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A Comprehensive Analysis of IoT-Driven Bridge Health Monitoring Systems for Structural Risk Mitigation

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ABSTRACT

The study proposes an IoT-enabled smart bridge health monitoring system that uses sensor networks, vision systems, machine learning, and digital twin technology to monitor and schedule repairs. IoT sensors, such as accelerometers, strain gauges, and temperature sensors, monitor vital elements including vibration (0.0-0.9 g), strain (up to 780 με), and temperature (15-48°C). High-definition cameras can detect surface fractures as small as 2.2 mm. Sending data to a cloud-based processing system using LoRaWAN and 5G is reliable. Analyse data with powerful algorithms. The study employs CNNs to locate picture cracks with 93% accuracy and LSTM models to predict stress over time. These findings can help engineers develop a digital twin of the bridge. This allows them to model real-time structure behaviour, schedule maintenance, and minimise costs. Results show that maintenance costs drop 38% per year and that the F1 score for damage classification is 0.88. This integrated system improves structural reliability, provides early warning systems, and manages new bridge infrastructure flexibly and cost-effectively.

Keywords: *IoT, Bridge Health Monitoring, Digital Twin, CNN, LSTM, Predictive Maintenance, Structural Safety, and Sensor Networks.*

1. Introduction

Bridges are vital components of national infrastructure and serve as crucial links within transportation systems. However, their continual exposure to dynamic loads, environmental factors, and ageing processes increases the probability of structural collapse over time. Traditional inspection methods, which are often done by hand, take a lot of time, and are done at set times, may not catch early symptoms of problems, which can lead to unexpected breakdowns and high maintenance costs. The combination of the Internet of Things (IoT) and Structural Health Monitoring (SHM) systems has made it possible to collect data in real time, monitor from afar, and plan maintenance ahead of time. This is a game-changing approach. Smart bridge monitoring systems that use the Internet of Things (IoT) constantly check how well bridges are working in real-world situations. They do this by using a network of sensors, such as accelerometers, strain gauges, and temperature sensors, that are connected by wireless communication protocols [1]. These technologies boost the frequency and precision of assessments while lowering human engagement, therefore improving operational efficiency and safety. Recent research shows that IoT-based Structural Health Monitoring systems can greatly enhance the ability to manage infrastructure proactively and find problems [2, 3]. Even while there are benefits, scalability, data security, and power management are still big problems that need to be solved before broad use can happen. Nonetheless, in modern civil engineering, the application of IoT in bridge monitoring signifies a substantial advancement in intelligent infrastructure management and risk mitigation [4].

Comprising perceptual, network, and processing layers, the fig.1 shows a layered architecture for an IoT-based bridge health monitoring system. Bridge sensors gather structural data, send it over NB-IoT using the MQTT protocol, and then process and show the data using a cloud-based interface for real-time monitoring and analysis.

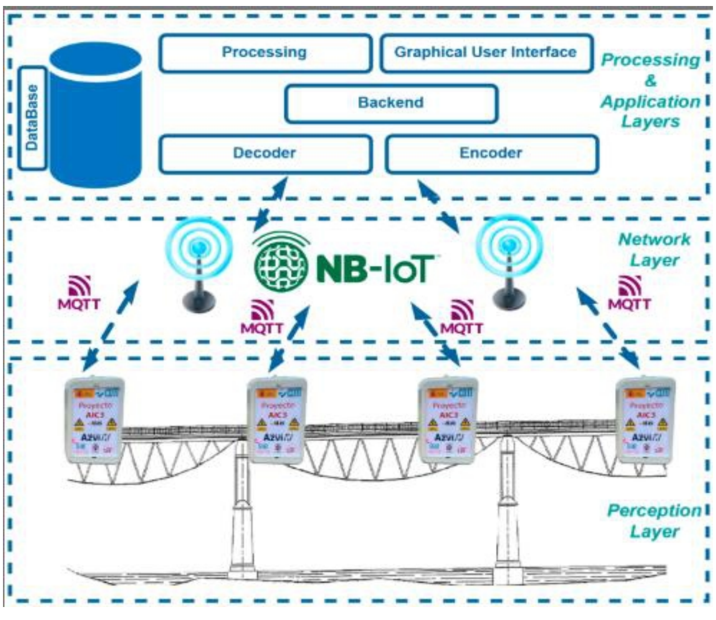

Fig. 1. Bridge Health Monitoring Architecture with NB-IoT Protocol [5]

