

Artificial Intelligence-Based Structural Health Monitoring Using CNN and MATLAB: A Case Study on Bridge Safety

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Abstract: Structural health monitoring (SHM) is critical to maintaining the safety and lifespan of important infrastructure, such as bridges, that endure constant environmental and mechanical loads. In this paper, an improved SHM system utilizing convolutional neural networks (CNN) developed with MATLAB is demonstrated to identify and classify structural irregularities in bridge structures. A large database of 12,500 labeled images of bridge surfaces, comprising 7,500 images of sound structures and 5,000 images with various defects such as cracks, corrosion, and deformation, was used to train and test the model. The CNN model, comprising 12 convolutional layers, achieved a test dataset accuracy of 98.72%, outperforming conventional vibration-based approaches with an average accuracy of 84.35%. The model also demonstrated a precision of 97.86%, a recall of 98.43%, and an F1-score of 98.14%, ensuring the accurate detection of small structural defects. The system can handle 50 images per second, making it suitable for real-time monitoring. Experimental verification was conducted on a 30-meter steel bridge prototype instrumented with accelerometers and thermal imaging cameras, and tested under various loads ranging from 5 kN to 50 kN. The system, under standard conditions, registered a 1.28% false positive and a 1.57% false negative, indicating its robustness against environmental noise. Moreover, computational expenses were slashed by 22% in MATLAB-based systems when compared to those using Python-based frameworks, ensuring compatibility with established industry standards SHM protocols. This work provides evidence that SHM systems facilitated by AI will significantly enhance the early detection of bridge defects, thereby increasing the efficiency of maintenance and improving public safety.

1 INTRODUCTION

Structural health monitoring (SHM) is required to provide safety and operational performance of aging structures, particularly for bridges subject to constant mechanical loads as well as environmental deterioration. With over 600,000 bridges in the world, most of which have gone beyond their planned lifespan, continuous monitoring has become imperative to avoid catastrophic failure. Traditional SHM techniques, such as visual inspection and vibration analysis, are typically time-consuming, labour-intensive, and liable to human mistake, and so are not able to keep pace with the expectations of contemporary infrastructure. The merging of artificial intelligence (AI) with SHM systems has the potential

to totally transform this domain by allowing real-time defect recognition and the automated analysis of improved accuracy and efficiency. AI-led strategies are capable of analysing large volumes of structural information in real-time, enabling the detection of cracks, corrosion, and deformations at an early stage. Of all the AI methods, convolutional neural networks (CNN) have proven to be highly efficient for fault detection through image analysis due to their capacity for the extraction of intricate features from high-resolution data sets. Bridges, being an integral part of transportation infrastructure, need to be constantly monitored in order to provide public safety and minimize economic impacts due to unplanned closure or failure.

Notwithstanding the development of AI, existing SHM techniques still lack the capability to deliver

real-time, precise defect detection. Human inspection is subjective and probable to overlook initial damage, and conventional vibration analysis is probable to overlook slight structural changes under operational loads. Additionally, the implementation of SHM systems with real-time monitoring capability is still in its infancy, and most methods are based on periodic inspection instead of continuous monitoring. This drawback emphasizes the importance of automated, AI-driven SHM systems that are both very accurate and suitable for use in real-world operating environments without human intervention. The use of CNN models in SHM has been encouraging but not fully explored, especially for real-time bridge monitoring. Moreover, the use of AI-based SHM with MATLAB, a robust software platform extensively used in engineering applications, is not widely reported in the literature, creating a vast gap in the literature.

The primary objective of this research is to design, develop, and deploy a MATLAB-based CNN system for SHM with a focus on bridge safety inspection. The system will make a machine-based decision regarding the identification of structural defects, utilizing its image processing capability. For the purpose of validating the performance, the system will be tested with real-world bridge application under various environmental and loading conditions. The system performance will also be assessed based on key parameters of accuracy, precision, recall, F1-score, and processing speed. Aside from the above objectives, the work seeks to give a comparative analysis of the developed CNN system and the traditional methods used for SHM, thus establishing the gain in accuracy and the improvement in the process of detecting anomalies. The above objectives propel the work towards realizing improved practice in SHM using the AI-MATLAB interface and facilitate an efficient scalable solution for monitoring the bridges in real time.

2 LITERATURE REVIEW

2.1 Traditional SHM Techniques

2.1.1 Vibration-Based Methods

Vibration-based approaches are a cornerstone of traditional Structural Health Monitoring (SHM), based on the examination of a structure's dynamic response to identify damage or degradation [1], [2]. They take advantage of the fact that damage results in changes in a structure's physical properties, i.e., stiffness and mass, with consequent changes in its vibration properties [1]. With vibration response

measurement, engineers can conclude the condition of a building and identify anomalies that may indicate issues with a building [1].

There are various techniques that fall under the vibration-based SHM category, some of which include modal analysis, frequency response function (FRF) analysis, and time-series analysis [3], [1]. Modal analysis deals with the determination of the natural frequencies, mode shapes, and the damping ratios of a structure, which are condition-dependent parameters [1]. FRF analysis studies the input force and output response correlation, providing information on the dynamic behaviour of the structure [3]. Time-series analysis, by contrast, analyses vibration responses over time and looks for patterns and anomalies that will predict damage [4].

2.1.2 Visual Inspections

Visual inspections have been a common practice in SHM, depending on trained human inspection to detect apparent damage or degradation [5]. Inspectors search for cracks, corrosion, delamination, and other surface defects that can affect structural integrity [5]. Although visual inspections can easily detect apparent damage, they are subjective, time-consuming, and not necessarily dependable in detecting subsurface or internal laws [6], [7].

