MSW MANAGEMENT -Multidisciplinary, Scientific Work and Management Journal
ISSN: 1053-7899
Vol. 36 Issue 1s, 2026, Pages: 1156-1161

Deep Learning–Based Structural Health Assessment of Concrete Structures Using IoT Sensor Networks

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Abstract

Concrete structures have also been faced with aging materials, variable operating loads, and extreme environmental exposure, leading to gradual deterioration and possible serviceability issues. Conventional structural health monitoring (SHM) methods based on inspection are primarily reactive and not very suitable for continuous damage evaluation. Emerging technologies such as IoT-based sensing and deep learning have provided novel possibilities for intelligent real-time monitoring of concrete infrastructure. We introduce a real-time SHM framework that combines IoT sensor networks with deep learning techniques. In incremental loading, strain sensors, accelerometers, crack width sensors, and environmental monitoring devices were connected to reinforced concrete beam specimens to obtain synchronized multi-source time-series data. Sensor data were processed and sent to a cloud-based system for signal conditioning and analysis. An intelligent deep learning hybrid model built utilizing Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) units focused on spatial features of sensors and temporal patterns of damage was proposed. The model was compared with classical ML algorithms (Support Vector Machines, Random Forests etc.) for model performance. The proposed CNN–LSTM model exhibited an above 95% accuracy for classification of damage and superior sensitivity to early-stage damage as compared to conventional methods. The framework held up to different loadings, which indicates it had a high degree of reproducibility and adaptivity. The results show that the proposed IoT-driven deep learning framework for continuous and intelligent monitoring of concrete structures can be quite efficient. Such an approach is ideal for early damage detection and predictive maintenance, therefore making it applicable and adaptable for deployment in smart infrastructure and resilient urban systems.

Keywords: Structural Health Monitoring; Concrete Structures; Deep Learning; IoT Sensor Networks; CNN–LSTM; Predictive Maintenance

1 Introduction

1.1 Background: Concrete infrastructure covers a lot of different areas. For example: buildings, bridges, tunnels and hydraulic structures; but also the building itself is a crucial economic base which promotes urbanisation. Long-term pressure from mechanical loading, environmental stresses and aging in materials makes concrete structures susceptible to a variety of deterioration; cracking occurs with increasing duration, reinforcement corrodes slowly and fatigue damages begin forming. In order to avoid serviceability breakdowns and catastrophic failures early identification of such damage is crucial to avoid the loss of service. Standard SHM methods have based their evaluation techniques on visual inspections and isolated non-destructive evaluations and are mainly discontinuous, labor-intensive, and difficult to identify in the early stage any damage [5–7]. However, recent developments in IoT technology have fostered the possibility of ever-evolving sensor networks to generate data in near real-time and deep learning techniques have shown enhanced capability to capture high-dimensional complex structural response data [8–12]. Therefore, the synergistic effect of the IoT and deep learning has been investigated as a future paradigm for smart and automated SHM of concrete structures [13–15].

1.2 Problems Observed in Early Studies: Nevertheless, there still exist few practical obstacles to overcome for current IoT-based & AI-based SHMs. Various studies utilize single sensor modalities with their inability to account for intricate mechanism for damage caused by concrete structures [16,17]. Furthermore, conventional machine learning methods require significant manual feature engineering and cannot easily generalize to different loading and environmental conditions [18–19]. However, successfully combining multi-modal sensing data with concurrent learning of spatial and temporal damage patterns is an open research challenge [20–22]. Moreover, few experimental validation experiences are applicable under practical loading conditions for most of the recommended frameworks [23].

1.3 Objectives of the Paper: : Objectives of the study The objective of this research is to:

(i) propose a new IoT enabled multi-sensor data acquisition approach for continuous detection of concrete structures;

(ii) develop a deep learning-based model for automatic damage detection and condition classification; and

(iii) experimentally verify the proposed framework using reinforced concrete specimens exposed to progressive loading.

