

Evaluating the Integrity of Marine Composite Panels Using LSTM Networks

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ABSTRACT

Structural health monitoring (SHM) is critical for ensuring the integrity and safety of composite structures subjected to dynamic loading conditions. Traditional damage detection methods are often limited in real-time applications, necessitating advanced data-driven approaches. This study investigates the use of Long Short-Term Memory (LSTM) networks for damage detection in composite panels under varying boundary conditions (fixed and pinned) and applied weights to assess their impact on vibrational characteristics. Time-series vibration data, including velocity, acceleration, and displacement, were collected under controlled conditions using a shaker-induced excitation. The LSTM model was trained to classify panels as intact or damaged, leveraging its ability to capture long-term dependencies in sequential data. The results show that the LSTM model effectively distinguishes between damaged and undamaged states, achieving high classification accuracy while adapting to variations in loading and boundary constraints. The model performed better under fixed boundary conditions, suggesting that structural stiffness enhances classification effectiveness by producing clearer vibrational patterns. To further evaluate performance, Precision-Recall curves and confusion matrices were analyzed, demonstrating the model's ability to balance false positives and false negatives. Additionally, a robustness analysis was conducted by introducing Gaussian noise (0.1, 0.2, and 0.3) into the dataset, confirming that the model maintains stable accuracy despite increasing noise levels, making it reliable for real-world applications. These findings highlight the potential of LSTM-based SHM systems for real-time damage detection in composite structures, with promising applications in aerospace, marine, and civil engineering.

1. Introduction

Composite materials particularly fiber-reinforced polymers (FRP) have gained significant traction in marine engineering due to their superior strength-to-weight ratio, resistance to corrosion and overall durability in harsh marine environments. These materials offer an ideal solution for applications in coastal and offshore structures. Composite panels are increasingly being used in the construction of offshore platforms, ships, boats and coastal infrastructures like piers, jetties and seawalls due to their lightweight nature and resistance to the aggressive effects of seawater [1,2]. Unlike traditional materials such as steel or concrete which are vulnerable to corrosion

from saltwater exposure, composite materials can maintain their structural integrity for longer periods without requiring frequent maintenance or costly repairs [3]. In offshore platforms where weight reduction is critical to optimize stability and reduce operational costs composite panels provide an excellent alternative to conventional construction materials by significantly lowering weight without compromising strength or safety [4]. Additionally, these materials exhibit high resistance to impact, fatigue and environmental degradation making them well-suited for the dynamic and often extreme conditions present in marine environments [5]. Furthermore, composite panels are integral to the development of sustainable

marine structures such as floating platforms for aquaculture and renewable energy generation [6]. As marine industries continue to push for more resilient, sustainable and efficient structures the role of composite panels in reducing costs, enhancing performance and extending the service life of marine infrastructures will only become more crucial [7]. However, composites pose unique challenges in SHM due to their heterogeneous nature, complex internal structures and susceptibility to damage modes like delamination, matrix cracking and fiber breakage [8]. Structural Health Monitoring (SHM) refers to the use of integrated systems for the continuous or periodic assessment of a structure's condition aiming to detect damage or degradation over time [9]. In engineering applications, SHM plays a critical role in ensuring the safety, reliability and longevity of structures. Traditionally, SHM has relied on visual inspections and periodic maintenance but these methods are often insufficient for detecting hidden or early-stage damages [10]. The advent of advanced sensing technologies and data-driven approaches such as machine learning and artificial intelligence, has revolutionized SHM by enabling real-time, automated damage detection and prognosis [11]. Among the most promising materials in modern engineering are composite materials. In particular, damage in composites is often difficult to detect with traditional methods making the integration of advanced monitoring techniques imperative [12]. Recent advances in data-driven methodologies such as the use of machine learning and artificial intelligence-based methods, have shown potential for capturing subtle patterns in time-series data generated from dynamic and static loading conditions [13]. These techniques offer a promising pathway to more effective and precise damage detection in composite materials, enabling earlier interventions and improving the overall safety and cost-effectiveness of engineered systems [14]. Damage detection in composite panels poses a significant challenge due to the inherent complexity of these materials [15]. the traditional methods of damage detection can be expensive, time-consuming and require significant manual intervention which limits their effectiveness for large-scale monitoring or real-time assessments [16]. A significant limitation of current damage detection methods is their inability to provide continuous monitoring [17]. For example, non-destructive testing (NDT) methods such as ultrasonic or X-ray imaging are typically performed at discrete intervals and require the structure to be taken offline, making them impractical for continuous or real-time health monitoring [18]. Additionally, these methods often struggle to detect early-stage damage or to assess the damage severity accurately [19]. For instance, minor damages or matrix cracks may be missed in the early stages leading to undetected deterioration that compromises the structural integrity

