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A Novel AI-Wavelet Based Framework for Benchmark Data Analysis in Structural Health Monitoring

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ABSTRACT: Structural Health Monitoring (SHM) plays a vital role in ensuring the safety, durability, and operational efficiency of critical infrastructure. Traditional SHM methods often fall short in detecting subtle damage patterns, particularly when faced with noisy signals, missing data, or the complex, time-varying behavior of real-world structures. To address these challenges, this study presents a hybrid framework that integrates Discrete Wavelet Transform (DWT) with a deep learning architecture combining Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks. The proposed approach begins by segmenting long-duration acceleration signals into fixed-length windows and applying DWT to extract informative time–frequency features. CNN layers are then used to learn spatial representations from the transformed data, while LSTM layers capture temporal dependencies critical for detecting structural changes over time. The model is trained and evaluated using benchmark SHM datasets under both healthy and damaged states. Moreover, supervised learning is utilized for accurate damage severity classification, while unsupervised learning are used to facilitate anomalies detection without relying on labeled samples. Experimental results demonstrate improved performance in classifying damage conditions compared to conventional machine learning approaches. This framework offers a robust and scalable solution for data-driven SHM, supporting more accurate diagnostics and paving the way for predictive maintenance in complex monitoring environments.

KEY WORDS: SHM; Deep Learning; Damage Detection; Wavelet; Hybrid AI Models.

1 INTRODUCTION

Structural Health Monitoring (SHM) has become an essential field across civil, mechanical, and aerospace engineering, ensuring the functionality, longevity, and safety of critical infrastructure. SHM enables periodic or continuous assessment of structural performance and supports the early detection of system degradation. This allows for timely maintenance interventions and reduces the risk of unexpected failures. As infrastructure systems age and endure increasing stress from environmental and operational loads, effective SHM plays a crucial role not only in ensuring safety but also in optimizing life-cycle costs and extending service life.

Over the past few decades, SHM has evolved significantly, with numerous techniques developed to detect and assess damage and degradation in critical infrastructure. Conventional SHM approaches frequently rely on manual feature extraction, threshold-based anomaly detection, and classical signal processing techniques such as the Fast Fourier Transform (FFT) and Principal Component Analysis to extract frequency-domain features and reduce data dimensionality [1]. While these methods have demonstrated effectiveness in controlled environments or specific applications, they often struggle in real-world conditions where non-stationary signals, sensor noise, and data loss are prevalent. Moreover, they are often inadequate for capturing the complexity of real-world structures, particularly those exhibiting nonlinear and time-varying behavior. The reliance on expert-defined thresholds and manual feature selection further limits their scalability and suitability for automated or large-scale SHM deployment. These limitations underscore the need for more adaptive, intelligent, and data-driven SHM methodologies capable of handling the dynamic behavior of structural systems.

To address these limitations, classical machine learning (ML) methods such as Decision Trees, k-Nearest Neighbors (k-NN), and Support Vector Machines (SVM) have been progressively applied to SHM tasks such as damage detection and anomaly classification [2]. These models offer greater adaptability than rule-based techniques and have shown effectiveness in certain SHM scenarios. However, they largely depend on handcrafted or engineered features, which may fail to capture the full complexity of structural responses. Also, classical ML algorithms often struggle with noisy, sequential data, or high-dimensional, limiting their scalability and generalizability in complex monitoring environments.

In response to the limitations of classical machine learning approaches, deep learning techniques have gained significant attention in SHM due to their ability to automatically learn hierarchical and abstract representations from raw sensor data. Models such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and their variants have shown promising results in tasks such as damage localization, classification, and prognostics. Unlike traditional methods, deep learning (DL) models can effectively capture nonlinear, time-dependent patterns in complex vibration signals without the need for manual feature engineering. Their robustness to noise, scalability to large datasets, and suitability for end-to-end learning make them especially well-suited for real-world SHM system operating under dynamic and uncertain conditions.

More recently, DL models, mainly CNNs and Long Short-Term Memory (LSTM) networks have demonstrated notable

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success in processing spatial and temporal data for SHM applications. CNNs are well-suited for extracting spatial features from raw sensor data or transformed representations such as spectrograms [3], while LSTMs effectively model long-term dependencies in time-series signals [4]. Several studies have also proposed hybrid CNN–LSTM frameworks that jointly capture spatial and temporal patterns, resulting in improved damage detection accuracy, especially in complex structural systems [5].

