

Article

Multipatch Deep Learning for Multilevel Damage Assessment of Carbon-Fiber-Reinforced Polymer Plates from Lamb-Wave Continuous Wavelet Transform Images

Olivier Munyaneza ¹ and Jung Woo Sohn ^{2,*}¹ Robot Specialized Research Center, Kumoh National Institute of Technology, Gumi 39177, Republic of Korea; olivis@kumoh.ac.kr² School of Mechanical Engineering, Kumoh National Institute of Technology, Gumi 39177, Republic of Korea

* Correspondence: jwsohn@kumoh.ac.kr

Abstract

To ensure the reliability of carbon-fiber-reinforced polymer (CFRPs) structures, robust structural health monitoring (SHM) is required for timely damage diagnosis. Over the decades, Lamb-wave-based techniques have been widely used to inspect composite structures owing to their high sensitivity to internal defects. Damage-sensitive features from nonstationary Lamb-wave signals can be captured in the frequency and time domains using the continuous wavelet transform (CWT). However, extracting localized damage features from these images is highly challenging. Accordingly, this study proposes a multipatch deep feature learning method for damage detection and severity classification in CFRP plates using Lamb-wave CWT images. The images are partitioned into multiple local patches for patch-wise deep feature extraction using a convolutional neural network (CNN). The proposed model is evaluated on CFRP composite plates with three simulated damage severity levels (D1, D2, and D3) produced using mass blocks of different weights. Among the evaluated patch configurations, the proposed physics-inspired patching achieves the highest classification accuracy of 98.2%, outperforming conventional uniform multipatch baselines. For damage detection, the proposed method achieves high classification performance, with precision, recall, and F1-scores of 100% for both healthy and damaged samples, outperforming comparison models, including a custom CNN, VGG19, and ResNet50. For damage severity classification, the proposed model achieves F1-scores of 0.98, 0.97, and 0.98 for D1, D2, and D3, respectively, consistently outperforming the baseline models across various evaluation metrics. Under Gaussian noise, the proposed method maintains a robust classification accuracy of 96.1% at 20 dB signal-to-noise ratio, corresponding to a performance reduction of 1.7% compared with noiseless data, suggesting its reliability for realistic SHM environments.

Keywords: composite plate; Lamb wave; multipatch deep learning; structural health monitoring; continuous wavelet transform

MSC: 68T01

Academic Editor: Francesco Aymerich

Received: 1 June 2026

Revised: 23 June 2026

Accepted: 30 June 2026

Published: 1 July 2026

Copyright: © 2026 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the [Creative Commons Attribution \(CC BY\)](https://creativecommons.org/licenses/by/4.0/) license.

1. Introduction

Carbon-fiber-reinforced polymers (CFRPs) have been employed in industrial applications since the 1960s [1]. These materials have emerged as an alternative to conventional metals that fail to satisfy the requirements for certain critical applications. Composites are extensively used in aerospace fuselages and flaps, automotive panels and monocoques, sporting products, military equipment, and wind turbine blades owing to their outstanding characteristics, such as lightweight nature, high specific strength and stiffness, and high fatigue and corrosion resistance [1,2]. However, the mechanical properties of composites may be compromised by damage arising during manufacturing, assembling, or service life [3]. Composites are often exposed to harsh environments and complex thermo-mechanical conditions that gradually reduce their reliability through damage mechanisms such as impact damage, delamination, and cracking [4,5]. To prevent catastrophic failures, both reliable nondestructive testing (NDT) for quality control during manufacturing and robust structural health monitoring (SHM) with timely and continuous data acquisition for in-service structures are crucial for quality control and safety performance [6,7]. Considerable effort has been devoted to developing reliable NDT methods for monitoring composite structures and enabling damage detection, localization, classification, and quantification [8]. State-of-the-art NDT methods for SHM include thermography, electromagnetic testing, ultrasonic testing, acoustic emission, guided wave analysis, laser ultrasonics, and vibration analysis [9]. Among guided waves for SHM, Lamb waves are widely applied to composite plates for damage detection because of their high sensitivity to defects and large area coverage. These are elastic waves that propagate in solid plates with free boundaries. Lamb waves can propagate in symmetric or antisymmetric modes with respect to the plate neutral axis [5]. Hence, various Lamb-wave-based methods have been proposed for damage detection and localization in composite structures [10–12]. Zhang et al. [13] proposed a damage assessment method to visualize defects in composite laminates using the Lamb-wave factorized method. Allen et al. [14] proposed a delamination detection technique based on the nonlinear response of Lamb waves, in which sequential scans were used to actuate and receive dual guided waves.

With the advent of deep learning in the Fourth Industrial Revolution, Lamb-wave signal processing has shifted from manual feature extraction to data-driven feature learning. Initially, machine learning was heavily adopted owing to its ability to detect damage without relying on physical knowledge of a structure [15,16]. However, it remained largely limited by the inability to extract robust features without human intervention [17,18]. In contrast, deep learning can automatically learn features and propagate them through deep layers as high-level representations [18]. Olivier et al. [19] proposed a multiscale one-dimensional convolutional neural network (CNN) for damage severity assessment and localization. CNN was trained on raw data and achieved an accuracy above 94% per class, outperforming state-of-the-art models. Muhammad et al. [20] developed a baseline-free imaging-based SHM framework for damage detection, severity assessment, and localization in CFRP plates. A graph convolutional network applied to Lamb waves classified damage severity with an accuracy of 96.09%. To address labeled data scarcity related to Lamb waves in SHM, Zhuojun et al. [21] proposed a data-driven transfer learning model for locating damage coordinates in plate structures with complex geometric features. To localize damage across different plates, a component-regression-based damage localization model was introduced to preserve the global properties of target data. The proposed model achieved lower regression errors than other transfer learning methods.

Deep learning models, especially CNNs, effectively handle two-dimensional data by extracting representative spatial features from image inputs [22]. CNN-based approaches for image data achieve high-performance detection and localization of damage in composites, even outperforming methods based on time-series data. Shao et al. [23] developed a method to identify, localize, and quantify damage in aircraft structures. Collected Lamb

waves were converted into two-dimensional images using Gramian angular fields and processed using a deep learning model with multidimensional feature fusion. The method used two neural network branches, with one branch processing time-series data to focus on local dynamic changes and the other branch processing two-dimensional images to emphasize global characteristics. Similarly, Gramian angular fields were adopted in [24–26] to preserve temporal representations while retaining global features. However, Gramian angular fields exhibit limited ability to describe spatial features, likely hindering damage localization and physical interpretability. Sue et al. [27] transformed Lamb waves into images using the Fourier transform to extract damage-related frequency features. The proposed stacked autoencoder identified damage with an accuracy of 99.48%. Muzammil et al. performed advanced signal processing using the MC-CAE-SVM model combined with empirical model decomposition for noise-robust delamination detection. Highly correlated intrinsic mode functions were extracted and transformed into time–frequency representations using the continuous wavelet transform (CWT). Furthermore, for accurate damage localization without requiring additional sensors, Raja et al. [28] aimed at improving delamination detection and localization through advanced signal processing. In their study, the interaction between the antisymmetric mode and delamination was analyzed and a defect was localized by measuring the time-of-flight (TOF) using the Hilbert transform (HT) and CWT. Moreover, the damage was localized with relative errors of 2.5% and 1.2% using the HT and CWT, respectively. However, relying on TOF measurements for damage localization may undermine accuracy owing to the influence of reflected waves from boundary edges. Feng et al. [29] proposed a CNN based on time–frequency features of guided waves extracted from CWT images to localize damage caused by low-velocity impacts, achieving an average localization error of 10.2 mm.

The CWT has demonstrated high performance in the detection and localization of damage in guided-wave-based SHM, primarily owing to its ability to describe localized time–frequency features of nonstationary signals. However, its effectiveness is constrained by several inherent limitations. Although the CWT preserves high temporal resolution across the target spectrum, it exhibits nonuniform spectral resolution, particularly at high frequencies [30]. Consequently, redundant representations and overlapping features can appear in the time–frequency domain, hindering the interpretation of wave interactions. These limitations directly affect data-driven methods. Although CNNs effectively extract local features, their performance on CWT-based imaging inherently depends on the quality of the underlying time–frequency patterns. In particular, dispersion, mode overlap, and resolution tradeoffs in CWT can produce distorted and indistinguishable local patterns, hindering robust and discriminative feature learning.

