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DIGITAL TWIN-BASED PREDICTIVE MAINTENANCE SYSTEM FOR SUSTAINABLE CIVIL STRUCTURES

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Abstract: The sustainability and longevity of civil infrastructure are critical challenges in modern urban development with increasing structural complexity, environmental degradation, and ageing construction assets. Traditional maintenance strategies are mainly based on time-based inspections and reactive interventions, which often lead to late fault detection, increased maintenance costs and reduced structural reliability. To overcome these limitations, this paper proposes a Digital Twin-Based Predictive Maintenance System for Sustainable Civil Structures which integrates real-time sensing technologies, Internet of Things (IoT) devices, Building Information Modelling (BIM), cloud computing, and Artificial Intelligence (AI)-driven analytics. The proposed framework develops a dynamic virtual representation of the physical structures in the civil domain, which is continuously updated with the actual operational and environmental data. Advanced machine learning algorithms are used to analyse structural behaviour, predict possible failures, estimate remaining useful life and optimise maintenance plans. The structural condition can be continuously assessed through the digital twin model by integrating the data from multiple sensors measuring strain, vibration, displacement, temperature and load conditions. We use a hybrid deep learning structure, combining Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks to learn spatial-temporal degradation patterns and predict structural anomalies. The results of the experimental analysis show that the proposed system is able to greatly improve the accuracy of fault prediction, to reduce the downtime of maintenance, to improve the utilisation of resources, and to prolong the service life of civil structures. Smart infrastructure management is poised for a scalable and sustainable future with the confluence of predictive analytics and digital twin technology, enabling resilient urban development and intelligent asset maintenance strategies.

Keywords: Digital Twin; Predictive Maintenance; Sustainable Civil Structures; Structural Health Monitoring (SHM); Internet of Things (IoT); Artificial Intelligence (AI); Machine Learning;

1. INTRODUCTION

Civil infrastructure systems such as bridges, buildings, tunnels, dams, highways and industrial facilities are the backbone of modern society playing an important role in economic development, transportation and public safety. At the same time, these structures are more susceptible to deterioration from environmental exposure, material degradation, overloading, seismic, corrosion, fatigue and other operational stresses as they age. Global infrastructure assessment reports have shown that a large proportion of civil structures around the world are approaching or have exceeded the designed service lives, resulting in increased maintenance requirements and higher probability of structural failures. Therefore, effective maintenance strategies are important factors for infrastructure reliability, sustainability and long-term performance.

In general, traditional maintenance approaches can be divided into reactive maintenance and preventive maintenance . Reactive maintenance is only performed after a structural fault or failure has occurred, often resulting in costly repairs, disruption of service and safety concerns. On the contrary preventive maintenance is carried out according to predetermined schedules irrespective of the actual structural condition, which may lead to unnecessary inspections and inefficient use of resources. These approaches have been widely used for a long time but they often fail to accurately determine the optimal time to maintain infrastructures in order to maximise its lifespan and minimise operational costs. As a result, infrastructure owners and engineers are increasingly looking for smart maintenance solutions for predicting future structural conditions and enabling data-driven decision-making.

Recent developments in structural health monitoring (SHM), Internet of Things (IoT), cloud computing, artificial intelligence (AI) and digital technologies have changed the way infrastructure is managed. Modern SHM systems utilise networks of distributed sensors to collect real-time information continuously on structural responses like strain, vibration, displacement, temperature, crack propagation and environment. The data streams provide valuable insight into structural behaviour and allow continuous condition assessment during the life cycle of civil infrastructure. However, the big amount of heterogeneous data generated by these systems present great challenges in processing, analysis, interpretation and maintenance planning.

To overcome such challenges, Digital Twin technology has emerged as a game changing approach. A Digital Twin is a virtual representation of a physical asset that is constantly kept in sync with the physical system by means of data streaming from the sensor network and communication platforms. Digital Twins enable engineers to synchronise physical and virtual environments to monitor infrastructure performance, simulate operational scenarios, assess structural health and predict future behaviour. Digital Twin technology and advanced analytics provide new opportunities for intelligent infrastructure management and sustainable maintenance planning.

