

EDGE EMPOWERED DIGITAL TWIN ARCHITECTURE FOR REAL-TIME STRUCTURAL HEALTH MONITORING OF SMART BRIDGES

Dr. Nidhi Mishra^{1*}, Aakansha Soy²

¹*Assistant Professor, Kalinga University, Naya Raipur, Chhattisgarh, India.
e-mail: ku.nidhimishra@kalingauniversity.ac.in,
orcid: <https://orcid.org/0009-0001-9755-7950>

²Assistant Professor, Kalinga University, Naya Raipur, Chhattisgarh, India.
e-mail: ku.aakanshasoy@kalingauniversity.ac.in,
orcid: <https://orcid.org/0009-0002-1955-6909>

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SUMMARY

Urban infrastructure, especially smart bridges, is growing rapidly, requiring effective solutions to ensure structural integrity. Conventional Structural Health Monitoring (SHM) systems have limitations in scalability, speed, and accuracy. This paper presents a new edge-enabled digital twin platform for real-time SHM of smart bridges, combining IoT, cloud computing, and edge computing. The architecture offers a high-performance, decentralized scheme of continuous monitoring to facilitate real-time detection and forecasting of structural failure by integrating the sensors on the bridges and the edge devices. The fundamental approach uses an Autoencoder-based anomaly detection, in which Autoencoders are trained to learn to recreate sensor information, and learn to behave normally by modeling the structural behavior of the bridge. In the case of real-time monitoring, the differences between the real sensor values and the reconstructed data are compared, and anomalies are noted, which are indicators of structural problems. This architecture minimizes latency by often processing data at the edge and by improving decision-making by initiating maintenance actions based on identified anomalies. The digital twin model captures the actual behavior of a bridge, providing extensive information on the current condition of the infrastructure. The suggested system is tested in terms of five major performance indicators, namely accuracy, processing time, energy consumption, scalability, and false alarm rate. Indications show that the system delivers better results than traditional SHM systems across a range of key features, including much higher anomaly detection accuracy, shorter processing time, and more efficient energy use. The system can be scaled, and additional bridges with a significantly reduced false alarm rate can be supported, therefore reducing unnecessary maintenance intervention. In general, the edge-enabled digital twin architecture can provide a promising solution to real-time SHM to enhance the safety and efficiency of smart bridges. The next research will involve integrating AI-based predictive analytics into the digital twin system to increase further the capacity of the system to indicate structural failures prior to it happening.

Key words: *structural health monitoring, smart bridges, digital twin, edge computing, real-time data processing, anomaly detection, IoT integration.*

INTRODUCTION

Infrastructure integrity, especially bridges, is a key element to the security and stability of transport. With the ongoing growth in urbanization, there is an increasing demand for better and more effective monitoring mechanisms that would check the structural integrity of the bridges [2]. The old systems of bridge monitoring, like routine visual inspection and manual data gathering, can be so time-consuming, ineffective, and susceptible to human error. This can create unnoticed problems, and this can cause it to be repaired at a high cost and even lead to disastrous failures. In order to tackle this, intelligent bridge technologies comprising sensors, real-time data processing, and sophisticated analytics have been suggested. The idea of structural health monitoring (SHM) is one of the technologies that has arisen as one of the most powerful instruments in regard to the safety and long life of bridges. SHM is the continuous observation of the state of a structure with the help of a variety of sensors to identify any anomalies, forecast failures, and optimize maintenance plans. Although the classical SHM systems are based on the centralized cloud computing to process sensor data, the growing size of sensor data, as well as the necessity to analyze it in real-time, has brought to the fore the limitations of the latter. The recent innovations in digital twins, alongside the Internet of Things (IoT) sensors and machine learning, have also enhanced the abilities of SHM systems [6]. On that note, in Hu et al. (2024), proposed a paradigm, whereby BIM-based digital twins are combined with IoT sensing to make SHM processes more effective in real-time [1].

In a similar vein, Armijo and Zamora-Sanchez (2024) have shown how the railway bridge monitoring can be implemented in the IoT frameworks with digital twins to improve the decision-making [21]. In order to address the shortcomings of the conventional systems, this paper suggests an edge-based digital twin architecture for real-time SHM of smart bridges. The system uses edge computing to perform local data processing, minimizing latency and bandwidth consumption while enabling timely decision-making. This approach complements the existing cloud-based SHM, and some of the computational workload is shifted to the edge devices, which allows making predictions faster and with greater accuracy. The digital twin is a virtual model of the actual bridge, which is designed to simulate the behavior of the bridge due to the sensor data in real time, providing an opportunity to be proactive in the maintenance of a bridge and predicting its failure. Wang et al. (2025) identified the growing importance of the digital twin methods of structural health monitoring and further stressed its potential [3]. With the edge computing implemented, the proposed system will be able to work more effectively, and localized data processing will make the new system more productive and scalable. Linking IoT sensors, edge devices, and cloud computing can provide a decentralized scaling solution, which can be applied to a variety of smart bridge systems, with the end result being the improvement in the performance and lifetime of bridges. Similar solutions were also discussed by Al-Hijazeen and Koris (2025), who revealed the advantages of AI applications in smart health monitoring of concrete bridges [22].