over time [20]. The dynamic nature of composite materials also complicates damage detection further. Under varying loading conditions such as vibrations or impacts, composites exhibit nonlinear and complex behavior making it challenging to distinguish between normal operational variations and damage-induced changes [21]. These challenges underscore the need for more advanced, automated and real-time methods of damage detection that can monitor the health of composite structures continuously, identify damage at its earliest stages and accurately assess its impact on performance [22]. With the rise of machine learning and deep learning techniques, the possibility of addressing these challenges has become more feasible by enabling the analysis of time-series data from dynamic and static loading conditions, offering the potential for more effective and reliable monitoring of composite materials. The integration of such technologies represents a significant advancement over traditional methods, paving the way for smarter, more efficient SHM systems. Dhiraj et al. discussed the integration of machine learning (ML) for the detection, localization, and quantification of damage in structural materials to help extend the service life of structures. They utilized a supervised learning model that analyzes sensor data, such as vibration signals, to identify and assess damage in materials, particularly composite structures. Their results demonstrated that the ML model was able to effectively detect and localize damage, offering a more automated and efficient alternative to traditional manual inspection methods. However, the authors noted that further optimization of the algorithms is required, and more complex structures need to be tested before the model can be fully integrated into real-world structural health monitoring (SHM) systems [23]. Azad and Kim proposed a multichannel wavelet-enhanced deep learning model for noise-robust damage detection in laminated composites. The model combines wavelet transforms to extract features from vibration signals and uses deep learning techniques to accurately identify damage in the composite material despite the presence of noise. The approach was applied to laminated composite structures, where traditional methods often struggle with noisy environments. The results showed that the model significantly outperformed conventional damage detection techniques by providing more accurate and reliable damage detection, even in noisy conditions. For future work, the authors suggested the need for further testing on larger-scale structures and improving the model's generalization ability to various types of composite materials, to ensure its broad applicability in real-world structural health monitoring scenarios [24]. Zhang et al. introduced a multilevel LSTM model for detecting ultrasonic lamination defects in carbon fiber composite plates. The model uses ultrasonic wave signals to identify defects at different layers of the composite material, utilizing a

multilevel LSTM architecture to capture complex temporal dependencies and detect subtle damage features. Their approach demonstrated high accuracy in detecting defects in carbon fiber composites, even in the presence of noise and varying material properties. The results indicated that the multilevel LSTM model provided superior performance compared to traditional methods, offering better sensitivity and reliability in identifying lamination defects. For future work, the authors suggested that the model could be further optimized for real-time damage monitoring and extended to other types of composite materials, aiming for broader applicability in structural health monitoring systems [25]. Tian et al. developed a two-stage residual network model for damage identification and location in stiffened composite panels using guided waves. The model employs a two-stage process: the first stage uses guided wave signals to capture the features indicative of damage, and the second stage utilizes a residual network to enhance the model's ability to detect and locate damage with high precision. Their approach was tested on stiffened composite panels, where traditional methods often struggle with complex geometries and variable damage patterns. The results showed that the two-stage residual network effectively identified and located damage in the composite panels, offering improved accuracy over conventional damage detection techniques. For future work, the authors suggested extending the model to more complex structural configurations and further refining its generalization capability for real-world applications in structural health monitoring [26]. Le-Xuan et al. proposed a novel damage detection model that combines 1D Convolutional Neural Networks (CNN) with LSTM and Residual Networks (ResNet) for analyzing signal data. This hybrid approach is designed to enhance the detection of damage by first using the 1D CNN to extract meaningful features from the signal data, followed by the LSTM to capture temporal dependencies, and finally applying the ResNet to improve the model's robustness and performance. The model was tested on damage detection tasks, demonstrating significant improvements in accuracy and efficiency compared to traditional methods. The results indicated that the combined approach was particularly effective in handling noisy and incomplete data, which is often encountered in real-world damage detection scenarios. The authors proposed further refinement of the model to expand its scalability and adaptability to a broader range of damage detection applications in structural health monitoring systems [27]. Huang et al. developed a CNN-LSTM network-based damage detection approach for copper pipelines using laser ultrasonic scanning. The model combines Convolutional Neural Networks (CNN) to extract spatial features from ultrasonic wave signals, followed by Long Short-Term Memory (LSTM) networks to capture the temporal dynamics of the damage. This

hybrid approach was applied to detect and assess damage in copper pipelines, where traditional methods often struggle with complex signal patterns and noisy data. The results demonstrated that the CNN-LSTM model provided high accuracy in detecting damage, even in the presence of noise, and was more efficient than conventional damage detection techniques. The authors suggested that future work could focus on expanding the model's application to other types of materials and refining its real-time capabilities for broader structural health monitoring [28]. Das and Guchhait proposed a hybrid GRU and LSTM-based deep learning approach for multiclass structural damage identification using dynamic acceleration data. The model integrates Gated Recurrent Units (GRU) and Long Short-Term Memory (LSTM) networks to effectively process the time-series acceleration data, allowing it to identify and classify different types of structural damage. The approach was tested on structural components subjected to dynamic loading, where traditional methods often face challenges in accurately detecting and classifying various damage states. The results showed that the hybrid GRU-LSTM model outperformed conventional methods in terms of classification accuracy and robustness, especially in handling multiple damage scenarios. The authors noted that further work should focus on optimizing the model for real-time damage detection and extending its application to larger, more complex structures in structural health monitoring systems [29]. However, this remains an emerging area of study, and more work is needed to refine these techniques to address the real-world complexities. While LSTM models are designed to process time-series data, the quality of the input data plays a crucial role in the model's performance. In marine environments, where conditions are subject to harsh weather, vibrations, and other external factors, sensor data may be noisy or incomplete, making it difficult for machine learning models to accurately detect damage. Techniques such as data fusion, which combines data from multiple sensor types (e.g., accelerometers and displacement sensors), could enhance model accuracy. Additionally, preprocessing methods, such as noise filtering and feature extraction, are essential to ensure the data fed into the LSTM model accurately reflects the structural health rather than being influenced by extraneous environmental factors. The integration of LSTM-based Structural Health Monitoring (SHM) systems into large-scale marine infrastructures represents the future of damage detection in composite panels. The development of more robust, adaptive, and computationally efficient models could lead to significant advances in real-time monitoring, enabling earlier damage detection and reducing the need for costly repairs and downtime. One notable gap in recent studies is the impact of varying boundary conditions on the vibrational characteristics of composite panels in the marine domain. Most studies