To address the aforementioned challenges, this paper presents a multipatch deep feature learning framework for multilevel damage assessment in CFRP plates. Unlike our previous work [19], which employed a multiscale 1D-CNN on raw one-dimensional Lamb wave, the proposed framework leverages two-dimensional CWT time–frequency representations combined with a physics-inspired patching strategy, to enable richer feature extraction in the image domain. Although image partitioning methods such as uniform patching and sliding-window analysis are well established in computer vision for localized feature learning [31–33], their application to Lamb-wave-based structural health monitoring (SHM) remains largely unexploited. Moreover, conventional approaches typically partition images according to geometric criteria without considering the underlying wave propagation stages. By contrast, the proposed framework divided the CWT images into patches, considering the propagation stages of Lamb wave corresponding to direct-wave propagation, damage-induced scattering, and boundary reflections. This propagation-stage-aware partitioning enables the extraction of physically interpretable local fea-

tures and facilitates more discriminative damage characterization. The main contributions are as follows:

1. Physics-inspired CWT image patching: partitions time–frequency representations into propagation-stage-aware regions corresponding to direct waves, damage-induced scattering, and boundary reflections. Unlike conventional uniform patching, the temporal boundaries are derived from the estimated TOF characteristics of the experimental Lamb waves, enabling CNN to learn stage-specific and mode-sensitive features rather than relying solely on global image representations.
2. A shared convolutional patch encoder: independently extracts localized spatial features from each CWT patch region. Then, the patch-wise features are concatenated and normalized through batch normalization for subsequent classification. This design improves sensitivity to subtle, localized damage patterns that are typically obscured in global CWT representations.
3. A systematic patch configuration analysis: is conducted by comparing the proposed physics-inspired patching based on direct waves, scattering waves, and boundary reflections with conventional equal-partition techniques involving 1, 2, 4, 5 patches. The analysis demonstrates that the proposed patching technique achieves the highest accuracy of 98.2% while maintaining moderate model complexity.
4. A comprehensive robustness evaluation: is performed under four Gaussian noise levels, with signal-to-noise ratio (SNR) ratios of 25, 20, 15, and 10 dB. The evaluation demonstrates that the proposed method maintains stable classification performance under moderate noise and outperforms baselines, including a custom CNN, VGG19, and ResNet50 regardless of the noise level.

2. Proposed Multipatch Deep Feature Learning Method

The proposed method, whose architecture is shown in Figure 1, performs multipatch deep feature learning for the detection and classification of multilevel damage in a CFRP plate. Preliminary experiments were conducted to acquire healthy and damaged Lamb waves from a CFRP plate. The acquired signals were processed and transformed into time–frequency representations by applying the CWT. These representations were then partitioned into multiple patches using physics-inspired patching and conventional patching for comparison. The resulting patches were fed into a shared patch encoder for feature extraction, then concatenated before proceeding to classification stage.

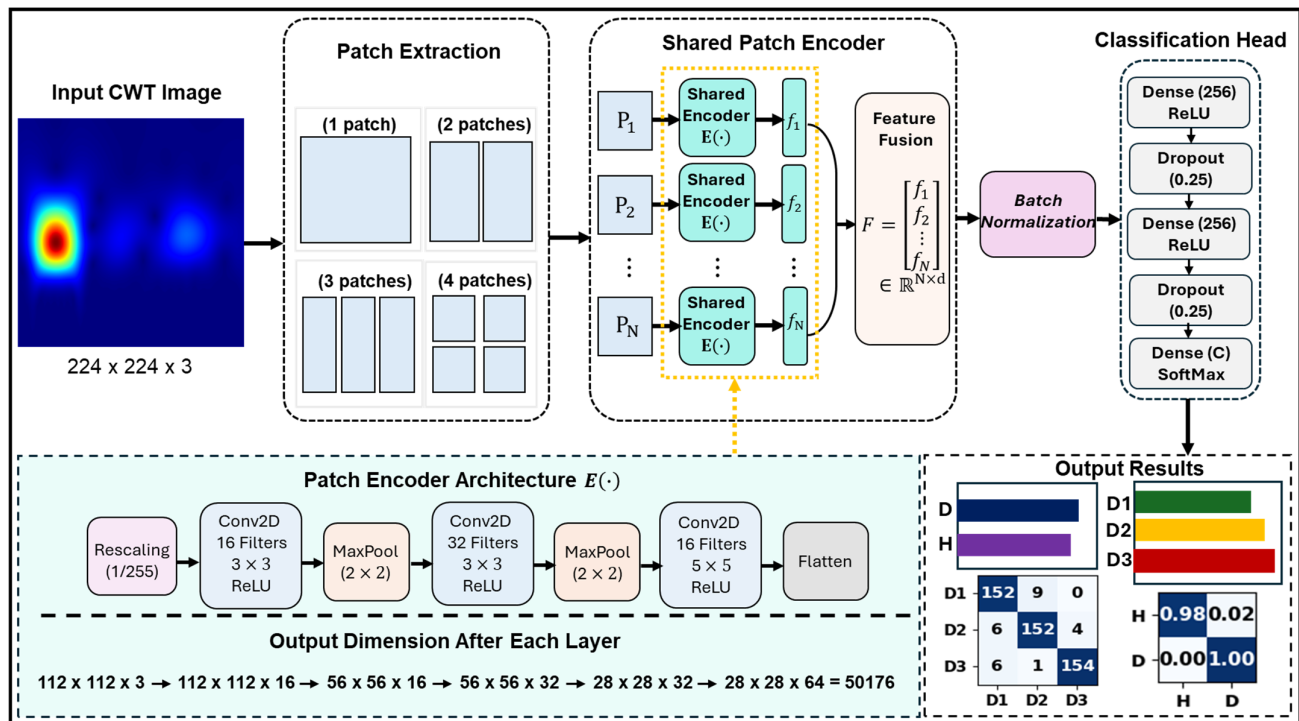


Figure 1. Architecture of proposed multipatch CNN for damage detection.

2.1. Time–Frequency Feature Extraction Using CWT

The CWT provides local features of Lamb waves across multiple time scales through wavelet functions, facilitating their representation in the time–frequency domain [34]. Wavelet-based methods have been extensively applied to data compression, noise reduction, and pattern recognition, with the discrete wavelet transform (DWT) and CWT being the most common approaches. DWT decomposes a signal into discrete components at different scales, while the CWT employs a continuously adjustable window function, providing a more flexible and detailed characterization of complex signals across scales [35].

Thus, the adaptive nature of the CWT makes it particularly effective for analyzing signals over broad ranges of temporal and spectral resolutions. Herein, we apply the CWT to represent Lamb wave $\ell(t)$ in the time–frequency domain using the following equations [36].

$$W_{f(a,b)} = \langle \ell(t), \Psi_{ab}(t) \rangle = \int_{-\infty}^{+\infty} \ell(t) \Psi_{ab}(t) dt, \quad (1)$$

where $\Psi(t)$ represents the mother wavelet, with parameters a and b being its scaling coefficients. The wavelet basis function in the time–frequency domain can be expressed as

$$\Psi_{ab}(t) = \frac{1}{\sqrt{a}} \Psi\left(\frac{t-b}{a}\right), \quad \Psi(t) = \frac{1}{\pi^{1/4}} e^{j\omega_0 t} e^{-t^2/2}. \quad (2)$$

To obtain time–frequency representations of Lamb waves, the Morlet wavelet is employed as mother wavelet $\Psi(t)$.

2.2. Physics-Inspired Patching

Patching technique segments an image into small regions that can be processed independently, allowing CNN to capture localized features rather than relying solely on global representations. We partition time–frequency images obtained from the CWT using physics-inspired patching. As illustrated on the left column of Figure 2, the acquired Lamb waves exhibit three distinct temporal regions corresponding to direct-wave propagation, damage-induced scattering, and boundary reflections. These regions are preserved

in the CWT representation, where the temporal axis reflects wave propagation and the frequency axis captures modal characteristics.