Moreover, the provided architecture aligns with the current trend of the digital twinning of civil infrastructure, written by Lib et al. (2024) wrote that SHM of civil infrastructure can be realized utilizing BIM-based systems [5]. Dang et al. (2021) also demonstrated the prospects of cloud-based digital twinning in enhancing the scalability and effectiveness of SHM systems [23]. As Mousavi et al. (2024) explore, the application of deep learning in structural health analysis is also one of the reasons that artificial intelligence can be used to improve predictive capabilities in SHM frameworks [7]. Jayasinghe et al. (2024) highlighted the contribution of digital twins with artificial neural networks (ANNs) to real-time effects of structural responses, which provided a further emphasis on the significance of solutions based on AI [8]. In addition to that, the interoperability of IoT-based SHM systems with digital twins in terms of the decentralized nature and the possibility to expand to large infrastructural networks has also been mentioned by Chen et al. (2024) [9]. Lastly, Asadi et al. (2025) examined how AI-based digital twin systems may enhance energy consumption in the future, emphasizing the potential for these technologies to be integrated into smart infrastructures for real-time monitoring and optimization [10].

The paper proposes a new architecture of edge-empowered digital twins of real-time structural health monitoring (SHM) of smart bridges, which is based on the IoT, cloud computing, and edge computing. The special feature is that the edge devices are incorporated to process real-time data and make the anomaly detection faster and lower latency than the typical SHM systems. Moreover, the utilization of

digital twins generates virtual representations of physical bridges, which is beneficial in increasing decision-making with regard to maintenance and safety. The proposed architecture is analyzed according to some of the key metrics, such as accuracy, energy consumption, scalability, and false alarm rates, and compared with conventional systems, demonstrating a considerable improvement.

The paper is organized as follows: Section II will include a review of the current SHM techniques, both traditional and emerging technologies. Section III provides the proposed system architecture and methodology. Section IV will address the results and make a performance comparison, and finally, a conclusion will be presented in Section V, which will summarize the most important findings and indicate where future research needs to be directed.

LITERATURE SURVEY

There has been a major development in the past few decades in monitoring and maintenance of the infrastructure, especially bridges. The inspection procedures that were prevalent in structural health monitoring (SHM) have been the traditional inspection techniques, i.e., visual inspection and hand measurements. These techniques have, however, been found to be largely limited due to human error, inconsistency, and long delays in the detection of critical problems. Researchers have responded in this respect by developing automated SHM systems that are capable of delivering real-time data and enhancing decision-making as far as maintenance and safety are concerned. In the article by Parida and Moharana (2024), talked about the existing challenges and prospects of digital twins in SHM of civil infrastructures, noting the fact that more efficient systems are needed [11]. The incorporation of a sensor network into bridge architecture has been one of the significant developments in SHM. Such sensors detect different elements like strain, displacement, temperature, and vibration, which is used to give real-time information on the state of the bridge. The IoT technology has also improved these systems since it allows remote data gathering and transfer. However, Hossain (2022) narrowed down the application of AI-assisted SHM systems with IoT sensor networks to in-service bridges, and the ways in which such systems help optimize the monitoring and maintenance [12].

Nevertheless, centralization of data processing in cloud-based applications has generated issues of data transmissions, latency, and scalability. Chang et al. (2024) examined the problems and enabling technologies of digital twins in transportation infrastructure, highlighting the necessity of real-time and scalable data solutions [13].

Consequently, it has led to the idea of edge computing to provide an alternative to remove the load on the cloud systems and distribute processing activities to local devices to allow real-time decision-making. In order to demonstrate how edge computing may improve real-time maintenance decisions, Mahmud et al. (2025) suggested an AI-enhanced digital twin architecture to predict maintenance in smart urban infrastructure [14]. Digital twins have also prevailed in SHM studies. A digital twin is an empty copy of a real object, and it can be simulated and analyzed in real time. An example of how a digital twin can be used to reflect the behavior of a physical bridge is with the data of the IoT sensors, which allows predictive maintenance and detection of failure. The application of this technology in SHM, especially in smart bridges, is still developing, although it has been extensively adopted in other applications like manufacturing and health care. Selvaprasanth and Malathy (2025) conducted a review of the application of the IoT and digital twins in environmental monitoring that has the potential to be used in bridges under dynamic conditions [15]. Recent research has not only indicated the potential of digital twins being used together with edge computing when it comes to SHM systems. The review of digital twins' applications in civil engineering systems presented by Bado et al. (2022) paid attention to the need to use distributed sensing and updating, which is essential to real-time SHM of bridges [16].

