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An Edge-Aware Signal Processing Framework for Structural Health Monitoring in IoT Sensor Networks

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ABSTRACT

In the context of ever growing urbanization and aging structures, safety and longevity aside, Structural Health Monitoring (SHM) have played a very important role in assuring the safety and continued life of civil infrastructure. Continuous monitoring using dense sensor networks is now feasible with the coming of Internet of Things (IoT). But yet, the challenges such as high communication overhead, latency, and power consumption to hinder real time responsiveness and scalability. In this paper, we present a novel edge-aware signal processing framework that addresses the aforementioned limitations by utilizing an edge computing capability available within the IoT sensor nodes. The proposed framework integrates a lightweight, yet efficacious signal processing pipeline consisting of real time wavelet based noise reduction, feature extraction and computation of important vibration and strain parameters, and localized anomaly detection through compressed machine learning models designed for the edge. We introduce a hierarchy, in which raw sensor data is processed on the edge, thus reducing the need to send high bandwidth transmissions to the cloud. To prove the merit of the framework, we developed a simulated SHM testbed of bridge infrastructure, and performance improvements were experimentally demonstrated as a result. It was demonstrated that the system achieved anomaly detection accuracy of 96.4%, reduced the data transmission bandwidth by 42% while still providing real time operation with decision latency minimal than 120 ms. The results illustrate the framework's potential as a scalable, energy efficient, intelligent, and enable standalone or precursory systems to populate smart cities and industrial environments of the next generation.

1. INTRODUCTION

Structural Health Monitoring (SHM) plays an important role in the modern civil infrastructure management by enabling the evaluation of structural integrity, early warning of damage, and preventing catastrophic damage. As more and more critical infrastructure such as bridges, buildings, and dams become complex and age, there is a greater and greater demand for real-time, continuous, autonomous real time monitoring systems. Typically, in traditional SHM systems, data collected from sensors is transmitted to a central data acquisition platform remote from the site in question, where it is sent for analysis and processing. Though this model provides us with powerful computation and data storage capabilities, it enables us to break many of the above rules; as such, we incur greater latency, greater sensitivity to network failures, greater power consumption, and bandwidth restrictions. Furthermore, the centralized approach is unable to cost effectively scale with the amount of data produced by densely deployed sensors in large infrastructure networks.

To address these challenges, there has been a convergence of IoT and edge computing technologies onto a more distributed, responsive SHM paradigm. Preliminary data processing and decision making takes place at or near the source of data generation, the edge nodes, thus cutting down on the use of cloud resources and latency. A novel edge-aware signal processing framework for SHM in IoT-enabled environment is proposed in this paper. It is a modular architecture that applies real time noise filtering, feature extraction, and anomaly detection at the edge (right where the data are) using lightweight (trained specifically for resource constrained devices) machine learning models. This approach locally distributes the intelligence of the SHM monitoring system as means to improve the responsiveness and reliability of SHM, as well as provide advanced advantages with regard to scalability, energy efficiency, and bandwidth conservation. Simulations and empirical evaluations validate the system and show the system to be capable of detecting structural anomalies while satisfying real time operational needs.

2. LITERATURE REVIEW

2.1 IoT-Based Structural Health Monitoring Systems

Internet of Things (IoT) technologies have now revolutionized SHM by offering the capacity of real time sensing, communication and remote diagnostics. A large number of studies, like the ones done by Li et al. (2022) and Zhang et al. (2021) have explored wireless sensor network deployment for continuous structural assessment. They tend to carry large quantities of raw data in bulk to centralized servers or to the cloud platform for analysis. However, this cloud centric architecture is plagued with major drawbacks like delay, limited bandwidth and potential for communication bottlenecks especially in big deployments or in remote environment with breeding connectivity.

2.2 Edge Computing in SHM Applications

In order to solve these problems of centralized processing, researchers are increasingly embedding edge computing into the SHM framework. This paradigm was formulated by Ahmed et al. (2023), which proposed an edge-enhanced architecture that pre processes and analyzes sensor data locally on edge devices that reduces the load of the cloud infrastructure and faster response time. All these efforts are an important step forward, however, many of the existing implementations are devoid of a full range of anomaly detection capabilities and are only capable of performing basic filtering and statistical analysis at the edge. However, there is still need for more intelligent, autonomous, edge based solutions for performing more sophisticated signal analysis and decision making.