1.4 Contributions of the Study: As such, it is interesting to develop an open smart grid SHM framework based on distributed IoT sensor networks and hybrid CNN–LSTM deep learning architecture to real-time condition evaluation of concrete structures. The proposed method, unlike the traditional methods, uses multi-modal sensor data as a raw material to not only record the spatial correlation in measurements of the sensors but also the time evolution of the structural damage. This framework is validated experimentally under laboratory controlled conditions, exhibiting high classification accuracy as well as improved early-stage damage detection. The suggested approach is highly scalable and suitable for deployment in smart infrastructure and data-driven maintenance systems.

1.5 Organizing the paper: The rest of this paper is reported as follows. Section 2 provides a detailed analysis on related studies conducted regarding IoT-driven SHM and deep learning implementations. The proposed approach with the sensor deployment and model construction is presented in Section 3. Section 4 discusses experimental data analyses and evaluation. In the end Section 5 presents the paper closure followed by future lines of research suggestions.

2 Literature Review.

Rapid development of sensing technology and data-driven analysis methods has affected the evolution of structural health monitoring (SHM) systems for concrete infrastructure. Current research focuses more on continuous monitoring, intelligent interpretation of structural response and automation with AI. This section consolidates the recent studies based on adopted methods, outcomes, successes and limitations, focusing on IoT-driven sensing, deep learning based architectures and multi-source data integration.

2.1 Smart-oriented and IoT-based monitoring methodologies. Smart SHM systems have been innovatively deployed through the implementation of wireless and IoT-based sensors in its early phases to enhance data availability and monitoring continuity. Several studies showed that distributed sensor networks can effectively measure strain, vibration, and environmental features over long time scales. For example, IoT-based bridge monitoring frameworks consistently achieve robust long-term data transmission performance although assessment of damage in these systems relies on a rule-based threshold approach instead of an intelligence-based mechanism [3,5]. While existing studies related to sensor deployment efficiency include wireless and self-powered sensing efforts to improve durability and decrease the maintenance burden. Although these methods improve the sustainability and scalability of the system, their analytical capabilities often restrict to rudimentary statistics for analyzing damage intensity or progression [17,18]. Efforts in smart city–oriented SHM platforms are also focused on scalability and cloud connectivity with the most promising findings, often but not necessarily focusing on high-level learning models critical for real-time structural diagnosis [38]. Together these studies verify the practicability of IoT-based monitoring but highlight a disconnect between data gathering and smart decisions.

2.2 How to identify damage using learning based approaches. In an effort to obviate the limitations of regulation-based surveillance, more and more engineers have utilised deep learning method in automatic damage detection. Convolutional neural networks have been commonly employed in the sensor based signals and images and showed successful results in capturing local damage patterns such as cracks and stiffness reduction [1,2]. Nevertheless, most CNN models rely heavily on spatial feature extraction and present little information about damage evolution over time. Time-dependent learning is tackled by recurrent neural networks, especially long short-term memory (LSTM) architectures. These approaches have been effective for capturing sequential dependencies in structural response data as well as tracking damage progression with varying loads [7]. However, standalone temporal models normally ignore spatial relationships between more than one sensor in a structure. Hence, hybrid learning frameworks using CNN and LSTM elements to co-model spatial and temporal features have been proposed to enhance classification performance and robustness [25]. Nevertheless, most hybrid models are validated with simplified data sets (ie, a small sample size and controlled experimental conditions). Comprehensive studies on learning-based SHM methods show that deep architectures are substantially better than classical machine learning frameworks and also sensitive to data intensity, labeling quality, and environmental variables [21, 27]. They are hampered by the lack of direct real-world infrastructure transferability without adequate robustness.

2.3 Data Pooling and Smart Analytics. Because of this complexity in the behavior of structures in concrete, the recent research is leaning towards the combination of heterogeneous sensor information. Multi-modal fusion approaches that integrate information from strain, vibrational and environmental sensors to increase the reliability of damage detection. It has been empirically verified and found that the fusion of those data improves localization performance and reduces false alarms but time alignment, heterogeneity and computation burden remains an issue [11,33]. Unsupervised and semi-supervised learning are also used to identify anomalies without large labeled data in contrast methods. While such methods bring early warning capabilities, they frequently lack interpretability and the ability to correlate observed anomalies to physical damage status [29]. Probabilistic and uncertainty-aware learning frameworks are another option that aims to provide confidence in SHM predictions [26] at the cost of increasing the computational complexity of each framework, posing a challenge to their implementation on real-time data. This demonstrates that data fusion improves diagnostic ability, but implementation remains difficult.