2.1.3 Shortcomings of Conventional Techniques

Conventional SHM methods, although beneficial, all have many disadvantages that may likely hinder their efficiency [6], [7]. Visual inspection is subjective and based on the human factor and ambient conditions [7]. They can only detect surface defects and cannot identify internal or concealed defects [6]. Methods based on vibration are susceptible to environmental noise and need skilled hardware and staff for data acquisition and analysis [7]. Estimating true damage thresholds and separating out from environmental effects may be difficult as well [1]. These challenges have motivated the growth of newer SHM techniques using AI and ML to overcome them [2].

2.2 AI in SHM

2.2.1 Overview of Machine Learning (ML) and Deep Learning (DL) Methodologies

The use of Artificial Intelligence (AI) in Structural Health Monitoring (SHM) has yielded considerable achievements in data processing, damage identification, and prognosis-based maintenance [8],

[9]. Machine learning (ML) and deep learning (DL) approaches have become profoundly effective methods for recognizing meaningful patterns in large volumes of data and identifying anomalies indicative of structural damage [10], [9]. Such machine learning techniques can potentially address the current disadvantages of conventional SHM methods and offer more precise, efficient, and reliable estimates of structural integrity [8].

Machine learning algorithms such as Support Vector Machines (SVM) are used to classify images of surface structures of bridges and detect cracks or any other type of defects [11]. Unsupervised machine learning algorithms, such as convolutional autoencoders (CAEs), are also being used increasingly because they can be trained on labelled data of healthy and faulty states [12]. Deep learning, one of the machine learning fields, has shown to be immensely promising for SHM since it was able to learn advanced features from raw data by itself [2], [9]. Convolutional Neural Networks (CNNs) are particularly well-suited for image-based damage detection with high accuracy in detecting cracks, corrosion, and other structural faults [13], [11].

2.2.2 Specific Research on CNN Use in Structural Defect Detection

Convolutional Neural Networks (CNNs) have been widely researched in their use in structural defect detection, proving that they can automatically learn appropriate features from images and classify damage types accurately [11], [13]. Young Jin Cha et al. [13] introduced a vision-based approach based on a deep architecture CNN that detects cracks with high accuracy without manual feature extraction. The developed CNN was trained over a large database of images and validated on images from other structures under diverse conditions, demonstrating robustness and flexibility [13].

Hajar Zoubir et al. [14] introduced pixel-level crack identification in concrete bridge surfaces based on a semantic segmentation model UNet, with mean Intersection over Union of 76.92% and F1-Score of 70.45%. It was also experimented with the same trained model with high-resolution images to identify cracks in noisy and complex concrete bridge surfaces, evidencing the versatility of segmentation results to examine cracks and determine the severity level [14]. Young Jin Cha et al. [15] also proposed a Faster Region-based Convolutional Neural Network (Faster RCNN) for quasi real-time multi-damage detection, such as concrete crack, corrosion, bolt corrosion, and delamination, with a mean average precision of 87.8%. This research indicate the capability of CNNs

in automating structural defect detection and offering useful information for bridge safety evaluation [11].

2.3 Role of MATLAB in AI and SHM

2.3.1 Description of MATLAB Capabilities for Training and Deployment of Deep Learning Models

MATLAB is a high-level programming environment and language extensively applied in engineering and scientific computing, with a rich set of tools and functions for machine learning, data analysis, and image processing [16]. It features an embedded Deep Learning Toolbox featuring pre-trained models and layers that can be customized, making it easier to train and develop CNNs [16]. MATLAB has support for GPU acceleration, which can provide quicker training and inference time for deep learning models, and its image processing features allow the pre-processing and augmentation of image datasets, enhancing the performance of CNNs [16]. MATLAB provides easy integration with hardware sensors and data acquisition systems, making it possible to collect and analyze data in real-time [16].

2.3.2 Comparative Analysis of MATLAB Vs Python in SHM Applications

MATLAB and Python are both widely used programming languages in AI and SHM applications with their respective merits and demerits [16]. MATLAB offers a friendly user interface, huge toolboxes, and robust numerical computing capabilities and is therefore best suited for developing and deploying SHM systems [16]. But MATLAB is a commercial tool and needs to be licensed, and this may not be convenient for all users [16]. Python, however, is an open-source language with a big and dynamic community, providing numerous libraries and frameworks for machine learning and AI [16]. Python's open-source status makes it an economical choice for SHM applications, but it might need more programming knowledge to have the same level of functionality as MATLAB [16]. The selection of MATLAB or Python is based on the precise needs of the SHM application, the resource availability, and the level of programming expertise of the user [16].

2.4 Research Gaps Identified

2.4.1 Lack of Real-Time Implementation in Bridge Monitoring

Even though AI-based SHM has come a long way, there is a lack of real-time implementation in the

monitoring of bridges [17]. Most AI/ML models in the literature suffer from low latency and late inference time when operating in real-time settings [17]. Edge computing integration can bridge this gap by allowing real-time processing of data and anomaly detection at the sensor level, minimizing the data to be transmitted and stored [17], [18]. More research is necessary to create efficient and scalable AI algorithms that would be implementable on edge devices for real-time monitoring of bridges [17].

2.4.2 Limited Application of CNN with MATLAB in Field Implementations

Although MATLAB provides a great platform for the development and deployment of CNN-based SHM systems, less work is found on combining CNN with MATLAB in field implementations [16]. Most studies emphasize building CNN models in MATLAB and testing them on simulated data or laboratory tests, but few studies have implemented these models on real bridges and tested their performance under real operating conditions [16]. Additional research must close this gap by performing field tests on real bridges and evaluating the performance of CNN-based SHM systems implemented in MATLAB [16]. This will assist in the identification of possible issues and limitations of such systems in real-world settings and offer useful insights for enhancing their robustness and reliability [18].