have primarily focused on fixed boundary conditions, which do not capture the full range of behaviors observed in real marine structures, such as those found in offshore platforms or floating vessels. Additionally, these studies have largely concentrated on uniform loading conditions or simple damage modes, overlooking the complexities present in real-world applications. This study addresses this gap by incorporating both pinned and fixed boundary conditions, offering a more accurate reflection of real-world marine applications. The dynamic response of composite panels to weights placed at varying positions under shaker-induced vibrations is a unique and under-explored area, setting our study apart from previous researches. Moreover, while some studies have utilized LSTM networks for damage detection in composite materials, few have considered the combination of dynamic loading with sensor data from multiple sources to monitor the health of composite panels continuously. By integrating data from different sensors and accounting for real-world variations in environmental conditions, the proposed approach not only enhances damage detection accuracy but also lays the foundation for continuous real-time health monitoring systems that could operate effectively on offshore platforms or ships. This combination of loading conditions, boundary condition variations, and real-time monitoring is a novel approach that has not been fully explored in the context of marine composite panels. In this study, a novel nondestructive method is proposed for the damage detection of marine composite panels subjected to dynamic loading conditions. The experimental setup involves both contact and non-contact sensors to capture comprehensive structural responses. These sensors are used for experimental vibration analysis to understand the vibrational characteristics of the composite panels under varying weight placements. Additionally, the sensors gather data for the damage detection procedure, specifically capturing vibrational behavior under dynamic loading. The data collected from these sensors are then processed using an LSTM network, integrated with a sliding window technique for efficient time-series data processing. The damage classification results from the LSTM model are evaluated using key performance metrics such as accuracy, confusion matrices, and loss to assess the model's effectiveness in real-time damage detection. This approach not only enhances damage detection accuracy but also integrates data-driven techniques for structural health monitoring in marine environments. The ultimate goal of this work is to bridge the gap by providing a more comprehensive and real-time damage detection system that addresses the unique challenges of marine engineering.

2. Methodology

2.1. Model description

In this study, to conduct the experimental tests a 10-layer rectangular composite panel is fabricated in the Composite Laboratory of the University of Tabriz. The fabrication of the experimental model of the composite panel was carried out based on guidelines and instructions from the relevant regulations, which are specifically intended for the production of composite structures in marine environments [30]. The final design of the composite panel is illustrated in Figure 1.



Figure 1. Final design of the composite panel

The dimensions of the composite panel are provided in Table 1.

Table 1. Geometric properties of the composite panel considered for the experiment

Panel properties	Numerical values
Length (L_x)	800 [mm]
Width (L_y)	750 [mm]
Thickness (t_h)	2 [mm]

The mechanical properties of the composite panel are determined using the DNV code formulation [30], which allows for the calculation of the elasticity modulus and other key mechanical properties, as presented in Table 2.

Table 2. Characteristics of the materials and the composite panel considered for the experiment

Material	Density [g/cc]	Elasticity modulus [Gpa]	Poisson's ratio	Shear modulus [Gpa]
Glass fiber	2.5	30.1	0.2	30
Resin	1.5	3.5	0.35	2
Composite panel	1.9	25.9	0.36	2.91

The composite panel is subjected to two distinct boundary conditions to simulate different structural support scenarios: fixed and pinned. The fixed boundary condition represents a scenario where the edges of the panel are rigidly constrained, preventing

any displacement or rotation at the boundaries. This condition closely mimics structures where the panel is fully anchored, such as in offshore platforms or coastal infrastructure where stability is crucial under dynamic loading. On the other hand, the pinned boundary condition allows for rotational movement but restrains the translational displacement of the panel at the edges. This setup is used to simulate situations where the panel is supported at specific points such as in certain marine vessel hulls or modular platforms. By evaluating the vibrational responses under both boundary conditions, this study aims to understand how the structural stiffness and vibrational behavior of composite panels are influenced by different support configurations which is critical for assessing the damage detection capabilities of the LSTM model under varying loading conditions.

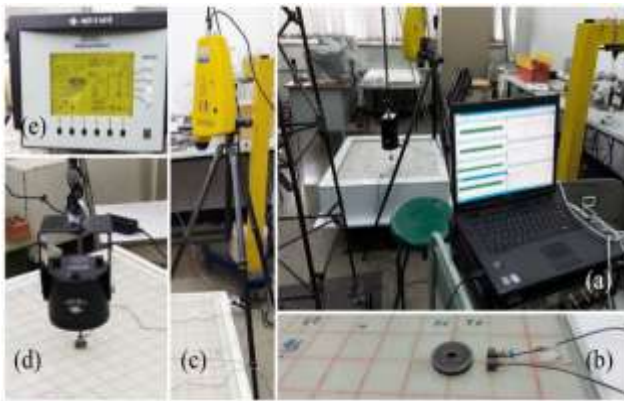


Figure 2. The layout of the vibration test: (a) Overall view of the experimental setup; (b) Attached accelerometers; (c) Laser doppler vibrometer; (d) Attached shaker; (e) Conditioning amplifier

2.2. Experimental Methodology

Vibration analysis is a crucial technique for evaluating the dynamic behavior of structures under various loading conditions. This method involves capturing vibrational responses, such as acceleration, velocity, and displacement, at different locations on the composite panel. In this study, vibration analysis is performed using a combination of contact and non-contact sensors. A Laser Doppler Vibrometer (LVD, VH3000+, Ometron Ltd), which is a non-contact sensing component, measures vibration velocity at multiple points on the panel's surface. Additionally, contact accelerometers (manufactured by Brüel & Kjær Engineering) are used to capture acceleration data. These acceleration signals are processed through a B&K conditioning amplifier, which then calculates the corresponding displacement by integrating the acceleration data. The experimental setup, including sensor placements, is depicted in Figure 2. A shaker is used to apply dynamic loading to simulate realistic vibrational environments. The use of both contact and non-contact sensors provides a comprehensive understanding of the composite panel's vibrational characteristics under varying conditions. For

excitation, a sinusoidal signal with a zero mean is applied under both pinned and fixed boundary conditions. The time histories for acceleration, velocity, and displacement are recorded at several points using both accelerometers and the LDV system. Over 20 sensors are distributed across the panel, capturing more than 40,000 data points each. The composite panel model is meshed and numbered based on the numerical model, allowing for precise identification of sensor locations and excitation points. The excitation force is applied at the center of the panel (Figure 3). Both intact and damaged models are tested under the two boundary conditions. Damage is introduced by adding mass at three locations using 100gr, 200gr, and 500gr weights, as shown in Figure 3.