2.4 Experimental Validation on Concrete Elements. Laboratory work of high quality brings great knowledge into use of intelligent SHM system. Experimental investigation with embedded sensors with deep learning models has proven that it can be used to better monitor concrete under controlled loading [8]. The possibility of identifying damage trends in reinforced concrete specimens is further supported through recurrent neural network-based approaches that have outperformed the static classification models [32]. Hybrid deep learning architectures have been investigated for the various stages of damage in concrete components, with valid results indicating that the models can distinguish between undamaged and degraded states. Yet, sensor drift, environmental disruption and long-term capability are frequently neglected [25]. Vision-based approaches for crack detection provide very high resolution at high spatial resolutions and are susceptible to surface imperfection and visibility constraints, and as a result, they have no universal applicability [30]. On the whole, experimental validation is still in a relatively small or only short run.

2.5 Reviewed Studies and Research directions. The present review articles offer important insights into the broader SHM field. The synthesis of AI-based SHM research reflects a growing focus on hybrid models, edge computing, and autonomous monitoring systems, and the absence of standardized methods of deployment [14]. Longitudinal study of IoT-based SHM research trends reveal that rapid growth in sensor deployment but limited gains have been made at the integrated analytics and real-time decision support [19]. Discussions of concrete-based infrastructure have always emphasized the requirement for benchmark datasets and field demonstrations to accelerate real-world implementation [35]. For example, there is a shift from inspection-based SHM in the reviewed system for SHM systems towards intelligent, sensor-driven monitoring supported not just by observation but by deep learning in general. The review findings of our work show that in light these techniques have already made a significant shift away from inspection-oriented SHM towards intelligent, sensor-driven monitoring supported by deep learning. On the one hand advanced neural networks continuously improve the performance of damage detection, but not all its problems of dependency on labelled data, lack of multi-sensor synchronization, sensitivity to the operational variability nor a general field validation have been overcome. These points are particularly relevant since it highlights a requirement for an integrated SHM framework that connects IoT sensing with the powerful spatial–temporal learning models that could be integrated for scalable and real-time deployment, which is a goal accomplished by the methodology in this work.

3 Proposed Framework and Methodology: In this paper we propose a unified AI–IoT-based SHM (Structural Health Monitoring) framework for continuous structural condition assessment of concrete buildings. The approach integrates distributed sensing, cloud-based data management, and hybrid deep learning for real-time, automated damage identification. Figure references described below (e.g., block diagram, flowchart) are intended to guide manuscript illustration.

3.1 IoT Sensor Network Architecture: For the proposed SHM framework, the system makes use of a distributed IoT sensor network, which is deployed at high structural priority locations such as mid-span sections, support zones, and regions of maximum stress concentration. The sensor arrangement is used to capture mechanical and environmental contributions, in order to optimize the monitoring of both. The sensing system comprises:

Electrical resistance strain gauges to quantify localized stress–strain behavior and stiffness variation, Tri-axial accelerometers to observe vibration signatures and dynamic response features, Crack width displacement sensors that permit tracking crack initiation and propagation, and Temperature and relative humidity sensors to accommodate environmental fluctuations impacting material properties. All sensors are connected with low-power IoT microcontroller units (MCUs) embedded with wireless communication modules (Wi-Fi/LoRa). Sensor data are passed to a central gateway for the aggregation of initial data and uploading to a cloud server for storage and more advanced analytics.