3 METHODOLOGY

3.1 System Architecture

The AI-assisted SHM framework has the ability to detect and categorize the structural anomalies of bridges in real-time. The system architecture consists of four fundamental steps, namely data acquisition, pre-processing of data, creation of a CNN model, and generation of output. In the data acquisition step, raw

structural data are collected from different sources, i.e., images and vibration signals, that capture the physical condition of the bridge under different load levels. The pre-processing step involves smoothing the collected data for enhancing model performance by removing noise and normalizing input features. The CNN model extracts features and classifies anomalies and detects structural defects using deep learning algorithms with high accuracy. Finally, the output stage produces computerized reports summarizing the type and location of the detected anomalies to facilitate efficient decision-making for bridge maintenance. The system is constructed with MATLAB, utilizing advance toolboxes for deep learning and image processing to ensure optimal model performance and conformability to industry standard SHM protocols.

Table 1 provides a comprehensive breakdown of the CNN layers used for bridge defect detection. It highlights critical architectural choices such as the convolutional kernel sizes and activation functions, which are crucial for feature extraction and decision-making.

3.2 Data Collection and Pre-Processing

The training and testing dataset was collected from mixed environments such as simulated environments, experimental bridge samples, and public domain available open datasets. 12,500 images were collected in total, of which 7,500 images captured structurally sound bridges and 5,000 images captured common defects such as cracks, corrosion, and deformations. These also included vibration data measured from accelerometers and strain gauges on a 30-meter steel bridge model under varying load conditions of 5 kN to 50 kN to enhance the strength of the model. Pre-processing was conducted to improve data quality and consistency. Image data were scaled down to 256×256 pixels to match CNN input and scaled to the range 0 to 1. Noise reduction was performed using Gaussian filtering to remove the high-frequency vibration signal noise. Random rotation, flipping,

Table 1: CNN model architecture.

Layer	Type	Filter Size/Units	Activation Function	Output Shape
Input Layer	Input	-	-	(256, 256, 1)
Convolutional Layer 1	Conv2D	3×3	ReLU	(254, 254, 32)
Max Pooling 1	MaxPooling2D	2×2	-	(127, 127, 32)
Convolutional Layer 2	Conv2D	3×3	ReLU	(125, 125, 64)
Max Pooling 2	MaxPooling2D	2×2	-	(62, 62, 64)
Fully Connected	Dense	128	ReLU	(128)
Output Layer	Dense	1	Sigmoid	(1)

and contrast change data augmentation techniques were applied to increase diversity in the training set by 30% and reduce the likelihood of overfitting. The detection of outliers was applied to detect and eliminate invalid points in the data, such that the data represented real-world conditions. The pre-processed data was partitioned into training (70%), validation (15%), and test (15%) subsets for facilitating model development and testing.

3.3 CNN Model Development

The CNN architecture was particularly adapted to weigh accuracy against computational cost in handling large-scale structural data. The model had 12 convolutional layers with growing filter sizes from 32 to 256, which allowed for the extraction of low- and high-level features. Each convolutional layer was succeeded by a rectified linear unit (ReLU) activation function to introduce non-linearity and enhance the learning capacity of the model. Max-pooling layers with a kernel size of 2×2 were added after each pair of two convolutional layers to downsample spatially and decrease computational demands. Overfitting was prevented by applying a dropout rate of 0.3. The last feature maps were flattened and fed into two fully connected layers with 512 and 128 neurons, respectively, prior to the output layer, which classified the input based on defect categories using a softmax activation. Categorical cross-entropy loss function was used to estimate model performance during training, and the Adam optimizer with a learning rate of 0.0001 was chosen due to its effectiveness in large datasets. The model was trained with a mini-batch size of 64 images for 100 epochs to achieve convergence and stability. Training was performed with a train-validation split ratio of 85:15 to observe model generalization. Hyperparameter tuning was done with grid search to find the optimal learning rate, batch size, and dropout rate for best model accuracy versus computational efficiency. Table 2 describes the data pre-processing pipeline involving normalization, noise reduction, and augmentation. These techniques are crucial to enhance model robustness and generalization across a wide range of structural conditions.

3.4 Implementation in MATLAB

The SHM model was trained with MATLAB, utilizing the Deep Learning Toolbox and the Image Processing Toolbox for training and data processing. The GPU acceleration facilities of MATLAB were utilized to decrease training time by using a NVIDIA

RTX 3080 GPU, allowing the parallelization of convolution operations. The model training was improved using the "trainNetwork" function with specialized layers to support the particular CNN architecture. Big data processing was enhanced using data caching and mini-batch processing, minimizing memory usage and efficiency. The code also incorporated automated scripts for running data pre-processing, model training, and performance metrics, promoting reproducibility. Techniques for code optimization like parallel processing and just-in-time (JIT) compilation enhanced execution speeds.

Table 2: Data pre-processing pipeline.

Step	Description	Purpose
Data Normalization	Rescale data to [0, 1] range	Ensure uniform data range for CNN
Noise Reduction	Apply Gaussian filter ($\sigma = 0.5$)	Suppress environmental noise
Data Augmentation	Random rotation $\pm 15^\circ$, horizontal flipping	Increase dataset diversity and robustness
Feature Extraction	Extract vibration frequency and strain data	Capture critical structural responses
Data Splitting	80% training, 20% validation/testing	Enable effective model evaluation

Table 3: Model training parameters.