To ensure physically meaningful temporal segmentation, the image partitioning process was guided by the expected propagation behavior of the Lamb-wave signals. The actuator–sensor distance was used to provide an approximate time-of-flight (TOF) reference for the direct-wave arrival region. Subsequently, the corresponding CWT energy distribution was examined to identify transitions between direct-wave propagation, damage-induced scattering, and boundary-reflection regions. Based on these propagation characteristics, temporal windows were defined to isolate physically meaningful regions within the time–frequency representation. The approximate arrival time for the p -th actuator–sensor path is estimated as

$$\tau_p \propto \frac{d_p}{V_g}, \quad (3)$$

where d_p represents the effective propagation distance of the p -th actuator–sensor path and V_g denotes the effective group velocity of the antisymmetric (A_0) Lamb wave mode. The temporal axis is divided into J regions as follows:

$$T_j = [\tau_j, \tau_{j+1}], \quad j = 1, 2, 3, \dots, J. \quad (4)$$

Similarly, the frequency axis is partitioned into N bands as follows:

$$F_n = [f_n, f_{n+1}], \quad n = 1, 2, 3, \dots, N. \quad (5)$$

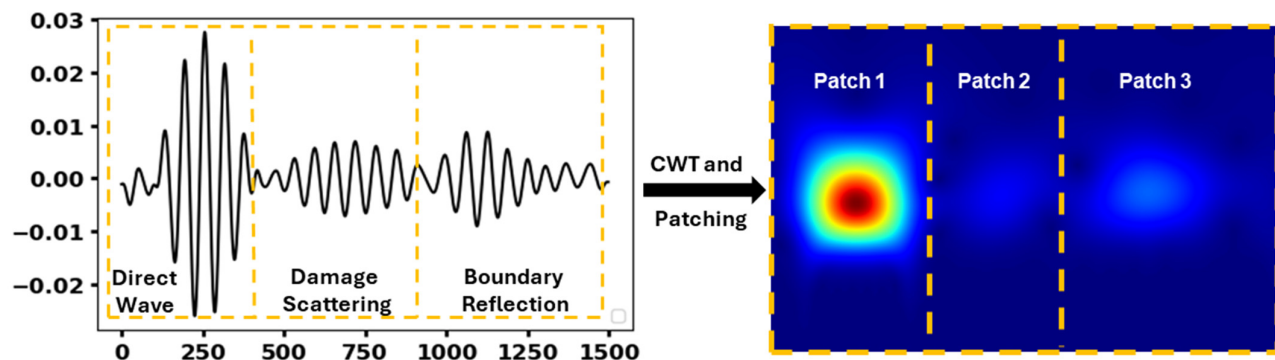


Figure 2. Schematic of proposed physics-inspired patching. Lamb-wave signal with three propagation regions (left) and corresponding CWT representation partitioned into patches (right).

Each patch is extracted from a CWT image as follows:

$$\mathcal{P}_{j,n}(\tau, f) = I(\tau, f) \cdot M_{j,n}(\tau, f); \quad \tau \in T_j, f \in F_n, \quad (6)$$

where $M_{j,n}$ denotes a binary mask selecting region $T_j \times F_n$. The number of extracted patches is $J \times N$, and all patches are resized to a fixed spatial resolution before being fed to the CNN.

The experimental Lamb-wave signals consisted of 1500 temporal samples acquired at a sampling frequency of 500 kHz, with a propagation distance of 270 mm between the actuator and sensor. Due to the use of the asynchronous data acquisition (ADA) scheme, the acquired signals exhibited highly consistent temporal alignment across all measurements. Consequently, the direct-wave, damage-scattering, and boundary-reflection regions appeared within approximately the same sample ranges throughout the dataset. Based on the estimated time-of-flight (TOF), and CWT energy distribution, a common set of temporal boundaries was adopted for all samples. For the investigated CFRP plate, these boundaries corresponded to sample intervals of 0–450, 450–950, and 950–1500, re-

spectively, representing the direct-wave, damage-scattering, and boundary-reflection dominant regions.

It should be noted that these sample indices are specific to the experimental configuration considered in this study and they are not intrinsic parameters of the proposed framework. For different structural dimensions, sensor layouts, material systems, or excitation conditions, the patch boundaries can be re-established using the same physics-guided procedure based on the estimated propagation characteristics and observed signal response. Therefore, while the numerical boundary locations may vary across applications, the underlying propagation-stage-aware patching methodology remains generally applicable.

2.3. Multipatch Deep Feature Learning for Damage Detection and Classification

The complexity of Lamb waves is inherently associated with their dispersive nature and mode overlapping. When these time-series waves are represented in the time–frequency domain using the CWT, the generated images may exhibit distortions and ambiguities owing to the wave complexity. Such effects can affect the performance of deep learning models by limiting their ability to effectively extract representative local features, such as those resulting from small damages. To address these limitations, we propose a multipatch deep learning method for detecting and classifying multilevel damage in CFRP plates based on time–frequency representations. The architecture of the proposed method shown in Figure 1 and comprises five components: CWT transformation, patch extractions, feature extraction from patches using shared encoder, classification head, and output using various metrics.

CWT images with dimensions of $224 \times 224 \times 3$ are partitioned into patches (P_N) using physics-inspired patching, as described in Section 2.2, with the segmented regions corresponding to the direct wave, damage scattering, and boundary reflections. As the extracted patches have different spatial dimensions owing to their distinct physical importance, they are resized to dimensions of $112 \times 112 \times 3$ before feature extraction for consistent representation and stable feature concatenation.

Each normalized patch configuration is then processed using shared convolutional patch encoder $E(\cdot)$. The proposed convolutional patch encoder, whose architecture is summarized in Table 1, consists of a sequence of convolutional layers, max-pooling operations, and activation function (rectified linear unit), followed by a flattening stage to transform the extracted feature maps into a one-dimensional latent feature vector. The shared encoder promotes generalization wavefield representation learning across multiple patches while minimizing the number of training parameters, thereby improving computational efficiency and preventing the risk of overfitting on a small dataset. Moreover, weight sharing facilitates feature-space consistency across patches, thereby improving feature aggregation and fusion.

The features $(f_1, f_2, f_3, \dots, f_N)$ generated from each patch are aggregated through a predefined feature concatenation operation to preserve the physical ordering of wave-propagation regions and form a unified latent representation. The concatenated features are then normalized using batch normalization before being passed into a fully connected classification module comprising two dense layers with dropout regularization to mitigate overfitting. Finally, a softmax output layer is employed for multiclass damage prediction. The proposed method enables the extraction of hierarchical and spatially localized wavefield features while improving the robustness to the complex propagation of Lamb waves, thereby enhancing the reliability and accuracy of damage detection and classification in CFRP plates.

Table 1. Architecture of proposed shared convolutional patch encoder E(·).

Layer	Output Shape	Parameters
Input	(None, 112, 112, 3)	0
Rescaling	(None, 112, 112, 3)	0
Convolution (1)	(None, 112, 112, 16)	448
Max-Pooling (1)	(None, 56, 56, 16)	0
Convolution (2)	(None, 56, 56, 32)	4640
Max-Pooling (2)	(None, 28, 28, 32)	0
Convolution (3)	(None, 28, 28, 64)	51,264
Flattening	(None, 50, 176)	0

3. Experimental Evaluation

An experimental evaluation was conducted on composite plates, with damage simulated using varying masses and healthy data obtained from undamaged samples. CFRP laminates were fabricated using carbon fiber prepreg (T700SC-12K-60E). As illustrated in Figure 3a, eight prepreg plies were cut to pieces of 310 × 310 mm and stacked in a symmetric layup sequence $[0/90/0/90]_s$ to ensure balanced in-plane stiffness and strength while eliminating bending–twisting coupling effects.