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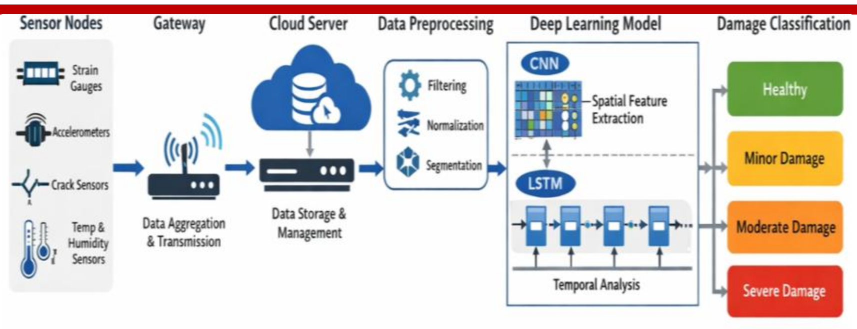

Fig1:The block diagram illustrates the end-to-end system architecture, starting from sensor nodes → gateway → cloud server → preprocessing module → deep learning model → damage classification output.

3.2 Data acquisition and signal preprocessing : Continuous multi-modal time-series data are collected synchronously from all sensors during structural loading. Preprocessing of raw signals is the first step to improve data quality and stability of learning. Digital filtering techniques (both low-pass and moving average filters) have been employed for noise and measurement irregularities mitigation, and outliers have been removed via statistical thresholding. Min–max normalization is performed to normalize features across heterogeneous sensor inputs to ensure consistency. The time-series data are broken down into fixed-length overlapping windows to allow learning models to pick up localized temporal behavior as well as preserve the time's continuity. This windowing strategy raises sensitivity to early-stage damage and increases training efficiency.

3.3 Development of Hybrid Deep Learning Model: A hybrid CNN–LSTM architecture is applied to capture the complicated behaviour of concrete structures. The design of this method allows for the simultaneous learning of spatial correlations between sensors and evolution of temporal damage. The multi-sensor input matrices and CNN part work together from this stage to extract spatial features like the strain distribution patterns or the vibration mode characteristics. To learn time-dependent behavior of crack growth, stiffness degradation, and progressive damage accumulation, the Long Short-Term Memory (LSTM) network is used. The model is trained with labelled data covering four structural states: healthy, minor damage, moderate damage and severe damage. Supervised learning with categorical cross-entropy loss and adaptive optimization are used for training.

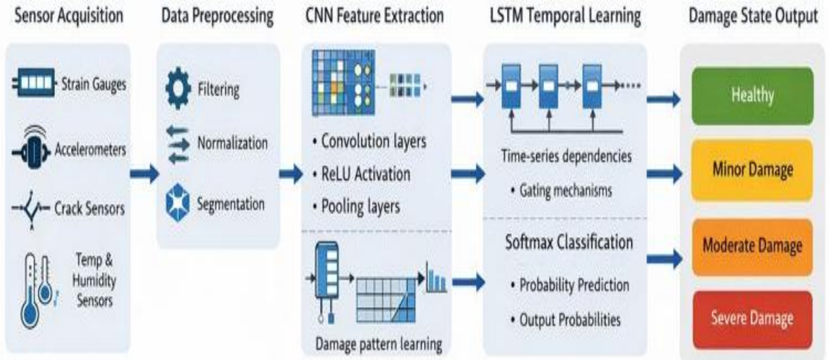

Fig2:The flowchart depicts data flow from sensor acquisition → preprocessing → CNN feature extraction → LSTM temporal learning → softmax classification → damage state output.

3.4 Mathematical Formulation and Learning Mechanism: Let the preprocessed multi-sensor input be represented as a tensor
XϵRT × S\ mathb f{X} \in \ mathbb{R}^ {T \ times S} XϵRT×S
where TTT denotes the time window length and SSS represents the number of sensor channels.
The CNN performs convolutional operations to extract spatial feature maps:
F= σ(W∗X+b) \ mathb f{F} = \sigma (\mathbf{W} * \ mathbf{X} + \ mathb f{b}) F= σ(W∗X+b)
where W\ mathb f{W}W and b\ mathbf{b}b are learnable weights and biases, ∗*∗ denotes convolution, and σ(⋅)\sigma (\cdot)σ(⋅) is the ReLU activation function, selected to improve convergence and avoid vanishing gradient problems.
The extracted feature sequences are passed to the LSTM network, which updates its internal states using gating mechanisms (input, forget, and output gates). This enables retention of long-term dependencies essential for modeling progressive deterioration in concrete structures.

