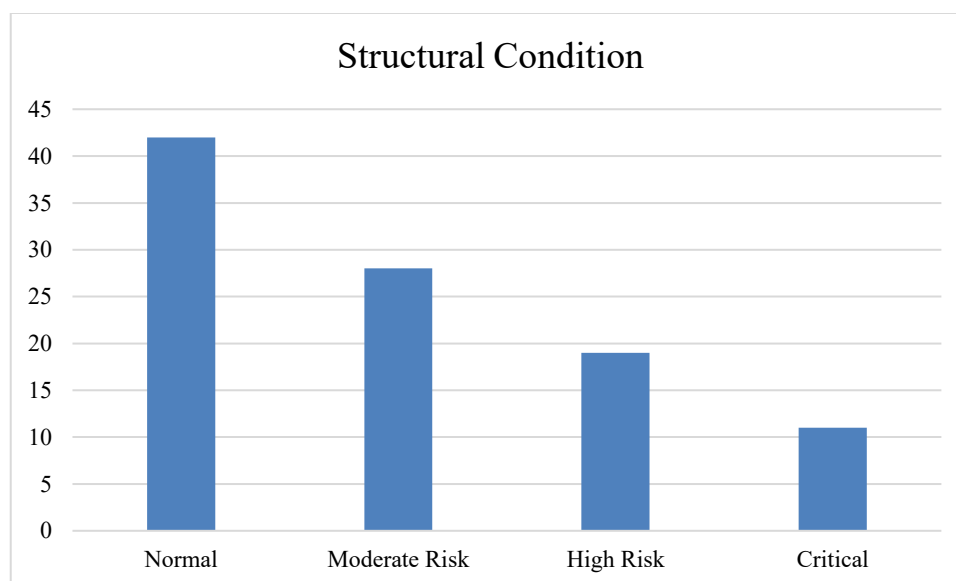


Figure 2: Graphical Representation of Distribution of Structural Health Conditions

In addition, it was found that 420 observations were normal (42.0%). Another 280 observations were found to be moderate risks (28.0%). It was also found that there were 190 observations (19.0%) high-risk situations and 110 (11.0%) observations were critical.

Therefore, 30.0% of the observations fell into the categories of high risks and critical situations. This means that a relatively large number of structural situations needed to be monitored or maintained. Moreover, the results showed the significance of continuous monitoring as the identification of moderate and high risks gives an opportunity to act preventively before critical situations appear.

4.3 Comparison of AI Model Performance

The machine learning algorithms used for health monitoring of structures include Random Forest, Support Vector Machine, Artificial Neural Network, and Gradient Boosting. The evaluation process was based on accuracy, precision, recall, and F1 score.

Table 4: Performance Comparison of AI Models

AI Algorithm	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Random Forest	91.2	90.5	89.8	90.1
Support Vector Machine	88.6	87.9	87.2	87.5
Artificial Neural Network	93.4	92.8	92.1	92.4
Gradient Boosting	94.1	93.6	93.0	93.3