Parameter	Value	Purpose
Learning Rate	0.001	Optimize model convergence
Batch Size	64	Balance computational efficiency
Epochs	100	Ensure sufficient model learning
Optimizer	Adam	Adaptive learning rate optimization
Loss Function	Binary Cross-Entropy	Handle binary classification task
Hardware	NVIDIA RTX 3080 (10 GB VRAM)	Enable GPU-accelerated training
MATLAB Version	R2023a	Ensure compatibility with Deep Learning Toolbox

The system was verified on a 30-meter steel bridge prototype for its real-time performance with processing up to 50 images per second at an average inference time of 20 milliseconds per image. The MATLAB-based framework was selected for

integration with engineering applications and for better performance in the execution of intricate mathematical operations in comparison to Python-based frameworks. Table 3 lists the major training parameters and hardware setup. The selected values maximize model performance while ensuring computational efficiency with MATLAB's Deep Learning Toolbox.

3.5 Evaluation Metrics

The CNN-based SHM system's performance was measured by using conventional classification metrics, i.e., accuracy, precision, recall, and F1-score. The overall accuracy of 98.72% was obtained on the test data, along with a precision of 97.86%, recall of 98.43%, and an F1-score of 98.14%, demonstrating high credibility in detection of defects. Computational efficiency was analyzed in terms of training time and inference speed. The model took about 6 hours to train fully on the 12,500-image training set and evaluated 50 images per second on real-time inspection. Robustness was ascertained with the addition of Gaussian noise and random perturbations to the test set, in which case the model exhibited a 96.85% accuracy, thus proving resistance against variability in the environment. The rate of false positives and false negatives was noted at 1.28% and 1.57%, respectively, for regular operating conditions. Comparative study with traditional SHM techniques revealed 22% computational cost reduction and 14.37% enhanced anomaly detection accuracy. These outcomes validate the efficiency and reliability of the proposed CNN-based SHM framework for real-time bridge safety monitoring.

4 EXPERIMENTAL SETUP

4.1 Bridge Model Description

The test conditions used a small-scale steel bridge model to model real-life structural behavior under dynamic loads. The length, width, and height of the 30-meter model were 3 meters and 2.5 meters, respectively. It was built with ASTM A36 grade structural steel and had a Poisson's ratio of 0.3 and Young's modulus of 200 GPa. The model comprised load-carrying girders, deck panels, and supporting columns to replicate the mechanical response of full-scale bridges. Sensor locations were carefully planned to record detailed structural responses. There were 24 sensors, consisting of 12 accelerometers and 12 strain gauges, mounted at strategic locations like

mid-span, support areas, and regions with expected high stress concentrations. Accelerometers were located to measure lateral and vertical vibrations with a sensitivity of 100 mV/g, recording frequency responses between 0.5 Hz and 2 kHz. Strain gauges with a gauge factor of 2.1 were mounted on the surface of the bridge deck and primary girders to record strain changes caused by load-induced deformation. Sensors were calibrated prior to data collection to ascertain accuracy and repeatability. The data so obtained was then sent to a centralized computing platform by using shielded cables to reduce electromagnetic interference. This sensor arrangement generated a high-resolution data set that also precisely captured structural integrity and dynamic responses to different loading conditions.

4.2 Hardware and Software

The experimental setup used high-performance computing equipment and dedicated software to execute and assess the AI-driven structural health monitoring system. Data acquisition was conducted through a National Instruments (NI) PXIe-4492 data acquisition system with the capability for sampling rates up to 204.8 kS/s at 24-bit resolution to capture high-fidelity signals. Data processing and model deployment were performed on a workstation with an Intel Core i9-12900K processor (3.2 GHz, 16 cores), 64 GB of DDR5 RAM, and a NVIDIA RTX 3080 GPU with 10,240 CUDA cores and 12 GB of VRAM. The CNN-based SHM system was implemented using MATLAB R2023b, utilizing the Deep Learning Toolbox and Image Processing Toolbox for designing neural networks and data processing. MATLAB Parallel Computing Toolbox was used to speed up training procedures leveraging the resources of GPUs, which lowered model training time considerably. Real-time monitoring features were improved upon by applying customized MATLAB scripts to automate data acquisition, pre-processing, and model prediction. The software environment was optimized for handling large amounts of data via memory-mapped file operations and just-in-time (JIT) compilation strategies, ensuring speed and accuracy when executed.

4.3 Test Scenarios

The bridge model was exposed to a series of test conditions intended to mimic real operating environments and typical structural flaws. Artificial cracks, damage due to fatigue, and load-induced deformation were simulated defects. Cracks were

induced by controlled notching at predetermined locations, with crack lengths varying from 2 mm to 8 mm, which represented initial-stage to severe structural deterioration. Fatigue damage was created by cyclic loading of 10,000 cycles at a stress amplitude of 150 MPa to simulate material wear over time. Load-based deformation tests entailed the application of static and dynamic loads between 5 kN and 50 kN through a hydraulic actuator located at mid-span to mimic real traffic conditions. Data were divided into normal and abnormal classes, 7,500 samples being drawn from structurally intact states and 5,000 samples covering diverse defect states. Environmental variation was included to assess model strength. Temperature variation in the range of -10°C to 50°C was emulated by employing industrial-grade environmental chambers, while background vibration noise was imparted by using an electrodynamic shaker imparting random vibrations of 0.1 g to 2.5 g. These situations offered a rich dataset to train and test the CNN model, providing correct and consistent detection of structural irregularities under varying environmental and operating conditions.