The laminate stack was consolidated and cured in a hot press at a maximum temperature of 150 °C under a pressure of 50 bar, resulting in a laminate with a final thickness of 1.03 mm. The cured composite plate was then removed and trimmed to a final dimension of 300 mm × 300 mm. Four piezoelectric transducers (PZT transducers from PI Ceramic) were surface bonded to the laminate with an inter-sensor spacing of 270 mm. Each transducer had a diameter of 10 mm, thickness of 0.5 mm, resonant frequency of 400 kHz, and capacitance of 1.28 nF. Subsequently, the composite plate surface was partitioned into nine equal grid sections, and three damage levels, denoted as D1, D2, and D3, were introduced using mass blocks of 6, 13, and 20 g, respectively. Each mass was sequentially placed at every grid location, resulting in systematic damage variation. Externally attached materials, such as masses, are widely employed as surrogate damage representations in guided-wave-based SHM studies of composite structures. Studies have employed various materials, such as absorbing sealants, absorbing mud, tacky tape, and damping soil, to simulate damage in composite structures. The resulting asymmetry in structural stiffness, wave energy absorption, phase shift, and amplitude attenuation closely resembles the characteristics observed in real damage [37–39]. Nevertheless, such simulated conditions do not fully replicate the complex physical mechanisms and wave scattering phenomenon associated with actual composite defects, such as delamination, cracking, and impact-induced damage.

The experimental setup Figure 3b comprised a data acquisition system (USB-6341, National Instruments, Seoul, South Korea), dual-channel piezo driver amplifier (Trek® PZD700A, Advanced Energy Korea, Sungnam, Republic of Korea), computer for signal generation and processing, and monitor for visualization. The excitation signal was generated in MATLAB (R2025a, MathWorks Korea, Seoul, Republic of Korea) as a Hanning-windowed tone burst with a center frequency of 150 kHz that ensured guided wave propagation within the composite plate. This signal was subsequently amplified to 50 V using the piezo driver amplifier and applied to a surface-bonded PZT transducer serving as the actuator. Upon excitation, guided waves propagated through the composite laminate, interacting with structural boundaries and regions containing simulated damage. These interactions produced reflected, transmitted, and scattered wave components in addition to the primary wave packet. The resulting wave responses were captured by the remaining PZT transducers, which served as sensors, and were captured using the NI-

DAQ system at a sampling frequency of 500 kHz. Based on a previous study [40], repeated measurements were performed to ensure the quality of the acquired dataset while capturing inherent variability and reducing measurement uncertainty, thereby improving the reliability of subsequent analysis. The measurements were repeated 10 times and used without averaging to preserve their variability. In total, 1080 signals (4 actuators $\times$ 3 paths $\times$ 9 locations $\times$ 10 repetitions) were acquired per damage category, while 600 signals were collected from the healthy samples.

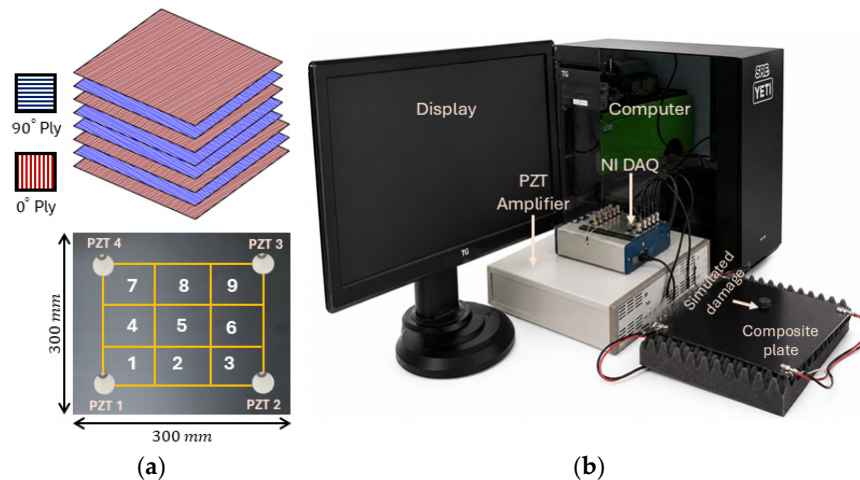


Figure 3. Experimental setup. (a) Diagram of composite plate manufacturing and (b) damage detection system.

3.1. Data Processing

Signal preprocessing was performed to minimize the redundancy in collected data and improve the computation efficiency of the proposed method. First, some generated Lamb waves were not centered around the zero axis, and linear detrending was thus applied to remove this drift. These signals were transformed into images by applying the CWT. To enhance the generalizability of the proposed model in different environmental conditions, different SNRs and a contrast of 0.02 were added to the test data as follows.

$$\text{signal to noise ratio (SNR}_{dB}) = 20 \log_{10} \left(\frac{S_r}{S_n} \right), \quad (7)$$

where S_r and S_n are the root mean square values of the raw and noise signals, respectively. By adding noise, the resulting signal was expressed as

$$R_n(t) = R_0(t) + \sigma_n r(t), \quad (8)$$

$$r(t) \sim \mathcal{N}(0,1) \text{ and } \sigma_n = \sqrt{\frac{S_r}{10^{\text{SNR}_{dB}/10}}}. \quad (9)$$

By substituting Equation (9) into Equation (8) and incorporating the contrast factor, the resulting expression was obtained as

$$R_n(t) = \beta R_0(t) + \sqrt{\frac{\frac{1}{T} \int R_0^2(t) dt}{\text{SNR}_{dB} \cdot 10^{-10}}} r(t), \quad (10)$$

where $R_0(t)$ and $R_n(t)$ represent the images before and after adding noise, respectively, and σ_n and β are the standard deviation of Gaussian noise and contrast factor, respectively.

3.2. Implementation and Evaluation

3.2.1. Implementation Details

An experimental study was conducted under identical conditions to ensure a fair comparison between the proposed and comparison methods. All corresponding models were trained on a 64-bit, 2.9 GHz central processing unit, Core i7-10700F (Intel, Santa Clara, CA, USA) equipped with 32 GB random-access memory (Samsung, Suwon, Republic of Korea) and an GeForce RTX 3060 graphics processor unit (NVIDIA, Santa Clara, CA, USA). The proposed method was implemented in Python 3.11.7 using the TensorFlow library in the Keras environment.

The CWT input images with dimensions of $224 \times 224 \times 3$ were partitioned into multiple patches and resized to $112 \times 112 \times 3$ before being processed by the patch encoder. To ensure consistency, the training parameters were maintained identical for the proposed and comparison state-of-the-art methods. The corresponding models were trained over 80 epochs, and early stopping and learning rate scheduling were used to mitigate overfitting. Sparse categorical cross-entropy was adopted as the loss function to optimize the model parameters. The adaptive moment estimation optimizer was used with a learning rate of 1×10^{-4} and weight decay of 1×10^{-5} to update the model weights and biases.

The dataset was manually distributed on class-wise basis, with 70% of the samples allocated to the training set and the remaining 30% of the samples equally shared between the validation and test sets. To prevent data leakage and sample bias, GroupShuffleSplit (scikit-learn) was employed using the damage location as the grouping variable. For each damage class, measurements were acquired at nine predefined grid locations with ten repeated acquisitions per location. All images corresponding to a given location were assigned exclusively to a single dataset partition. Consequently, repeated measurements from the same damage location were never shared between the training, validation, and test sets, ensuring complete separation of groups during model development and evaluation. Additionally, class weights were applied during model training to mitigate the imbalance between damage and healthy samples and ensure balanced learning across all classes.

3.2.2. Evaluation Criteria

To assess the performance of the proposed method in detecting and classifying damage severity, we adopted four common evaluation metrics, namely, accuracy, precision, recall, and *F1*-score. These metrics were calculated from the confusion matrix using the numbers of true positives (*TPs*), true negatives (*TNs*), false positives (*FPs*), and false negatives (*FNs*) as follows [41,42]:

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

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

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

$$F1 = \frac{2TP}{2TP+FN+FP'} \quad (14)$$

4. Results and Discussion

To validate the effectiveness of the proposed multipatch deep learning method, comparison state-of-the-art damage detection methods, including a custom CNN, VGG19, and ResNet50, were implemented and trained under identical conditions. Figure 4 shows the training results of the proposed method over 80 epochs. The cross-entropy loss gradually converges to zero as the number of training epochs increases. The training and validation

accuracies stabilize after approximately 50 epochs, reaching 98.6% and 97.2%, respectively. Furthermore, the accuracy and loss curves show stable convergence without noticeable overfitting.