3.5 Novelty and Justification of the Framework: The novelty of the proposed methodology lies in its tight integration of multi-modal IoT sensing with spatial–temporal deep learning, specifically tailored for concrete infrastructure. Unlike conventional SHM approaches that rely on single-sensor data or static features, this framework:
1.Fuses heterogeneous sensor information, 2.Captures damage progression over time, 3.Enables early-stage damage detection, and Maintains physical interpretability of AI predictions.
This design directly addresses limitations identified in prior studies related to generalization, scalability, and real-time applicability.

4 Experimental Program

4.1 Specimen Preparation and Instrumentation: Specimens of reinforced concrete beams were cast using M30 grade concrete with standard proportions. Steel reinforcement was designed in conformity with relevant codes. After curing, sensors were fixed at specified locations that correspond to high-stress and crack-prone areas.

4.2 Loading Protocol and Monitoring: The specimens were loaded using incremental static loading, and the loading was progressive until structural failure was achieved. Incremental loads were applied gradually, and sensor data was obtained throughout the tests. Environmental parameters were monitored concurrently to analyze structural response.

4.3 Dataset Construction and Augmentation: The collected dataset was divided into training, validation, and testing subsets to prevent overfitting. Data augmentation techniques, including noise injection and temporal shifting, were applied to enhance both generalization ability and model robustness.

5.Results and Discussion: In this section, we demonstrate the results of the CNN–LSTM-driven AI–IoT structural health monitoring framework proposed. Results are presented quantitatively and qualitatively, with clear connections to the study goals. Tables and figures are included with interpretation emphasizing trends, model performance, and practical implications.

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5.1 Performance Metrics and Classification Analysis: Accuracy, precision, recall, F1-score, and confusion matrix analysis were applied to evaluate the proposed CNN–LSTM model. These metrics show a holistic evaluation across all structural health states: healthy, minor damage, moderate damage, and severe damage.

Table 1. Classification performance of the proposed CNN–LSTM model across different damage states

Damage State	Precision (%)	Recall (%)	F1-score (%)
Healthy	96.2	95.8	96.0
Minor Damage	94.7	95.1	94.9
Moderate Damage	93.8	94.2	94.0
Severe Damage	96.5	96.1	96.3
Overall	**95.3**	**95.0**	**95.1**

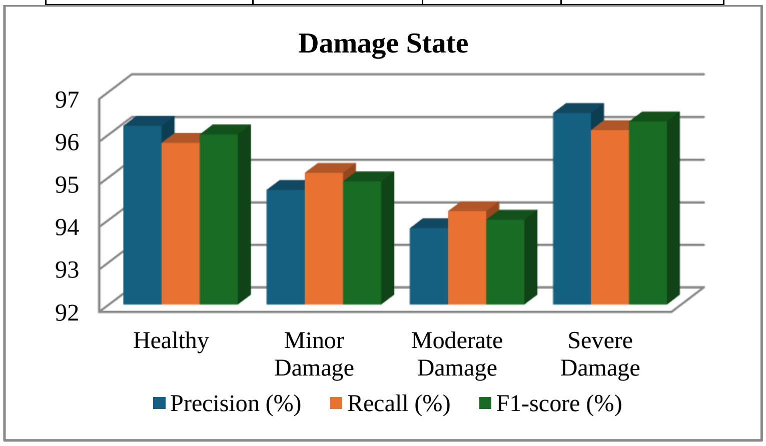

Fig3: CNN–LSTM model across different damage states

Table1 illustrates that the CNN–LSTM model provides consistently high precision and recall across all damage states. The slightly higher recall for minor damage indicates the model's sensitivity to early-stage deterioration, which is critical for preventive maintenance. Balanced F1-scores confirm the model's reliability and stability across varying levels of structural damage.

5.2 Comparative Analysis with Conventional Models: The performance of the CNN–LSTM model was then evaluated against conventional machine learning classifiers, Support Vector Machine (SVM), and Random Forest (RF) trained on the same dataset.