Despite these advancements, significant challenges remain in applying AI to SHM, including the presence of noise, missing data, and the continued need for domain-specific feature engineering. Furthermore, many existing AI-based SHM approaches tend to overlook the advantages of time–frequency domain analysis an essential component for capturing complex, transient structural responses [6]. To address this gap, wavelet transforms have garnered significant attention in SHM due to their ability to localize features simultaneously in both the time and frequency domains. Unlike the FFT, which provides only a global view of frequency content, wavelet analysis enables the detection of localized, transient events such as those caused by impact damage or cracking [7]. The Discrete Wavelet Transform (DWT) has been widely used for feature extraction, denoising, and time–frequency characterization in structural vibration signals.

However, wavelet-based methods typically require the manual selection of proper mother wavelet and decomposition level, and often depend on thresholding heuristics. Also, wavelets are often used only as preprocessing tools, rather than being fully integrated into modern AI systems [8]. These limitations constrain their effectiveness in contemporary deep learning–based SHM frameworks. Although progress has been made, a clear gap remains in the integration of wavelet-based signal processing with advanced AI architectures. Existing approaches often either apply wavelets solely for noise reduction without enabling feature learning, or use DL models without exploiting the time–frequency structure inherent in SHM signals [9], [10].

To bridge these gaps, this study proposes a novel deep learning framework that seamlessly integrates the DWT with a hybrid CNN–LSTM architecture. The DWT is employed to extract multiscale time–frequency features from segmented acceleration signals, capturing both transient and stationary structural behaviors. These wavelet-derived features are then processed by a CNN to learn spatial patterns, followed by an LSTM network that models temporal dependencies across time steps. The framework supports both supervised damage classification and unsupervised anomaly detection, making it adaptable to a wide range of SHM scenarios and contributing to the advancement of intelligent, data-driven infrastructure monitoring.

2 PROPOSED FRAMEWORK

This section describes proposed SHM, which integrates wavelet-based signal processing with a hybrid deep learning combining CNN and LSTM networks as shown in Figure 1. The framework is designed to extract meaningful spatial and temporal features from structural vibration signals to enable reliable damage detection and anomaly identification under complex monitoring scenarios.

The process begins with long-duration signals, which are preprocessed and segmented into fixed-length time windows to standardize the input size and ensure consistency. Each segment is then processed using the DWT, which decomposes the signal into multiscale time–frequency components. These wavelet coefficients capture both localized and global signal characteristics and serve as rich input features for the deep learning model.

The CNN component s used to extract spatial features from the wavelet coefficients, while the LSTM network captures temporal dependencies across time window. This combination allows the system to recognize both long-term structural trends and transient events, improving its effectiveness in both damage classification and anomaly detection tasks. Both learning strategies are supported within the framework: supervised learning uses labeled damage states, while unsupervised learning applies autoencoders and clustering on latent features.

This integrated architecture leverages the strengths of both wavelet-based signal processing and DL: it enables automated feature learning from rich time–frequency data, enhances robustness to noise and nonstationary, and improves classification and anomaly detection performance across a variety of structural conditions. The following sections detail the data preprocessing, wavelet-based signal decomposition, and the architecture and training process of the DL model.

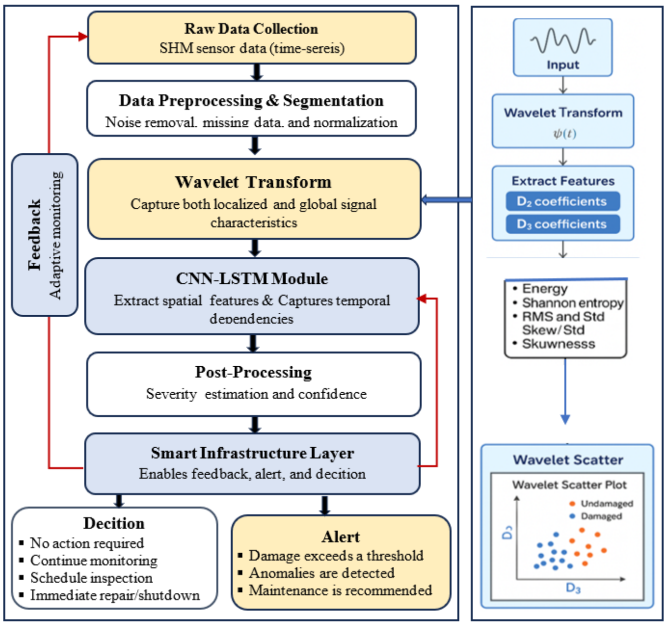

Figure 1. Hybrid methodology combining wavelet-based signal processing with deep learning.

