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Prediction of stiffness and fatigue in polymer matrix composite using artificial neural networks

Layth Saleem Kamal[1], Ali Jasim Atiyah[1], Raied Qaied Ajmi[1], Ahmed Abdullah Amanah[2*]

[1] Department of Mechanical Engineering, Babylon Technical Institute, Al-Furat Al-Awsat Technical University, Najaf, Iraq
[2] Business Management Department, Faculty of Administration and Economics, Kerbala University, Kerbala, Iraq
* Corresponding author's e-mail: ahmed.a@uokerbala.edu.iq

ABSTRACT

Determining fatigue and stiffness in polymer matrix composites helps with assessing their structural stability and longevity. We propose a model based on deep learning that uses attention aggregation networks to detect fatigue damage in composite materials, combining feature extraction, ensemble learning, and time – frequency analysis. First, sensor data are converted to scalogram images through continuous wavelet transforms to capture the complex, non-stationary features of Lamb wave data. These scalograms are then analyzed using AlexNet – a deep convolutional neural network (CNN) used is a transfer-learning approach with a pre-trained architecture – to obtain high-level spatial information with a low likelihood of overfitting due to data augmentation and dropout procedures. A minimum redundancy – maximum relevance (MRMR) algorithm is then used to clarify the relationships between the extracted features and both the fatigue states and optimal feature space. Finally, an ensemble learning technique is used to make the classification generalizable. Thus, we combine time–frequency feature extraction, CNN-based deep feature learning, MRMR feature optimization, and ensemble classification into a single pipeline to predict fatigue and stiffness in polymer matrix composites, achieving accuracy in excess of 99.77% on controlled laboratory datasets using CFRP specimens under Lamb wave interrogation.

Keywords: fatigue prediction, polymer matrix composite, artificial neural networks continuous wavelet transform, deep learning.

INTRODUCTION

Experimenting with polymer matrix composites has expanded knowledge on their mechanical behavior under diverse loading conditions, from temperature-induced buckling phenomena in thin-walled profiles[1] to dynamic impact responses in fiber-reinforced systems [2], while simultaneous investigations into surface topography characterization [3] and unconventional joining methodologies have [4] illuminated the complex interplay between material architecture and structural performance [5].

The polymer matrix composites (PMCs) have become eminent in a varied range of engineering fields, especially aerospace, automotive and structure applications, on account of their high strength-weight ratio, resistance to corrosion and durability [6]. These materials are, however, vulnerable to fatigue related damage thus undermining structural integrity in the long run. Due to the safety and reliability of the composite based structures, proper modeling of the degradation of stiffness and fatigue property is critical in PMCs [7, 8]. Conventional fatigue testing techniques (including destructive tests, and conventional non-destructive evaluation (NDE) techniques are not relevant because they are time consuming in terms of laboratory analysis and inapplicable to real-time structural health monitoring (SHM).

AI-driven approaches offer compelling advantages over traditional SHM methods: automated detection of subtle damage patterns in Lamb wave signals that human operators might miss, real-time processing of high-frequency ultrasonic data streams. Studies have demonstrated that optimal particle loadings can improve fatigue life by up to eight times in thermoplastic composites, while multi-scale approaches combining nano and macro reinforcements show improvements in fracture toughness [9–11]. The emergence of recent progresses in artificial intelligence (AI) and deep learning has provided an opportunity to come up with effective, data-driven business acumen capable of diagnosing and predicting fatigue in composite materials [12, 13].

The need to develop a fatigue prediction capability in the PMCs is provoked by the growing level of demand in the application of cost-effective and dependable SHM systems in engineering applications. Failure can occur in the structure because of unidentified fatigue damage resulting in disastrous effect especially to the aerospace industry and automotive industry where safety is much needed [13]. The predictive maintenance strategies, used when the stiffness degradation and fatigue damage are detected early, reducing the downtime in the operation and minimizing the prices spent on maintenance [14]. This paper describes an effective approach using artificial neural networks in predicting fatigues in polymer matrix composites. Unlike existing methodologies that rely on traditional time-domain or frequency-domain analysis, this research introduces a sophisticated time-frequency representation through scalogram transformation. The validation through extensive datasets from Stanford Structures and Composites Laboratory and NASA Ames Research Center aims to benchmark for predictive maintenance technologies in composite materials.