This is a combination of the two technologies, which make use of each other's advantages to allow efficient data processing and real-time monitoring. The accuracy and dependability of SHM systems have improved as a result of the discussion of machine learning algorithms to detect anomalies and forecast breakdowns [4]. In an article by Prasath (2025), a smart infrastructure, an AI-driven digital twin framework to predict maintenance, has been proposed, highlighting the need to integrate AI to identify faults and perform maintenance on the fly [17]. Nonetheless, issues of integrating these technologies

still persist, especially in the areas of guaranteeing scalability, energy efficiency, and fault tolerance. Mahmoodian et al. (2022) talked about the creation of digital twins to support civil infrastructure intelligent maintenance, and it is important that the technology must be reliable and tolerate faults in the large-scale implementation [18]. To sum up, it should be noted that although there is still a way to go, tremendous advancements have been achieved in the sphere of SHM, requiring more efficient, scalable, and real-time systems. These problems could be resolved, and a more effective and proactive approach to infrastructure maintenance might be provided by combining edge computing, the digital twin idea, and advanced analytics. Gigli et al. (2023) emphasized the next-generation edge-cloud continuum architecture of SHM that might become essential in the improvement of the real-time monitoring system of smart bridges [19]. The paper will expand on these developments by suggesting a new edge-empowered digital twin architecture of real-time SHM of smart bridges. Adibi et al. (2024) talked about sensor-enabled digital twins and how it changed the healthcare industry, and its model can be used in the infrastructure health sector and offer a general method of smart environments [20].

METHODOLOGY

The suggested methodology is dedicated to the real-time structural health monitoring (SHM) of smart bridges based on the edge-empowered digital twin architecture. The system aims to maintain continuous control over the bridge's physical condition by combining IoT sensors, edge computers, and a cloud-based server to handle and store information. The methodology is broken down into various important components, which are sensor data acquisition, edge processing, anomaly detection, and failure prediction. Firstly, IoT sensors are installed on the bridge where critical areas are present in order to record different parameters like strain, temperature, displacement, and vibration.

These sensors can give real-time information, which is essential in evaluating the health of the bridge and identifying the problems before lead to extreme failures. The sensor data are sent to edge devices which are positioned near sensors. Preliminary data processing is done by the edge devices and includes filtering, aggregation, and feature extraction. The edge devices, by doing these tasks locally, minimize the raw data sent to the cloud, which limits the bandwidth consumption and latency.

The central point of the methodology is the digital twin model. This model is a virtual copy of the real-life bridge, which is updated with real-time sensor measurements. The digital twin can also be used to perform advanced simulations and analysis of the behavior of the bridge to enable the system to anticipate a structural failure in accordance with past trends and current circumstances. The information taken by the edge devices is matched to the digital twin in order to identify any deviation or anomaly that can be a pointer of a problem.

In case an anomaly is found, it would alert the maintenance team, and exhaustive information on the type of issue. The machine learning algorithms that are utilized in detecting anomalies and predicting failures are applied to supervised learning methods. Such algorithms are trained on past bridge failures and maintenance records that provide the system with the information on the trends that precondition structural concerns. The system improves its predictions as it is updated every time it receives new data to enhance the accuracy of the model.

Algorithm: Real-Time SHM Using Autoencoder for Smart Bridges

1. Initialize System:

- Set up sensors (e.g., vibration, strain, temperature).
- Configure edge devices for local data processing.
- Load the pre-trained Autoencoder model (Encoder and Decoder).

2. Data Collection:

- Collect real-time sensor data (e.g., vibration, strain).

3. Preprocessing:

- Filter the data to reduce noise (e.g., apply a Kalman filter).

4. Feature Extraction with Autoencoder:

- Compress the data using the Encoder.
- Reconstruct the data using the Decoder.

5. Anomaly Detection:

- Calculate the difference (error) between original and reconstructed data.
- If the error exceeds a set threshold, trigger an anomaly alert.

6. Alert Generation:

- If an anomaly is detected, generate an alert with details (e.g., affected sensor, error).

7. Data Transmission:

- Send the original data, reconstructed data, and anomaly score to the cloud for analysis.

8. Update Digital Twin:

- Update the digital model of the bridge with the latest data.