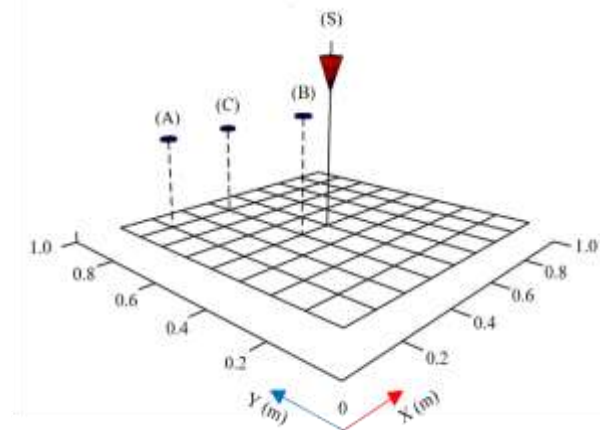


Figure 3. A schematic of the panel including: (A, B, and C) Location of the weights; (S) Shaker position

2.3. Data Preprocessing

The vibration data from a composite panel was preprocessed using the sliding window technique to prepare it for training with an LSTM model. The raw data consists of five columns: Time, Force, Velocity, Displacement, and Acceleration. The first preprocessing step involved converting the raw data into sequences to capture the time-series dynamics. The raw data was divided into sequences of N number of sequences, with each sequence containing T data points. In this study, a window size of 3 time-steps was used for each sequence. This hyperparameter was found to be the best during experimentation, as it effectively captured the history of the time-series dynamics without significantly increasing computational costs. Using the sliding window technique, compared to passing the data as a single column, showed a 3% improvement in accuracy in the experiments. The window slides one step at a time across the data, with overlap between consecutive windows. For each sequence, all features (Time, Force, Velocity, Displacement, and Acceleration) were used to capture temporal relationships and patterns for model training. The sequencing process is illustrated by the following equation:

$$X_{Seq} = [(X_1, X_2 \dots, X_T) + (X_2, X_3 \dots, X_{T+1}), \dots, (X_{N-T+1}, X_{N-T+2} \dots, X_N)] \quad (1)$$

Where X_{Seq} represents the set of sequences, each containing T time-steps, and X_i represents the raw data at the i – th time-step. In this case, $T = 3$, meaning each sequence consists of 3 consecutive time-steps. This ensures that the temporal dynamics are captured effectively within each sequence for model training. After the sliding window transformation, the data was normalized using standard scaling. The standard scaling was performed using the following equation:

$$X_{scaled} = \frac{X - \mu}{\sigma} \quad (2)$$

Where X represents the raw data, μ is the mean of the feature, and σ is the standard deviation. This normalization step improved the accuracy by 2%, as it scaled the features to a common range, making it easier for the model to understand the temporal dynamics during training.

The data was labeled based on damage detection criteria: intact data was labeled as 0 and damaged data was labeled as 1. Damage detection was based on measurements from the Velocity, Displacement, and Acceleration data. The dataset was split into 80% training, 10% validation, and 10% test sets. These splits were performed to ensure an equal distribution across different conditions such as intact vs damaged and pinned vs fixed boundary conditions. This balance ensures that the model is trained on a representative dataset and that the training process is not biased toward a single label or data subset. No additional preprocessing steps, such as handling missing values, resampling, or feature engineering, were performed, as the data was assumed to be clean and appropriately formatted.

2.3. LSTM Model

LSTM model has been widely used in sequence prediction problems, such as sequence classification and sequence-to-sequence prediction, which may differ based on the input and output sequences. LSTM is a type of recurrent neural network (RNN). It has recurrent connections that use the state of neuron activation from the previous time step to determine the output [31]. RNNs are designed for sequence prediction, for example, multi-layer perceptron adding loops. RNNs face the challenge of getting trained effectively owing to vanishing gradient problems. LSTM is designed to overcome this challenge. Moreover, LSTM can learn long-term dependencies better than an RNN [32]. LSTM uses gates that process the information contained in the incoming data sequences. The gates include a forget gate, an input gate and an output gate, each of which can be considered a neural network [33, 34, 35]. The output from an LSTM cell depends on the long-term memory

(referred to as the cell state), output from the previous time step, and data of the input sequence of the current time step. Figure 4, shows a typical example of an LSTM cell.