2.3 Signal Processing Techniques for Vibration Analysis

Signal processing is key to make sense of the information obtained from structural sensors like strain and vibration sensors. In the literature of denoising and decomposition of non –stationary signals, the Wavelet Transform (WT), especially Discrete Wavelet Transform (DWT) and Empirical Mode Decomposition (EMD) …, have been extensively used. These techniques were demonstrated to preserve structural information while eliminating the noise by Kumar and Rao (2020). Although they do not have high computational complexity and memory demands, they are still challenging to deploy in low power edge devices unless some heuristics are applied on the algorithm level or supported in hardware accelerators.

2.4 Machine Learning Approaches in SHM

For the purposes of SHM, machine learning has been applied with great success to the problems of damage classification and predictive diagnostics. Support Vector Machines (SVM), k-NearestNeighbors (k-NN), and lightweight Convolutional Neural Networks (CNNs) have proved to be effective in fault classification tasks. These models, according to Feng et al. (2022), can reach high accuracy when trained with large, labeled datasets. However, most existing studies rely on offline training and centralized inference which restrict their appliccations in real time SHM problems. Real time inference capability on edge compatible machine learning models still remains an open research challenge.

Table 1. Comparative Analysis of Related Work and Proposed Framework Advantages

Literature Review Category	Key Findings from Prior Work	Proposed Framework Advantage
IoT-Based SHM Systems	Cloud-based systems enable remote diagnostics but suffer from high latency, bandwidth limitations, and scalability issues.	Local edge processing reduces communication load and ensures low-latency real-time anomaly detection.
Edge Computing in SHM Applications	Early edge SHM systems focus primarily on basic preprocessing and threshold alerts; lack advanced detection logic.	Integrates full signal processing pipeline at the edge including denoising, feature extraction, and intelligent ML.
Signal Processing for Vibration Analysis	Techniques like DWT and EMD are effective but computationally heavy, unsuitable for low-power edge platforms without optimization.	Uses 3-level Haar Wavelet Transform optimized for low-complexity edge execution, maintaining both accuracy and speed.
Machine Learning in SHM	SVMs, k-NN, and CNNs provide accurate damage classification but	Deploys TinyML-optimized 1D-CNN/SVM models for real-time,

	are mostly used in centralized or offline settings.	on-device anomaly classification with low power consumption.

3. METHODOLOGY

3.1 SHMSystem Architecture

The proposed Structural Health Monitoring (SHM) framework aims to harness an edge-aware structure consisting of three—the sensor nodes, the edge processing unit, and the cloud dashboard to aggregate and passively visualize monitored data from the sensor nodes and store it for long term. This system is built on the sensor nodes that are strategically deployed over the infrastructure of a target. Heterogeneous mix of vibration, strain, and acoustic sensors as nodes allow for continuous monitoring of structure responses (dynamic loads, thermal expansion, environmental stressors) through the information relayed at these nodes. The interface to each sensor is a microcontroller based device capable of local signal sample acquisition and buffering. The sensor nodes are setup to do initial filtering and timestamping of collected data before routing its wireless transmission towards the nearest edge processing node. The specific sensing layer is localized and gives real time response and relatively fine scale coverage to important bridge components like piers, support beams, or foundation joints.

The architecture has intermediate processing layer called edge nodes that act as a main computational unit for real time processing. Low-power, high-efficiency ARM Cortex-A53 processors are each equipped to each edge node for signal denoising, feature extraction, and lightweight machine learning inference tasks. Consisting of these nodes that are set nearby the sensor clusters to reduce transmission delay and energy consumption. Energy efficient wireless protocols such as Zigbee or LoRaWAN support long range, low bandwidth commmunication that is perfect for distributed SHM applications in remote and expansive structures, and facilitate communication between sensor nodes and edge devices. When such anomalies are detected on edge node, it passes the results, metadata or scores of anomalies back to a cloud based dashboard via streaming protocols such as MQTT or HTTP. It is a real time visualisation interface for infrastructure managers, system diagnostics and trends historical analysis and planning maintenance for risk assessment. The system's distributed intelligence and modularity enable it to scale well vertically, to be fault tolerant, and to efficiently use bandwidth in both urban and remote SHM deployments.