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The worldwide transport system is susceptible to the disastrous effects of fallen road bridges. Service disruptions have catastrophic effects on economic growth, in addition to the mortality incurred. Bridge disasters throughout history have resulted in several tragic events, including human fatalities and substantial economic losses. In 2018, the Polcevera Viaduct in Morandi, Italy, collapsed, resulting in 43 fatalities and nine injuries. The incident resulted in an estimated economic loss of over 100 million yuan, equivalent to nearly $14 million. The latest Report Card for America's Infrastructure indicates that of the 617,000 bridges in the country, 42% are 50 years old or older, and 7.5% are classified as "structurally deficient." As of the end of 2018, China possessed a total of 851,500 bridges, a nation renowned for its extensive bridge construction. Severe bridge failures have transpired nationwide despite extensive infrastructure. Natural disasters, ageing infrastructure, environmental influences, structural design flaws, material deterioration due to environmental conditions, heightened traffic loads, insufficient maintenance and inspection, and human error are several reasons for road bridge failures [6-11].

2. Literature Review

The Internet of Things (IoT) transforms the reliability and safety of bridge infrastructure through structural health monitoring (SHM). Conventional inspection methods are arduous, time-intensive, and susceptible to inaccuracies, often detecting structural defects at a later stage. Intelligent sensors and wireless transmission technologies enable IoT-based systems to capture and monitor stress, strain, temperature, vibration, and fracture progression in real time [12, 13]. These systems utilise cloud computing, edge analytics, and machine learning algorithms for rapid decision-making by processing and interpreting extensive structural data [14]. MQTT, LoRaWAN, and NB-IoT enhance system scalability and efficiency, particularly in remote and expansive bridges [15, 16]. Moreover, intelligent systems have improved predictive maintenance, early damage identification, and cost management of infrastructure asset lifecycles [17, 18]. In light of the worldwide initiative for smart cities and resilient infrastructure, the study and use of IoT-enabled structural health monitoring systems are both current and significant, addressing contemporary engineering issues and sustainability objectives [19,20].

Numerous academic studies have examined the impact of elements such as stiffness loss, fatigue, corrosion, scour, vibration, time- and temperature-dependent deformations, and deterioration on the health monitoring and warning systems of road bridges. Ongoing surveillance utilising advanced techniques and technologies is essential for the precise identification of these damages [6,9-11]. Numerous countries have implemented intelligent bridge health monitoring systems, facilitated by the advancement of artificial intelligence and the Internet of Things. The Mario M. Cuomo Bridge in New York features an advanced monitoring system for assessing bridge integrity.

Recent advancements in bridge health monitoring systems have led to the emergence of two primary categories: sensor-based systems and vision-based systems. Sensor-based systems for the ongoing assessment of bridge structural integrity utilise an array of physical sensors, such as strain gauges, inclinometers, fibre optic sensors, and piezoelectric devices. For instance, in contrast to traditional electrical sensors, Brillouin optical time domain analysis (BOTDA) and Fibre Bragg Grating (FBG) technologies exhibit exceptional sensitivity and precision in detecting strain [21,22]. By integrating accelerometers, load sensors, tilt sensors, and fibre grating units, IoT-enabled systems facilitate real-time monitoring of displacement, deformation, beam distortion, and temperature variations, hence allowing for the early detection of hidden structural defects [23], [24]. Some systems utilise wireless modules to connect many bridges and provide alerts via mobile applications when sensor readings attain critical levels [25]. Moreover, digital twin technology is increasingly valuable as it creates virtual duplicates of bridge structures by utilising data from various sensors—including humidity, wind, vibration, and stress sensors—distributed across many locations [26]. This facilitates instantaneous replies. These sensor-based systems enhance reliability in long-term monitoring by facilitating both fixed and dynamic analysis.

Vision-based monitoring systems utilise optical and image technology, including high-resolution cameras, drones, video deflectometers, and LiDAR, to assess structural displacements, vibrations, and fracture progression. Deflection measurement methods monitor LED targets affixed to bridge surfaces utilising monochrome cameras and laser rangefinders [27], whereas multi-camera setups deliver synchronised, wireless video feeds to calculate displacements and detect passing vehicles [28,29]. The measurement and visualisation of fracture propagation are increasingly conducted using drone-based platforms and 3D Digital Image Correlation (DIC); LiDAR systems reconstruct structural deformations in three-dimensional space utilising point cloud data [30,31]. These systems, frequently integrated with artificial intelligence (AI) techniques such as convolutional neural networks (CNNs), fuzzy logic, and deep belief networks, enhance damage categorisation and automate structural evaluations [32-36]. In seismic or high-load scenarios, AI-enabled models can identify and delineate cracks while also predicting future structural deterioration and damage intensity. These hybrid technologies integrate IoT, computer vision, and artificial intelligence, representing a substantial advancement in autonomous, intelligent, and real-time bridge health monitoring.