RELATED WORKS

When the applications of a range of different machine learning (ML) regression models were explored, combined with materials informatics, to make predictions of post-fatigue residual strength of CFRPs and GFRPs. The training of the model was done by the ten fatigue-related features (classified by material, testing, manufacturing, and composite properties). The experiment involved contrasting the regressors which included a linear, non-linear, decision tree, ensemble, support vector and ANN. R 2, MAE, MedAE, and RMSE were used as a measure of performance. Conclusions indicated that Multi-Layer Perceptron (MLP) was found accurate in terms of R 2, which gave 0.88 and 0.95 on the validation and test data respectively [15].

Underpinning fatigue life prediction methods of CFRP composites characterised semi-empirical methods, the finite element approaches, non-destructive testing (NDT)-related methods, and data-driven methods [5]. All the methods, their pros, cons, and usability are discussed. Semi-empirical models provide quick estimations at the cost of low flexibility in using a wide range of materials and constructions. The finite element methods can accommodate complicated geometries, whereas they need a significant number of experiments to be calibrated. The methods, which are based on NDT technology, allow the assessment of fatigue damage quickly, with the evaluation of its accuracy of correlation with the types of fatigue damage being the remaining problem. Modeling based on past records exploits past information at the expense of being unable to sieve out fatigue-related data. New fast prediction techniques are also discussed in the review.

To estimate a laminated composite fatigue life, ANN- integrated and non-dominated sorting genetic algorithm (NSGA-II) were integrated [16]. The model has been trained using experimental carbon/epoxy composite data, which consists of 14 cases where the loading level varied and stress concentration and stacking sequences. On test and validation sets, the ANN-NSGA-II model produced R^2 scores of 88 percent and 90 percent, respectively. With data augmentation, the scores amounted to 97% and 98%.

The effectiveness of deep neural networks (DNN) was considered to create a data informed failure model of Fiber-reinforced Polymer (FRP) composites [17]. The model was trained on experimental failure data on laminates to biaxial and triaxial stresses based on a fully connected DNN architecture with 20 input units and one output unit. The length of the failure vector in the zone was the output and the inputs included the loading condition, the properties of lamina and the layup sequence of the laminate. The DNN model potential was shown to perform accurate failure prediction in FRP composites due to the comparison of the DNN-based failure boundary with other well-known theories regarding failure predictions such as the Tsai1971TsaiWu, CuntzeCuntze. The DNN model gave more satisfactory predictions.

Determining the issues of damage in carbon fiber reinforced plastics (CFRP) composites that suffer because of their extreme anisotropy and multifaceted failure modes [18]. In order to overcome the drawbacks of data-driven approaches, lacking physical interpretability, and relying on experimental data, the authors integrate monitoring data and physical modeling of simulation tasks by simulating CFRP structures in diverse damage states numerically. Experimental and simulated data are then combined using deep transfer learning model to fix the discrepancies between them.

Existing algorithms reported in the composites literature have not been tested for their effectiveness in stiffness or fatigue prediction in polymer matrices but only in pre-filled or hybrid composite systems. Prior studies have compared neural networks with models for axial load capacity prediction in concrete columns with fiber-reinforced plastic (FRP) [19] and have examined tensile and impact strength in natural fiber/aluminum oxide polymer nanocomposites, delamination and thrust force in glass-reinforced (GLARE) laminates using machine-learning (ML) models, and fractographic analysis in FRP laminates for marine applications [20], Similar computational techniques were used to assess fiber volume fraction effects on hybrid tensile properties [21], low-velocity impact in hybrid laminates [22], dielectric property prediction in banana-fiber-filled polypropylene composites using ANN [23], and steel fiber composites with brittle and ductile matrices [24]. These illustrate the range of ways in which AI/ML have been used to assess the performance parameters of composites without degradation using adversarial transformer and multi-domain attention aggregation network (MDAAN) architectures [25, 26].

