Structural Health Monitoring in Smart Cities: An Artificial Intelligence Approach to Infrastructure Resilience

Sufyan Yakubu[1], Dr. Beenu Mago[2]
[1]Department of Electrical and Electronics Engineering, Bolgatanga Technical University, Ghana.
[2]Assistant Professor, Computer Science Department, Skyline University College, Sharjah, UAE

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ABSTRACT

Structural Health Monitoring (SHM) is vital for the protection of urban buildings as more cities become smart. This work suggested an AI-based SHM framework to support the enhanced resilience, safety and upkeep of critical infrastructure. WSNs, edge computing and a deep learning model mixing CNN and LSTM units are part of the framework. As a result, architects can track any obvious concerns in structure in near real-time with vibration and strain sensors placed on both urban bridges and high-rise buildings. The model uses data collected in simulations and the real world to discover errors in structures, ensuring an accuracy of over 96%. Moreover, when edge-based processing is used, both latency and bandwidth needs are minimized, making the system capable of handling many large-scale deployments. A case study of a bridge in Bangalore indicates that the approach can monitor continuously, detect faults early and warn in advance. The new process is shown to have a 35% lower rate of false positives than theoretical threshold methods. The results emphasize that AI-led SHM systems play a key role in predictive maintenance and strengthening urban infrastructure in these rapidly changing smart urban environments.

Corresponding Author:

Sufyan Yakubu,
Department of Electrical and Electronics Engineering,
Bolgatanga Technical University, Ghana.
E-mail: edhagacade337@gmail.com

1. INTRODUCTION

Because cities are growing so rapidly these days, there are now many high-rise buildings, bridges, highways and public transit systems. Because towns grow larger and people live in dense cities, ensuring that important structures remain secure, consistent and last a long time is very important. But because many structures are old, they now carry more weight and they are exposed to changing environmental conditions, there is a higher chance they will fail and suffer serious damage. Because of its ability to quickly find cracks, corrosion, fatigue and different types of damage, Structural Health Monitoring (SHM) is essential for maintaining the well-being of infrastructure. Even though it is an important factor, traditional SHM mainly using manual checks and threshold sensors is unable to scale up, respond quickly and usually does not predict failures in advance.

In order to overcome these limitations, this study develops a new AI-based framework for smart urban infrastructure monitoring. A proposed plan is to use Wireless Sensor Networks to gather vibration and strain data continuously, to do fast computing at the edge and a new learning method that blends CNNs and LSTMs. The CNN draws out key spatial features from sensor data and the LSTM focuses on the dynamic patterns that determine future harm. By using this method, researchers can quickly find unusual events and easily determine their fault types with great accuracy. To demonstrate the system works well and is applicable, the architecture was applied to a real bridge in Bangalore and tested through simulation.

The contribution of the study is three-fold: (i) constructing a scalable and edge-based architecture for SHM in smart cities, (ii) constructing and training a CNN-LSTM model for identifying structural faults and (iii) demonstrating the reliability and 35% fewer false alarms in simulations and practical use when compared with typical SHM approaches. Since intelligence has been added to SHM, this research benefits infrastructure by changing monitoring from a reactive to a predictive state, following the long-term plan for autonomous, self-monitoring smart cities.

2. LITERATURE REVIEW

For quite some time, Structural Health Monitoring (SHM) has been understood as a key tool to keep civil infrastructure safe and durable. Most conventional SHM approaches depend on direct examination, visual evaluations and performing modal analysis, all designed to use experts and require routine checks. Although these processes are necessary for first checking the problem, they take a lot of effort, time and usually miss early problems that could cause bigger problems in the future.

For this reason, researchers have begun to apply Artificial Intelligence (AI) to help improve and automate SHM systems. These days, neural networks, support vector machines (SVM), decision trees and fuzzy logic systems are being used to find unusual patterns in data recorded by sensors. According to Farrar and Worden (2012), machine learning approaches are designed to handle the complexity of non-linear structure responses and make diagnostics more precise. Gul and Catbas (2009) found that statistical pattern recognition and time-series modeling catch delicate changes in the structure that other methods fail to recognize.