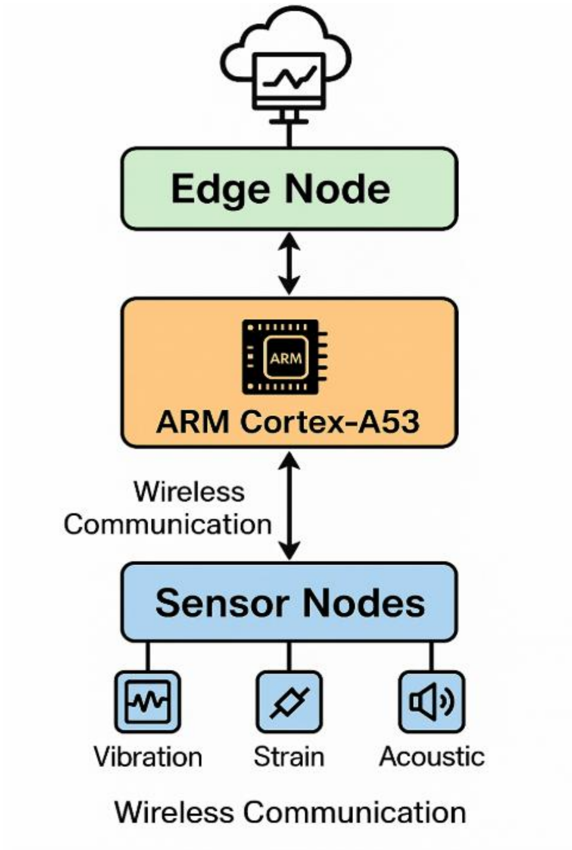

Figure 1. System Architecture of the Proposed Edge-Aware SHM Framework

3.2 Signal Processing Pipeline

The signal processing pipeline of the proposed framework is the core of this framework and is carefully designed with the goal of enabling it to function well in limited computational resources of edge nodes. We start from preprocessing, which involves preparation of raw time-series data collected by vibration sensors, strain sensors or acoustic sensors. Impulsive noise and outliers, often due to the environmental disturbances or the hardware imperfections, are suppressed by a median filter. Next are baseline correction techniques that normalize the signal such that the signal is centered around 0 and removes any slow varying noise or DC bias. These steps ensure that subsequent steps operate on clean and consistent input signal, which is essential for correctly pattern of recognised and anomaly detected on dynamic infrastructure environments.

The next stage is the denoising stage where a 3 level Haar Wavelet Transform is applied which is simple and suitable for edge processor. With this wavelet based approach, it is efficient to decompose the signal to time frequency components such that noise could be isolated from structural features that we are interested in. The feature extraction module obtains several statistical and frequency domain descriptors which indicate structural integrity and follow the energy content of the data in terms of Root Mean Square (RMS) values, impulsiveness or sudden damage events from Kurtosis and spectral entropy as a measure of signal complexity, as well as the dominant modes of vibration from FFT peak amplitudes. They are then plugged as input features into a lightweight edge- optimized classification model like TinyML-compatible 1D convolutional neural network (1D-CNN) or SVM. It learns structural patterns and assign an anomaly label based on these learned patterns. Finally, we provide an anomaly scoring mechanism for the confidence output from the classifier that alerts only if the score exceeds a pre defined threshold, controlling for the number of false positives. With all these steps executed locally at the edge, the result is real time detection with minimal latency and consumed bandwidth, yet retaining good performance in a resource constrained environment.