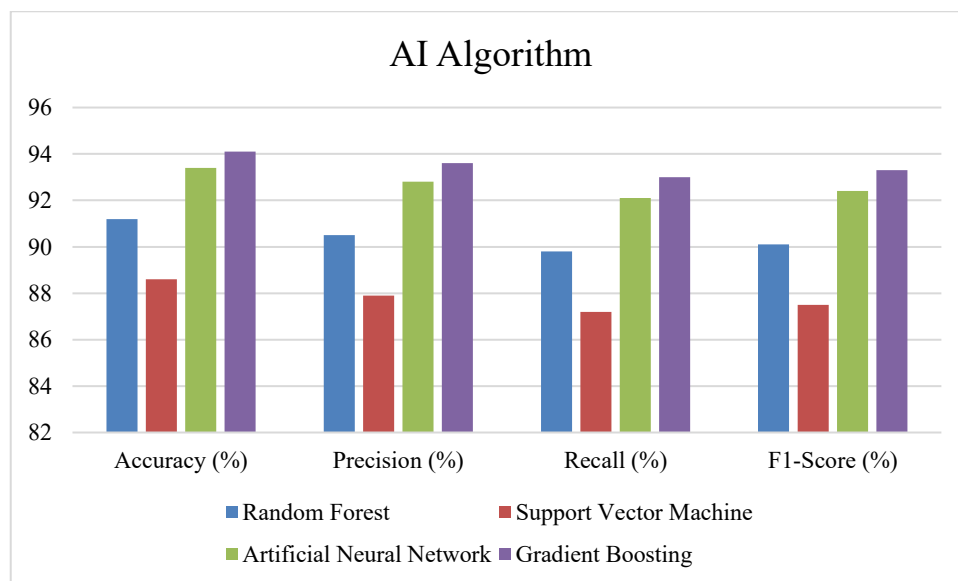


Figure 3: Graphical Representation of Performance Comparison of AI Models

It could be observed that all four of the AI models had relatively good classification performances. Gradient Boosting had the best accuracy of 94.1%, while the Artificial Neural Network performed with 93.4% accuracy. The accuracy of Random Forest model was 91.2%, while the lowest accuracy was recorded by the Support Vector Machine model, which performed with 88.6%. The Gradient Boosting

model had the best precision (93.6%) and recall (93.0%), as well as the best F1-score of 93.3%. These results showed that the model provided relatively good balance between recognizing correct structural conditions and making mistakes. It can be concluded that these AI algorithms were able to process multiple structural parameters and identify different conditions of the structure. Therefore, based on the results obtained, Gradient Boosting could be regarded as the best of the tested algorithms.

4.4 Feature Importance Analysis

Feature importance analysis was performed to determine which factors had the greatest influence on the classification of structural conditions. It was helpful for knowing which factors have an impact on the AI model and which factors should be monitored via sensors.

Table 5: Feature Importance of Structural Parameters

Structural Parameter	Importance Score
Crack Width	0.26
Strain	0.21
Vibration	0.18
Displacement	0.14
Load	0.10
Humidity	0.07
Temperature	0.04

The analysis results showed that the crack width has the highest feature importance value (0.26) compared to strain (0.21), vibration (0.18), displacement (0.14), load (0.10), humidity (0.07), and temperature (0.04). The high level of crack width importance suggests that structural deteriorations play an important role in determining the structural performance state. Strain and vibration have relatively high importance values, which means that changes in these parameters can indicate changes in structural behavior. Temperature had the lowest importance value among all the features; however, this does not

mean that temperature is unimportant for determining structural performance. It may affect the structural behavior indirectly.

4.5 Predictive Maintenance Performance

Predictive maintenance module was assessed in terms of its capability to establish the right maintenance needs for the predicted state of the structure. The four types of maintenance were: no maintenance, inspection, preventive maintenance, and urgent maintenance.

Table 6: Predictive Maintenance Performance

Maintenance Category	Actual Cases	Correct Predictions	Prediction Accuracy (%)
No Immediate Maintenance	420	398	94.8
Routine Inspection Required	280	258	92.1
Preventive Maintenance Required	190	173	91.1
Immediate Intervention Required	110	102	92.7

In terms of accuracy, it can be noted that the predictive maintenance model was very accurate in predicting conditions within each of the four maintenance types. In particular, the highest level of accuracy was observed for the category of no immediate maintenance, where 94.8% was reached. It means that the predictive maintenance model worked very well in predicting conditions that did not need immediate intervention. The second level of accuracy is 92.1%, which was observed for the needs for routine inspection. The needs for preventive maintenance were predicted with an accuracy of 91.1%. Finally, 92.7% of cases requiring immediate interventions were accurately predicted by the model.