3 EXPERIMENTAL VALIDATION USING TIANJIN YONGHE BRIDGE MONITORING DATA

The proposed framework was validated using data from the Tianjin Yonghe Bridge, a cable-stayed structure located in China connecting Tianjin and Hangu. The bridge spans 510 m, consisting of a 260 m main span and two 25.15 + 99.85m side spans. The bridge wide is 11m (9m for vehicles and 2x1m for pedestrians [21]. Originally constructed in 1983 and opened to traffic in 1987, the bridge began exhibiting structural degradation after nearly two decades of service, including the development of 2 cm cracks in the midspan and signs of

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corrosion in the stay cables. To address these issues, major repairs were carried out between 2005 and 2007, including full replacement of all stay cables and reinforcement of the midspan girder [16], [17]. Following these repairs, a SHM system was installed by the Harbin Institute of Technology to monitor the bridge's condition under both undamaged (January 17, 2008) and damaged (e.g., July 31, 2008) states. The system included over 150 sensors at critical structural components such as the deck, towers, and cables including 14 single - axis accelerometers installed along the deck and a dual-axis sensor mounted at the top of the south tower.

The vibration data collected by this SHM system were used to evaluate the effectiveness of the proposed wavelet-based CNN–LSTM framework for damage detection and anomaly identification. The signals were segmented and preprocessed to ensure consistency, then processed using discrete wavelet transform before being fed into the hybrid deep learning model. This case study demonstrates the applicability of the proposed method to complex, real-world SHM scenarios and confirms its potential for robust damage classification and condition assessment.

Figure 2. General view of Tianjin Yonghe bridge

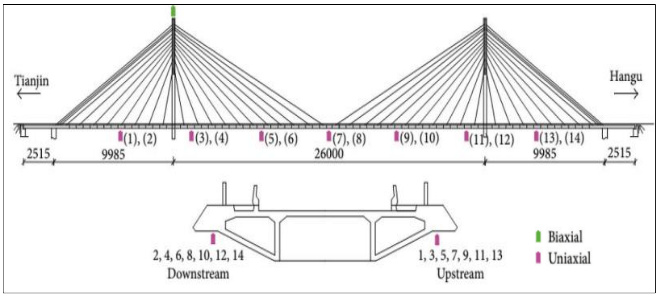

Figure 3. Tianjin Yonghe bridge elevation and health monitoring system

3.1 *Visualization of structural acceleration data*

To illustrate the structural vibration data characteristics, Figure 4 shows time-domain acceleration signals recorded from the bridge deck over a duration about 3600 s for healthy and damaged conditions state. These signals reflect the structure dynamic response under operational conditions. As shown, there is transient spikes, variations in amplitude and frequency content indicate changes in structural behavior, making them suited for SHM applications. Also, the acceleration data show nonstationary behavior that motivate the use of advanced time–frequency analysis. In this study, long-duration acceleration signals were segmented into fixed-length windows (15 minutes) to standardize input size and increase the number of training samples. Figure 5 shows segmentation of a 1-hour acceleration signal into four 15-minute windows. Each segment is color-coded and vertically offset for clarity. This approach facilitates data preparation for time-series learning models and ensures consistency across training samples [4]–[6]. Also, these visualizations help highlight differences in dynamic response and support the need for data-driven SHM approaches.