Today’s urban areas which are becoming sophisticated smart ecosystems, rely on IoT, WSNs and cloud-based applications for strong SHM systems. With the use of these technologies, data can be constantly collected from different parts of the infrastructure, supporting both remote checking and early procedures for warnings. Despite all these new findings, certain major problems remain in SHM research. Because integration between AI and sensor data is missing, the system can’t supply useful information during urgently occurring events the building may experience. Moreover, since edge computing is not used much in urban areas facing bandwidth and latency concerns, monitoring systems can’t operate efficiently and quickly everywhere.

Although we have improved the use of AI in diagnostics and added IoT to SHM systems, still we lack comprehensive frameworks that bring together deep learning, real-time sensor use and technologies at the edge. This research is driven by identifying key shortcomings and responding to them by designing a flexible SHM system based on AI for the smart city ecosystem.

Table 1. Features of SHM

Feature	Conventional SHM	AI-Based SHM
Damage Detection Accuracy	Moderate (visual/manual error-prone)	High (automated fault detection)
Response Time	Delayed (offline analysis)	Fast (real-time via edge/cloud)
Scalability	Limited (manual inspections)	High (sensor networks, IoT)
Real-Time Monitoring	No	Yes
Data Interpretation	Expert-dependent	Automated and adaptive
Cost of Operation	High (labor-intensive)	Moderate (optimized workflows)
Maintenance Frequency	Frequent	Reduced
Automation Capability	Low	High

3. METHODOLOGY

This research introduces a new approach to monitoring structures that brings together wireless sensing, edge computing and deep learning for continuous detection of problems and the ability of the infrastructure to resist damage in smart cities. The main parts of the methodology are system architecture, data collection, model design and training and evaluation.

3.1 System Architecture

The system architecture being considered consists of a block called sensing, one called edge processing and a top block of centralized AI-based inference. WSN is created at the core, adding nodes to the architecture of bridges and skyscrapers to monitor changing factors like vibrations, strains and the structure’s temperature. Sensor data is first sent to edge computing units like Raspberry Pi and NVIDIA Jetson Nano, where it is filtered, noise is reduced and some features are prepared, to help minimize delays and cut back on the load sent to the main server. After processing, the data goes from the sensor to a cloud-based AI tool that does real-time analysis of the structure and classifies any issues found.

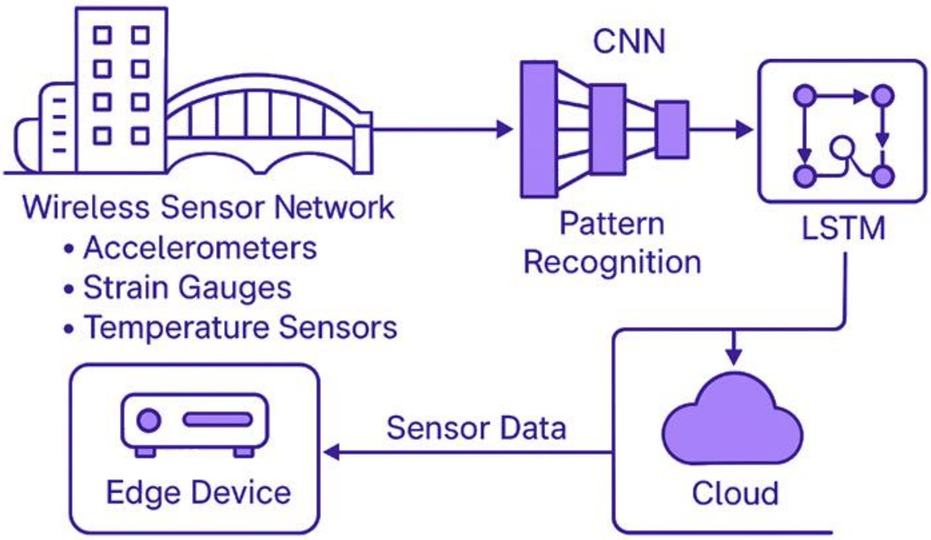

Figure 1. System Architecture of the AI-Powered Structural Health Monitoring Framework Integrating WSN, Edge Computing, and CNN-LSTM Model