The forget gate determines which information of the cell state is useful based on the previous hidden state and the current input data. The previous hidden state and the current input data are fed to the forget gate, generating a vector between 0 and 1 using sigmoid activation. A value of 0 indicates that the input component is irrelevant, whereas 1 indicates the input component is relevant. In the following equations, W and W_h are the input and hidden state weights for the forget gate f , input gate i , and output gate o .

$$f_t = \sigma(x_t \times W_f + h_{t-1} \times W_{hf}) \quad (3)$$

Where x_t , h_{t-1} and f_t denote the data at time instant t , the previous hidden state, and the forget gate at t , respectively. σ is the sigmoid activation function. The input and hidden state are multiplied by the weights. The weight matrix remains the same and it does not change from one time step to another. The amount of information sent is based on this value. More information is sent when the value is closer to 1. The output from this part of the forget gate is multiplied pointwise by the previous cell state. The output of pointwise multiplication is given by Eq. (4) or Eq. (5) when f_t is 0 or 1, respectively. When it is 1, all previous cell states are sent.

$$C_{t-1} * f_t = 0 \text{ for } f_t = 0 \quad (4)$$

$$C_{t-1} * f_t = C_{t-1} \text{ for } f_t = 1 \quad (5)$$

Where C_{t-1} denotes the previous cell state. The next stage is the input gate. The input gate uses the current input and the previous hidden states to quantify the amount of new information to be retained along with the previous cell state. The equation for the input gate can be expressed as:

$$i_t = \sigma(x_t \times W_i + h_{t-1} \times W_{hi}) \quad (6)$$

Where i_t is the input gate at time instant t . Using a sigmoid function, the input gate outputs a vector ranging from 0 to 1. The new information is a function of the previous hidden state and current input data. It uses the (tanh) activation function to output the new information ranging from -1 to 1. The new information is determined as:

$$I_N = \tanh(x_t \times W_c + h_{t-1} \times W_{hc}) \quad (7)$$

The new information generated using the input gate can help to reduce the previous-state information in the cell state, if necessary. A negative value using the activation function (tanh) helps to achieve this. However, the necessity of retaining all the new input data is unknown. The output from the input gate is multiplied pointwise by the new input vector to

determine the amount of new input data that can be retained. This output is added to the cell state. The current cell state is given as:

$$C_t = C_{t-1} * f_t + I_N * i_t \quad (8)$$

The output gate is the last gate, which determines the new hidden state. It uses the current input data and previous hidden state, similar to the forget and input gates. The equation for the output gate can be expressed as:

$$o_t = \sigma(x_t \times W_o + h_{t-1} \times W_{ho}) \quad (9)$$

The new hidden state is the output of the pointwise multiplication of the value of the output gate and new cell state. The (tanh) activation function is applied to the current cell state, resulting in a new output ranging from -1 to 1. The new hidden state can be expressed as:

$$h_t = \sigma(x_t \times W_o + h_{t-1} \times W_{ho}) * \tanh(C_t) \quad (10)$$

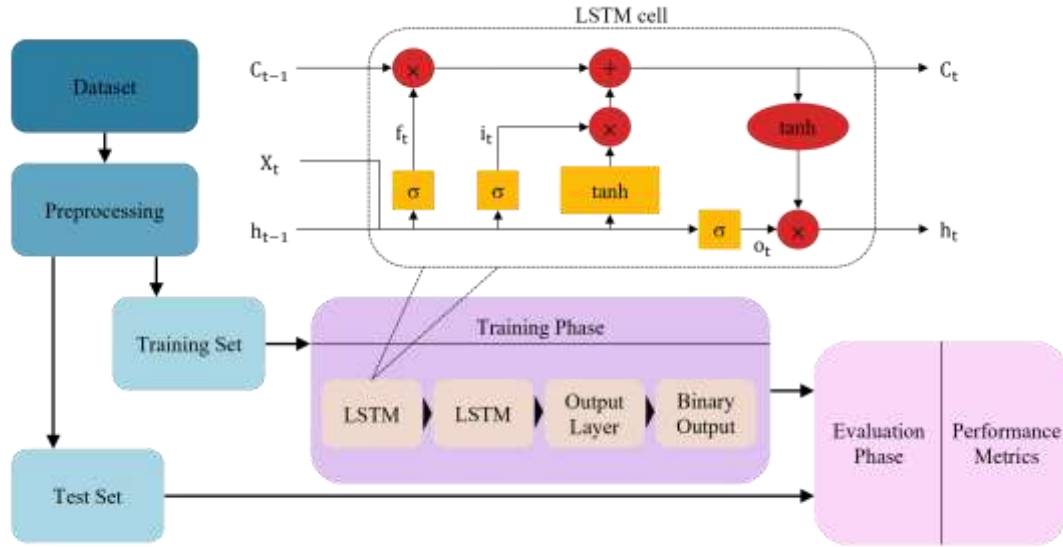


Figure 4. An optimized machine learning pipeline for time-series data using LSTM for damage detection

2.3.1. Architecture Details

The LSTM model used for damage detection in this study consists of an input layer with dimensions (3, 5), where 3 represents the number of time steps and 5 corresponds to the feature dimensions (Force, Velocity, Displacement, and Acceleration). This is followed by a first LSTM layer with 64 neurons, using the default (tanh) activation function and returning sequences for the next layer. The second LSTM layer, also with 64 neurons, processes the sequences to capture more complex temporal patterns. A fully connected dense layer then generates predictions based on the features learned by the LSTM layers, with the final output layer using a sigmoid activation function to produce a binary classification result (intact or damaged). As shown in Figure 4, the optimized machine learning pipeline outlines the process from dataset collection and preprocessing to model training, evaluation, and performance metrics, ensuring a systematic approach to damage detection using the LSTM method.

2.3.2. Training Details

The training process of the LSTM model is designed to ensure efficient learning and convergence, optimizing performance for the binary classification task of detecting structural damage. The model is built to process sequences of 3 time-steps, with 5 features (Time, Force, Velocity, Displacement, and

Acceleration) at each time-step. The ADAM (Adaptive Moment Estimation) optimizer is used to adjust the weights during training due to its efficiency in handling sparse gradients and providing fast convergence. Binary cross-entropy is employed as the loss function, appropriate for this binary classification task (intact vs. damaged). The batch size is set to 64, which is a common choice for time-series data, meaning the model processes 64 samples at a time before updating its weights. The model is trained for 2 epochs to ensure sufficient learning while avoiding overfitting. During the training process, the best model is saved after each epoch based on validation data performance, ensuring the retention of the most accurate model throughout the training. The performance of the model is evaluated using accuracy as the primary metric.