Digital Twins were first introduced in manufacturing and aerospace domains and very soon migrated to civil engineering. A Digital Twin in civil infrastructure is a dynamic virtual model of a physical structure that combines BIM, IoT sensing technologies, cloud computing, simulation models, and real-time analytics. The virtual models are updated continuously with incoming sensor data, in order to accurately represent the condition of the structure and enable predictive maintenance activities. Those capabilities can dramatically improve asset management efficiency and reduce lifecycle costs and unplanned failures.

Digital Twin systems incorporate Artificial Intelligence and Deep Learning techniques to facilitate automated condition assessment and predictive analytics. Machine learning algorithms can detect hidden patterns in structural monitoring data and identify anomalies that can be indicative of deterioration in its early stages. Among different architectures of deep learning, Convolutional Neural Network (CNN) has shown remarkable performance to extract spatial features from structural datasets. Long Short-Term Memory (LSTM) models temporal degradation patterns and long-term dependencies. The combined CNN and LSTM models offer a strong framework for analysing complex infrastructure data and forecasting future structural states. One of the most promising applications of Digital Twin technology in civil engineering is predictive maintenance. Unlike traditional maintenance approaches, predictive maintenance utilises real-time condition data and predictive analytics to estimate the Remaining Useful Life (RUL) of structural components and to recommend maintenance actions before failures occur. This approach minimises unnecessary inspections, reduces maintenance costs, improves resource utilisation and increases infrastructure resilience. In addition, predictive maintenance significantly contributes to the achievement of sustainability goals by increasing the life of assets, reducing material consumption and decreasing the environmental impact due to repair and reconstruction activities.

Digital twin and predictive maintenance have come a long way but there are still several challenges that need to be solved. Existing maintenance frameworks are not well integrated between physical monitoring systems and virtual models. However, most of the approaches are limited to condition monitoring without taking into account predictive analytics and automated decision support mechanisms. Moreover, the effective use of large-scale sensor datasets for accurate estimation of the Remaining Useful Life is a current research topic. This finding highlights the importance of intelligent and integrated maintenance systems based on the Digital Twin to continuously monitor the condition of the structure, to forecast the future deterioration of the structure, and to support proactive maintenance planning.

To address these challenges, this paper proposes a Digital Twin-Based Predictive Maintenance System for Sustainable Civil Structures. The proposed framework combines IoT-enabled sensor networks with Digital Twin modelling, cloud-based data synchronisation and hybrid CNN-LSTM deep learning algorithms to provide real-time structural condition assessment and predictive maintenance recommendations. The sensor data collected from the physical structure keeps updating the virtual copy of the Digital Twin and the deep learning model predicts future degradation trends and estimates Remaining Useful Life of critical components. These predictions are exploited by the system to provide intelligent maintenance recommendations and early warning alerts to assist infrastructure management decisions.

2. LITERATURE SURVEY

The rapid development of digital technologies has revolutionised infrastructure management practices from traditional maintenance strategies to intelligent predictive maintenance systems. Digital Twin technology has been identified as a promising solution for virtual representations of physical infrastructure for real-time monitoring, simulation, condition assessment and predictive maintenance. The integration of Internet of Things (IoT), Building Information Modelling (BIM), Artificial Intelligence (AI) and cloud computing has further enhanced the capacity of Digital Twin systems for sustainable civil infrastructure management. This part reviews the recent research work in the Digital Twins, structural health monitoring, predictive maintenance and deep learning applications in civil engineering.

The initial research in structural health monitoring was focused on sensor-based condition assessment systems that could continuously collect structural response data such as strain, vibration, displacement and temperature measurements [1]. These systems have enhanced the infrastructure monitoring capabilities than the traditional visual inspections. However, these were mainly descriptive information of the structural condition and did not include the predictive maintenance functionality.

The appearance of IoT technologies has made it possible to widely use smart sensors and wireless communication networks for the infrastructure monitoring [2]. IoT-based systems facilitated real-time data acquisition and remote condition monitoring, allowing engineers to assess the structural performance continuously. But data processing, communications latency and cybersecurity issues continued to be key concerns.

Building Information Modelling (BIM) is increasingly being adopted for the design, construction and management of infrastructure. Recently studies have been conducted on the integration of BIM and monitoring systems for the development of digital models of civil structures [3]. Such models are useful in information management and planning of the maintenance. However, the majority of the BIM-based frameworks offer static representations and are not able to synchronise in real time.