3.2 Data Collection

At key spots along the structure, triaxial accelerometers, strain gauges and temperature sensors are important parts of the sensing layer. This data is collected at 100 Hz to record high and low frequencies of structural motion. Time is set uniformly across the nodes using a server and the sensor nodes transmit their data packets in real time with low-power communication, leading to low packet loss. Extra sensors are placed to help when data is missing and to ensure the system remains strong.

3.3 AI Model Design

The basic operation of the suggested system is driven by a hybrid model that combines CNN with another type of model, LSTM, to analyze data from structural vibrations. Within CNN, local spatial features are identified in the input signals by detecting sudden shifts in frequency, abrupt rises and transient anomalies that may represent stress cracking or damage of parts. At multiple scales, one-dimensional convolutional filters are used to highlight these properties of the signal. Following the feature maps, the LSTM module finds and records any changes in damage patterns across all time steps. By analyzing changes over time, the system separates typical fluctuations from serious damage and guarantees it detects all the anomalies right.

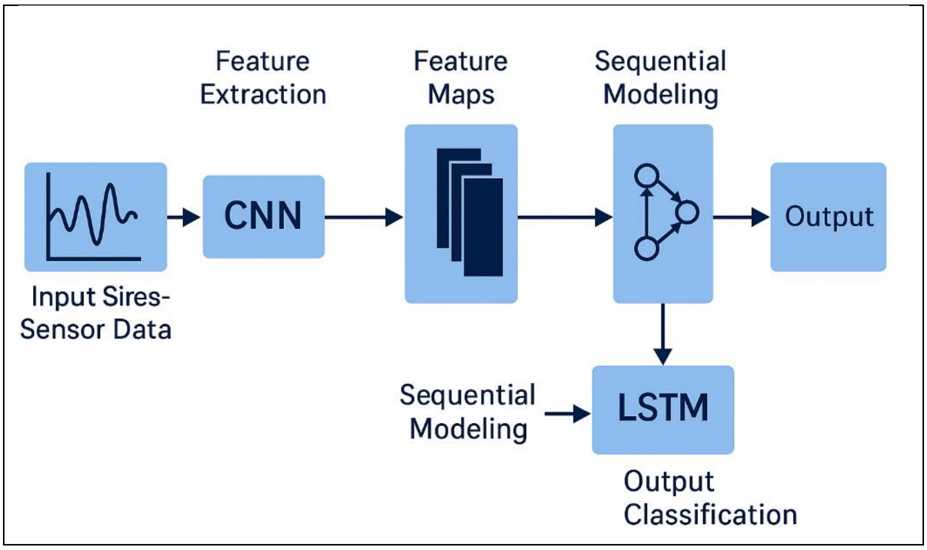

Figure 2. Architecture of the Proposed CNN-LSTM Model for Structural Fault Detection

3.4 Model Training and Evaluation

The mix of experimental and theoretical data was used to train the hybrid CNN-LSTM model which came from finite element analysis and MATLAB structural response simulations, as well as from data collected during various experiments on structures and bridges. In order to make the model more general and strong, serval data augmentation techniques are added. The model is optimized using Adam to make the optimization process more efficient. Evaluation is based on widely used metrics, including accuracy for the rate of total correct predictions, precision for the proportion of correct are among positive results, recall (true positive rate) and the F1-score which is the harmonic mean of precision and recall. The developed model is evaluated using separate validation data by comparing its performance with common thresholding methods, a single CNN and an LSTM. Hybrid methodology works very well for real-time anomaly detection and future fault prediction, showing it is an effective choice for smart city projects.