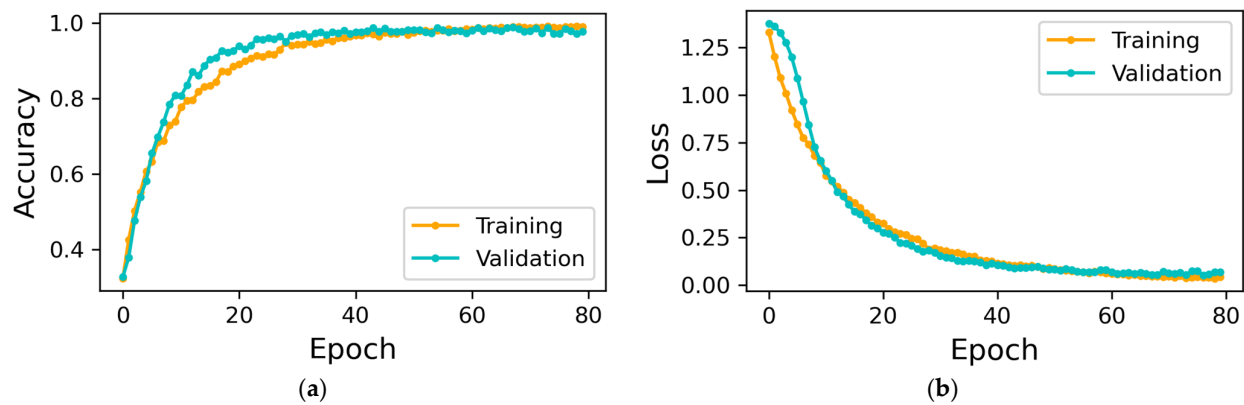


Figure 4. Evaluation metrics for proposed model during training and validation: (a) accuracy and (b) loss.

4.1. Optimal Patch Configuration

A systematic study was conducted to assess patching by comparing the proposed physics-inspired patching with conventional uniform patching for one, two, four, and five patches. In the proposed method, the CWT image was partitioned into three regions corresponding to direct waves, scattering waves, and boundary reflections, whereas the remaining configurations were generated by dividing the image into equal non-overlapping intervals along the time and frequency axes. The optimal configuration was identified based on the classification performance, computational complexity, and feature representation capability. Figure 5 shows that the classification accuracy increases by adding patches and training parameters, underscoring the tradeoff between performance and computational cost. A single patch leads to the lowest accuracy of 95.3% with approximately 13.1 million training parameters, whereas the highest accuracy of 98.2% is achieved using three patches. Thus, increasing the number of patches enhances the spatial localization of time–frequency features. However, further increasing the number of patches causes the accuracy to decline and plateau at approximately 97%, while the number of training parameters continues to increase up to 65.3 million for five patches. This suggests that excessive patching fragments global contextual information and substantially increases the computational cost. Therefore, the three-patch configuration was identified as optimal in terms of balancing classification accuracy and model complexity.

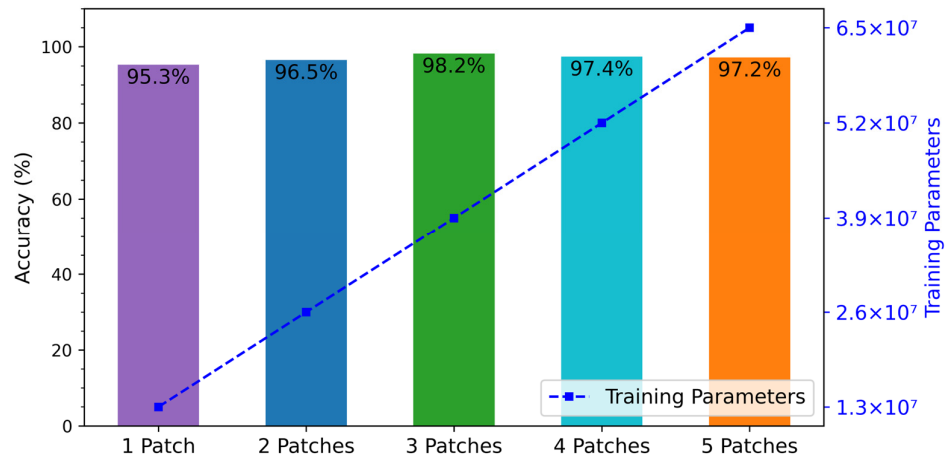


Figure 5. Accuracy and training parameters according to considered number of patches.

4.2. Patch-Wise Feature Contribution Analysis

To investigate the underlying mechanism of the proposed physics-inspired patching, an additional patch-wise ablation was conducted, where each temporal region was individually used as input to the classification network. As summarized in Table 2, the accuracy obtained was 82.1%, 90.3%, and 88.0% for direct-wave (patch 1), damage-scattering (patch 2), and boundary-reflection region (patch 3), respectively.

Table 2. Contribution of different Lamb wave propagation stages to damage severity classification.

Input Patch	Physical Interpretation	Test Accuracy (%)
Single patch 1	Direct-wave region	82.1
Single patch 2	Damage-scattering region	90.3
Single patch 3	Boundary-reflected region	88.0
Combined 3-patches	Combined propagation regions	97.7

The results demonstrated that the damage-scattering region provides the most discriminative information for damage assessment. This observation is physically consistent with Lamb wave propagation behavior, since scattered wave components are directly generated by wave-damage interactions and therefore contain more information concerning damage presence and related severity. Although both direct-wave and boundary-reflection regions shared useful information, their individual performance was lower than that of the scattering region. Additionally, the highest overall performance was achieved when all patches were combined, demonstrating that the proposed framework effectively exploits complementary information distributed across different propagation stages.

4.3. Damage Detection Performance

Table 3 lists the damage detection performance of various deep learning models for classifying the input CWT images into healthy (H) and damaged (D) classes. All methods achieve average classification accuracies exceeding 98%. For class damaged (D), both the custom CNN and VGG19 achieve 99% in precision, recall, and F1-score, while ResNet50 and the proposed method achieve 100% across all metrics. For class healthy (H), the comparison methods misclassify a few healthy samples. VGG19 shows the lowest performance, with precision, recall, and F1-score of 95%, 93%, and 94%, respectively, misclassifying six out of 90 healthy samples. Hence, VGG19 likely struggles to align well with the time–frequency representation of Lamb waves, leading to suboptimal feature extraction.

ResNet50 improves the performance compared with the custom CNN and VGG19, with precision, recall, and F1-score of 100%, 98%, and 99%, respectively.

Table 3. Damage detection results for evaluated methods.

Class	Method	Precision	Recall	F1-Score
D	CNN	0.99	0.99	0.99
	VGG19	0.99	0.99	0.99
	ResNet50	1.0	1.0	1.0
	Proposed	1.0	1.0	1.0
H	CNN	0.95	0.96	0.95
	VGG19	0.95	0.93	0.94
	ResNet50	1.0	0.98	0.99
	Proposed	1.0	1.0	1.0

Overall, the proposed multipatch method outperforms the baselines across evaluation metrics. Its superior performance is attributed to patch-based feature extraction, which improves the localization of damage-sensitive time–frequency features and enhances the discrimination between healthy and damaged states.

4.4. Damage Severity Evaluation

The performance comparison of all evaluated models is presented in Table 4 and Figure 6a–d. This evaluation was conducted by excluding healthy samples and assessing the discrimination ability of the proposed method and baselines in distinguishing damage levels D1–D3. The results show a clear difference in the method’s ability to classify the damage levels from the CWT images of Lamb waves. The proposed multipatch deep feature learning method achieves the best and most consistent performance across evaluation metrics, followed by ResNet50, while the custom CNN and VGG19 demonstrate lower classification performance.

Table 4. Classification performance of evaluated methods for damage severity.