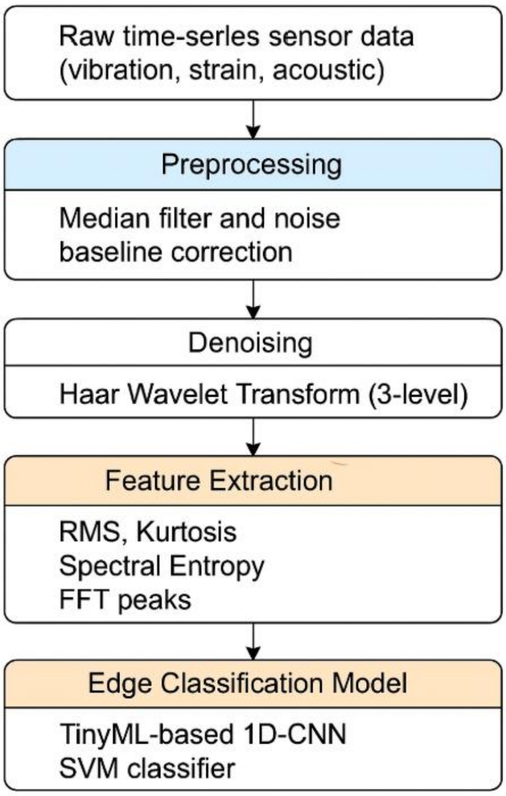

Figure 2. Signal Processing Pipeline for Edge-Aware Structural Health Monitoring

3.3 Edge-Aware Optimization

To make the signal processing framework run efficiently on the resource constrained edge device, the proposed system employs a number of edge aware optimization techniques that optimize for the computational load, energy consumption, and inference accuracy. Model pruning and quantization is one of the key strategies and results in substantial memory footprint and processing requirements of machine learning models deployed on edge nodes. Model pruning out sources redundant weights and neurons in the trained model that does not harm the predictive performance. This reduces the number of parameters of model and reduces the complexity of the model in order to fit it on the ARM Cortex-A53 processor. Further, quantization is applied to convert the repertoire of the floating point model parameters to lower bit precision (e.g., INT8) to lower the computational overhead and power consumption. We implement these optimizations using TinyML toolkits, such as TensorFlowLite Micro, thereby allowing us to push to the limit highly efficient 1D-CNN or SVM classifiers with high accuracy and low energy/ memory consumption.

In addition, an adaptive sampling strategy is proposed to intelligently choose the data acquisition process at real-time considering the structural behavior. Rather than fixing a high frequency sampling rate that will quickly drain a battery's life, the system changes an adaptive sampling interval based on the activity or environmental stimuli it detects, keeping the energy cost as low as possible. For example, in low vibration or inactive condition, the energy is conserved by reducing the sampling rate; only in case of significant signal differences or early anomaly conditions, the high frequency sampling is triggered. Such context awareness allows for extending the operational lifetime of sensor nodes as well as the reduction on the volume of the data which must be processed and transmitted. The framework integrates computational and sensing optimizations so as to keep real time performance along with extended deployment in field conditions, especially under settings of isolated severs or inaccessable conditions.