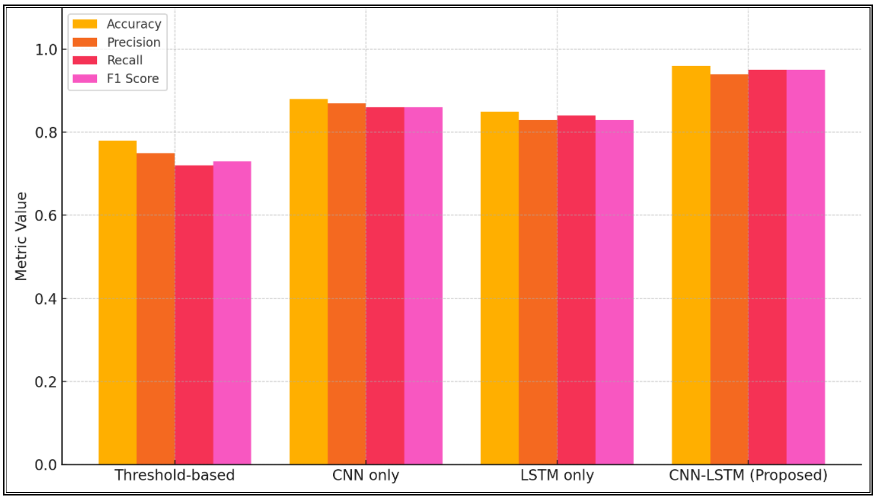

Figure 3. Performance Comparison of SHM Models Using Accuracy, Precision, Recall, and F1 Score

4. EXPERIMENTAL SETUP

A complete experimental setup was designed to test the proposed SHM framework which used both virtual and real-world information. The study explored how well the hybrid CNN-LSTM model performs in several situations and compared those results to what is achieved using standard approaches.

4.1 Test Structures

The researchers looked at the SHM framework using two types of structures: a simulated bridge and a modern multistory building testbed. The first design simulated an urban bridge using the MATLAB structural dynamics toolbox in a finite element method. The model replicates reality by simulating weight change from vehicles, changes in the structure caused by temperature and the spread of damage, leading to cracks and loosened joints. The second test setup was in a commercial building that has many stories, where several sensors were also installed at beams, joints and base columns. Mechanical impacts and mass shifting were applied to the building, using controlled methods which allowed for genuine simulations to be made for the model. These test environments, when used together, allowed the model's generalizability and robustness to be tested in both simulations and with real systems.