Methods for distinguishing normal from anomalous composite behavior during fatigue testing that combine convolutional feature extraction using AlexNet with minimum redundancy–maximum relevance (MRMR) optimization and ensemble learning have been found to have area-under-the-curve (AUC) values approaching 0.997 and overall accuracy rates of 99.8% [26, 27]. We therefore tested the effectiveness of advanced ML architectures–including wavelet-based convolutional neural networks (WVD-CNNs), adversarial transformer networks, and MDAANs – to detect fatigue and predict stiffness degradation in polymer matrix composites.

METHOD

We feature time-frequency representation of sensor signal through Continuous Wavelet Transform (CWT)-based scalogram generation by extracting features with the assistance of scalogram transformation. Scalogram is an efficient method of extraction time-frequency feature and has various merits. It allows monitoring of changes in both time and domain frequency, thus it is of great use in analyzing nonlinear and non-stationary signals.

The schematic diagram of the proposed method is presented in Figure 1. The complete pipeline follows this sequence: (1) PZT actuator generates 5-cycle Hanning-windowed tone-burst at 50kHz, (2) sensor captures Lamb wave response at 1 MHz sampling rate, (3) signals segmented into 1024-sample windows with 50% overlap, (4) CWT applied using Complex Morlet wavelet ($\omega_0 = 6$) with 64 scales spanning 1-500 kHz, (5) resulting scalograms resized to 227×227×3 RGB format, (6) pre-trained AlexNet extracts 4096 features from fc7 layer, (7) MRMR selects top 500 features based on mutual information criteria, (8) ensemble bagging classifier (Random Forest with 100 trees) performs binary classification (Figure 2).

In Figure 3 the sample of actuator signal, together with the associated sensor response, that was captured on the CFRP dataset is displayed. To carry out the extraction of features of these recorded signals, Scalogram of Continuous Wavelet Transform (SCOT) of scalogram transformation is carried out to facilitate fatigue detection in CFRP composites, as detailed below.

Extracting cwt-based time-frequency features from sensor signals

The time-frequency domain transformations are essential to pattern recognition methods. By employing fundamental wavelet functions, this model transforms nonstationary signals, and actuator signals – into a time-frequency spectrogram. The continuous wavelet transform (CWT) is mathematically defined as follows.

$$Z(a.b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} s(t)\psi^{*}\left(\frac{t-b}{a}\right) dt \qquad (1)$$

where: $s(t)$ denotes the finite-energy input signal (sensor or actuator signal);
$\psi(\cdot)$ represents the complex conjugate of the mother wavelet function*;
a is the scaling parameter that controls the width of the wavelet (frequency resolution);
b is the translation parameter that controls the time localization of the wavelet;
$Z(a,b)$ is the resulting wavelet coefficient at scale a and position b.

For this study, the Complex Morlet mother wavelet $\psi(t) = \pi^{(-1/4)} \exp(i\omega_0 t) \exp(-t^2/2)$ with central frequency $\omega_0 = 6$ was selected based on its optimal time-frequency resolution for Lamb wave analysis. The scale parameter ‘a’ ranges from 1 to 64 in logarithmic steps, corresponding to frequency range 0.8–50 kHz suitable for A_0 and S_0 mode detection. The translation parameter ‘b’ shifts across the entire signal duration with sampling interval $\Delta t = 1$ μs. Figure 4 illustrates an example of a received sensor signal and its corresponding scalogram. In general, scalogram transformation, by combining the benefits of precise time-frequency analysis and dynamic change detection, serves as an ideal tool for diagnosing damage in composites. The extracted time-frequency patterns from this transformation are provided to deep networks for feature extraction and final classification, enabling the detection of fatigue and structural defects in composite materials.