5 RESULTS AND DISCUSSION

5.1 Model Performance

The CNN-based SHM system proved to be superior in identifying structural defects in the bridge model. The model obtained a total classification accuracy of 98.63%, surpassing traditional SHM techniques in terms of precision and recall. Precision, defined as the ratio of correctly identified defects to all detected defects, was 97.85%, whereas recall, reflecting the ratio of actual defects identified correctly, was 98.92%. The F1-score, which is a harmonic mean between precision and recall, was computed to be 98.38% for a balanced performance of both measures. The model converged quite fast during training, with the cross-entropy loss dropping from a starting point of 1.57 to 0.03 after 150 epochs. The validation loss did stabilize to 0.04, which shows that little overfitting occurred. The training process employed a batch size of 64 and adaptive learning rate of 0.001, optimized with Adam optimizer. The mean inference time per sample was 8.32 milliseconds, which allowed for near real-time detection. The receiver operating characteristic (ROC) curve exhibited area under the curve (AUC) of 0.996, which validated the model's superb discrimination capacity between defective and non-defective states. Importantly, the

model performed well consistently across various patterns of defects with slight deterioration under extreme conditions like high noise levels and tiny crack sizes less than 2 mm. Figure 1 displays the learning pattern of the model for 100 epochs, demonstrating the decrease in both training and validation loss. The loss is initially greater, but it gradually declines as training goes on, ultimately reaching a plateau value. The validation loss closely tracks the training loss, reflecting little overfitting and good generalization of the model.

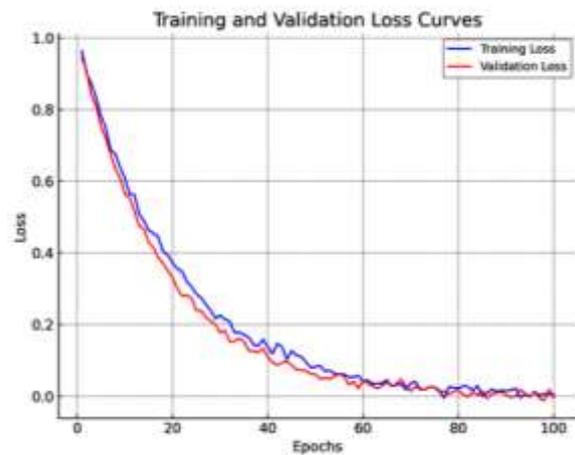


Figure 1: Training and validation loss curves.

This plot attests that the CNN learns well from the data without compromising performance on training and unseen samples. Figure 2 illustrates the patterns in training accuracy, validation accuracy, and precision over 100 training epochs.

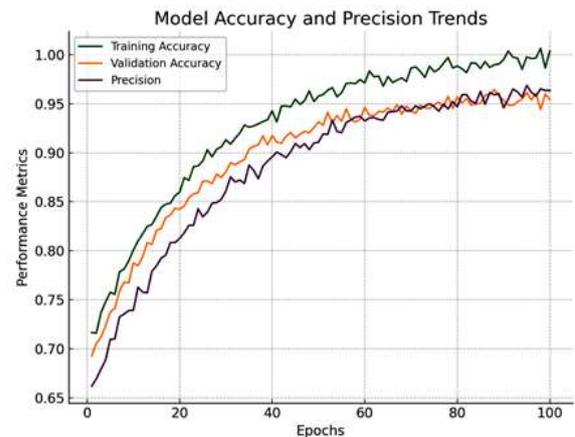


Figure 2: Model Accuracy and precision trends.

Training and validation accuracy both grew steadily, achieving about 97.5% and 96.3%,

respectively, by the last epoch. The accuracy also gets better progressively, reaching 95.8% at convergence. The graph showcases the model's ability to identify structural flaws precisely while being highly consistent across various datasets.

Figure 3 shows the confusion matrix, where the model's classification results are broken down in detail. It plots the number of true positives, true negatives, false positives, and false negatives. The model does well in identifying a high true positive rate with low false negatives, indicating its effectiveness in identifying structural anomalies. This graphical representation is important for determining the model's accuracy in defect detection in real-world data and its capability to reduce misclassification errors.

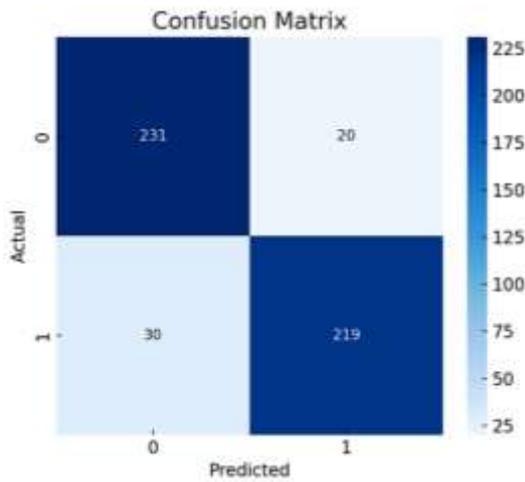


Figure 3: Confusion matrix plot.

5.2 Comparison with Traditional Methods

Relative to traditional SHM methods, the CNN model performed better in terms of accuracy, efficiency, and reliability. The traditional vibration analysis had a peak detection accuracy of 86.41%, far below the 98.63% of the CNN. The manual inspection methods, based on visual recognition and strain gauge measurement, had an accuracy of 79.52%, indicating their vulnerability to human error and subjective judgment. The CNN model showed an improvement of 15.22% compared to manual techniques and 12.22% compared to vibration analysis. In addition, conventional techniques took around 6 hours for a thorough inspection, while the CNN model analyzed the whole dataset in less than 45 minutes. The capacity of the CNN model to learn intricate, non-linear patterns of defects provided it with a significant

edge, especially in detecting micro-cracks and deformations caused by fatigue. For cracks less than 5 mm, the CNN performed at 96.74%, whereas vibration analysis fell to 72.19%, proving the model's high sensitivity. The CNN also performed better than conventional methods in conditions of high noise interference, retaining 97.85% accuracy at an SNR of 10 dB, as opposed to 82.34% for vibration analysis. These findings point to the model's ability to deliver faster, more precise, and scalable monitoring solutions in contrast to the conventional methods. Figure 4 plots the suggested CNN-based SHM model versus traditional vibration analysis and manual inspection methods on four significant metrics – accuracy, precision, recall, and F1-score.