2.3.3. Model Evaluation

The model's performance is evaluated using the following metrics:

1. Precision-Recall Curves: The PR curves are used to assess the model's ability to correctly classify damaged vs intact panels, especially given the potential class imbalance in real-world damage detection tasks.
2. Confusion Matrix: To identify false positives (FP), false negatives (FN), true positives (TP), and true

negatives (TN), and better understanding of the model behavior.

3. Accuracy: Measures the overall correctness of the model (see Eq. 11).

$$\frac{TP + TN}{TP + TN + FP + FN} \quad (11)$$

4. Precision: Measures the accuracy of positive predictions (see Eq. 12).

$$\frac{TP}{TP + FP} \quad (12)$$

5. Recall: Measures the ability to correctly identify positive instances (see Eq. 13).

$$\frac{TP}{TP + FN} \quad (13)$$

6. F1-Score: The harmonic mean of precision and recall (see Eq. 14).

$$2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (14)$$

7. Robustness Analysis.

3. Results and Discussion

3.1. Overall Results

The heatmap shown in Figure 5, provides a visual representation of the classification distribution of the dataset based on different weights (100gr, 200gr, and 500gr) and boundary conditions (Fixed and Pinned). Additionally, the heatmap distinguishes between damaged and intact panel, offering insights into how the model classifies structural conditions under varying load and support configurations.

This heatmap highlights the imbalance present in the dataset, where certain categories are overrepresented while others are underrepresented. The heatmap highlights significant imbalance in the dataset, particularly in the classification of panels under different weight placement and boundary conditions.

100gr	1.83091e+06	1.7111e+06	0
200gr	1.83808e+06	1.75411e+06	0
500gr	1.53907e+06	0	0
Fixed	0	0	614401
Pinned	0	0	983040
	Damaged Fixed	Damaged Pinned	Intact

Figure 5. Heatmap showing the distribution of the damaged and undamaged dataset across different weights and boundary conditions

The overrepresentation of "Damaged" instances, especially under the Fixed boundary condition, poses a challenge for the model to generalize well. Addressing this imbalance will be critical to improving the model's performance and ensuring that it can effectively classify damage under all conditions.

3.2. Both Fixed and Pinned Boundary Conditions

As shown in Figure 6, the Precision-Recall (PR) curve illustrates the performance of the LSTM model in distinguishing between damaged and undamaged states across both fixed and pinned boundary conditions. The curve starts with a high precision (~1.0) at low recall values, indicating that when the model is highly selective, it makes very few false positive predictions. As recall increases, precision gradually decreases, reflecting the trade-off between capturing more true positives while introducing some false positives.

The model maintains high precision above 95% across a large portion of the recall range, demonstrating its effectiveness in correctly classifying damage with minimal false alarms. The gradual decline in precision, rather than an abrupt drop, indicates that the model is well-calibrated and maintains a balanced classification ability. However, at very high recall values (~0.9 - 1.0), precision drops below 85%, suggesting an increase in false positives as the model attempts to capture all instances of damage.

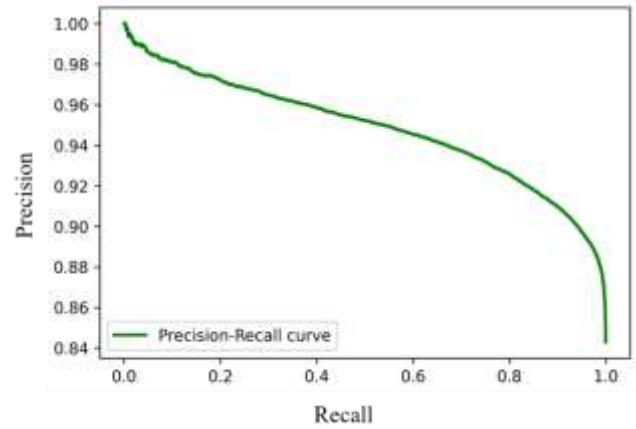


Figure 6. Precision-Recall curve for the LSTM model for both fixed and pinned boundary conditions

The confusion matrix, as shown in Figure 7, represents the overall performance of the LSTM model across both fixed and pinned boundary conditions. It illustrates the distribution of true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN), providing insight into the model's accuracy, precision, recall, and effectiveness in detecting damage under varying structural constraints.

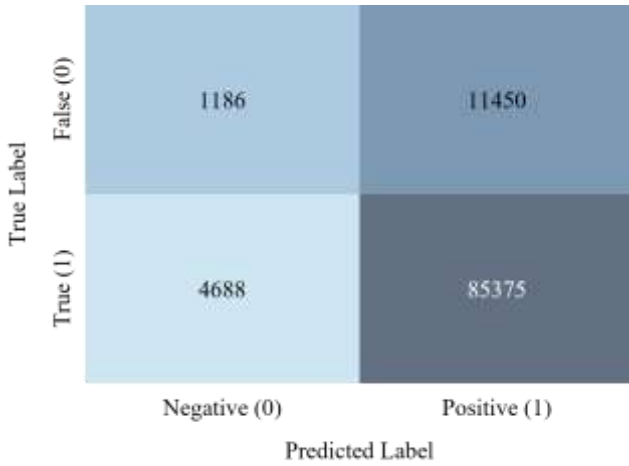


Figure 7. Overall confusion matrix for both fixed and pinned boundary conditions

The overall performance of the LSTM model across both fixed and pinned boundary conditions demonstrates its effectiveness in detecting damage with a high recall of 98.63%, indicating that the model successfully identifies most instances of actual damage. The accuracy of 87.70% reflects the model's overall correctness in classification, while the precision of 88.17% suggests that the majority of predicted damage cases are indeed accurate, minimizing false alarms. Furthermore, the F1-score of 93.11% balances precision and recall, confirming that the model maintains strong predictive power while effectively distinguishing between damaged and undamaged states.