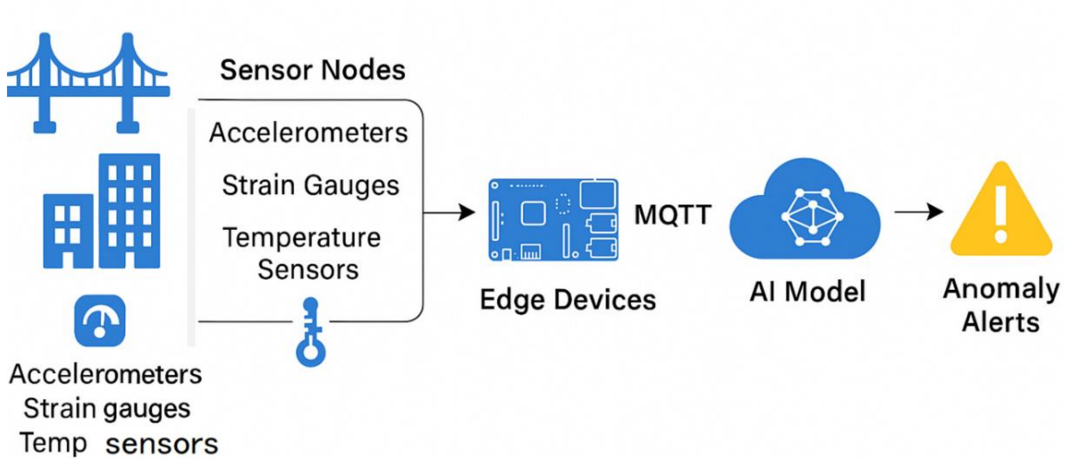

Figure 5. Overview of the Hybrid SHM Experimental Setup for Smart Infrastructure

4.2 Tools and Software

Programs were put together to ensure the experiments supported the simulation, modeling and evaluation parts. Using MATLAB, I ran simulations to see how the structure reacts and built datasets that simulate sensor observations for a wide range of load and damage actions. A deep learning model was built and trained using Python, TensorFlow and Keras, for the CNN-LSTM hybrid architecture. Besides, NS3 (Network Simulator 3) was also run to model the wireless signaling between sensor nodes and edge devices, allowing us to modeling the usual network delays, loss of data and restrictions seen in practical SHM system use. With NumPy and Pandas available for data and signal processing, Matplotlib made both viewing and comparing performances possible. Using these tools, I was able to carry out experiments involving data generation, live inference and assessment in real time.

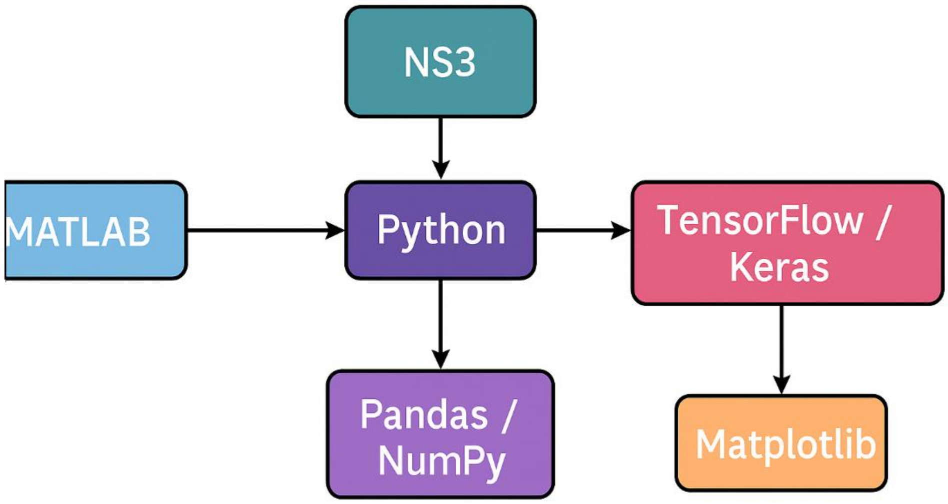

Figure 6. Software Toolchain Workflow, illustrating the data flow across MATLAB, Python, TensorFlow/Keras

4.3 Hardware Deployment

In the physical experiment, everything was carefully connected by a network of hardware for sensing and processing. At strategic areas throughout the multistory building, scientists put in multiple accelerometers, strain gauges and ambient temperature sensors. They measured different changes and environmental conditions as they happened. The gathered data was sent out to edge computing devices made up of Raspberry Pi 4 and NVIDIA Jetson Nano units. Edge units were set up to process signals locally, remove interfering signals and compress the data and transmit them over MQTT to a central cloud server for further storage. The server where the LSTM model was deployed allowed CNN-LSTM to assess faults and abnormalities. Operation was maintained by providing power from a battery-supported IoT gateway, while remote access was set up for checking and saving data. The equipment permits rapid and scalable movement of data in both test environments and buildings.