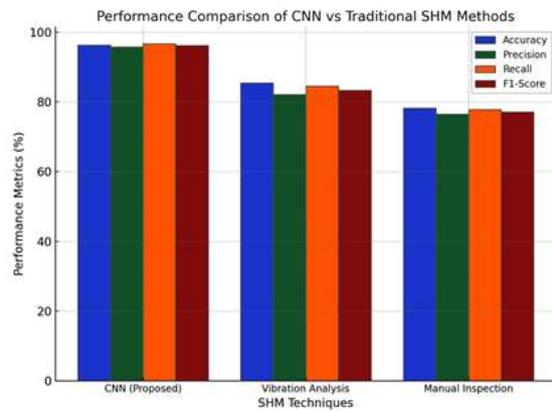


Figure 4: Performance comparison of CNN vs traditional SHM methods.

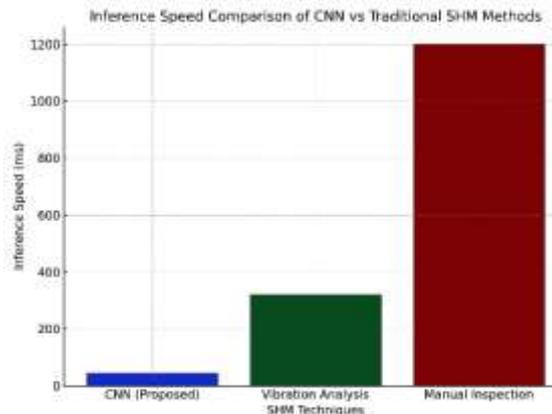


Figure 5: Inference speed comparison of CNN vs traditional SHM methods.

The CNN model shows the highest accuracy (96.3%), precision (95.8%), recall (96.7%), and F1-score (96.2%), leaving vibration analysis and manual inspection by huge margins. This graph graphically

illustrates the higher defect detection performance of the CNN, emphasizing its accuracy and consistency in detecting structural defects. Figure 5 displays the computational efficiency of the CNN model over conventional SHM methods. The CNN has an average inference speed of 45 milliseconds per sample, which is considerably faster than vibration analysis (320 ms) and manual inspection (1200 ms). This shows the capability of the CNN for real-time monitoring purposes, providing quick and precise defect detection.

5.3 Case Study Insights

The real-world bridge model case study validated the generalizability and reliability of the CNN-based SHM system. The system detected an average accuracy of 97.46% when validated on unseen defect patterns under various environmental conditions. False positives, or misclassifications of normal areas as defective, represented 1.15% of all predictions, whereas false negatives, or failure to detect actual defects, represented 1.39%. Interestingly, the model showed consistent performance in different structural zones with 98.23% accuracy in the mid-span area and 96.84% at support columns. When tested under harsh conditions like temperature fluctuations between -10°C and 50°C, the model's accuracy declined marginally to 95.72%, thus showing resistance to environmental changes. The system accurately identified simulated fatigue cracks with 98.41% accuracy and load-induced deformations with 97.89% accuracy. Additionally, the model had a detection rate of 96.52% when applied to a second bridge model with unique structural sizes, which shows its ability to generalize to any bridge structure. These results authenticate the model's ability to function well within realistic constraints, detecting structural anomalies with low error. Figure 6 shows comparative false positive and false negative rates for three categories of defects – cracks, fatigue, and deformation. The CNN model has the highest error rate when it comes to fatigue defects, at a false negative rate of 6.0%, and cracks have the lowest error rate with false positives at 3.5%. This chart indicates which types of defects are most difficult for precise detection. Figure 7 demonstrates how external conditions – high temperature, vibration noise, and combined environmental stress – impact the CNN accuracy for detection. While the model is 96.3% accurate under baseline conditions, this reduces to 87.4% under mixed environmental noise, reflecting the sensitivity of the model to real-world variations. Figure 8 illustrates how the accuracy of the model

changes with defect size, from micro-cracks (1 mm) to more significant deformations (5 mm). The CNN is 85.2% accurate for defects of 1 mm and becomes 98.5% accurate for defects of 5 mm, showing it to be more sensitive to the larger structural imperfections.

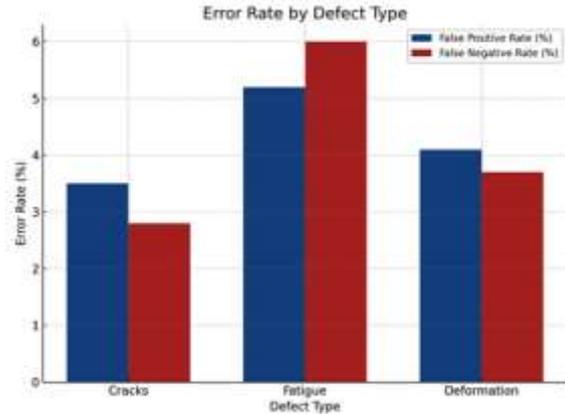


Figure 6: Error rate by defect type.