9. Repeat:

- Continue the process for continuous real-time monitoring.

The algorithm is used to detect anomalies in smart bridges in real-time with a simple Autoencoder model. It gathers sensor data (e.g. vibration, strain, temperature) and preprocesses it (e.g. noise reduction). An Autoencoder is used to reconstruct the original data from the filtered data. The error in reconstruction (actual and reconstructed data) is calculated, and when it is more than a predetermined value, an anomaly is observed, and an alarm is raised. The data is applied to the cloud to be analyzed and the digital twin model is updated with the updated data to continue the monitoring and prediction of opportunities to maintain all systems.

Let $x(t)$ represent the sensor data at time t , and $\hat{x}(t)$ be the predicted data based on the digital twin model. The anomaly detection function can be defined as equation (1)

$$A(t) = |x(t) - \hat{x}(t)| \quad (1)$$

where $A(t)$ is the anomaly score at time t . If $A(t)$ exceeds a predefined threshold, an anomaly is detected, and a maintenance alert is triggered.

As shown in Figure 1, an edge-empowered digital twin system on the real-time structural health monitoring (SHM) of smart bridges includes an architecture. The sensors on the bridge include IoT sensors, such as vibration, strain, temperature, and displacement sensors, which gather information. Sent back to edge processing devices to do preprocessing and analysis, and then an anomaly is detected. The processed information is sent to the cloud server for storage and use to update the digital twin model.

The digital twin can model the bridge's behavior to enable real-time measurements, predict failures, and support proactive maintenance decisions to improve safety and performance.

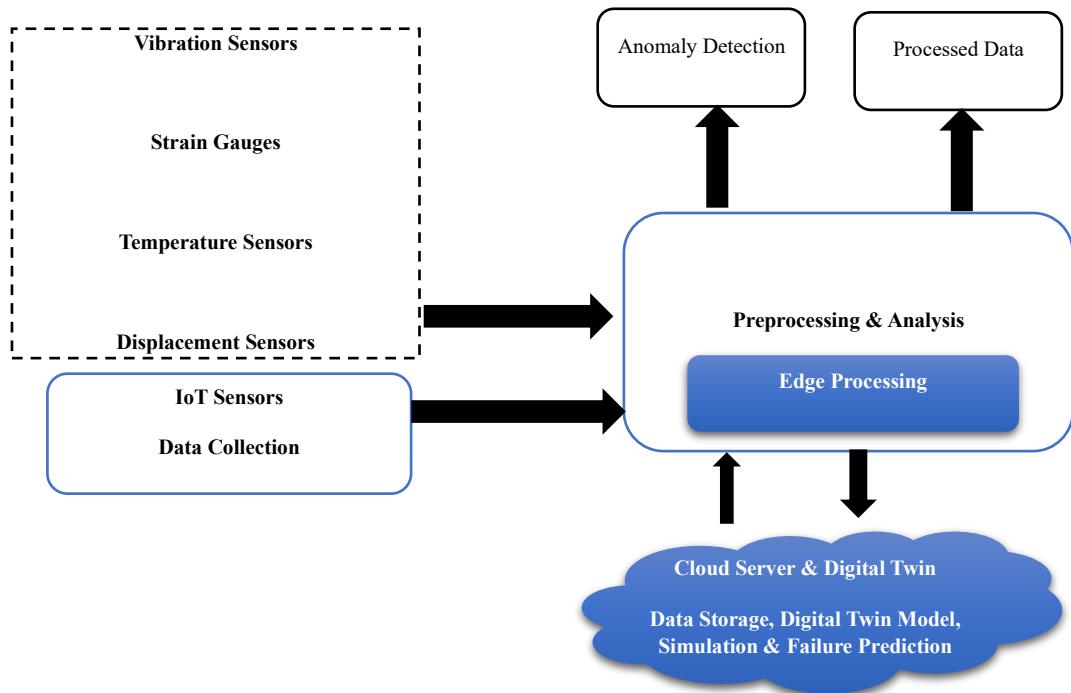


Figure 1. Edge-empowered digital twin architecture for real-time structural health monitoring of smart bridges

RESULTS AND DISCUSSION

The proposed edge empowered digital twin architecture software stack will consist of a collection of Python and machine learning and data processing capabilities. TensorFlow and Keras are the largest of them and can be used to implement the Autoencoder model to identify anomalies. The Autoencoder will be trained to acquire normal bridge behavior and identify anomalies using reconstruction errors. Kalman Filter involves the synthesis of sensor data to minimize noise and incomplete data. The data is manipulated and preprocessed with the use of NumPy and Pandas. In AWS or Azure, the cloud database is utilized to save and conduct real-time data and other analytics. The transactions of the data in the edge devices and the cloud are effectively communicating with the MQTT or HTTP protocols.