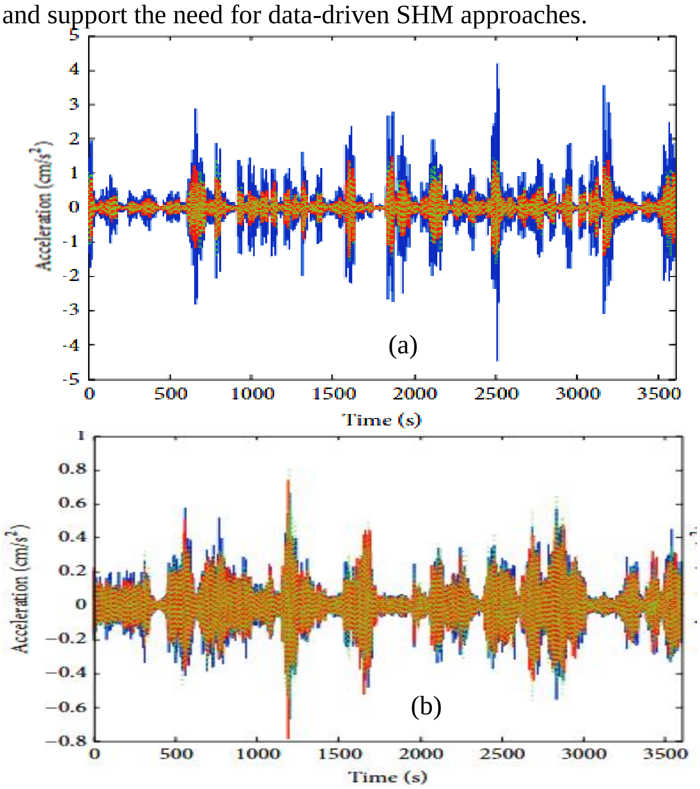

Figure 4. Acceleration signals for Sensor 1 (a) and Sensor 2 (b), showing healthy (bottom) and damaged (top) states.

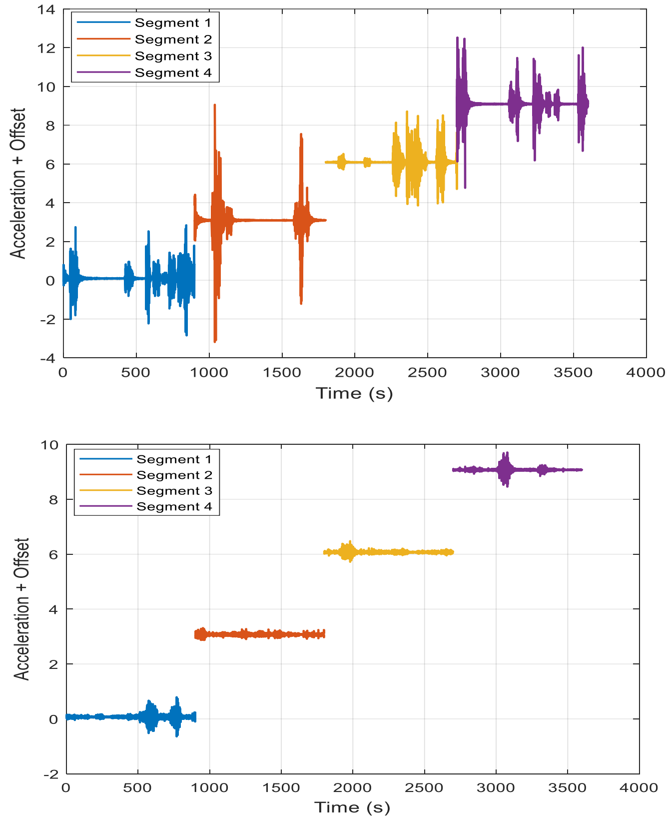

Figure 5. Segmentation of a 1-hour acceleration signals into four 15-minute windows

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4 SIGNAL DECOMPOSITION USING DISCRETE WAVELET TRANSFORM

To capture both time and frequency characteristics of structural vibration signals, the DWT was employed for signal decomposition. Unlike the FFT, which provides only global frequency information, DWT enables multiresolution analysis by breaking the signal into approximation and detail coefficients across multiple levels. This allows transient events and localized structural responses often indicative of damage to be effectively identified. In this study, each acceleration signal segment was decomposed using an appropriate mother wavelet and a predefined number of levels, facilitating the extraction of discriminative time–frequency features suitable for both supervised and unsupervised learning models. Based on our previous studies [11], [12], the db3 wavelet was selected as due to its effectiveness in capturing signal characteristics relevant to structural changes and level 4 was chosen as optimal level for further analysis based on optimal energy and classification performance observed in all extracted features Figure 5.