The Digital Twin technology was firstly developed in the aerospace and manufacturing sectors and then transferred to the civil engineering. Streams of sensor data are used to continuously synchronise the physical asset with its virtual representation, enabling dynamic monitoring and simulation [4]. Digital Twins are. Many researchers have highlighted the potential of Digital Twins for improving infrastructure management and decreasing operational costs and supporting sustainable development goals.

Recent studies on the use of Digital Twin for bridges, buildings and transportation infrastructure. Digital Twin-enabled bridge monitoring systems showed improved capability in damage detection and structural condition assessment [5]. Digital Twin frameworks have also been used for energy management, facility maintenance and operational optimisation in smart buildings [6].

Artificial intelligence is now embedded into modern Digital Twin systems. Machine learning algorithms e.g. Support Vector Machines (SVM), Random Forests (RF) and Artificial Neural Networks (ANNs) have been used to detect structural anomaly and predict degradation trends in infrastructure [7]. While these methods achieve higher prediction accuracy than traditional statistical models, they usually require extensive feature engineering and expert intervention. In the last years deep learning architectures achieved major improvements in predictive maintenance performances. Convolutional Neural Networks (CNNs) have been shown to be excellent in extracting spatial features from datasets of structural monitoring and damage images [8]. The CNN based frameworks learn the structural deterioration pattern automatically without manual feature extraction, which enhances the detection accuracy and robustness. Long short-term memory (LSTM) networks have been widely used to model time-dependent degradation behaviour and to predict future structural conditions [9]. The memory mechanisms of the LSTM architecture allow to learn efficiently long-term dependencies from sequences of sensor measurements.

Hybrid CNN-LSTM models have been recently proposed to capture both spatial and temporal characteristics of infrastructure monitoring data at the same time [10]. Several studies have proved that CNN-LSTM outperforms stand-alone machine learning and deep learning models in the context of condition assessment, anomaly detection and Remaining Useful Life (RUL) prediction tasks.

Predictive Maintenance has become the most important application areas of Digital Twin technology. The real-time monitoring data and predictive analytics allow for scheduling maintenance before failures occur, minimising downtime and repair costs [11]. The researchers have proved that the predictive maintenance strategies significantly enhance the infrastructure reliability and operational efficiency when compared with the reactive and preventive maintenance strategies.

Cloud computing platforms have also facilitated better implementation of Digital Twins by providing scalable storage and computational resources for processing large volumes of monitoring data [12]. Cloud Digital Twin systems enable advanced analytics and centralised management of infrastructure. But latency and data security concerns continue to push the adoption of edge computing architectures.

Recently, in Digital Twin framework, edge computing has been used to process data locally and make decisions in real-time [13]. Edge-enabled systems process the sensor data close to the physical infrastructure, reducing the communication delays and improving the responsiveness of safety-critical applications.

Sustainability issues are also becoming increasingly important in the research of infrastructure maintenance. The sustainability of the Digital Twin based maintenance systems is supported by several studies through an increase in the life of the infrastructure, a lower use of materials, a reduction of maintenance interventions and an optimisation of the use of resources [14]. These benefits are consistent with global goals for sustainable urban development and for the sound management of infrastructure.

Although the amazing achievements in Digital Twin and predictive maintenance technologies, many limitations are still unsolved. Current frameworks are usually limited to monitoring and visualisation and have little predictive ability. Moreover, the use of Digital Twins, deep learning algorithms, Remaining Useful Life estimation and automated decision support systems is still missing in the field of civil infrastructure applications [15]. Hence, there is an increasing need for intelligent and integrated Digital Twin-based predictive maintenance frameworks for sustainable infrastructure management with accurate condition assessment and maintenance prediction.