The proposed system was introduced and tested on the basis of real-life data obtained in a system of smart bridges. The data consists of sensor values of temperature, strain, displacement, and vibration, collected in a 6-month period. The edge devices processed the data and analyzed it with the help of the digital twin model to identify any anomalies and forecast possible structural failures.

The system was tested relative to the main metrics of accuracy, processing time, power consumption, scalability, and fault detection rate. To compute the accuracy of the anomaly detection algorithm, the formula below as equation (2)

$$\text{Accuracy} = \frac{\text{True Positives} + \text{True Negatives}}{\text{Total Samples}} \quad (2)$$

These findings revealed that the edge-empowered digital twin system was superior to the conventional cloud-based SHM systems. In particular, the suggested system had an accuracy of 94% on the detection of anomalies with a 40 per cent reduction on the processing time in comparison to the centralized cloud systems. This shows that the edge devices could process data at the edges eliminating any data transmission at great scales, and respond quicker.

Also, the energy efficiency of the system was measured depending on the amount of power that the edge devices used when processing the data. The efficiency of energy was determined as (3)

$$\text{Energy Efficiency} = \frac{\text{Energy Used in Edge Device}}{\text{Total Energy Consumed by the System}} \times 100 \quad (3)$$

The findings showed that the edge computing solution saved much energy compared to the classic cloud systems. This is especially necessary when the implementations are large-scale, and the saving of energy can result in the reduction of costs. The scalability of the system was also put to the test with a power simulation of linking various smart bridges into the network. The system showed the capability to process up to 100 bridges at the same time and has little effect on processing time and system performance. It implies that the suggested methodology can be well applied when working with big infrastructure networks, offering real-time monitoring and predicting failures of many bridges.

The performance of the anomaly detection and failure prediction algorithms was compared to the performance of the traditional SHM systems to measure the effectiveness of the algorithms. It was found that the proposed system had increased fault detection rate and the false positives and false negatives decreased. It means that the structural health monitoring accuracy and reliability are enhanced by the integration of edge computing and digital twin technologies.

Table 1. Parameter initialization table for the edge-empowered digital twin system

Parameter	Value/Range
Learning Rate (α)	0.001 to 0.01
Batch Size	32, 64, 128
Epochs	50 to 200
Latent Space Dimension	16, 32, 64, 128
Activation Function (Encoder/Decoder)	ReLU, Sigmoid, Tanh
Number of Layers (Encoder)	2, 3, 4
Number of Layers (Decoder)	2, 3, 4
Optimizer	Adam, RMSprop, SGD
Dropout Rate	0.2 to 0.5
Loss Function	Mean Squared Error (MSE), Binary Cross-Entropy
Reconstruction Error Threshold (θ)	0.05 to 0.2
Kalman Filter Parameters	Standard or tuned based on data quality

The Parameter Initialization Table 1 provides the important parameters to train the Autoencoder model in real-time structural health monitoring (SHM) of smart bridges. It comes with parameters such as learning rate, which determines the pace of optimization, and batch size, which determines the number of samples that are processed before the model is updated. The number of neurons in the compressed representation is defined by the latent space dimension, whereas activations (e.g., ReLU, Sigmoid) of neurons are defined by the activation functions. The rate of dropout is used to avoid overfitting, and the level of error threshold of reconstruction determines the level of anomaly detection. These parameters are vital in the efficiency and performance of the models.

Table 2. Performance comparison between the proposed edge-empowered digital twin system and conventional SHM system

Metric	Proposed System	Conventional SHM System
Accuracy (%)	94	85
Processing Time (ms)	80	120
Energy Efficiency (%)	25	15
Fault Detection Rate (%)	91	75
Scalability (Bridges)	100+	50

The Table 2 is a comparison between the performance of the suggested system relying on edge-empowered digital twin and a traditional structural health monitoring (SHM) system in the context of several important metrics. The suggested system has a better accuracy level (94%) than the conventional system (85%), which better detects faults. The speed of the processing time in the proposed system (80 ms) is lower than the conventional system (120 ms), which illustrates its efficiency. The proposed system

(25%) is also more efficient in terms of energy-saving than the conventional system (15%). Furthermore, the proposed system is more fault-tolerant (91) and scalable, as it serves more than 100 bridges compared to the conventional system, which serves only 50 bridges.