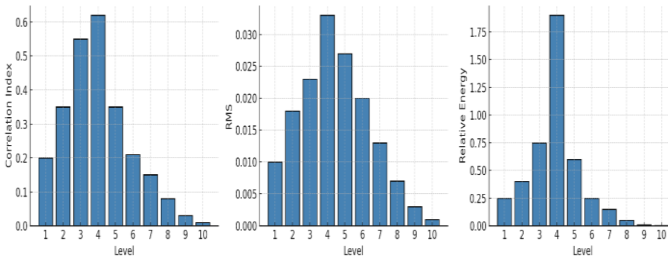

Figure 6. correlation index, root mean square and relative energy versus decomposition level

The signal is decomposed up to level 4, resulting in one approximation signal (A4) and four detail signals (D1–D4). In wavelet analysis, signal decomposition is carried out by projecting the signal onto subspaces of scaling and wavelets basis functions at different scales and their transmission. Figure 7 shows multi-level wavelet decomposition process of the signal. The original signal is recursively decomposed into approximation and detail components. Each approximation captures low-frequency trends (global behavior and long-term structure), while the corresponding detail captures high-frequency information related to transient events or damage. After 4 levels, the final detail and approximation components are used for damage detection and anomaly identification.

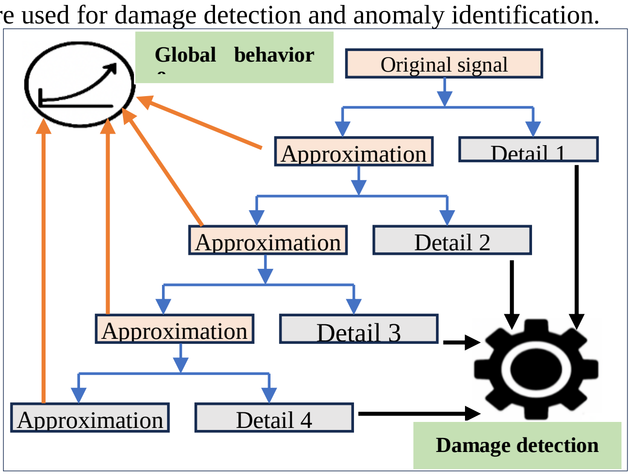

Figure 7. multi-level wavelet decomposition process of the signal.

Figure 8 illustrates the four-level wavelet decomposition of the second 15-minute segment of the acceleration signal using the db3 wavelet. The signal is decomposed into detail coefficients (CD1–CD4) capturing high- to low-frequency components, and an approximation (CA4) representing the global, low-frequency trend. This multilevel decomposition enables the extraction of both transient and long-term structural behaviors, supporting more effective damage detection and anomaly identification in SHM applications.

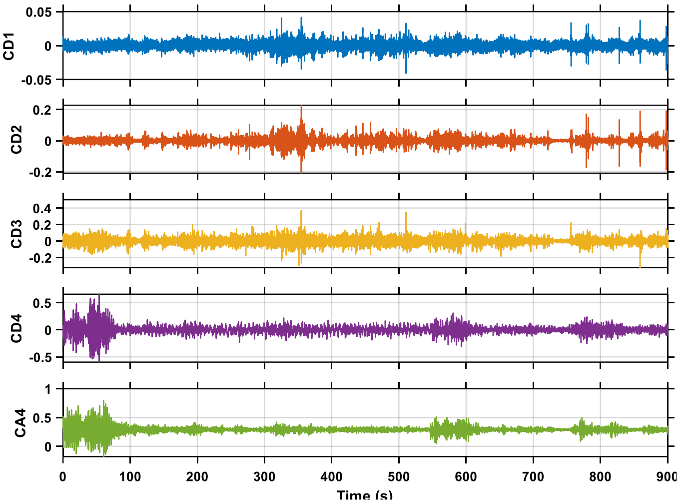

Figure 8. Multi-Level Discrete Wavelet Coefficients of the Acceleration Signal (db3, 4 Levels)

4.1 Features extraction

Feature extraction is a vital step in data-driven structural health monitoring (SHM), converting raw acceleration signals into meaningful representations that support effective damage detection and classification. In this study, wavelet-based time–frequency decomposition is applied to one signal segment, and from each of the four detail sub-bands (D1 to D4), seven statistical features are computed: mean, standard deviation, root mean square, energy, skewness, kurtosis, and Shannon entropy. This results in 28 features for that segment, as summarized in Table 1. While additional segments and features were extracted in the full analysis from detail and approximation coefficients, only this representative example is presented here due to space constraints. These features serve as inputs to deep learning models, enabling them to learn complex structural dynamics and behavioral patterns.