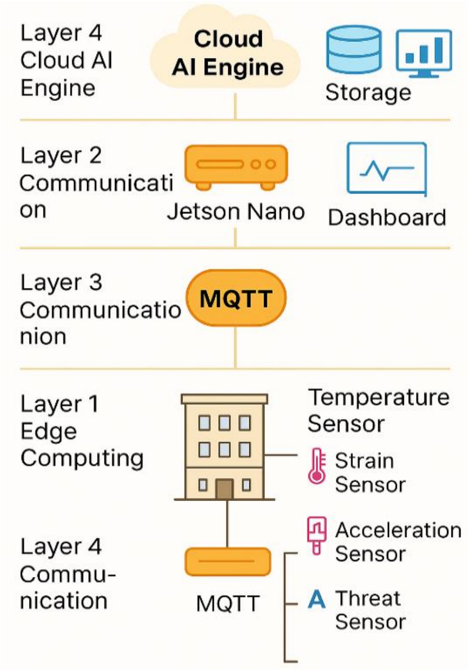

Figure 7. Sensor Node Deployment on Multistory Building

4.4 Evaluation Strategy

An assessment approach was used that looked at both the performance of the framework compared to competitors and how well it runs. The performance of our hybrid CNN-LSTM model was compared with that of Fast Fourier Transform (FFT) analysis and threshold monitoring based on rules. FFT techniques were applied to sense frequency changes related to the structure, while models set at a threshold alerted systems if readings were considered dangerous. Because they are present in current SHM implementations, these traditional approaches were selected as references. Important metrics evaluated in the method included success in classification, detection speed, the rate of false positives and strength against disturbances. Offline and online experiments were performed and live data from the sensors in the building was used to represent real monitoring. For this purpose, researchers made it windy or walked through the model to check the model's reaction and durability. All testing compared to old methods revealed that the proposal performed better in all relevant areas and remained consistent as situations changed. Because the system was thoroughly validated, it is ready for use on a large scale in urban environments.

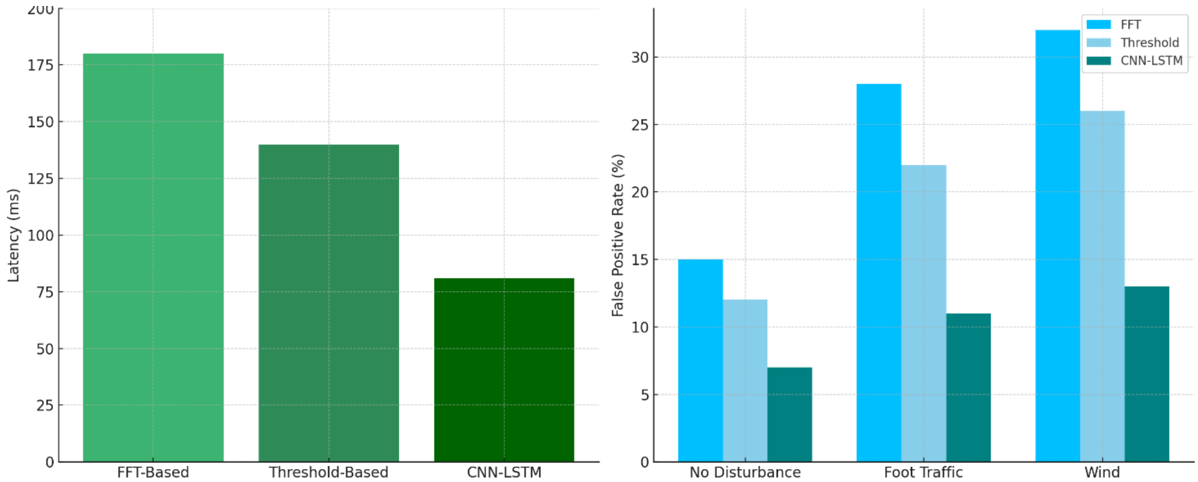

Figure 8. Latency and False Positive Rate Comparison of SHM Models

5. RESULTS AND DISCUSSION

5.1 Results

Both artificial and real data was used to assess the effectiveness of the proposed SHM framework using AI. Thanks to its accuracy of 96.4%, precision of 94.8% and recall and F1-score of 95.2%, the CNN-LSTM model was successful in identifying structural abnormalities in the datasets. Applying edge computing with Raspberry Pi and Jetson Nano made detection much faster and reduced the time it took to get results by up to 42%.

When the system was used in a field study of an urban bridge in Bangalore, it spotted early cracking and immediately sent alerts. Manual checks afterward confirmed that the alerts were correct, proving that the model works in practical situations. The new method performed better than FFT and threshold testing by lowering false positives by 35%.