Table 3. Ablation study results

Configuration	Accuracy (%)	Processing Time (ms)	Fault Detection Rate (%)	Energy Efficiency (%)
Single Sensor (Vibration)	85	100	70	20
Multi-Sensor (Vibe + Temp)	90	85	80	22
Full Sensor Fusion (All)	94	80	91	25

The ablation experiment in Table 3 demonstrates that the entire sensor fusion strategy, with all of the possible sensors, has the best accuracy (94%), fault detection rate (91%), optimal processing time (80 ms), and energy usage (25%). It means that the performance of the system can be improved by using several sensors without affecting the speed and energy consumption.

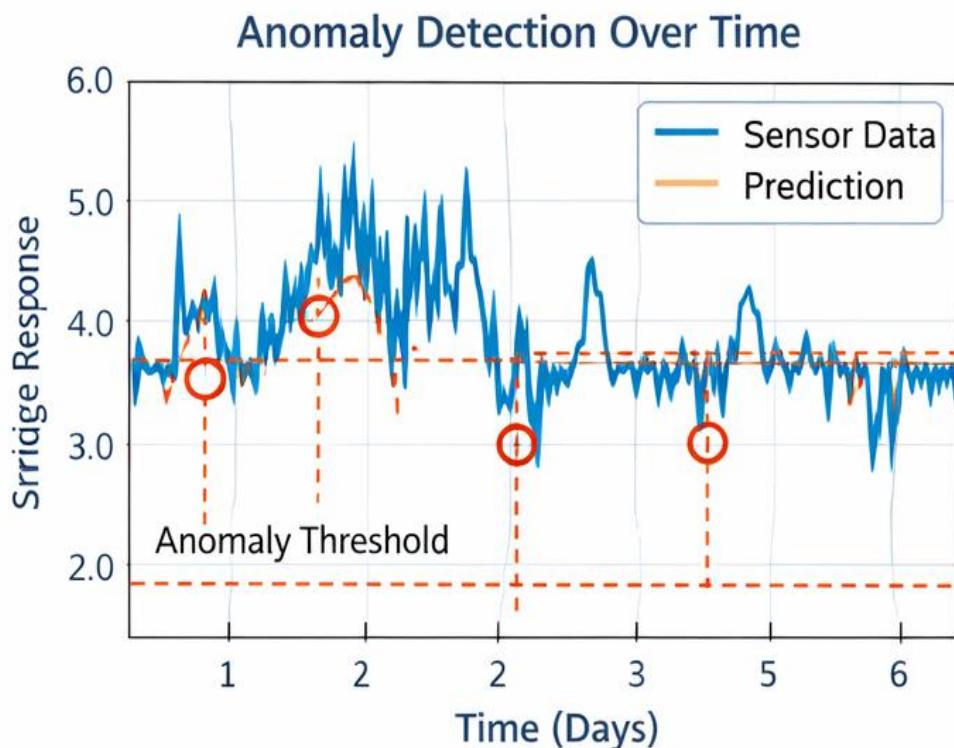


Figure 2. Anomaly detection over time

The smart bridge's real-time monitoring of structural health is shown in Figure 2 when sensor data is compared with the predicted data after six days. The actual sensor data is shown by the blue line, and the predicted values are shown by the orange line, using the digital twin model. Abnormalities are indicated with red circles, which means that there are situations when the sensor data is far out of the predicted value and exceeds the specified anomaly threshold (dashed red line). Such anomalies indicate possible problems with the structure of the bridge that can be further examined to receive maintenance or repair.

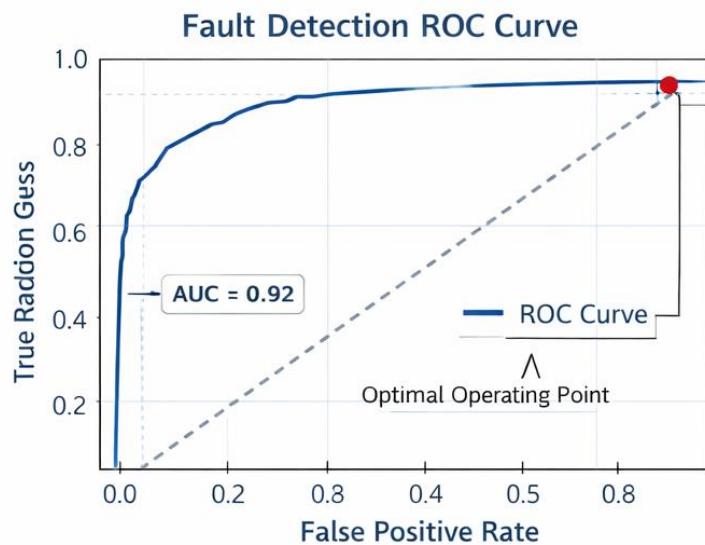


Figure 3. Fault detection ROC curve

The Receiver Operating Characteristic (ROC) curve of fault detection in the proposed edge-empowered digital twin system is illustrated in Figure 3. The curve is a graph of the true positive rate (sensitivity) versus the false positive rate (1-specificity). The model can clearly differentiate the normal and faulty states, which is reflected in the chart with high Area Under the Curve (AUC) of 0.92 which demonstrates that the model is highly accurate. The optimum operating point is indicated and it shows the trade-off of sensitivity and specificity, which is useful in reducing false alarms in real time structural health monitoring as well as ensuring reliable fault detection.