Table 1. Extracted Wavelet-Based Statistical Features

Level	Sub band	Mean	Std. Dev	RMS	Energy	Skewness	Kurtosis	Entropy
Level 1	D1	D1_F1	D1_F2	D1_F3	D1_F4	D1_F5	D1_F6	D1_F7
Level 2	D2	D2_F1	D2_F2	D2_F3	D2_F4	D2_F5	D2_F6	D2_F7
Level 3	D3	D3_F1	D3_F2	D3_F3	D3_F4	D3_F5	D3_F6	D3_F7
Level 4	D4	D4_F1	D4_F2	D4_F3	D4_F4	D4_F5	D4_F6	D4_F7

To improve model interpretability and efficiency, feature importance analysis is carried out to select the most informative variables, allowing the AI model to concentrate on features with the highest predictive value. Figure 9 shows feature importance ranking showing the relative effect of each input variable on the model's prediction. Features with higher importance values contribute more to decision-making, highlighting the most critical parameters for accurate structural condition assessment.

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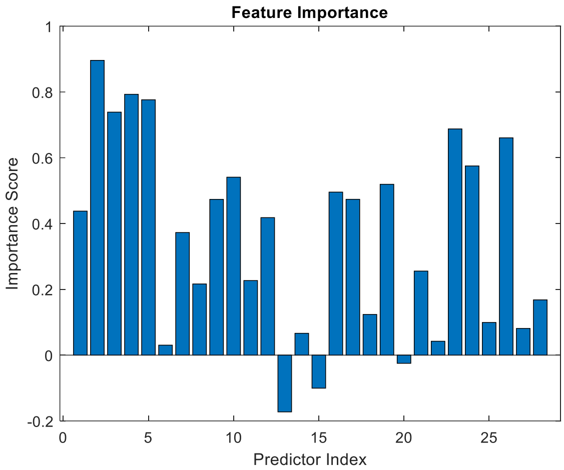

Figure 9. Feature importance ranking illustrating the relative influence of each input variable

5 NEURAL NETWORKS MODEL

Neural networks have widely used in SHM due to their ability to model complex data patterns. Deep architectures like CNNs and LSTMs are mainly effective for capturing spatial and temporal features. A CNN usually includes convolutional layers, pooling operations, and one or more fully connected layers. These components collaboratively extract and refine informative features from input data. The fully connected layers serve as the classifier based on the learned features. Through a sequence of operations, the CNN can reduce the dimensionality, which improves computational efficiency and support more effective model training [15]. LSTM is a variant of recurrent neural networks designed to learn long-term dependencies in sequential data. Its internal structure includes memory cells and gating mechanisms, exactly the input, forget, and output gates, which control the info flow through time. This architecture allows the LSTM to retain relevant time-based features and discard irrelevant ones, making it effective in time-dependent tasks [16]. Combining these models offers improved performance in analyzing dynamic, time-varying signals. This hybrid model is well-suited for SHM tasks, as it can capture both spatial features, such as vibration signatures, and temporal patterns, such as degradation over time both of which are critical for accurate classification and anomaly detection. A detailed summary of the proposed hybrid CNN-LSTM configuration is given in Table 2. Further architectural specifications and theoretical background can be found in [12].

Table 2. A detailed summary of the proposed hybrid CNN-LSTM configuration

Layer	Input Shape	Output Shape	Kernel Number	Kernel Size	Activation
Convolution 1-D	(500, 1)	(496, 32)	32	5	ReLU
Max Pooling 1-D	(496, 32)	(248, 32)	—	2	—
Convolution 1-D	(248, 32)	(244, 64)	64	5	ReLU
Max Pooling 1-D	(244, 64)	(122, 64)	—	2	—
LSTM	(122, 64)	(122, 64)	—	—	tanh
Dropout	(122, 64)	(122, 64)	—	—	—
Flatten	(122, 64)	-7808	—	—	—
Dense	-7808	-512	—	—	ReLU
Dense	-512	-5	—	—	Softmax