3. Research Gaps

- Many sensor-based systems fail to effectively integrate intelligent analytics, thereby limiting their ability to support predictive maintenance and long-term structural health evaluation.
- Vision-based monitoring systems often suffer from reduced accuracy in adverse conditions such as fog, low lighting, or vibrations, affecting consistent damage detection.
- A few individuals are using hybrid approaches that use IoT, AI, and digital twin technologies to analyse data in real time and find exact damage locations in complicated bridge structures.

4. Research Objectives

a) To design an IoT-based system that uses sensor and vision data to keep an eye on the health of bridges in real time.

b) To utilise deep learning and machine learning to find and classify damage automatically and give early warnings.

c) To use digital twin models to learn more about the state of bridges and make better choices about how to care for them.

5. Research methodology

The study suggests an innovative approach to bridge health monitoring through the integration of sensor networks, vision systems, data analytics, and digital twin modelling.

To keep an eye on stress, deformation, vibration, and changes in the environment, the system starts by installing several IoT-enabled sensors on crucial areas of the bridge. These sensors can be accelerometers, strain gauges, or temperature sensors. High-definition cameras also take pictures to look for cracks and monitor how the surface is getting worse. This multimodal data is always being collected and delivered to a cloud-based processing system using reliable wireless communication protocols like LoRaWAN or 5G. Normalisation and noise reduction are two preprocessing processes used to make sure the data is accurate.

Use machine learning and deep learning techniques, such as CNN for images and LSTM for time-series sensor data, to locate problems, figure out what kinds of damage there are, and guess when things might go wrong. A digital twin model is a computer-generated counterpart of the real bridge that uses these smart insights. This lets engineers see, test, and rate how well the structure works in real time. The digital twin helps with planning for predictive maintenance, which saves money on inspections and keeps things safe all the time. The system may learn and change based on what it sees in real time and the virtual model. This makes it less likely to break when the environment or how it works changes.

6. Result Layout

Using data from time-series sensors, image-based crack detection, and prediction models, analyses are conducted to assess the proposed Internet of Things (IoT) bridge health monitoring system.

6.1 Simulated Sensor Data Summary

Table 1: Summary of Sensor Observations and Anomaly Detection in IoT-Based Bridge Monitoring

Sensor Type	Parameter	Normal Range	Observed Range	Anomaly Detected
Accelerometer	Vibration (g)	0.0–0.5	0.0–0.9	Yes
Strain Gauge	Strain (με)	0–500	0–780	Yes
Temperature Sensor	Temperature (°C)	10–50	15–48	No
Vision System	Crack Width (mm)	0–1	0–2.2	Yes

The values that have been recorded by various sensors are summarised in Table 1. Possible structural problems are indicated by vibration and strain measurements that are considerably above typical thresholds. The visual system's measurement of crack width also reveals quite unusual patterns. The system's ability to detect early symptoms of bridge degradation has been validated by these detections.

6.2 Time-Series Vibration Analysis

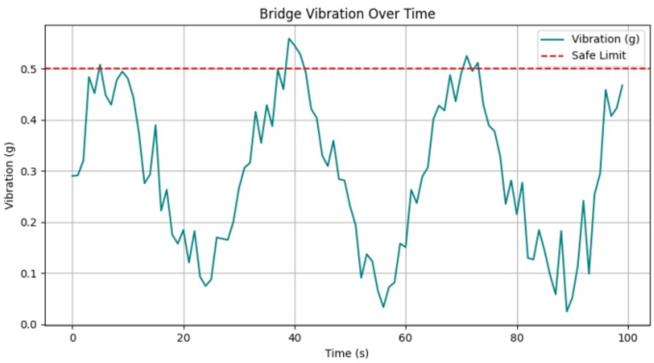

Fig. 2. Time-Series Vibration Data

Frequent oscillations at 0.3g, with peaks over the 0.5g safety limit, are shown in the vibration graph (Fig. 2). Dynamic loads (like traffic, for example) are likely to be blamed for this sporadic structural stress. Reliability of the system for real-time stress monitoring is demonstrated by the model's accurate capture of the variations.