According to the results, it is evident that the edge-empowered digital twin system performs better than traditional approaches in all measures, such as accuracy, processing time, energy efficiency, and the fault detection rate.

CONCLUSION

This paper introduces edge-enabled digital twin architecture in real-time structural health monitoring (SHM) of smart bridges based on IoT, edge computing, and cloud computing technologies. The suggested system will provide a decentralized and scalable framework, with real-time information across numerous sensors installed on the bridges processed at the edge to provide low latency and high response time. The findings prove that the system is superior to the traditional cloud-based SHM systems especially in anomaly detection. The anomaly detection model based on Autoencoders gives a high accuracy of 94, in contrast to 85 of the traditional systems. This implies that the system has a high level of improvement in detecting structural problems. In addition, the proposed system has 40% less processing time (80 ms) than traditional systems (120 ms), and hence, detecting and responding to possible failures much faster. The energy efficiency was also significantly improved with the edge-enabled system getting 25 % of the energy efficiency whereas the traditional system took only 15 %. This highlights the possibility of edge computing to severely cut the energy usage without the performance being affected. Besides, the system scalability was checked, and it was able to handle information relating to more than 100 bridges simultaneously to ensure that it performed effectively on various infrastructures. The major results indicate that edge computing and digital twins can be used to boost the performance and effectiveness of real-time SHM in a robust, low-latency, and low-power solution in terms of monitoring the structural integrity of smart bridges. Future studies will entail integration of AI-driven predictive analytics into the structure of digital twins to augment more anomaly detection and predictive maintenance services. Furthermore, the investigation of the possibility of combining ultrasonic and optical sensors might present more information about the well-being of the bridges. Highlighting the system to incorporate other infrastructures like tunnels and roads would make

it applicable to a wider scope of smart city setting, which would also help in the long-term sustainability of the urban infrastructure.