3.2. Pinned Boundary Condition

As shown in Figure 8, the Precision-Recall (PR) curve provides an evaluation of the LSTM model's performance in classifying damaged and undamaged states under pinned boundary condition. The curve maintains a high precision near 1.0 at the beginning when recall is low, indicating that the model effectively identifies damaged cases while keeping false positives minimal in this region. As recall increases, precision gradually declines, reflecting the model's trade-off between identifying more true positives and introducing more false positives. Compared to other PR curves (Figure 6, and Figure 10), this one demonstrates a more extended stability in precision, maintaining values above 95% for most recall values. However, at high recall levels (~0.8 - 1.0), precision begins to decline more steeply, dropping below 85% as recall approaches 1.0. This suggests that while the model captures almost all damaged instances at high recall, it also classifies more undamaged cases incorrectly, leading to an increase in false positives.

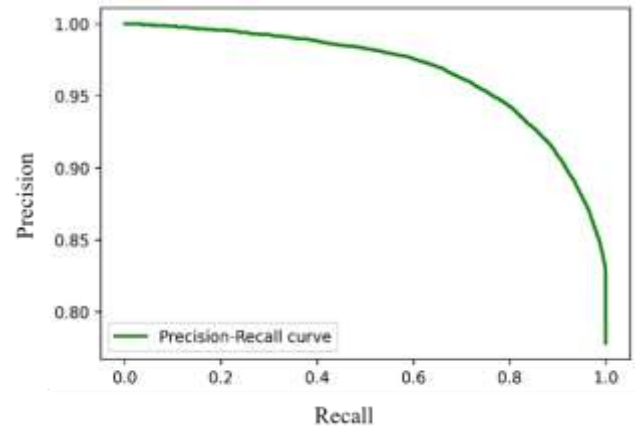


Figure 8. Precision-Recall curve for the LSTM model under the pinned boundary condition

The confusion matrix, as shown in Figure 9, represents the performance of the LSTM model under pinned boundary condition. It illustrates the distribution of true positives, true negatives, false positives, and false negatives, providing insight into the model's accuracy, precision, recall, and effectiveness in detecting damage under varying structural constraints.

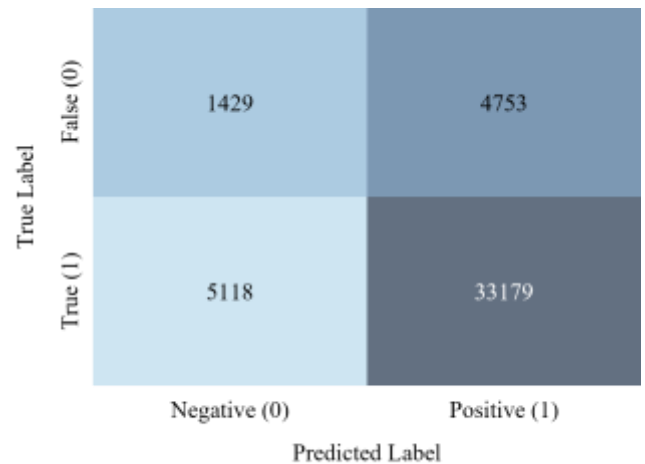


Figure 9. Confusion matrix for pinned boundary condition

The overall performance of the LSTM model under the pinned boundary condition demonstrates strong accuracy and reliability in damage detection. With an accuracy of 86.10%, the model maintains a high level of correct classifications. The recall of 95.87% indicates that the model is highly effective in identifying actual damage cases, minimizing false negatives. Precision, at 87.47%, shows that the majority of predicted damage cases are accurate, reducing the occurrence of false alarms. The F1-score of 91.48% balances precision and recall, highlighting the model's robust performance in distinguishing between damaged and undamaged states. These results confirm the effectiveness of the LSTM model in structural health monitoring under pinned boundary conditions.

3.3. Fixed Boundary Condition

As shown in Figure 10, the Precision-Recall (PR) curve provides insights into the performance of the LSTM model in classifying damaged and undamaged states under fixed boundary condition. The curve starts with

high precision near 1.0 at low recall values, indicating that the model effectively detects damage with minimal false positives when it is highly selective. As recall increases, precision gradually declines, reflecting the trade-off between capturing more true positives while introducing more false positives. Unlike an abrupt drop (see Figure 8), the precision decreases smoothly, maintaining values above 90% for most recall values, demonstrating that the model effectively balances precision and recall across a wide range of thresholds. However, at high recall levels ($\sim 0.9 - 1.0$), precision falls below 90%, indicating an increase in false positive predictions as the model attempts to classify all damaged instances.

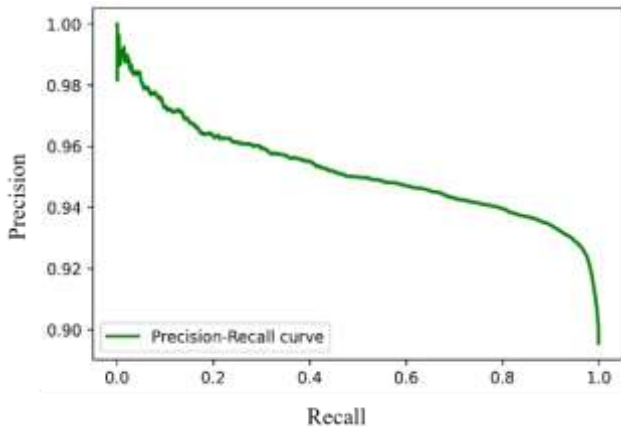


Figure 10. Precision-Recall curve for the LSTM model under the fixed boundary condition

The confusion matrix, as shown in Figure 11, represents the performance of the LSTM model under fixed boundary condition. It illustrates the distribution of true positives, true negatives, false positives, and false negatives, providing insight into the model's accuracy, precision, recall, and effectiveness in detecting damage under varying structural constraints.