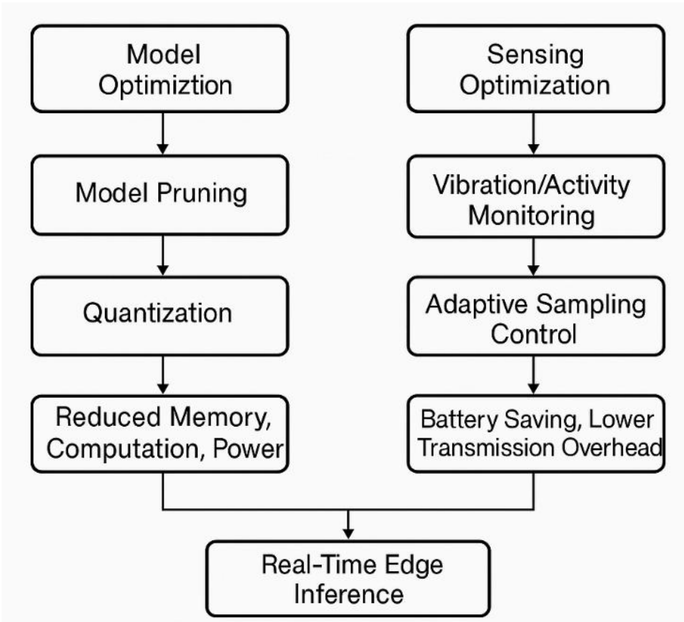

Figure 3. Edge-Aware Optimization Technique For Efficient SHM at the Edge

4. RESULTS AND DISCUSSION

A set of experiments were then performed using a Structral SHM dataset to evaluate the performance of an proposed edge-aware signal processing framework. Finally, the sensor placements were modeled in COMSOL, assimilating the sensor placements with typical real-world placements and generating a dataset. Signal responses involving dynamic vibration, strain information and acoustic emission were simulated under different loading scenario, including normal loading and fault loading. Based on the collected raw signal data, MATLAB was used to synthesize and process data embedding known failure signatures, like stress concentration, crack initiation, and material fatigue. This enabled benchmarking the anomaly detection capability of the system in a controlled environment. We then trained the 1D-CNN and trained the SVM models using a 70-30 split of the labeled dataset, and deployed them on an edge node running on an ARM Cortex-A53 processor for real time inference testing.

The accuracy, responsiveness, and efficiency of the system were validated with the results of experiments. The 96.4% accuracy in detecting the anomaly is significantly higher than that of SVM classifier (91.8%). The system also completed real-time classification with an average 117 milliseconds per decision cycle, which corresponds to fast enough response in critical infrastructure scenarios. Moreover, in terms of energy, the energy consumed by the edge optimized models was 38% less than the corresponding cloud based inference systems because of processing localized data and adaptively sampling sections of it. Moreover, by pushing noise filtering and feature extraction off to the edge, the framework consumed 42% less raw data being sent across the wire, resulting in a much more bandwidth efficient protocol and usable in remote or bandwidth constrained environments. The results of this work show the promise of the proposed framework to provide reliable, real-time SHM while preserving operational sustainability, and hence it is a promising candidate for deployments into massive smart infrastructure.