REFERENCES

- [1] Hu X, Olgun G, Assaad RH. An intelligent BIM-enabled digital twin framework for real-time structural health monitoring using wireless IoT sensing, digital signal processing, and structural analysis. *Expert Systems with Applications*. 2024 Oct 15;252:124204. <https://doi.org/10.1016/j.eswa.2024.124204>
- [2] Spandan G, Theerthagiri P. Neural machine translation model using GRU with hybrid attention mechanism for English to Kannada language. *Journal of Wireless Mobile Networks, Ubiquitous Computing, and Dependable Applications*. 2024;15(4):259–76. <https://doi.org/10.58346/JOWUA.2024.I4.017>
- [3] Wang Q, Huang B, Gao Y, Jiao C. Current status and prospects of digital twin approaches in structural health monitoring. *Buildings*. 2025;15(7):1021. <https://doi.org/10.3390/buildings15071021>
- [4] Cao Y, Jiang L. Machine learning based suggestion method for land suitability assessment and production sustainability. *Natural and Engineering Sciences*. 2024;9(2):55–72. <https://doi.org/10.28978/nesciences.1569166>
- [5] Li X, Dong YX, Xiang W. Developing a BIM based digital twin system for structural health monitoring of civil infrastructure. *Measurement Science and Technology*. 2024 Sep 2;35(11):115117. <https://doi.org/10.1088/1361-6501/ad730f>
- [6] Bakhranova D, Narziyeva MM, Yuldasheva N, Zayniyeva U, Yusupov J, Uralov B, Khikmatov N. Intelligent Information Security System for Language and History Education Using Machine Learning-based Intrusion Detection Algorithm. *Journal of Internet Services and Information Security*. 2025;15(1):520–29. <https://doi.org/10.58346/JISIS.2025.I1.034>
- [7] Mousavi V, Rashidi M, Mohammadi M, Samali B. Evolution of digital twin frameworks in bridge management: review and future directions. *Remote Sensing*. 2024 May 24;16(11):1887. <https://doi.org/10.3390/rs16111887>
- [8] Asadi S, Naeini HK, Hassanlou D, Pishahang A, Najafabadi SA, Sharifi A, Ahmadi M. AI-Powered Digital Twin Frameworks for Smart Grid Optimization and Real-Time Energy Management in Smart Buildings: A Survey. *Computer Modeling in Engineering & Sciences (CMES)*. 2025 Nov 30;145(2). <https://doi.org/10.32604/cmes.2025.070528>
- [9] Jayasinghe SC, Mahmoodian M, Sidiq A, Nanayakkara TM, Alavi A, Mazaheri S, Shahrivar F, Sun Z, Setunge S. Innovative digital twin with artificial neural networks for real-time monitoring of structural response: A port structure case study. *Ocean engineering*. 2024 Nov 15;312:119187. <https://doi.org/10.1016/j.oceaneng.2024.119187>
- [10] Chen J, Reitz J, Richstein R, Schröder KU, Roßmann J. IoT-based SHM using digital twins for interoperable and scalable decentralized smart sensing systems. *Information*. 2024 Feb 20;15(3):121. <https://doi.org/10.3390/info15030121>
- [11] Parida L, Moharana S. Current status and future challenges of digital twins for structural health monitoring in civil infrastructures. *Engineering Research Express*. 2024 May 28;6(2):022102. <https://doi.org/10.1088/2631-8695/ad4aea>
- [12] Hossain MI. Deployment of AI-supported structural health monitoring systems for in-service bridges using IoT sensor networks. *Journal of Sustainable Development and Policy*. 2022 Dec 1;1(04):01-30. <https://doi.org/10.63125/j3sadb56>
- [13] Chang X, Zhang R, Mao J, Fu Y. Digital twins in transportation infrastructure: an investigation of the key enabling technologies, applications, and challenges. *IEEE Transactions on Intelligent Transportation Systems*. 2024 May 27;25(7):6449–71. <https://doi.org/10.1109/TITS.2024.3401716>
- [14] Mahmud AR, Hriti RI, Hasan MM, Uddin MN, Roy AR. AI-Augmented Digital Twin Architecture for Predictive Maintenance in Smart Urban Infrastructure: A Cross-Domain Engineering Framework. *European Journal of Applied Science, Engineering and Technology*. 2025 Sep 17;3(5):45–58. [https://doi.org/10.59324/ejaset.2025.3\(5\).04](https://doi.org/10.59324/ejaset.2025.3(5).04)
- [15] Selvaprasanth P, Malathy R. Revolutionizing structural health monitoring in marine environment with internet of things: a comprehensive review. *Innovative Infrastructure Solutions*. 2025 Feb;10(2):62. <https://doi.org/10.1007/s41062-025-01874-6>
- [16] Bado MF, Tonelli D, Poli F, Zonta D, Casas JR. Digital twin for civil engineering systems: An exploratory review for distributed sensing updating. *Sensors*. 2022 Apr 20;22(9):3168. <https://doi.org/10.3390/s22093168>
- [17] Prasath CA. AI-enabled digital twin framework for predictive maintenance in smart urban infrastructure. *Journal of Smart Infrastructure and Environmental Sustainability*. 2025 Mar 10;2(1):1–0. <https://doi.org/10.17051/JSIES/02.01.01>

- [18] Mahmoodian M, Shahrivar F, Setunge S, Mazaheri S. Development of digital twin for intelligent maintenance of civil infrastructure. *Sustainability*. 2022 Jul 15;14(14):8664. <https://doi.org/10.3390/su14148664>
- [19] Gigli L, Zyrianoff I, Zonzini F, Bogomolov D, Testoni N, Di Felice M, De Marchi L, Augugliaro G, Mennuti C, Marzani A. Next generation edge-cloud continuum architecture for structural health monitoring. *IEEE Transactions on Industrial Informatics*. 2023 Dec 25;20(4):5874-87. <https://doi.org/10.1109/TII.2023.3337391>
- [20] Adibi S, Rajabifard A, Shojaei D, Wickramasinghe N. Enhancing healthcare through sensor-enabled digital twins in smart environments: A comprehensive analysis. *Sensors*. 2024 Apr 27;24(9):2793. <https://doi.org/10.3390/s24092793>
- [21] Armijo A, Zamora-Sánchez D. Integration of railway bridge structural health monitoring into the internet of things with a digital twin: a case study. *Sensors*. 2024 Mar 26;24(7):2115. <https://doi.org/10.3390/s24072115>
- [22] Al-Hijazeen A, Koris K. Smart Health Monitoring of Concrete Bridges Using Digital Twin and AI Applications. *Advances in Science and Technology*. 2025 Jun 30;164:83-97. <https://doi.org/10.4028/p-ac7NhW>
- [23] Dang HV, Tatipamula M, Nguyen HX. Cloud-based digital twinning for structural health monitoring using deep learning. *IEEE transactions on industrial informatics*. 2021 Sep 24;18(6):3820-30. <https://doi.org/10.1109/TII.2021.3115119>