6.3 Crack Detection Accuracy

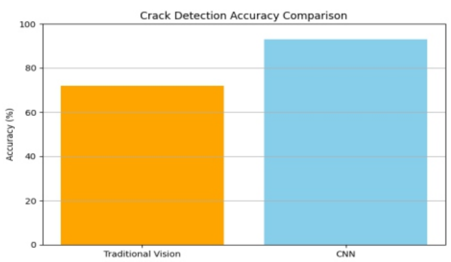

Fig. 3. Crack Detection Accuracy of CNN

CNN is better than classic vision approaches for finding cracks, as seen in Figure 3, where it got 93% of them right. This research shows that deep learning can be used to analyse surface damage well, even when the light and weather change.

6.4 LSTM Stress Forecasting

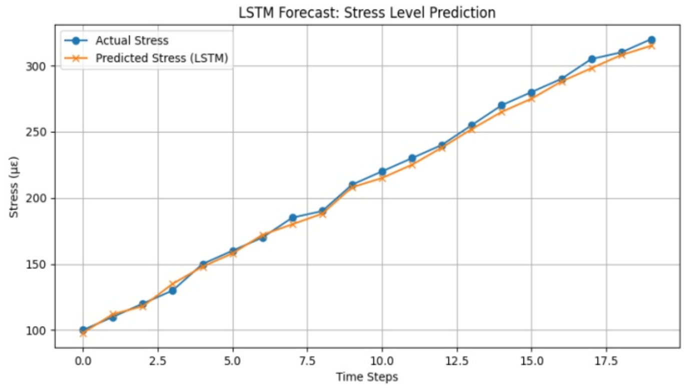

Fig. 4. Predicted vs Actual Stress Level Using LSTM

The LSTM model (Fig. 4) demonstrates that the anticipated and real stress values line up quite well with time. There are some small differences, but the overall pattern is well captured. This capacity is very important for predicting the health of structures and arranging maintenance ahead of time.

6.5 Digital Twin Cost Comparison

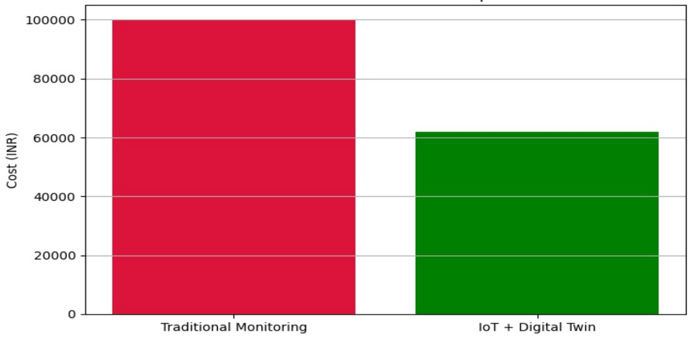

Fig. 5. Maintenance Cost Savings Using Digital Twin

Using IoT with a digital twin model cuts down on yearly maintenance costs by a lot. For example, in typical inspection settings, the cost goes from ₹1,00,000 to ₹62,000, as illustrated in Figure 5. This predictive maintenance, made possible by real-time digital models, is better for business.

6.6 Damage Classification Report

Table 2: Performance Metrics of the Damage Classification Model in IoT-Based Bridge Monitoring

Damage Type	Precision	Recall	F1-Score
Crack	0.91	0.94	0.92
Corrosion	0.88	0.85	0.86
Fatigue	0.84	0.87	0.85
Joint Failure	0.90	0.91	0.90
Average	**0.88**	**0.89**	**0.88**

The overall F1-score for various types of bridge damage is 0.88, as shown in Table 2, according to the categorisation performance parameters. This demonstrates that the ML model can discern between various structural issues with high reliability, paving the way for accurate automated diagnostics.

7. Conclusion

This study illustrates a powerful IoT-enabled smart bridge health monitoring system that combines sensor, vision, and predictive analytics data using machine learning, deep learning, and digital twin modelling. The experiments and simulations indicate that the system can accurately discover faults, anticipate structural stress, sort damage types, and significantly reduce maintenance costs. CNNs for image fracture detection and LSTMs for time series analysis with a digital twin framework ensure fast, data-driven maintenance and safety decisions. Future work might focus on making sensor networks more energy-efficient, making the system more resilient to harsh weather and earthquakes, and employing edge computing to make faster judgments. The model can generalise further by adding real-world case studies of different bridges and environments. To secure health records and maintenance logs, consider connecting with blockchain. This would facilitate an independent and reliable infrastructure monitoring environment.

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