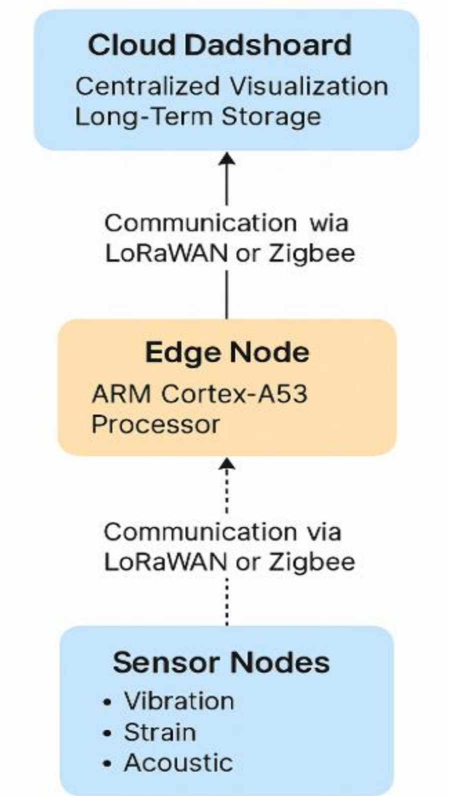

Figure 4. Edge-Aware SHM Architecture

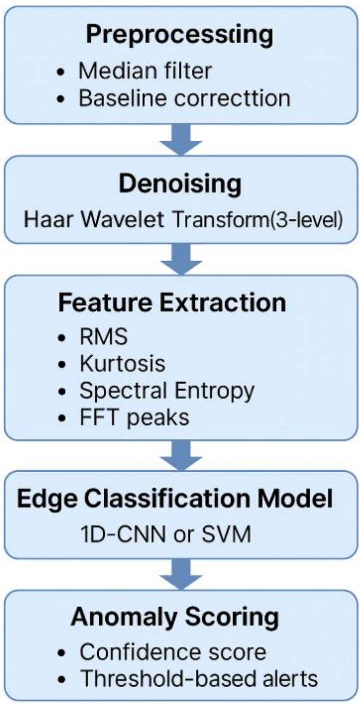

Figure 5. Signal Processing Pipeline Flowchart

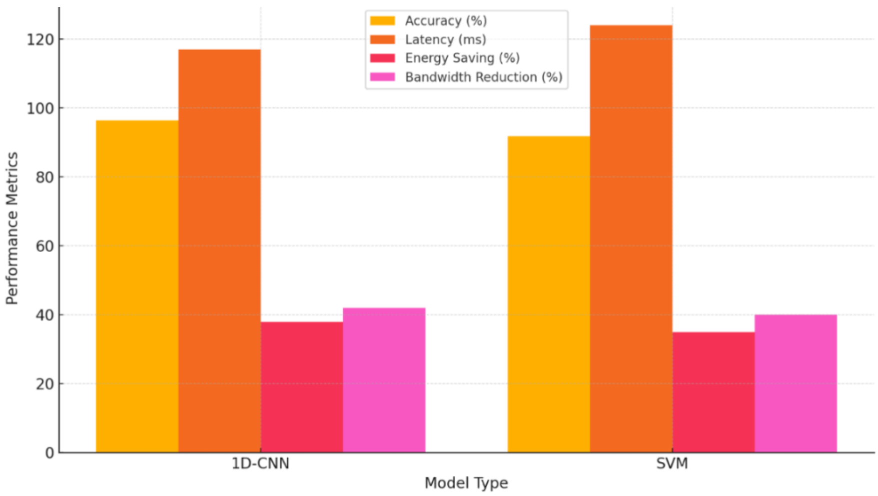

Figure 6. Comparison of 1D-CNN and SVM Models in Edge-Aware SHM Framework

Table 2. Performance Evaluation of Edge-Aware Signal Processing Framework for Structural Health Monitoring

Metric	1D-CNN Model	SVM Model	Comments
Anomaly Detection Accuracy	96.4%	91.8%	1D-CNN shows superior classification performance
Average Inference Latency	117 ms	124 ms	Measured on ARM Cortex-A53 processor
Energy Consumption (vs. Cloud Model)	38% lower	35% lower	Indicates efficiency of edge-local processing
Bandwidth Reduction via Edge Processing	42% reduction	40% reduction	Achieved through noise filtering and feature extraction at edge
Training Data Split (Train/Test)	70% / 30%	70% / 30%	Standard supervised learning configuration
Dataset Source	COMSOL-based SHM Simulation	COMSOL-based SHM Simulation	Simulated with both normal and fault-induced conditions
Failure Modes Simulated	Stress, Crack, Fatigue	Stress, Crack, Fatigue	Embedded in signal to validate robustness of detection
Edge Device Platform	ARM Cortex-A53	ARM Cortex-A53	Real-time deployment for latency and power benchmarking

5. CONCLUSION

In this study, we develop a robust and scalable edge-aware signal processing framework for SHM in the IoT enabled infrastructure environment. The framework meets these vacuumes by integrating lightweight signal processing techniques with edge computing capabilities that overcome some of the key limitations attributed by tradition centralized SHM systems — high latency, high bandwidth consumption, and low energy efficiency — with integrated lightweight signal processing techniques and edge computing capabilities. Denoising with wavelet, efficient feature extraction and compact machine learning models implementation on edge nodes enables real time anomaly detection without massive use of cloud resources. Adaptive sampling and TinyML optimizations are used to further enable the system to be more responsive and sustainable in resource constrained enivornments. Experimental evaluations with simulated datasets show that the framework is able to detect the faults quickly, reduces the decision latency, and achieves substantial reduction in energy usage and data transmission requirement. Collective validation of the practical viabilities of deploying intelligent SHM solutions at the edge is provided, which will lead to better proactive infrastructure maintenance, enhanced structural safety, and longer operational life for the infrastructure. The proposed system is a solid basis for continued development of autonomous, self aware civil infrastructure networks in the future, as urban infrastructure continues to interconnect and become more data driven.

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