4.6 Digital Twin-Based Real-Time Structural Monitoring

The Digital Twin framework integrated the physical modular reinforced concrete structure with the sensor network and AI-based analytical system. The operational process of the proposed framework was structured as follows:

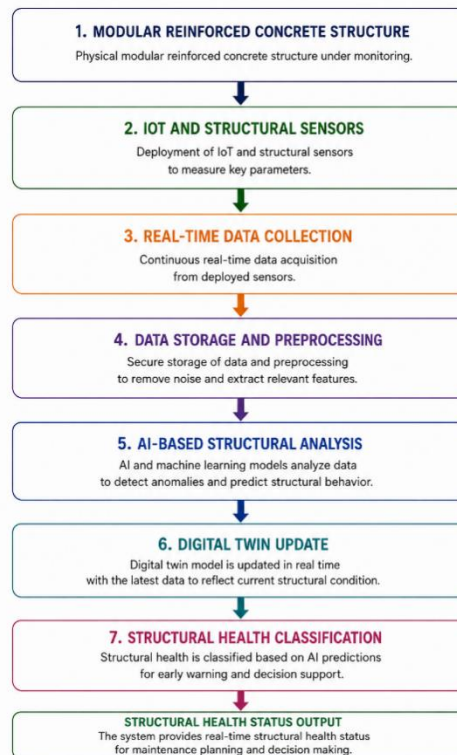


Figure 4: Digital Twin-Based Real-Time Structural Monitoring Framework for Modular Reinforced Concrete Structures

The Digital Twin provided a continuously updated virtual representation of the physical structure. The sensor data were processed and incorporated into the digital model, allowing changes in structural condition to be identified.

Each structural module could be assigned a health status according to the AI-based assessment:

- **Normal:** Structural performance remained within the acceptable range.
- **Moderate Risk:** Minor abnormalities were identified and continued monitoring was required.
- **High Risk:** Significant structural changes were detected and maintenance was recommended.
- **Critical:** Severe abnormalities were identified and immediate inspection or intervention was required.

The integration of real-time monitoring with the Digital Twin therefore provided a centralized platform for structural condition visualization and maintenance decision-making. It could also assist engineers

and facility managers in identifying high-risk structural modules without depending exclusively on periodic manual inspections.

4.7 Overall Interpretation of Findings

The overall findings demonstrated the potential of the proposed AI-enabled Digital Twin framework for improving structural health monitoring and predictive maintenance of modular reinforced concrete structures.

The descriptive analysis showed that structural and environmental parameters varied considerably, indicating that structural condition assessment required the simultaneous consideration of multiple variables. The classification results further demonstrated that AI models could effectively distinguish between different structural health conditions.

Among the evaluated algorithms, Gradient Boosting achieved the best overall performance, with an accuracy of 94.1%, precision of 93.6%, recall of 93.0%, and F1-score of 93.3%. The feature importance analysis indicated that crack width, strain, and vibration were the most influential parameters in structural condition classification.

The predictive maintenance analysis also demonstrated strong performance, with prediction accuracy exceeding 90% across all maintenance categories. This suggested that the AI-based system could support condition-based and predictive maintenance rather than relying exclusively on fixed inspection schedules.

The Digital Twin further strengthened the proposed framework by providing a dynamic digital representation of the physical structure. By integrating sensor data, AI analysis, structural condition assessment, and maintenance recommendations, the framework provided a more comprehensive approach to structural management.

Overall, the findings indicated that the integration of Artificial Intelligence, real-time sensing, Digital Twin technology, and predictive maintenance could provide an effective approach for improving structural safety, maintenance planning, and lifecycle management of modular reinforced concrete structures.

5.CONCLUSION

The study developed an AI-enabled Digital Twin framework for real-time structural health monitoring and predictive maintenance of modular reinforced concrete structures. The findings showed that multiple structural parameters are important for reliable condition assessment, with Gradient Boosting achieving the highest performance of 94.1% accuracy and 93.3% F1-score. Crack width, strain, and vibration were the most influential parameters. The predictive maintenance model achieved over 90% accuracy across all maintenance categories, demonstrating its potential for early risk identification and timely intervention. Overall, the integration of AI, IoT sensors, Digital Twin technology, and predictive maintenance provides an effective approach for improving structural safety, maintenance planning, and lifecycle management.

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