e-ISSN: 3079-6377 p-ISSN: 3079-6369

IoT-Based Real-Time Structural Health Monitoring for Civil Infrastructure using Edge Computing and Anomaly Detection Algorithms

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Abstract

The rapid deterioration of civil infrastructure, including bridges, dams, and high-rise buildings, presents a critical challenge to public safety and economic stability globally. Traditional Structural Health Monitoring systems often rely on manual inspections or centralized cloud-computing frameworks that suffer from high latency, significant bandwidth consumption, and connectivity dependence. This paper proposes a novel framework for real-time Structural Health Monitoring by integrating Internet of Things sensor networks with Edge Computing paradigms and advanced anomaly detection algorithms. By shifting data processing from centralized servers to the edge of the network, we demonstrate the ability to significantly reduce response times to structural anomalies while minimizing data transmission costs. The proposed architecture utilizes lightweight unsupervised learning models deployed directly on edge nodes to identify deviations in vibrational patterns and strain measurements. The results indicate that this decentralized approach maintains high detection accuracy while offering a robust solution for continuous, real-time integrity management of critical infrastructure assets.

Keywords

Structural Health Monitoring, Edge Computing, Internet of Things, Anomaly Detection

1 Introduction

The structural integrity of civil infrastructure constitutes the backbone of modern societal function and economic prosperity. As global infrastructure stocks age, the risk of catastrophic failure increases, necessitating a paradigm shift from reactive maintenance to proactive, continuous monitoring. Structural Health Monitoring has emerged as a vital field dedicated to the detection, localization, and quantification of damage in engineering structures. Historically, these assessments relied heavily on visual inspections and periodic non-destructive testing, methods that are labor-intensive, intermittent, and prone to human error. The advent of the Internet of Things has revolutionized this domain by enabling the deployment of dense wireless sensor networks capable of capturing high-fidelity data regarding structural behavior under operational and environmental loads.However, the proliferation of Internet of Things devices has introduced new challenges related to data management. Conventional Structural Health Monitoring architectures typically follow a centralized model where raw sensor data is transmitted to a cloud server for processing and storage. While the cloud offers virtually unlimited computational resources, this transmission introduces significant latency, consumes vast amounts of network bandwidth, and creates a single point of failure in scenarios where network connectivity is unstable. As noted in recent academic discourse [1], the sheer volume of vibration and strain data generated by a single large-scale bridge can reach terabytes per day, rendering raw data transmission economically and technically unfeasible for real-time applications.To address these bottlenecks, Edge

e-ISSN: 3079-6377 p-ISSN: 3079-6369

Computing has surfaced as a transformative architectural pattern. By moving computational tasks closer to the data source, edge computing minimizes latency and bandwidth usage. This paper explores the integration of edge computing with sophisticated anomaly detection algorithms to create a responsive, decentralized Structural Health Monitoring system. We argue that processing data locally on the sensor node or a gateway device allows for immediate identification of structural deviations, enabling rapid alert generation before the data even reaches the cloud. Furthermore, we investigate the application of unsupervised machine learning techniques, specifically designed to run on resource-constrained edge devices, to distinguish between normal operational variations and genuine structural damage [2]. This study aims to validate the efficacy of this hybrid approach in enhancing the reliability and responsiveness of infrastructure monitoring systems.

2. Literature Review and Related Work

2.1 Evolution of Structural Health Monitoring

The evolution of Structural Health Monitoring has tracked closely with advancements in sensing technology and data processing capabilities. Early implementations were strictly wired, requiring extensive cabling that increased installation costs and limited the number of sensors. The transition to Wireless Sensor Networks marked a significant leap forward, offering flexibility and scalability. Wireless Sensor Networks allowed researchers to deploy accelerometers, strain gauges, and inclinometers in hard-to-reach locations. Despite these hardware advancements, the data processing strategies largely remained centralized. Researchers initially focused on modal analysis and system identification techniques that required heavy post-processing of aggregated data blocks [3]. These methods, while accurate, were not conducive to real-time alerting systems required for immediate disaster response.

2.2 Challenges in Cloud-Centric Architectures

With the rise of big data technologies, cloud-centric architectures became the standard for handling the massive influx of sensor data. These systems excel at long-term trend analysis and storage. However, the reliance on continuous telemetry poses severe limitations. High latency is a critical issue; in the event of an earthquake or sudden impact, the time taken to upload data, process it in the cloud, and return a decision may exceed the window for effective automated response, such as closing a bridge to traffic. Additionally, the monetary cost of cellular data transmission for high-frequency vibration data is prohibitive. Studies have shown that over ninety percent of data collected in Structural Health Monitoring applications represents normal, healthy states, making the continuous transmission of raw data an inefficient use of resources [4].