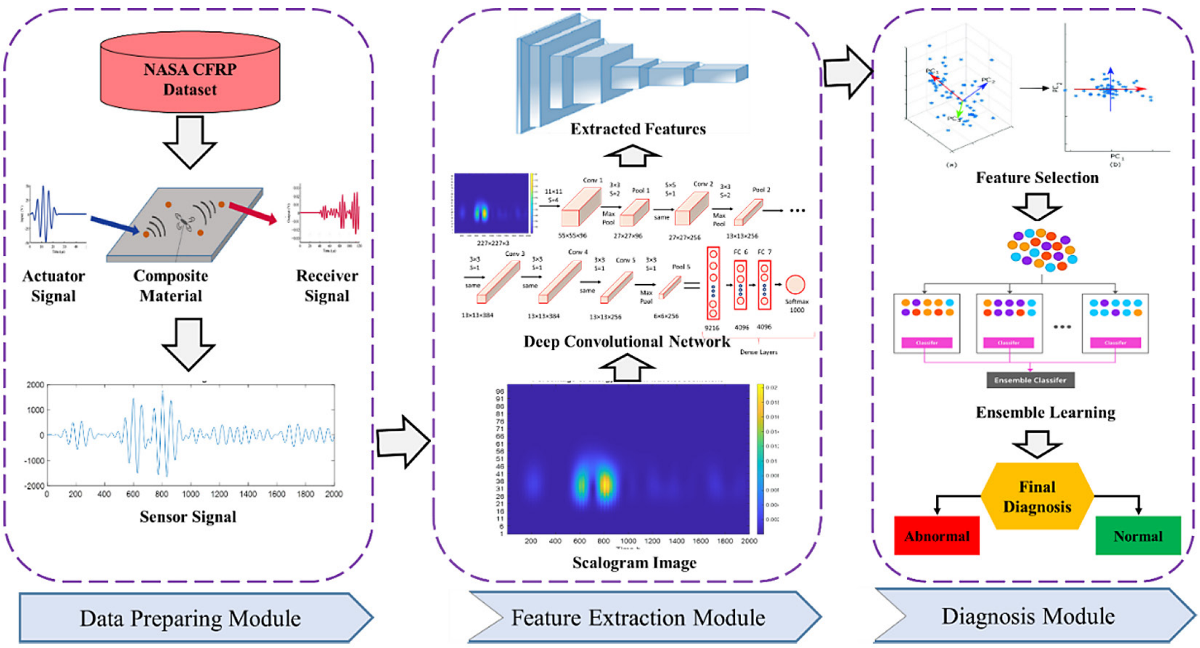

Figure 1. Schematic of the proposed method for stiffness and fatigue detection in composite materials