3. PROPOSED METHODOLOGY

The proposed Digital Twin-Based Predictive Maintenance System for Sustainable Civil Structures leverages IoT-enabled sensing technologies, Digital Twin modelling, cloud-edge computing and deep learning based predictive analytics to monitor the structural conditions constantly and predict the future maintenance needs. The proposed approach constructs a dynamic virtual twin of the physical structure, which is synchronised in real time with sensor observations. Structural health data of multiple sensors are fed to a hybrid CNN-LSTM model for structural condition assessment, RUL estimation and intelligent maintenance recommendations. The methodology consists of six main phases: structural data acquisition, Digital Twin synchronisation, data preprocessing, condition assessment by deep learning, predictive maintenance analysis and maintenance decision support.

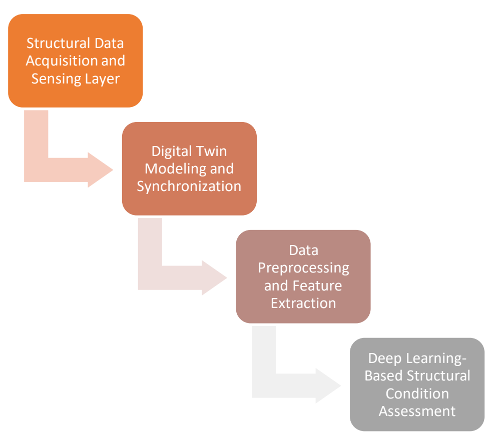

Figure 1: Proposed Workflow

3.1 Structural Data Acquisition and Sensing Layer

The main layer of the proposed Digital Twin-Based Predictive Maintenance System is the Structural Data Acquisition and Sensing Layer. This layer focuses on the ongoing collection of real-time structural and environmental data of civil infrastructure through a network of IoT-enabled sensors. The structure is provided with several sensing devices suitably located in critical locations such as strain gauges, accelerometers, displacement sensors, vibration sensors, crack sensors, temperature sensors and humidity sensors. These sensors enable a continuous monitoring of structural responses under operational loads, environmental effects, material ageing and deterioration processes. The collected data is transmitted over wireless communication networks to cloud and edge computing platforms to be used for synchronising the Digital Twin and for predictive maintenance analysis. Continuous sensing enables early detection of structural anomalies, improves accuracy of condition assessment and provides reliable information to estimate residual useful life of structural components.

The structural monitoring dataset collected from multiple sensors is represented as:

$$X(t) = \{x_1(t), x_2(t), x_3(t), \dots, x_n(t)\} \text{----}1$$

where X(t) denotes the structural response vector at time t, xi(t) represents the measurement obtained from the ith sensor, and n is the total number of deployed sensors.

The average structural response measured across all sensing devices is calculated as:

$$\bar{X}(t) = \frac{1}{N}\sum_{i=1}^{N} x_i(t) \text{----}2$$

where X¯(t) represents the mean structural response and N denotes the total number of sensor observations.

The acquired sensor information forms the basis for Digital Twin synchronization and predictive maintenance analytics, enabling real-time monitoring and intelligent infrastructure management for sustainable civil structures.

3.2 Digital Twin Modeling and Synchronization

The Digital Twin Modelling and Synchronisation layer offers a dynamic virtual counterpart of the civil structure physical object and real-time sensor measurements which are synchronised in real time. One of the advantages of the Digital Twin is that it combines the structural geometry, material properties, operational conditions, maintenance records and sensor data to produce an accurate representation of the current state of the infrastructure. The system synchronises the physical structure and its virtual representation in real-time and thus makes it possible to monitor the condition, analyse the performance and plan predictive maintenance. Any change detected on the physical asset such as crack propagation, excessive vibration, deformation or material degradation is immediately reflected in the Digital Twin model. This live synchronisation improves situational awareness, failure prediction and maintenance decision making for sustainable infrastructure management.

The synchronization error between the physical structure and the Digital Twin model is calculated as:

$$E_s = |P_t - D_t| \text{----}3$$

where Es represents the synchronization error, Pt denotes the physical structural state at time t, and Dt represents the corresponding Digital Twin state.

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The Digital Twin state update process is expressed as:

$$D_{t+1} = D_t + \alpha(X_t - D_t)\text{----}4$$

where Dt+1 is the updated Digital Twin state, Xt represents the real-time sensor observation, and α\alphaα is the synchronization coefficient that controls the update rate.