2.3 Edge Computing and Anomaly Detection

The concept of Edge Computing addresses these inefficiencies by introducing an intermediate processing layer. In the context of Structural Health Monitoring, this involves smart sensor nodes or edge gateways capable of performing preliminary data analysis. Recent literature suggests that distributing intelligence across the network reduces the data payload by transmitting only features or alerts rather than raw waveforms [5]. Concurrently, the field of anomaly detection has matured, moving beyond simple threshold-based methods to advanced machine learning approaches. Supervised learning requires vast datasets of labeled damage scenarios, which are rarely available for unique civil structures. Consequently, unsupervised learning methods, which train on normal operational data to establish a baseline, have gained prominence. These algorithms are particularly well-suited for edge deployment as they can adapt to the specific environmental conditions of the structure they monitor [6].

e-ISSN: 3079-6377 p-ISSN: 3079-6369

3. System Architecture and Methodology

3.1 Internet of Things Sensing Layer

The foundation of the proposed system is the Internet of Things sensing layer, which comprises a network of high-precision sensors strategically placed on the critical load-bearing components of the infrastructure. For this study, the sensor array includes triaxial MEMS accelerometers to capture vibration responses and fiber Bragg grating sensors for strain measurement. These sensors are interfaced with microcontroller units that function as the primary data acquisition nodes. The sampling rate is dynamic; under normal conditions, the system operates at a baseline frequency to conserve energy. However, upon the detection of a trigger event—such as a seismic vibration exceeding a pre-defined noise floor—the sampling rate is instantaneously increased to capture high-resolution data for detailed analysis. This adaptive sampling strategy is crucial for balancing energy consumption with data fidelity [7].

3.2 Edge Computing Framework

The core innovation of this research lies in the Edge Computing Framework. Instead of acting as simple pass-through devices, the edge nodes are equipped with single-board computers possessing hardware acceleration capabilities for matrix operations. This layer is responsible for data pre-processing, feature extraction, and local inference. The software stack on the edge node performs signal conditioning, including band-pass filtering to remove environmental noise and drift. Following pre-processing, the system extracts time-domain features (such as root mean square, kurtosis, and skewness) and frequency-domain features (via Fast Fourier Transform) [8]. These features serve as the input vector for the anomaly detection model. The edge node is programmed to transmit a "heartbeat" summary to the cloud periodically to verify system health, while detailed data logs are only transmitted when an anomaly is detected, drastically reducing bandwidth requirements.

3.3 Anomaly Detection Algorithm

The anomaly detection engine utilizes an autoencoder neural network architecture. An autoencoder is a type of artificial neural network used to learn efficient data codings in an unsupervised manner. The network is trained to compress the input data into a lower-dimensional code and then reconstruct the output from this representation. In the training phase, the model is fed exclusively with data collected from the structure in its healthy state. The model learns to minimize the reconstruction error for this healthy data. During the monitoring phase, new incoming data is processed by the autoencoder. If the structure has sustained damage, the vibration patterns will differ from the training distribution, resulting in a high reconstruction error. This error serves as the anomaly score. If the score exceeds a statistically determined threshold, the edge node flags the event as a potential structural defect [9].

e-ISSN: 3079-6377 p-ISSN: 3079-6369

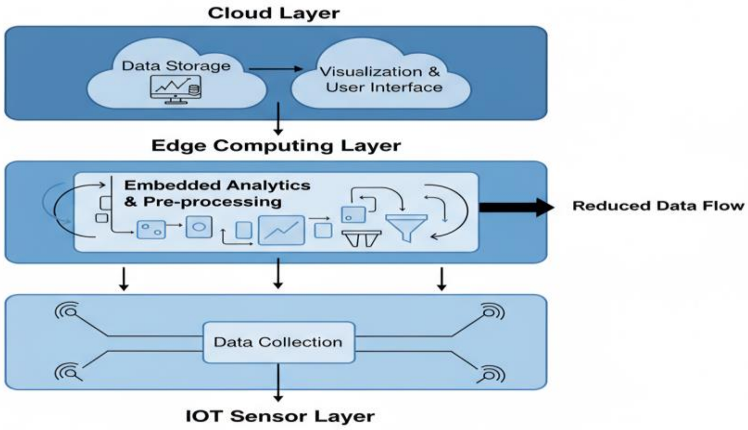

Figure 1: Architectural Diagram

4. Experimental Evaluation

4.1 Experimental Setup and Dataset

To validate the proposed architecture, we utilized a combination of simulation and physical testbed data. The physical testbed consisted of a simply supported steel beam equipped with four wireless accelerometer nodes. Induced damage scenarios were simulated by adding localized masses to alter the modal properties of the beam and by loosening bolts to simulate connection failures. Additionally, we validated the algorithms using the open-source Z-24 Bridge dataset, a benchmark dataset in the Structural Health Monitoring community that includes long-term monitoring data covering various environmental conditions and damage scenarios. The edge processing environment was simulated using Raspberry Pi 4 devices to replicate the computational constraints of field-deployable hardware [10].