Class	Method	Precision	Recall	F1-Score
D1	CNN	0.89	0.88	0.88
	VGG19	0.92	0.88	0.90
	ResNet50	0.93	0.96	0.95
	Proposed	0.99	0.97	0.98
D2	CNN	0.90	0.88	0.90
	VGG19	0.92	0.83	0.87
	ResNet50	0.96	0.93	0.94
	Proposed	0.97	0.98	0.97
D3	CNN	0.91	0.94	0.92
	VGG19	0.86	0.95	0.90
	ResNet50	0.95	0.96	0.96
	Proposed	0.98	0.99	0.98

The confusion matrices support the findings by indicating the distribution of correctly and incorrectly classified samples per method. For minor damage D1, the custom CNN achieves precision, recall, and F1-score of 89%, 88%, and 88%, respectively, indicating reasonable detection of minor damage. Figure 6a shows that nine and two D1 samples are misclassified as D2 and D3 samples, respectively. Similarly, 15 D2 samples from D2 are incorrectly predicted as D1 samples. Thus, the shallow CNN struggles to extract discriminative local features from the CWT images, particularly for subtle damage. Although

VGG19 slightly improves the precision to 92% and F1-score to 90%, the recall remains at 88%, indicating persistent difficulty in classifying D1 samples. Figure 6b shows 21 D1 samples incorrectly classified as D2 samples, representing the highest misclassification rate across the evaluated methods for this class. Moreover, 11 D2 samples are misclassified as D3 samples, confirming that VGG19 struggles in distinguishing classes. This VGG19 limitation may be inherited from being trained on natural image data with less noise, undermining its handling of the complex characteristics of Lamb-wave CWT images. ResNet50 considerably improves the classification performance for D1 samples, achieving 93% precision, 96% recall, and 95% F1-score. The proposed method achieves the highest performance for D1 samples with 99% precision, 97% recall, and 98% F1-score. As shown in Figure 6d, only one D1 sample is misclassified as a D2 sample, and two D1 samples are misclassified as D3 samples. This confirms that the proposed method captures subtle damage-related features from time–frequency representations.

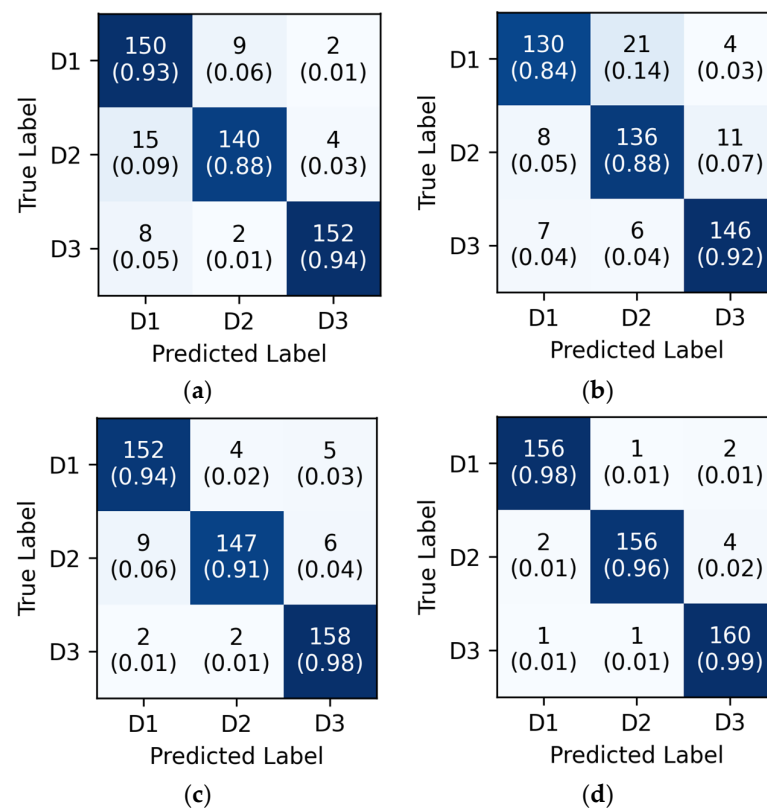


Figure 6. Confusion matrices for (a) CNN, (b) VGG19, (c) ResNet50, and (d) proposed method.

For class D2, all methods exhibit lower performance than for the other classes. The custom CNN achieves precision, recall, and F1-score of 90%, 88%, and 90%, respectively. The confusion matrix shows that 15 and 4 D2 samples are misclassified as D1 and D3 samples, respectively, indicating the method's inability to distinguish intermediate damage from minor or severe damage. VGG19 provides the lowest recall of 83% and F1-score of 87%, which are reflected in the confusion matrix, where most D2 samples are misclassified. In contrast, ResNet50 achieves 96% precision, 93% recall, and 94% F1-score, with only nine and three D2 samples being misclassified as D1 and D3 samples, respectively. Again, the proposed method outperforms all other models, achieving 97% precision, 98% recall, and 97% F1-score. Its confusion matrix demonstrates highly accurate predictions, with only two and four D2 samples being misclassified as D1 and D3 samples, respectively, indicating robust detection of moderate damage.

For damage severity D3, the features are easily distinguished by all evaluated methods, achieving higher accuracy compared with damage severities D1 and D2. The custom CNN achieves 91% precision, 94% recall, and 92% F1-score, although its confusion matrix shows several misclassifications between D3 and D1 samples. VGG19 achieves 86% precision, 95% recall, and 90% F1-score. Despite the relatively high recall, its lower precision indicates a high false-positive rate, with the confusion matrix showing several D1 and D2 samples being misclassified as D3 samples. ResNet50 demonstrates strong and balanced performance with 95% precision, 96% recall, and 96% F1-score, with only two D3 samples being misclassified as D1 or D2 samples. The proposed method achieves the best results, with 98% precision, 99% recall, and 98% F1-score. The confusion matrix confirms this excellent performance, showing one D3 sample misclassified as a D1 or D2 sample, while the remaining 160 samples are correctly classified.

The confusion matrix reveals that intermediate damage D2 is the most challenging category to classify across the evaluated methods, showing 59 misclassified samples compared with the 48 and 29 misclassifications for damage severities D1 and D3, respectively. Thus, moderate damage likely exhibits transitional wavefield characteristics that overlap with both minor and severe damages, thereby increasing the classification ambiguity. In contrast, D3 samples produce more distinguishable scattering patterns, resulting in fewer misclassifications.

Overall, the analyses of the evaluation metrics and confusion matrices demonstrate that deeper architectures, particularly ResNet50 and the proposed method, effectively learn complex and discriminative features from CWT images. The custom CNN provides limited feature extraction owing to its shallow structure, while VGG19 struggles to adapt to the noisy and complex nature of Lamb-wave CWT representations. In contrast, the proposed method consistently achieves the highest precision, recall, and F1-score with the fewest misclassifications across damage levels, confirming its superior robustness and classification performance.

4.5. Robustness of Proposed Method

Mechanical vibrations and environmental disturbances, such as wind, commonly affect Lamb-wave-based SHM of composite structures. These disturbances degrade the quality of measured signals through waveform distortion, noise-induced signal degradation, and feature shifting, undermining the deep learning accuracy for detecting and classifying structural damage [42]. To evaluate the robustness and generalizability of the proposed method under noisy conditions, Gaussian noise at four SNR levels (25, 20, 15, and 10 dB) was added to the test data. Table 5 summarizes the classification performance of the proposed and comparison methods under varying noise levels.

The pretrained models, VGG19 and ResNet50, exhibit considerable performance degradation under noisy conditions. At 25 dB SNR, VGG19 and ResNet50 show accuracy reductions of 29.8% and 17.8%, respectively, compared with the noiseless condition. Under severe noise (10 dB SNR), the accuracy of both pretrained models falls below 50%, indicating limited robustness against signal distortion. Although the custom CNN demonstrates comparatively stable performance across noise levels and outperforms the pretrained models, its performance degrades as the noise intensity increases.

The proposed multipatch deep learning method demonstrates strong robustness and generalizability under moderate noise of 25 and 20 dB, with minor performance reductions of 0.4% and 1.7%, respectively. Under severe noise of 10 dB, the proposed method experiences a larger performance drop of 33.5% compared with the noiseless condition. This degradation is associated with substantial distortion in the time–frequency representations, including scattered noise artifacts, reduced contrast, and masking of localized damage-scattering features. Nevertheless, the proposed method consistently outperforms

all baseline CNN models at every noise level, indicating superior robustness and stable feature extraction under low SNR.