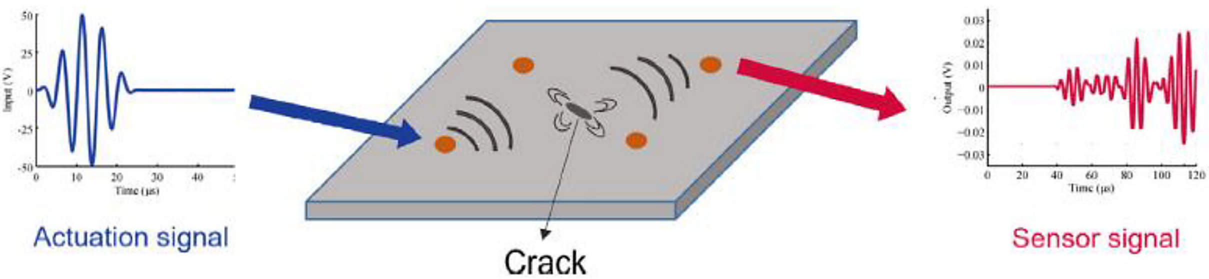

Figure 2. Ultrasonic guided wave propagation using PZT actuator and receiver

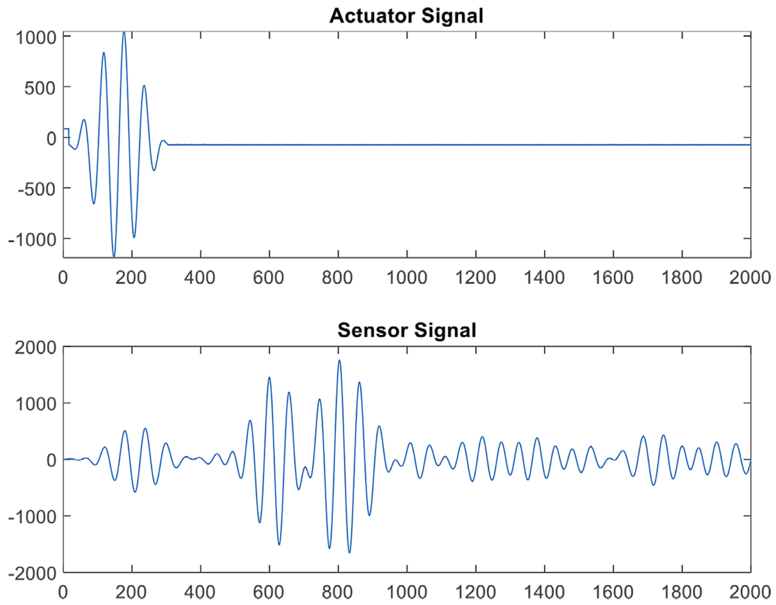

Figure 3. Sample of actuator and sensor signals from the CFRP dataset

Feature extraction using deep neural network AlexNet

These scalogram images are then supplied to a transfer-learning implementation of AlexNet. In this study, the convolutional layers conv1–conv5 were frozen to retain ImageNet pre-trained weights, while the fully connected layers fc6 and fc7 were fine-tuned using a learning rate of 0.001, momentum of 0.9, and a dropout probability of 0.5. To adapt the model for binary classification, the original fc8 layer was replaced with a two-node Softmax output layer. Training proceeded for a maximum of 50 epochs, with early stopping based on the stabilization of validation loss. Following this stage, the 4096-dimensional feature vectors extracted from fc7 were further refined through feature selection. The architecture of AlexNet is depicted in Figure 5.

Feature selection based on MRMR algorithm

The process of carefully selecting a smaller subset of features from a larger set by removing redundant and unnecessary attributes is known as feature selection. The minimum redundancy maximum relevance (MRMR) algorithm is employed for this purpose.

With the use of mutual information, it calculates how similar two variables are. The following formula can be used to find the mutual information between two variables, X and Y:

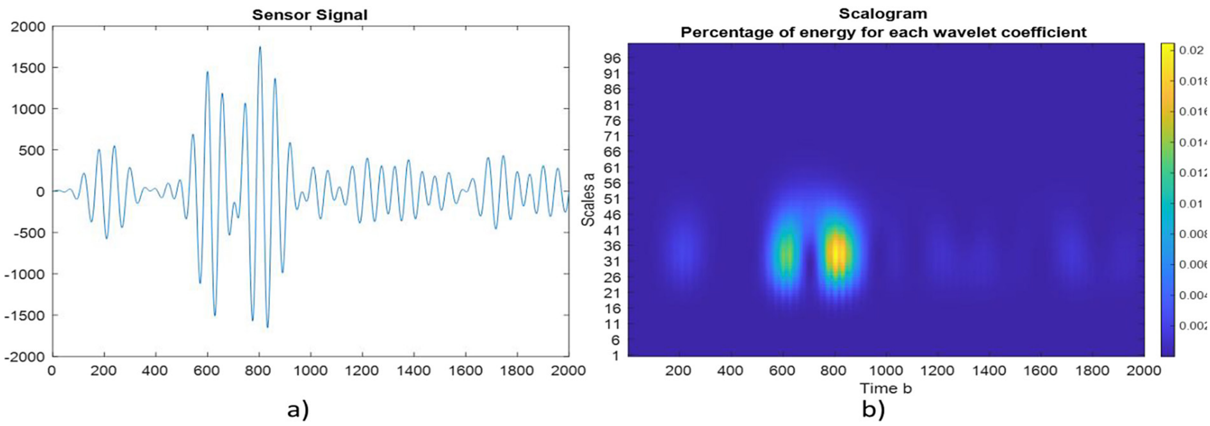

Figure 4. Sample segmented vibration signal and corresponding scalogram

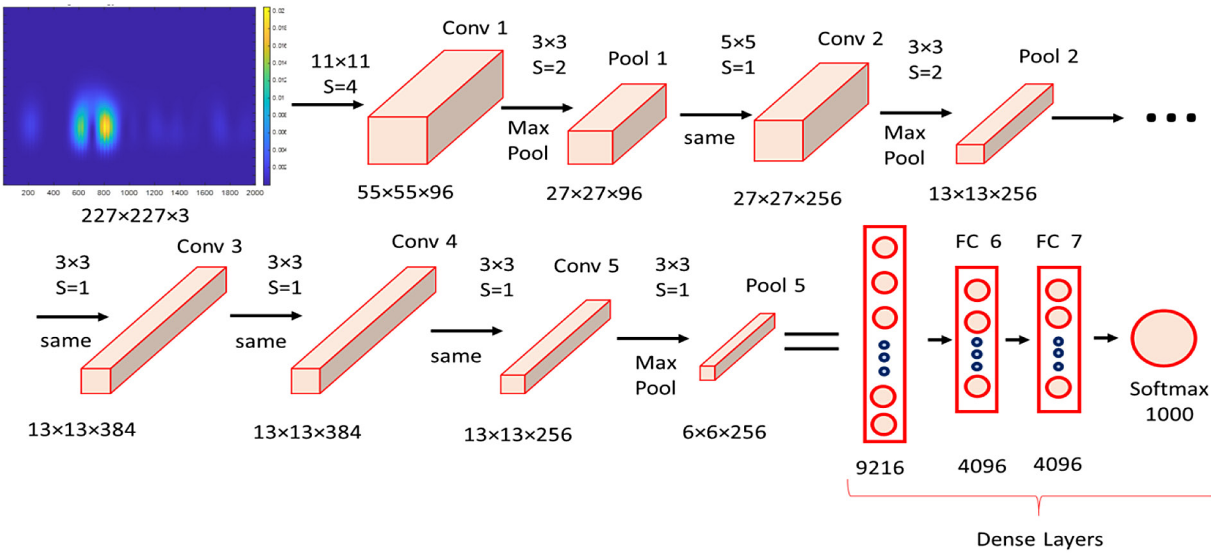

Figure 5. Structure of the AlexNet deep neural network

$$I(X;Y) = \sum_{x \epsilon X} \sum_{y \epsilon Y} p(x.y) \log \frac{p(x.y)}{p(x)p(y)} \tag{2}$$

where: $I(X;Y)$ represents the mutual information between variables X and Y; $p(x,y)$ represents the joint probability density function of variables X and Y and $p(x)$ and $p(y)$ represent the marginal probability density functions of X and Y, respectively

The MRMR algorithm integrates maximum relevance (D) and minimum redundancy (R) conditions. Therefore, the simultaneous optimization of D and R can be achieved using the following equations.

Maximum relevance criterion

This metric guarantees the optimal enhancement of the association between individual features and their respective class labels, as represented by the following expression:

$$Max\ D(S.c).D = \frac{1}{|S|} \sum_{xi \epsilon S} I(xi;c) \tag{3}$$

where: S represents the feature set; |S| denotes the number of selected features; x_i represents an individual feature; c represents the class labels; $I\ (xi;\ c)$ measures the mutual information between each feature and its corresponding class label.