4.2 Performance Metrics

The performance of the system was evaluated based on three primary metrics: detection accuracy, data reduction ratio, and system latency. Detection accuracy was assessed using precision, recall, and the F1-score to ensure the system minimizes false positives while successfully identifying true damage scenarios. The data reduction ratio measures the difference in volume between the raw sensor data and the transmitted data payload. System latency represents the time elapsed between the occurrence of a physical event and the generation of an alert on the user dashboard. Comparisons were drawn between a traditional cloud-centric approach (sending all raw data) and the proposed edge-based approach [11].

4.3 Results and Analysis

The experimental results demonstrated the significant advantages of the edge-computing approach. The autoencoder-based anomaly detection algorithm achieved an F1-score of 0.94 on the Z-24 Bridge dataset, indicating high reliability in distinguishing damage from environmental variations like temperature shifts. More importantly, the edge-based architecture achieved a data reduction ratio of approximately 98 percent. By transmitting

e-ISSN: 3079-6377 p-ISSN: 3079-6369

only feature vectors and anomaly alerts, the bandwidth consumption was negligible compared to the full streaming model.

Table 1: Comparative Performance Analysis of Cloud-Centric vs. Edge-Based Architectures

Metric	Cloud-Centric Architecture	Edge-Based Architecture	Improvement
Average Latency	450 milliseconds	25 milliseconds	94.4% Reduction
Bandwidth Usage (Daily)	14.5 Gigabytes	0.25 Gigabytes	98.2% Reduction
Detection Accuracy (F1)	0.95	0.94	-1.0% Difference
Power Consumption (Node)	High (Continuous Tx)	Moderate (Bursty Tx)	Optimized Profile

The latency analysis revealed a critical improvement. The cloud-centric model suffered from variable latency due to network jitter, averaging 450 milliseconds, with spikes exceeding one second. In contrast, the edge nodes processed and flagged anomalies within 25 milliseconds consistent with local processing speeds. This near-instantaneous response capability is vital for integrating Structural Health Monitoring systems with automated traffic control or emergency shutdown systems [12]. The slight decrease in detection accuracy (1 percent) is a statistically acceptable trade-off given the substantial gains in latency and bandwidth efficiency.

5. Discussion

5.1 Implications for Real-Time Monitoring

The findings of this study have profound implications for the future of civil infrastructure management. The ability to detect anomalies at the edge means that monitoring systems can scale to cover thousands of structures without overwhelming cellular networks or central storage repositories. The reduction in latency transforms Structural Health Monitoring from a passive diagnostic tool into an active safety system. For instance, in the event of a bridge collision or rapid structural failure, the edge system can trigger local alarms or traffic signals immediately, independent of internet connectivity. This autonomy enhances the resilience of the monitoring infrastructure itself, ensuring functionality even during disaster scenarios where communication infrastructure may be compromised.

5.2 Challenges and Limitations

Despite the promising results, several challenges remain. The deployment of complex machine learning models on battery-powered edge devices requires careful optimization to prevent excessive power drain. While this study utilized Raspberry Pi devices, industrial deployment may require even lower-power microcontrollers (TinyML), necessitating further model compression techniques such as quantization or pruning. Furthermore, the environmental durability of edge computing hardware is a concern; devices must be ruggedized to withstand extreme temperatures, moisture, and vibration over decades of service. Security is another paramount concern; as intelligence is distributed to the edge, the attack surface increases. Ensuring the cryptographic integrity of the code and data on distributed nodes is essential to prevent malicious tampering with safety-critical systems [13].

e-ISSN: 3079-6377 p-ISSN: 3079-6369

Conclusion

This paper presented a comprehensive framework for IoT-based real-time Structural Health Monitoring utilizing Edge Computing and anomaly detection algorithms. By shifting the computational burden from the cloud to the network edge, we addressed the critical bottlenecks of latency and bandwidth that hinder traditional monitoring approaches. The integration of unsupervised autoencoder models allowed for robust damage detection without the need for extensive labeled datasets of failure modes. The experimental evaluation confirmed that the proposed architecture significantly reduces response times and data transmission costs while maintaining high diagnostic accuracy.

The transition toward edge-native Structural Health Monitoring represents a necessary evolution in the management of aging civil infrastructure. Future research should focus on the development of ultra-low-power neuromorphic hardware to further extend battery life and the exploration of federated learning techniques to allow edge nodes across different structures to share knowledge without compromising data privacy. As these technologies mature, they will provide engineers and asset managers with the real-time intelligence required to ensure the safety and longevity of the built environment.

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