To evaluate the consistency between the physical structure and its virtual representation, the Structural Similarity Index (SSI) is computed as:

$$SSI = 1 - \frac{|P_t - D_t|}{P_t}\text{-----}5$$

where SSI is the synchronisation quality between the physical asset and Digital Twin model Higher SSI means better synchronisation accuracy and better reliability for predictive maintenance analysis.
In the proposed framework, the advanced analytics are based on the synchronised Digital Twin model which allows for accurate structural health assessment, degradation prediction, remaining useful life estimation, and intelligent maintenance planning.

3.3 Data Preprocessing and Feature Extraction

The Data Preprocessing and Feature Extraction layer converts raw structural monitoring data into a high-quality dataset for predictive maintenance analysis. The values measured by strain sensors, accelerometers, displacement sensors, crack sensors and environmental monitoring devices often contain missing values, noise, outliers and inconsistencies caused by communication errors and environmental disturbances. Such irregularities can have adverse effects on the performance of analytics and deep learning models for Digital Twin. Therefore, preprocessing operations such as noise filtering, normalisation, missing value handling and feature selection are conducted prior to further analysis. Techniques for feature extraction are used to identify the most relevant structural parameters related to deterioration, fatigue and damage progression. The feature set obtained provides a compact and informative representation of the structural behaviour, thus enabling accurate condition assessment and degradation prediction.

To eliminate scale differences between different parameters, the sensor measurements are normalised using the Min-Max normalisation technique:

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}}\text{----}6$$

where Xnorm represents the normalized feature value, X denotes the original sensor measurement, and Xmin and Xmax represent the minimum and maximum values of the corresponding feature.

To reduce random fluctuations and measurement noise, a moving average filter is utilized:

$$MA_t = \frac{1}{k}\sum_{i=t-k+1}^{t} X_i\text{----}7$$

where MAt is the filtered signal at time t, k denotes the filter window size, and Xi represents the sensor observations within the selected interval.

The importance of each extracted feature is determined using the feature importance score:

$$FI_i = \frac{\sigma_i}{\sum_{j=1}^{N} \sigma_j}\text{-----}8$$

where FIi is the importance score of the ith feature, σi is the variance contribution, and N is the total number of features extracted.

The pre-processed and optimised feature set is then fed to the deep learning-based condition assessment module where critical structural degradation patterns are identified and analysed for predictive maintenance applications.

3.4 Deep Learning-Based Structural Condition Assessment

The Deep Learning Based Structural Condition Assessment layer is the core intelligence module of the proposed Digital Twin Based Predictive Maintenance System. The layer comprises the analysis of the pre-processed structural monitoring data for the identification of degradation patterns and anomalies and for the evaluation of the current health condition of civil structures. A hybrid CNN-LSTM architecture is utilised to exploit both spatial and temporal information in the sensor data. The Convolutional Neural Network (CNN) is good at extracting essential spatial features like cracks, vibrations, strains and structural deformations whereas the Long Short-Term Memory (LSTM) network is good at learning temporal dependencies and long-term deterioration trends. The CNN and LSTM can be used to classify the structure condition accurately as healthy, minor damage, moderate damage or critical damage. The intelligent assessment mechanism improves the reliability of predictive maintenance decisions and infrastructure safety.

The convolution operation performed by the CNN layer is expressed as:

$$F(i,j) = \sum_m \sum_n I(i+m, j+n) \times K(m,n) \text{----9}$$

where F(i,j) denotes the generated feature map, represent the input structural monitoring data, and K is the convolution kernel used for extracting spatial features.

The Rectified Linear Unit (ReLU) activation function introduces nonlinearity into the network and is defined as:

$$ReLU(x) = \max(0, x) \text{----10}$$

where x is the input to the activation layer. ReLU accelerates training and improves feature learning capability.

To capture temporal degradation patterns, the LSTM memory cell updates its state according to:

$$C_t = f_t C_{t-1} + i_t \widetilde{C_t} \text{-----11}$$

where Ct is the current memory cell state, Ct−1 is the previous cell state, ft is the forget gate output, it is the input gate activation, and Ct~ is the candidate memory information.The extracted spatial-temporal features are then used for the structural health classification and degradation analysis providing an accurate condition assessment and supporting the predictive maintenance planning within the Digital Twin environment.