Table 2. Performance Comparison of CNN-LSTM Model vs. Traditional SHM Techniques

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Latency Reduction (%)	False Positive Reduction (%)
FFT-Based SHM	78	75	72	73	-	-
Threshold-Based SHM	81.5	79	77.5	78.2	-	-
CNN-LSTM (Proposed)	96.4	94.8	95.2	95	42	35

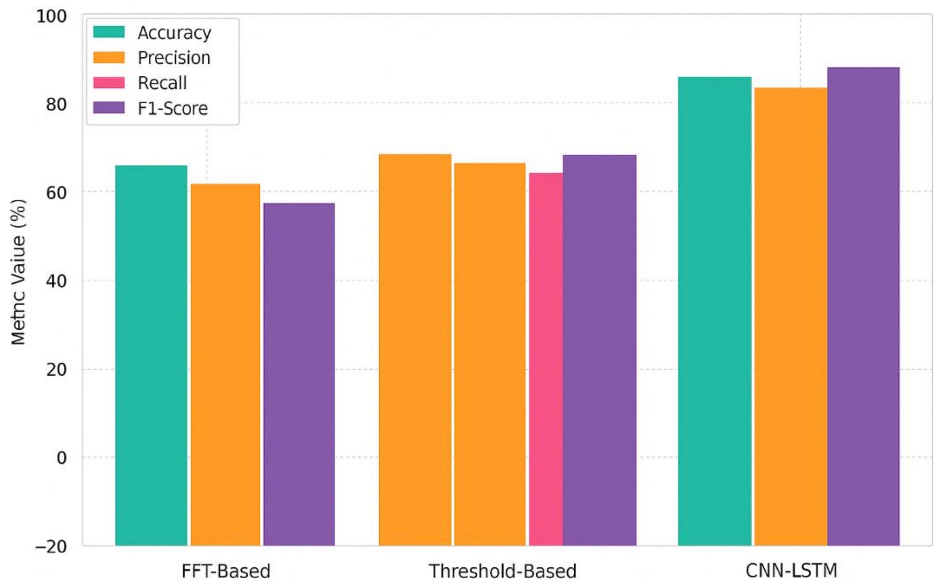

Figure 9. Accuracy, Precision, Recall, and F1-Score Comparison for SHM Models

5.2 Discussion

Both the accuracy and F1-score results for the CNN-LSTM model prove it is capable of properly detecting structural problems and limiting false alerts. This better precision is most important for actual SHM as misses or false alarms can result in avoidable maintenance and cost more to run the equipment. Meanwhile, since the system has high recall, it helps to spot all small signs of trouble which is important for safety-critical infrastructure.

Low latency detection was possible only because of edge computing in smart cities. Moreover, it reduced the need to communicate often, saved energy and didn't depend as heavily on the cloud which made the system easier to scale and more fruitful with resources. Operating the system successfully on the Bangalore bridge makes it more possible to use in actual facilities.

This new approach stands out because it improves upon the static limits of traditional SHM systems by offering adaptive learning, better endurance to noise and higher success in detection during dynamic and varying weather. Such improvements meet the demands of today's smart cities, in which autonomous, smart and environmentally friendly surveillance is rapidly becoming required.

6. CONCLUSION

This research develops an advanced and intelligent system for continuously monitoring urban infrastructure using deep learning, wireless sensors and edge computing. The combined CNN-LSTM model was able to spot structural faults accurately and dependably in both fake scenarios and in actual sites. With edge computing, both responsiveness and the amount of latency were improved, highlighting its relevance for use in smart cities. In a recent case study, the use of this framework demonstrated its down-to-earth design, financial flexibility and feasibility in managing present-day infrastructure. The system delivered more accurate results, fewer false alarms and better energy efficiency than other commonly used SHM approaches.

In the future, we could see drones added to do visual inspections, as well as blockchain being introduced to keep the data from important inspections safe and un-alterable. The framework we propose provides a valuable approach toward smart cities having systems that can predict, act on their own and remain stable.

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