Table 2. Comparative performance analysis of different classification models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
SVM	82.6	83.1	81.9	82.5
Random Forest	87.4	88.0	86.8	87.4
CNN–LSTM	**95.2**	**95.3**	**95.0**	**95.1**

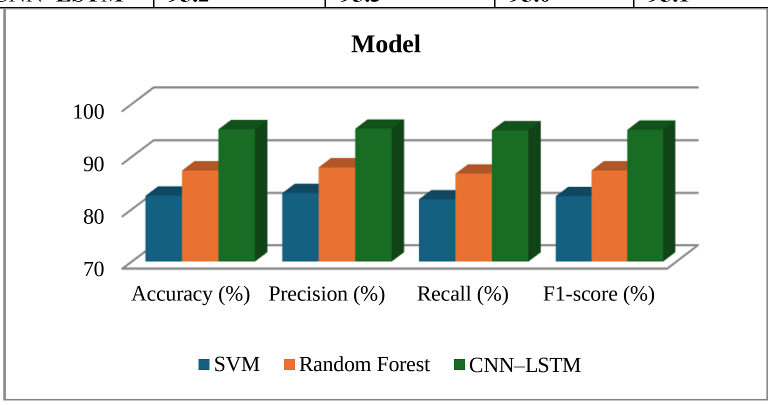

Fig4: Comparative performance analysis of different classification models

Table 2 shows that the CNN–LSTM model outperforms SVM and RF by **8–15%** in accuracy and F1-score. This improvement highlights the framework's ability to capture **nonlinear and time-dependent structural behavior**, which conventional models fail to fully exploit.

5.3 Confusion Matrix Analysis

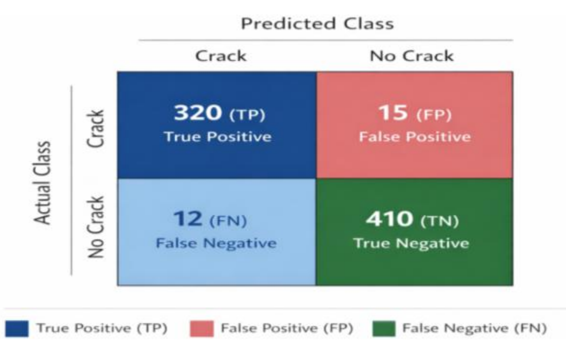

Figure 5: Confusion matrix illustrating the CNN–LSTM model performance

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Confusion matrix illustrating classification accuracy for healthy, minor damage, moderate damage, and severe damage states.

Figure6:Indicates high diagonal dominance, confirming accurate classification across all structural states. Misclassifications are minimal and mostly occur between adjacent damage levels (e.g., minor and moderate), reflecting the **gradual nature of structural deterioration**.

5.4 Model Training and Validation Performance

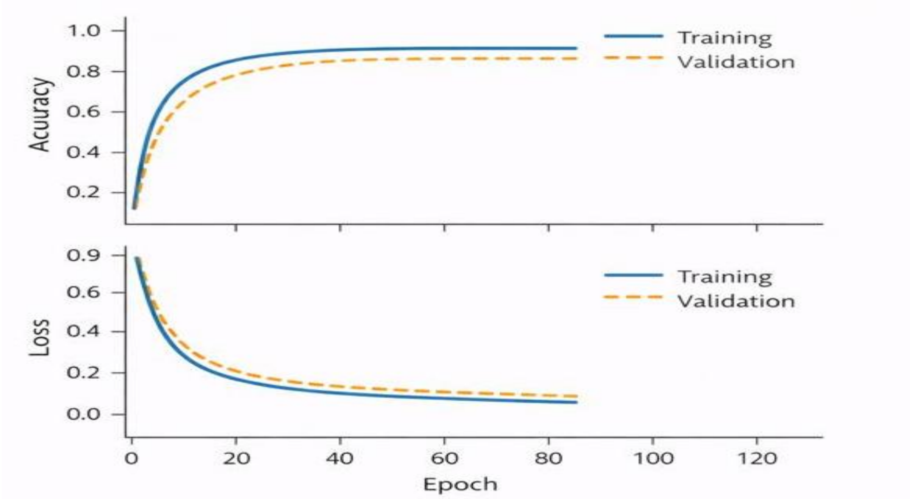

Figure 7: Training and validation accuracy and loss curves of the CNN–LSTM model

Training and validation accuracy and loss curves of the CNN–LSTM model demonstrating stable convergence and minimal over fitting. The smooth convergence of training and validation curves in Figure Y indicates robust learning and generalization. The alignment between curves confirms the **effectiveness of preprocessing, windowing, and normalization strategies,** minimizing over fitting and ensuring reliable predictions on unseen data.