Table 5. Classification performance of evaluated methods under different noise levels.

Method	No Noise	25 dB	20 dB	15 dB	10 dB
CNN	88.8	80.1	71.8	62.4	52.3
VGG19	88.6	62.2	56.0	51.0	40.2
ResNet50	94.8	78.3	70.6	59.7	48.4
Proposed	97.7	97.3	96.08	88.4	66.5

5. Conclusions

This study proposes and evaluates a multipatch deep learning method for damage detection and classification in composite plates. Experimental Lamb waves are represented in the time–frequency domain by applying the CWT. Physics-inspired patching partitions the input images into multiple patches. Among several patch configurations, the three-patch configuration is identified as optimal in terms of balancing classification accuracy and a moderate number of trainable parameters. Each patch is processed using a shared encoder, and the extracted time–frequency features are concatenated and normalized for subsequent classification. The proposed method outperforms baselines, including a custom CNN, VGG19, and ResNet50, in both damage detection and severity classification across multiple evaluation metrics.

Robustness tests under four different SNRs confirm that the proposed method demonstrates stable and strong performance under moderate noise (25 and 20 dB). Even under severe noise (15 and 10 dB), this method consistently outperforms the baselines, indicating its robustness and reliability for noisy SHM environments. Future work will extend the validation of the proposed framework using cross-plate datasets, real damage scenarios, realistic environmental conditions, and location-wise evaluation protocols to further assess its generalization capability. In particular, investigating robust feature learning strategies that improve performance for previously unfamiliar damage locations remains an important direction for improving the applicability of Lamb-wave-based damage assessment.

Author Contributions: Conceptualization, J.W.S.; methodology, O.M.; writing—original draft preparation, O.M.; writing—review and editing, O.M. and J.W.S.; supervision, J.W.S. All authors have read and agreed to the published version of the manuscript.

Funding: This work was supported by a National Research Foundation of Korea (NRF) grant funded by the Korean Government (Ministry of Science and ICT, MSIT) (No. RS-2023-NR076925, 50%). This work was partly supported by the Institute of Information & Communications Technology Planning & Evaluation (IITP)—Innovative Human Resource Development for Local Intellectualization program grant funded by the Korea Government (MSIT) (IITP-2026-RS-2020-II201612, 25%). This work was also partly supported by the IITP—Information Technology Research Center (ITRC) grant funded by the Korea Government (MSIT) (IITP-2026-RS-2024-00437190, 25%). This work was supported by the Regional Innovation System & Education (RISE)–(Specialized University) program through the Gyeongbuk RISE Center, funded by the Ministry of Education (MOE) and the Gyeongsangbuk-do, Republic of Korea (2026-rise-15-105).

Data Availability Statement: The original contributions presented in this study are included in the article. Further inquiries can be directed to the corresponding author.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Liu, L.; Jia, C.; He, J.; Zhao, F.; Fan, D.; Xing, L.; Wang, M.; Wang, F.; Jiang, Z.; Huang, Y. Interfacial characterization, control and modification of carbon fiber reinforced polymer composites. *Compos. Sci. Technol.* **2015**, *121*, 56–72. <https://doi.org/10.1016/j.compscitech.2015.08.002>.
2. Guo, R.; Li, C.; Niu, Y.; Xian, G. The fatigue performances of carbon fiber reinforced polymer composites—A review. *J. Mater. Res. Technol.* **2022**, *21*, 4773–4789. <https://doi.org/10.1016/j.jmrt.2022.11.053>.
3. Gharehbaghi, V.R.; Noroozinejad Farsangi, E.; Noori, M.; Yang, T.Y.; Li, S.; Nguyen, A.; Málaga-Chuquitaype, C.; Gardoni, P.; Mirjalili, S. A critical review on structural health monitoring: Definitions, methods, and perspectives. *Arch. Comput. Methods Eng.* **2022**, *29*, 2209–2235. <https://doi.org/10.1007/s11831-021-09665-9>.
4. Sumaiya, S.A.; Riddhie, A.S.; Karnati, N.; Kannan, M. The influence of foreign object damage on the mechanical degradation of aerospace materials: A review. *J. Alloys Compd.* **2026**, *1051*, 185935. <https://doi.org/10.1016/j.jallcom.2026.185935>.
5. Diamanti, K.; Soutis, C. Structural health monitoring techniques for aircraft composite structures. *Prog. Aerosp. Sci.* **2010**, *46*, 342–352. <https://doi.org/10.1016/j.paerosci.2010.05.001>.
6. Salski, B.; Gwarek, W.; Korpas, P.; Reszewicz, S.A.; Chong, Y.B.; Theodorakeas, P.; Hatzioannidis, I.; Kappatos, V.; Selcuk, C.; Gan, T.H.; et al. Non-destructive testing of carbon-fibre-reinforced polymer materials with a radio-frequency inductive sensor. *Compos. Struct.* **2015**, *122*, 104–112. <https://doi.org/10.1016/j.compstruct.2014.11.056>.
7. Rocha, H.; Semprinoschnig, C.; Nunes, J.P. Sensors for process and structural health monitoring of aerospace composites: A review. *Eng. Struct.* **2021**, *237*, 112231. <https://doi.org/10.1016/j.engstruct.2021.112231>.
8. Sheiati, S.; Chen, X. Advances in computer vision-based structural health monitoring techniques for wind turbine blades. *Renew. Sustain. Energy Rev.* **2025**, *224*, 116078. <https://doi.org/10.1016/j.rser.2025.116078>.
9. Etxaniz, J.; Aranguren, G.; Gil-García, J.M.; Sánchez, J.; Vivas, G.; González, J. Ultrasound-based structural health monitoring methodology employing active and passive techniques. *Eng. Fail. Anal.* **2023**, *146*, 107077. <https://doi.org/10.1016/j.eng-failanal.2023.107077>.
10. Su, C.; Zhang, W.; Liang, L.; Zhang, Y.; Sui, Q. Damage imaging identification of honeycomb sandwich structures based on Lamb waves. *Materials* **2023**, *16*, 4658. <https://doi.org/10.3390/ma16134658>.
11. Sun, L.; Wei, J.; Peng, C.; Hao, W.; Teng, F.; Fan, L.; Zhang, L.; Sui, Q.; Jiang, M. Ultrasonic guided wave-based probabilistic diagnostic imaging method with single-path-scattering sparse reconstruction for multi-damage detection in composite structures. *Mech. Syst. Signal Process.* **2025**, *223*, 111858. <https://doi.org/10.1016/j.ymssp.2024.111858>.
12. Zeng, X.; Zhao, B.; Liu, X.; Yu, Y.; Guo, J.; Qing, X. Lamb wave-based damage assessment for CFRP composite structures using a CHMM-based damage localization algorithm and a damage quantitative expression. *Mech. Syst. Signal Process.* **2023**, *184*, 109750. <https://doi.org/10.1016/j.ymssp.2022.109750>.
13. Zhang, N.; Zhai, M.; Zeng, L.; Huang, L.; Lin, J. Damage assessment in composite laminates with the Lamb wave factorization method. *Compos. Struct.* **2023**, *307*, 116642. <https://doi.org/10.1016/j.compstruct.2022.116642>.
14. Pineda Allen, J.C.; Ng, C.T. Damage detection in composite laminates using nonlinear guided wave mixing. *Compos. Struct.* **2023**, *311*, 116805. <https://doi.org/10.1016/j.compstruct.2023.116805>.
15. Manujesh, B.J.; Prajna, M.R. Damage detection and classification for sandwich composites using machine learning. *Mater. Today Proc.* **2022**, *52*, 702–709. <https://doi.org/10.1016/j.matpr.2021.10.088>.
16. Li, Y.; Xiong, F.; Liu, H.; Li, X.; Ding, H.; Liao, Y.; Zeng, Y. In situ damage detection method for metallic shear plate dampers based on the active sensing method and machine learning algorithms. *Sensors* **2026**, *26*, 2203. <https://doi.org/10.3390/s26072203>.
17. Yang, Z.; Yang, H.; Tian, T.; Deng, D.; Hu, M.; Ma, J.; Gao, D.; Zhang, J.; Ma, S.; Yang, L.; et al. A review in guided-ultrasonic-wave-based structural health monitoring: From fundamental theory to machine learning techniques. *Ultrasonics* **2023**, *133*, 107014. <https://doi.org/10.1016/j.ultras.2023.107014>.
18. Cha, Y.J.; Ali, R.; Lewis, J.; Büyüköztürk, O. Deep learning-based structural health monitoring. *Autom. Constr.* **2024**, *161*, 105328. <https://doi.org/10.1016/j.autcon.2024.105328>.
19. Munyaneza, O.; Sohn, J.W. Multiscale 1D-CNN for damage severity classification and localization based on Lamb wave in laminated composites. *Mathematics* **2025**, *13*, 398.
20. Azad, M.M.; Jung, J.; Kim, H.S.; Munyaneza, O.; Sohn, J.W. Physics-guided graph convolutional network for damage severity and zone identification in industrial composites. *Adv. Eng. Inform.* **2025**, *68*, 103701. <https://doi.org/10.1016/j.aei.2025.103701>.
21. Xu, Z.; Hao, L.; Yu, J.; Yu, J. A transfer learning approach for data-driven localization of damage areas in plate-like structures of CFRP materials. *Eng. Struct.* **2024**, *314*, 118352. <https://doi.org/10.1016/j.engstruct.2024.118352>.