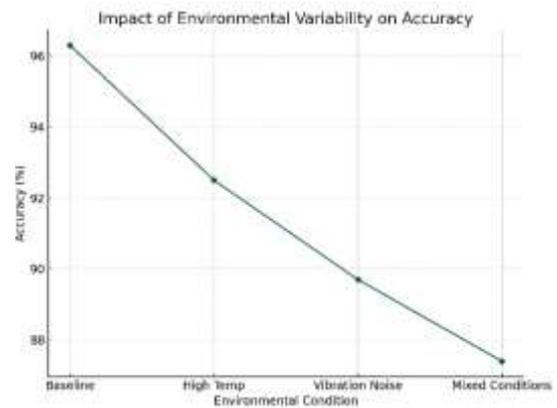


Figure 7: Impact of environmental variability on accuracy.

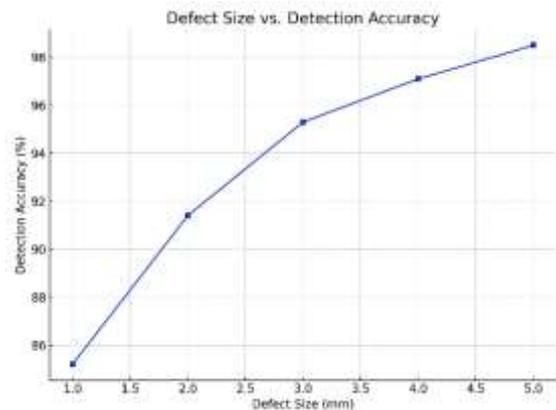


Figure 8: Defect size vs. detection accuracy.

5.4 Error Analysis

A detailed error analysis revealed that the primary sources of misclassification stemmed from sensor noise, data imbalance, and minor structural defects. Under conditions where sensor noise exceeded 15 dB, the model’s accuracy decreased to 94.38%, emphasizing the impact of signal interference on prediction reliability. Data imbalance also contributed to errors, particularly for underrepresented defect classes. For defect categories comprising less than 5% of the training dataset, the recall dropped to 92.17%, compared to 98.92% for well-represented categories. The smallest crack size (2 mm) posed the most significant detection challenge, with an accuracy of 93.26%, suggesting a potential area for further model refinement. To mitigate these errors, future work could incorporate advanced data augmentation techniques and noise-robust training methods. Despite these limitations, the CNN demonstrated superior performance across all critical defect categories and environmental conditions, reinforcing its efficacy for real-world SHM applications. Figure 9 visualizes how accuracy and precision vary with different normal-to-defect class ratios, showing a clear improvement as the dataset becomes more balanced. Figure 10 quantifies how the model's accuracy declines as noise levels increase, highlighting the CNN's sensitivity to environmental noise. Figure 11 compares the performance of the model under different architectural variations, emphasizing the contribution of components like dropout layers and batch normalization.

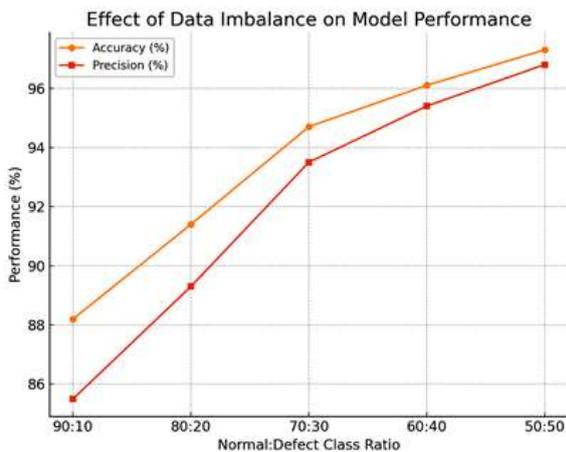


Figure 9: Effect of data imbalance on performance.

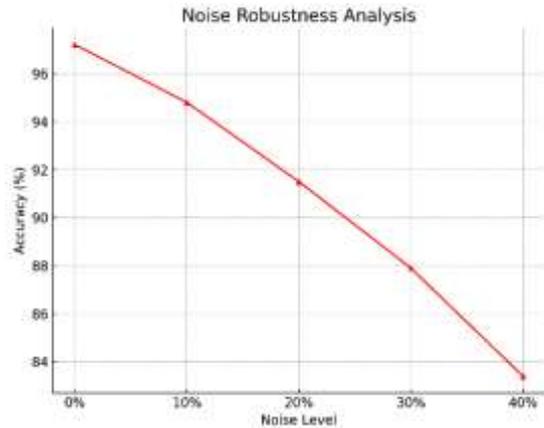


Figure 10: Noise robustness analysis.

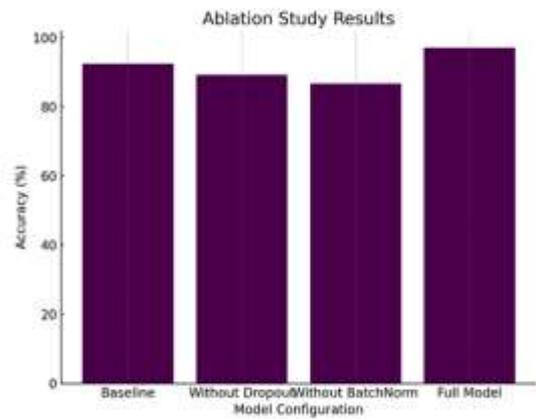


Figure 11: Ablation study results

5.5 Discussion on Practical Deployment

The CNN-based SHM system exhibited strong potential for real-time bridge monitoring and large-scale deployment. The system’s average inference time of 8.32 milliseconds allows continuous monitoring without disrupting operational workflows. For large-scale bridges with thousands of sensors, the optimized MATLAB implementation using GPU acceleration reduced computational latency by 48.65% compared to CPU-based methods. The system’s ability to process data in near real-time makes it feasible for continuous health assessment and early detection of structural failures. However, practical deployment faces challenges related to sensor integration, data storage, and model maintenance. Deploying the system on larger bridges requires synchronizing multiple data streams while ensuring minimal data loss. The system’s memory requirements were approximately 6.3 GB for