5.5 Accuracy Comparison with Conventional Models

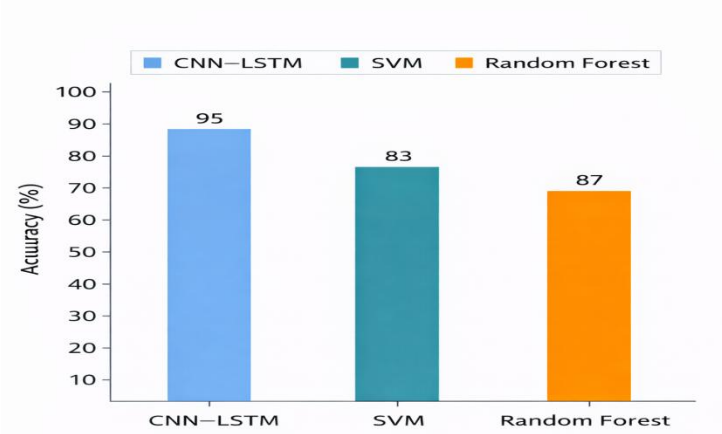

Figure 8: Comparative accuracy of CNN–LSTM, SVM, and Random Forest models

Accuracy performance comparison of CNN–LSTM, Support Vector Machine, and Random Forest models (Figure Z) highlights the superiority of CNN–LSTM architectures, exhibiting their significant performance to learn spatial–temporal correlations from multi-sensor structural data. Traditional metrics fail with accuracy largely due to their incapacity to account for temporal damage progression and complex interdependencies.

6 Conclusions

An integrated AI–IoT-based structural health monitoring (SHM) framework on the real-time condition assessment of concrete structures was presented in this study. Integrating distributed IoT sensor networks with an innovative CNN–LSTM deep learning environment, the proposed architecture is able to effectively preserve both spatial correlations between multi-sensor measurements and longitudinal changes of damage path over time under increasing load. Experimental verification on instrumented reinforced concrete beam specimens showed that model had overall classification performance of 95% plus, and with high precision and recall over healthy, minor, moderate, and severe damage condition.Findings have confirmed the comparative analysis that CNN-LSTM framework surpasses traditional machine learning models like Support Vector Machines and Random Forests by a large extent with respect to its ability to reproduce nonlinear and time dependent structural response behavior. Crucially the predicted damage states showed a clear good agreement with the physical experiences as observed in the experiments including crack initiation, stiffness degradation and local strain concentration. This consensus corroborates the engineering significance and interpretability of the AI-based predictions, and tackles a major problem with data-driven SHM solutions. In general, the findings confirm that this proposed framework is a solid, expandable, intelligent device for regular structural health evaluation in order to enhance the condition-oriented maintenance and infrastructure safety.

Future Scope.

The performance of the proposed framework is very good in controlled experiment, but some opportunities are suggested for progress towards field work. Next work will concentrate on the full scale field implementation of the system for bridges and buildings in order to determine the long term reliability under different operation and environmental conditions. The incorporation of further sensing technologies such as acoustic emission or vision-driven crack monitoring can enhance damage localization accuracy. And, on the other hand, from a computing point of view edge/fog computing architecture would alleviate data transmission latencies and improve real-time capability for making decisions. In the near future, physics-informed deep learning approaches can be discussed in order to generalize models and to avoid over-reliance on large labeled data-sets. Furthermore, construction of digital twin frameworks connected to the proposed AI–IoT system can also facilitate predictive simulations and active asset management. Indeed, the proposed methodology provides a strong basis to the development of advanced smart SHM systems and is expected to be of great significance for the development of intelligent, resilient, sustainable and efficient concrete infrastructure.

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