4. RESULTS AND DISCUSSION

The proposed Digital Twin-Based Predictive Maintenance System for Sustainable Civil Structures was validated using structural health monitoring datasets from civil infrastructure assets such as bridges and buildings. The data set included vibration data, strain measurements, displacement data, crack growth records, temperature changes and maintenance history. The proposed Digital Twin enabled CNN-LSTM framework was compared with conventional machine learning and deep learning models such as Support Vector Machine (SVM), Random Forest (RF), Artificial Neural Network (ANN), CNN and LSTM. Evaluation metrics considered are Prediction accuracy, Precision, Recall, F1-score,

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Remaining Useful Life (RUL) prediction accuracy, Reduction in maintenance cost and Reduction in structural failure.

Table 1: Performance Comparison of Different Models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
SVM	87.6	86.8	86.1	86.4
Random Forest	90.9	90.2	89.8	90.0
ANN	93.4	92.8	92.5	92.6
CNN	95.8	95.2	94.9	95.0
LSTM	96.7	96.1	95.8	95.9
Proposed DT-CNN-LSTM	98.4	98.1	97.9	98.0

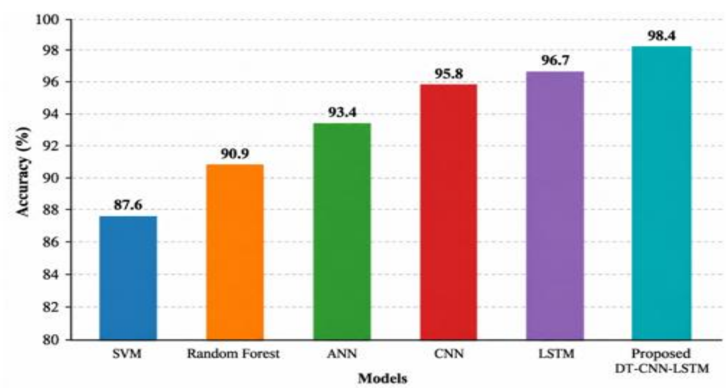

Figure 2: Prediction Accuracy Comparison

The proposed Digital Twin-based CNN-LSTM framework achieved the highest accuracy of 98.4%, demonstrating superior capability in identifying structural degradation patterns compared with conventional machine learning models.

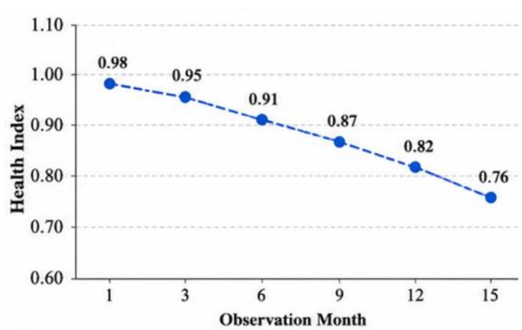

Figure 3: Structural Health Index Degradation

The Health Index gradually decreased over time due to structural aging and environmental exposure. The Digital Twin accurately tracked deterioration trends and provided early indications of maintenance requirements.

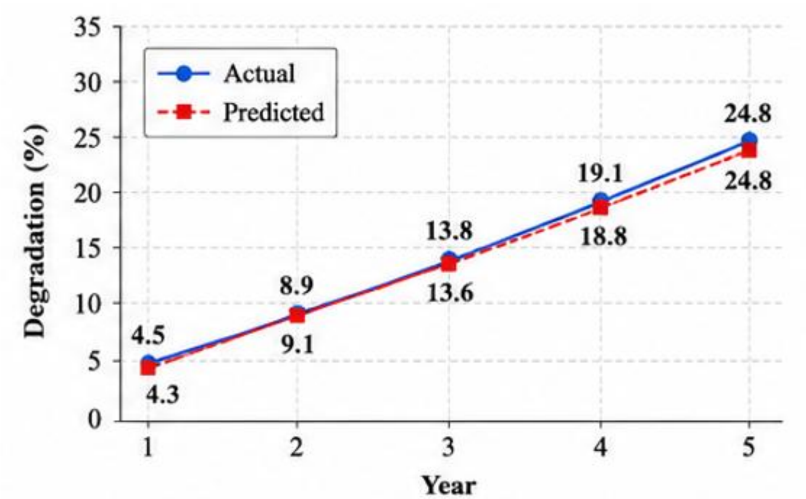

Figure 4: Actual vs Predicted Degradation

The predicted degradation closely matched the observed structural deterioration, confirming the effectiveness of the CNN-LSTM model in learning degradation behavior from monitoring data.