22. Yan, Y.; Zhang, Y.; Wu, X.; Guo, Q.; Zhang, D.; Li, C.; Liu, Y.; Zhang, J.; An, L.; Wang, Z.; et al. Deep learning paradigm shift in composite materials performance prediction: A review of state-of-the-art applications. *Compos. Commun.* **2025**, *58*, 102542. <https://doi.org/10.1016/j.coco.2025.102542>.
23. Shao, W.; Liao, Y.; Wang, Y.; Yin, J.; Chen, G.; Qing, X. A damage identification method for aviation structure integrating Lamb wave and deep learning with multi-dimensional feature fusion. *Ultrasonics* **2025**, *151*, 107623. <https://doi.org/10.1016/j.ultras.2025.107623>.
24. Wei, L.; Peng, X.; Cao, Y. Rolling bearing fault diagnosis based on Gramian angular difference field and improved channel attention model. *PeerJ Comput. Sci.* **2024**, *10*, e1807. <https://doi.org/10.7717/peerj-cs.1807>.
25. Liao, Y.; Qing, X.; Wang, Y.; Zhang, F. Damage localization for composite structure using guided wave signals with Gramian angular field image coding and convolutional neural networks. *Compos. Struct.* **2023**, *312*, 116871. <https://doi.org/10.1016/j.compstruct.2023.116871>.
26. Ma, J.; Bao, W.; Yang, Z.; Yang, H.; Ma, S.; Yang, L.; Wu, Z. Guided-wave-based real-time damage detection in composite structures: A gramian angular field image coding lightweight network approach. *IEEE Trans. Instrum. Meas.* **2025**, *74*, 3533621. <https://doi.org/10.1109/TIM.2025.3533621>.
27. Su, C.; Jiang, M.; Liang, J.; Tian, A.; Sun, L.; Zhang, L.; Zhang, F.; Sui, Q. Damage assessments of composite under the environment with strong noise based on synchrosqueezing wavelet transform and stack autoencoder algorithm. *Measurement* **2020**, *156*, 107587. <https://doi.org/10.1016/j.measurement.2020.107587>.
28. Papanaboina, M.R.; Jasiuniene, E.; Žukauskas, E. Numerical analysis of guided waves to improve damage detection and localization in multilayered CFRP panel. *Materials* **2022**, *15*, 3466. <https://doi.org/10.3390/ma15103466>.
29. Feng, B.; Cheng, S.; Deng, K.; Kang, Y. Localization of low-velocity impact in CFRP plate using time–frequency features of guided wave and convolutional neural network. *Wave Motion* **2023**, *119*, 103127. <https://doi.org/10.1016/j.wavemoti.2023.103127>.
30. Moca, V.V.; Bărzan, H.; Nagy-Dăbâcan, A.; Mureșan, R.C. Time-frequency super-resolution with superlets. *Nat. Commun.* **2021**, *12*, 337. <https://doi.org/10.1038/s41467-020-20539-9>.
31. Xie, H.; Xu, T.; Yang, H.; Lyu, M.; Chen, C.; Tong, C.; Liu, S. HIPPA-DGCN: Survival analysis on whole slide images via hyper-image patches and position-aware dense graph convolutional networks. *Comput. Methods Programs Biomed.* **2026**, *282*, 109407. <https://doi.org/10.1016/j.cmpb.2026.109407>.
32. Saini, A.; Dogra, A.; Goyal, B.; Lepcha, D.C. Patch-wise local principal component analysis-based medical image denoising: A method noise approach. *Open Neuroimag. J.* **2026**, *19*, e18744400424702. <https://doi.org/10.2174/0118744400424702251121110449>.
33. Todescato, M.V.; Garcia, L.F.; Balreira, D.G.; Carbonera, J.L. Multiscale patch-based feature graphs for image classification. *Expert Syst. Appl.* **2024**, *235*, 121116. <https://doi.org/10.1016/j.eswa.2023.121116>.
34. Zhang, T.; Wu, X.; Wang, Q.; Zhang, L.; Li, Z.; Peng, Y.; Bian, Q.; Shi, H.; Liu, Y.; Wang, S. Continuous wavelet transform-based method for high-sensitivity detection of image signals of fluorescence lateral flow assay. *Sensors* **2025**, *25*, 3846. <https://doi.org/10.3390/s25133846>.
35. Xu, L.; Yang, J.; Ge, M.; Su, Z. Three-dimensional fatigue crack quantification using densely connected convolutional network-assisted ultrasonic guided waves. *Int. J. Fatigue* **2024**, *180*, 108094. <https://doi.org/10.1016/j.ijfatigue.2023.108094>.
36. Akansu, A.N.; Serdijn, W.A.; Selesnick, I.W. Emerging applications of wavelets: A review. *Phys. Commun.* **2010**, *3*, 1–18. <https://doi.org/10.1016/j.phycom.2009.07.001>.
37. Wang, Y.; Liao, Y.; Cui, X.; Huang, Y.; Qing, X. A heterogeneous decision voting-based transfer domain adaptation method for damage localization of CFRP composite structures. *Mech. Syst. Signal Process.* **2025**, *224*, 112015. <https://doi.org/10.1016/j.ymsp.2024.112015>.
38. Lv, S.; Qin, X.; Wei, J.; Sun, L.; Zhang, L.; Sui, Q.; Jiang, M. Linear annular path damage probability distribution based ultrasonic guided wave method for position imaging and tracking of multi-damage on plate-like carbon fiber composite structure. *Thin-Walled Struct.* **2023**, *183*, 110362. <https://doi.org/10.1016/j.tws.2022.110362>.
39. Song, R.; Sun, L.; Gao, Y.; Peng, C.; Wu, X.; Lv, S.; Wei, J.; Jiang, M. Global-local feature cross-fusion network for ultrasonic guided wave-based damage localization in composite structures. *Sens. Actuators A Phys.* **2023**, *362*, 114659. <https://doi.org/10.1016/j.sna.2023.114659>.
40. Giurgiutiu, V. *Structural Health Monitoring with Piezoelectric Wafer Active Sensors*, 2nd ed.; Academic Press: Waltham, MA, USA, 2014. <https://doi.org/10.1016/C2013-0-00155-7>.

41. Muzammil, A.; Izaz, R.; Sohail, M.; Kim, H.S. Structural health monitoring of composite laminates using lightweight transfer learning. *Machines* **2024**, *12*, 589. <https://doi.org/10.3390/machines12090589>.
42. Luo, K.; Li, C.; Zhang, H.; Zhang, Y. Baseline-free multimodal damage detection framework for composite plate-like structures using Mamba with guided waves. *Measurement* **2026**, *257*, 118958. <https://doi.org/10.1016/j.measurement.2025.118958>.

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.