6 RESULTS AND DISCUSSION

All experiments were executed in MATLAB R2023a using built-in toolboxes for signal processing and deep learning. Signal processing tasks and wavelet analysis, were done using DWT with db3. Features were extracted from detail components obtained through decomposition, up to level 4. For supervised classification tasks, SVM, Random Forest, CNN, LSTM, and CNN-LSTM hybrids models were trained with appropriate layer configurations. A max of 100 epochs was used with early stopping if validation performance stagnated for 10 epochs. The Adam optimizer with a learning rate of 0.001, cross-entropy loss, mini-batch size of 64, and dropout (rate = 0.3**)** were used to ensure convergence and prevent overfitting. For unsupervised anomaly detection, autoencoders were trained using wavelet-based features extracted from database. MSE between reconstructed and raw signals was used as the reconstruction loss. Thresholds were determined from the 95th percentile of reconstruction error on training data. To assess performance, multiple evaluation metrics were used, accuracy, precision, recall, F1-score, and area under the ROC curve. Visual diagnostics such as ROC curves were generated for comprehensive interpretation. Model strength was validated using 5-fold cross-validation with stratified sampling to preserve balanced class distributions across damage states. The proposed WCNN-LSTM framework outdid existing SHM methods across many assessment metrics. The CNN-LSTM without wavelet achieved 86–accuracy, and wavelet-based models exceeded 89 accuracies, with notably higher F1-scores and. The WCNN-LSTM hybrid further contributed by capturing both spatial and temporal features, leading to better generalization across damage types and environmental conditions. As shown in Table 3, model assessment using metrics such as accuracy, precision, and recall confirms that the proposed framework's robustness.

Table 3. Model assessment using metrics such as accuracy, precision, and recall

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
SVM (RBF kernel)	78.2	75.5	74.8	75.1
Random Forest	80.6	78.1	76.5	77.3
CNN Only	83.7	82	81.3	81.6
LSTM Only	84.1	82.5	82	82.2
CNN-LSTM Hybrid	86.4	85.1	84.2	84.6
Proposed Wavelet-CNN-LSTM	**89.2**	**88**	**87.4**	**87.7**

For unsupervised anomaly detection, autoencoders were trained using wavelet-based features extracted from database. To evaluate classification performance across five classes, we compared per-class ROC curves for the baseline CNN and the enhanced WCNN model. The comparison of ROC curves in Figure 10 highlights that the Wavelet-Combined CNN (WCNN) model offers more balanced and robust performance across all damage classes compared to the conventional CNN. While the CNN model achieves higher AUC values in some individual classes (e.g., Class 4), it performs poorly in others (e.g., Class 0). In contrast, the WCNN demonstrates more consistent AUC scores across all classes, indicating improved generalization and reliability for multi-class damage detection. This suggests that integrating wavelet-based time–frequency features enhance the model’s ability to capture both transient

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and global signal characteristics, leading to superior classification performance in structural health monitoring applications.

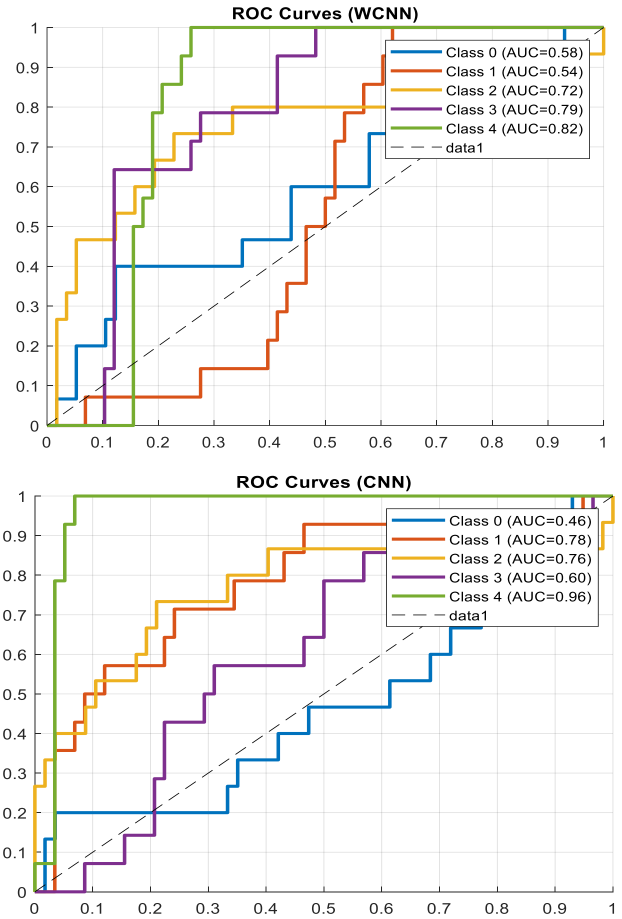

Figure 10. ROC curves for both CNN and WCNN models

Figure 11 shows the progression of training and validation accuracy over 100 epochs. While both curves show consistent improvement and reach above 93%, a slight performance gap remains, particularly toward the final epochs. The training accuracy marginally exceeds the validation accuracy, suggesting that some degree of overfitting may still be present. Also, the flattening of both curves indicates that the model has reached a learning plateau, beyond which additional training yields diminishing gains. This suggests that while the current architecture is effective, there is still room for enhancement, particularly in improving generalization, increasing robustness across classes, or reducing confusion between structurally similar samples. Future improvements could include techniques such as attention mechanisms, hybrid feature fusion, or advanced assembling strategies to push performance beyond the current ceiling.