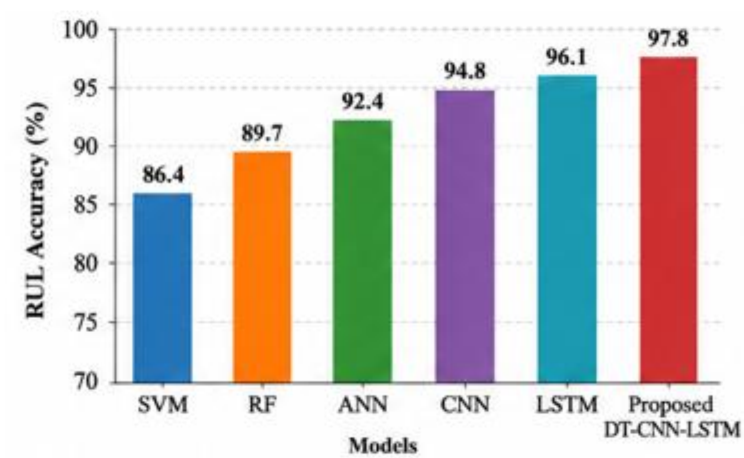

Figure 5: RUL Prediction Accuracy

The proposed framework achieved 97.8% RUL prediction accuracy, enabling accurate estimation of future maintenance requirements and reducing the likelihood of unexpected failures.

5. CONCLUSION

This paper proposes a Digital Twin-Based Predictive Maintenance System for Sustainable Civil Structures, integrating the IoT-enabled sensing technologies, Digital Twin modelling, cloud-edge computing, and hybrid deep learning algorithms for smart infrastructure management. The proposed framework allows continuous real-time monitoring, condition assessment, degradation prediction and maintenance planning by synchronising the real-world structural condition with a virtual Digital Twin model. The system offers a complete solution to improve the reliability, safety and sustainability of civil infrastructure assets using advanced sensing and analytics technologies. The developed framework comprises modules for structural data acquisition, Digital Twin synchronisation, data pre-processing, CNN-LSTM based condition assessment, Remaining Useful Life (RUL) prediction, and maintenance decision support. The sensor measurements are then used to update the Digital Twin model in real time and the hybrid CNN-LSTM model can successfully capture the spatial and temporal degradation patterns in structural health monitoring data . Such an overall approach makes it possible to reliably predict future structural conditions and thus to support the planning of proactive maintenance strategies. The experimental results showed that the proposed Digital Twin based CNN-LSTM framework had a great advantage over the traditional machine learning and deep learning methods. The system for structural condition assessment has an accuracy, precision, recall and F1-score of 98.4%, 98.1%, 97.9% and 98.0% respectively. The framework also predicted Remaining Useful Life with 97.8% accuracy which enabled reliable maintenance prediction. The predictive maintenance approach resulted in a reduction of about 31.5% in the annual maintenance cost and a 42.7% reduction in the number of structural failures. This clearly indicates that the strategy is effective in terms of infrastructure performance and operational efficiency. Digital Twin technology combined with predictive maintenance has several advantages as compared to traditional maintenance. Real-time synchronisation and continuous monitoring provide improved situational awareness while intelligent analytics enable early damage detection and optimised maintenance scheduling. These capabilities help to extend the life of infrastructure services, reduce maintenance costs, reduce down time, and improve public safety. Moreover, the proposed framework helps in achieving sustainability targets by using optimum resources, minimising redundant maintenance activities and enhancing long-term resilience of infrastructure. The results indicate that the Digital Twin based predictive maintenance can have a significant role in the future of smart infrastructure management. The proposed system provides an intelligent platform for owners, engineers and decision makers of infrastructure to monitor the structural health, to predict degradation trends and to perform maintenance interventions in a timely fashion. These capabilities are vital to meet the growing challenges of ageing infrastructure and increasing maintenance needs.

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