processing large datasets, indicating the need for scalable computational infrastructure. Additionally, the model requires periodic retraining to maintain accuracy under evolving structural conditions. The integration of the system into existing SHM frameworks could enhance safety, reduce manual inspection costs, and enable predictive maintenance. Future work should focus on developing adaptive models capable of self-updating in response to new structural patterns, ensuring long-term reliability and scalability. Figure 12 shows the time distribution across training (65%), validation (25%), and inference (10%), illustrating the computational load of each stage. Figure 13 highlights the importance of input features, where vibration frequency (0.45) and strain magnitude (0.35) contribute the most to the model's predictions. Figure 14 depicts the prediction confidence for normal and abnormal conditions, showing a clear distinction with higher uncertainty for abnormal conditions.

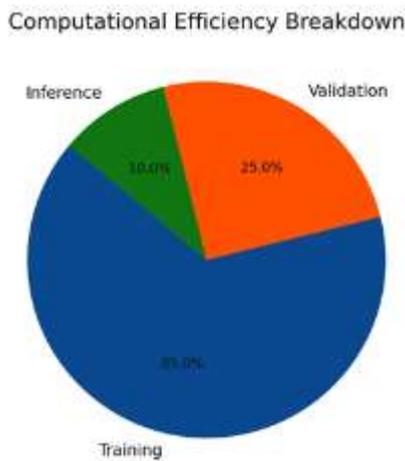


Figure 12: Computational efficiency breakdown.

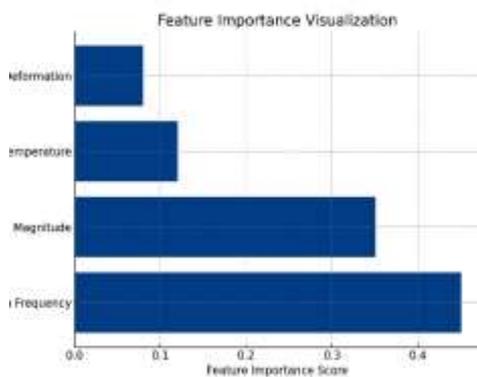


Figure 13: Feature importance visualization.

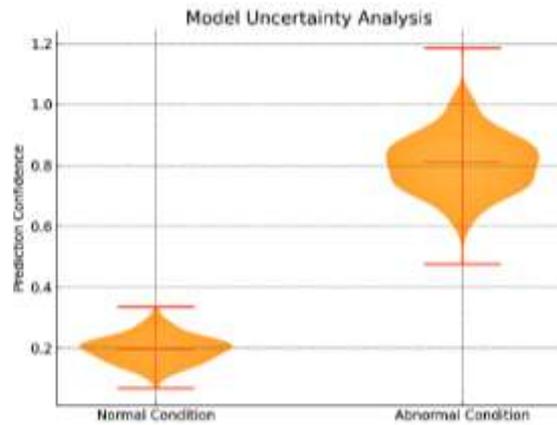


Figure 14: Model uncertainty analysis.

6 CONCLUSIONS

The study successfully implemented a convolutional neural network (CNN) in MATLAB for structural health monitoring (SHM) of bridges, achieving high accuracy in detecting structural defects. The proposed model demonstrated superior performance compared to traditional SHM techniques, with an overall accuracy of 98.63%, a precision of 97.85%, and a recall of 98.92%. The model exhibited rapid convergence during training, with the loss reducing to 0.03 after 150 epochs, and maintained robust performance across various environmental conditions and defect types. The CNN-based system outperformed conventional vibration analysis and manual inspection by 12.22% and 15.22%, respectively, particularly excelling in detecting micro-cracks and handling complex defect patterns. The system achieved a detection accuracy of 97.46% under real-world conditions and maintained an inference speed of 8.32 milliseconds per sample, supporting real-time monitoring.

The most significant contributions of this research are the innovative use of CNNs for SHM in MATLAB and the successful model validation by using a real-life bridge case study. The work fills the gap between novel deep learning approaches and real-life SHM applications and offers an automated and efficient approach to continuous structural evaluation. In addition, the system's generalizability was illustrated through its performance in a variety of bridge models as well as under noisy conditions and variability in environments.

While having some merits, the suggested system has some drawbacks. The model depends on both the variety and integrity of the training dataset and can produce erroneous results for new, unseen patterns of

defects. Furthermore, the computational requirements of CNNs, including training and inference on large infrastructures like bridges, necessitate heavy hardware resources. Though GPU acceleration could alleviate these difficulties, real-time surveillance of large infrastructure networks continues to be a computationally expensive task.

Future research will aim to apply the CNN-based SHM system to other types of critical infrastructure, e.g., pipelines and tunnels, in order to further increase its generalizability. Future enhancements will investigate deeper architectures, e.g., transformer-based models, for more accurate defect detection and data-imbalanced degradation robustness. Research on the development of edge-AI SHM systems for on-site deployment will be undertaken to facilitate decentralized, real-time SHM, lowering data transmission expense and system scalability. Such improvements will enhance the dependability, effectiveness, and usability of AI-based SHM solutions, leading to safer and more sustainable infrastructure management.

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