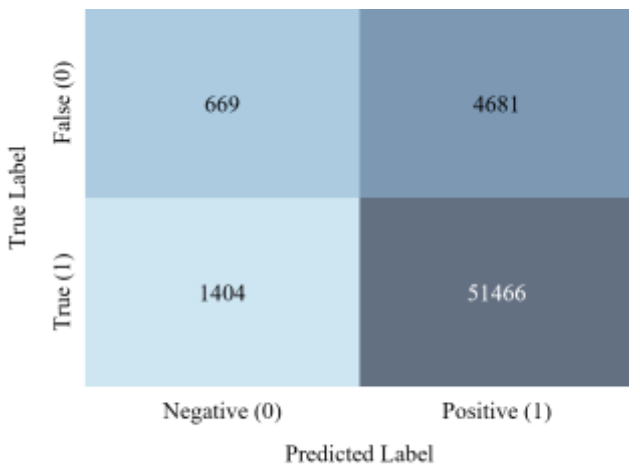


Figure 11. Confusion matrix for fixed boundary condition

The overall performance of the LSTM model under the fixed boundary condition demonstrates impressive results in damage detection. With an accuracy of 90.76%, the model effectively classifies both damaged

and undamaged panels. The recall of 98.66% indicates that the model successfully identifies nearly all actual damage cases, minimizing false negatives. Precision, at 91.66%, shows that most of the predicted damage instances are correct, reducing false alarms. The F1-score of 95.03% reflects a strong balance between precision and recall, highlighting the model's effectiveness in distinguishing between damaged and undamaged panels under fixed boundary conditions.

3.4. Robustness Analysis

In real-world applications, structural health monitoring systems often encounter noisy data due to environmental disturbances, sensor inaccuracies, and external vibrations. To assess the robustness of the LSTM model under such conditions, Gaussian noise was introduced into the dataset at three different levels (0.1, 0.2, and 0.3) to evaluate its impact on validation accuracy over multiple training epochs. This analysis helps determine how well the model generalizes when subjected to increasing noise levels.

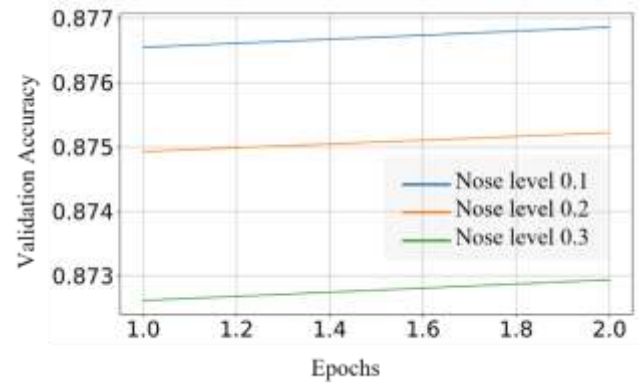


Figure 12: Validation accuracy of the LSTM model across training epochs under different noise levels

Figure 12, presents the validation accuracy trends across training epochs for each noise level. The results indicate that despite the presence of noise, the model maintains a relatively stable validation accuracy, with only minor variations observed between different noise levels. The highest accuracy is achieved under the lowest noise condition, while a slight decline is observed as noise levels increase. However, the overall upward trend suggests that the model continues to learn and adapt even in noisy conditions. These findings highlight the model's robustness to moderate noise, demonstrating its ability to generalize effectively despite minor performance degradation.

4. Conclusions

This study presented a novel approach for damage detection in marine composite panels subjected to dynamic loading conditions using an LSTM-based structural health monitoring (SHM) system. The experimental setup incorporated both fixed and pinned boundary conditions, providing a more comprehensive analysis of how vibrational characteristics vary under different structural constraints. The LSTM model

effectively classified intact and damaged states by analyzing time-series data, demonstrating strong performance in distinguishing damage states across varying weight placements and boundary conditions. The relevance results of the research could be summarized as follows:

- The overall evaluation metrics, including accuracy (87.70%), precision (88.17%), recall (98.63%), and F1-score (93.11%), confirmed the model's high reliability in damage detection, regardless of boundary conditions. However, when analyzing the model's performance separately for fixed and pinned boundary conditions, the results indicate that the model performed better under fixed boundary conditions, achieving higher precision (91.66%) and recall (98.66%), compared to the pinned boundary condition where the precision and recall were slightly lower. This suggests that fixed boundary conditions provide a more stable vibrational response, allowing the LSTM model to make more accurate classifications.
- Precision-Recall curves highlighted the model's ability to balance false positives and false negatives effectively, while the confusion matrices provided insight into classification performance across both boundary conditions.
- The LSTM model demonstrated strong efficiency in handling the imbalanced dataset, achieving high recall for damage detection while slightly compromising precision, indicating a tendency toward false positives.
- A robustness analysis was conducted by introducing Gaussian noise (0.1, 0.2, 0.3) into the dataset, demonstrating that the model maintains a stable validation accuracy despite increasing noise levels.

The findings of this study emphasize the potential applications of LSTM-based SHM systems in marine and offshore engineering, where composite materials are widely used. The integration of deep learning models with real-time monitoring systems can significantly improve structural safety, maintenance efficiency, and cost-effectiveness.

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