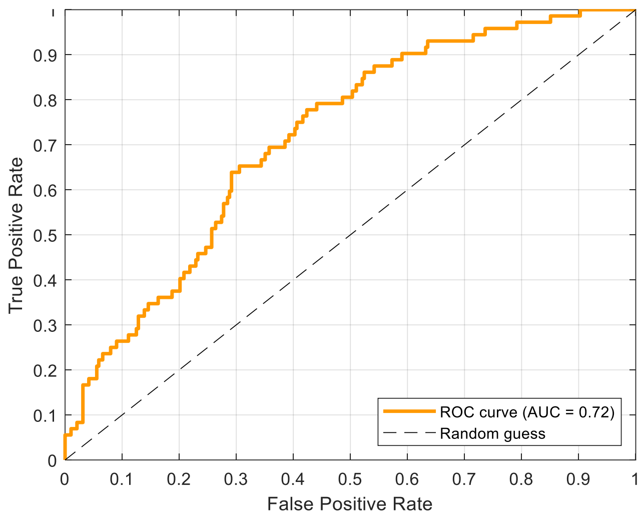

Figure 11. Receiver Operating Characteristic in Class 1 vs. Rest AUC = 0

Figure 12 shows the reconstruction errors distribution for normal and anomalous data. Normal samples exhibit low reconstruction errors, predominantly below the threshold of 0.03, indicating accurate reconstruction by the model. In contrast, irregular samples show higher reconstruction errors, with important portion exceeding the threshold. This separation reveals the effectiveness of reconstruction error as a discriminative feature for anomaly detection, with the threshold serving as a decision boundary between damaged and healthy states. The results confirms that error of reconstruction effectively separates anomalous and normal states, supporting its use as a reliable indicator for anomaly detection in SHM.

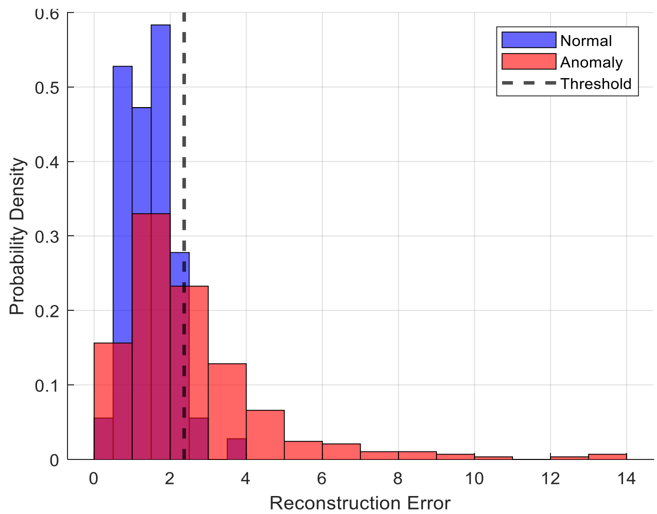

Figure 12. Wavelet-Autoencoder Reconstruction Error Distribution

7 CONCLUSION AND FUTURE WORK

This paper presented a wavelet-based deep learning framework for structural health monitoring (SHM) using benchmark data. By combining Discrete Wavelet Transform (DWT) for time–frequency feature extraction with a hybrid CNN–LSTM architecture, the method aimed to address some of the limitations in conventional SHM approaches, particularly under noisy and complex signal conditions. Experimental results showed that the proposed approach offered

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improvements over baseline ML and standard DL models in terms of classification performance, including accuracy and AUC. The framework supported both supervised and unsupervised learning modes, making it adaptable to different data labeling scenarios.

Nevertheless, further research is needed to improve the framework's performance and adaptability under more diverse operational conditions, larger datasets, and real-time deployment constraints. Future work may focus on optimizing the model architecture, exploring additional feature representations, and validating performance under real-world deployment scenarios.

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