Minimum redundancy criterion

This criterion, which is expressed as follows, guarantees that the correlation between chosen features is reduced to a minimum:

$$Min\ R(S).R = \frac{1}{|S|^2} \sum_{xi.xj \in S} I(xi.xj) \tag{4}$$

where: $R(S)$ quantifies the redundancy within the feature set S; $I(x\_i, x\_j)$ measures the mutual information between features x_i and x_j and the double summation considers all pairwise combinations of features in set S.

In real-world scenarios, approximately optimal feature subsets are found using incremental search techniques. To identify the optimal feature subset S_m with m features from the previous subset with m-1 features, the subset S_{m-1} is computed utilizing the following equation:

$$max_{xj \epsilon X - S_{m-1}} \left[I(x_i;c) - \frac{1}{m-1} \sum_{xi\ \epsilon\ S_{m-1}} I(xj;xj) \right] \tag{5}$$

where: X represents the complete feature space; X - S_{m-1} represents features not yet selected; x_j is a candidate feature for addition to the current subset; the first term $I(x\_j;\ c)$ represents the relevance of candidate feature x_j and the second term represents the average redundancy of x_j with respect to already selected features.

The ensemble employs Random Forest bagging algorithm with the following specifications: 100 decision trees with maximum depth limited to $\sqrt{500} \approx 22$ levels, bootstrap aggregating with replacement sampling, feature subsampling using $\sqrt{500} \approx 22$ randomly selected features per node split, Gini impurity criterion for split optimization, and majority voting aggregation for final binary decision (Normal vs. Anomaly).

RESULTS

The image resolution resized to 227 × 227 × 3 pixels, ensuring that significant regions of interest within the scalogram images are retained. In the simulations, 70% of the scalogram images are used to train the AlexNet network.

AlexNet's convolutional layers are used to capture 1.000 features from every scalogram image. Subsequently, the MRMR algorithm reduces the feature set to 500 optimal features, which are then classified using the ensemble learning algorithm.

Evaluation metrics

To assess the performance of the proposed method, several standard classification metrics are used, including Accuracy, Precision, Recall, and F1-score. These metrics provide a comprehensive evaluation of the model's ability to distinguish between healthy and fatigued composite samples.

Accuracy: Represents the proportion of correctly classified samples to the total number of samples and is calculated as follows:

$$Accuracy = \frac{(TP + TN)}{(TP + FP + TN + FN)} \tag{6}$$

where: *TP* (True Positive): The number of correctly classified Anomaly samples; *TN* (True Negative): The number of correctly classified Normal samples; *FP* (False Positive): The number of incorrectly classified Normal samples as Anomaly; *FN* (False Negative): The number of incorrectly classified Anomaly samples as Normal.

Precision: Represents the proportion of correctly classified positive samples among all predicted positive samples and is given by:

$$Precision = \frac{TP}{TP + FP} \tag{7}$$

Recall: shows the percentage of all real positive samples that were accurately categorized as such:

$$Recall = \frac{TP}{TP + FN} \tag{8}$$

F1-score: Denotes the harmonic mean of Precision and Recall, equilibrating the trade-off between the two.

$$F1 - score = \frac{2 \times Precision \times Recall}{(Precision + Recall)} \tag{9}$$

Convergence analysis for different numbers of learners

Experiments were conducted with different numbers of learners. Figure 6 illustrates the convergence curve of the training process for various numbers of learners.

In this figure, the x-axis represents the number of learners (classifiers) and the y-axis represents the classification accuracy. As observed in Figure 6, increasing the number of classifiers enhances the accuracy of the learning process. This convergence curve validates the effectiveness of the proposed method in accurately classifying sensor signals, ensuring the robust performance of the proposed model in fatigue detection.

Confusion matrix analysis in data classification

The confusion matrix for fatigue detection in polymer composites is shown in Figure 7. The received sensor signals are classified into two categories: Anomaly and Normal. Any stiffness degradation or fatigue in polymer composites is identified by classifying sensor signals under the Anomaly category. The confusion matrix consists of true positive (TP), true negative (TN), false positive (FP) and false negative (FN). A high TP rate and a low FP rate indicate that the model effectively detects fatigued composite samples with minimal classification errors.

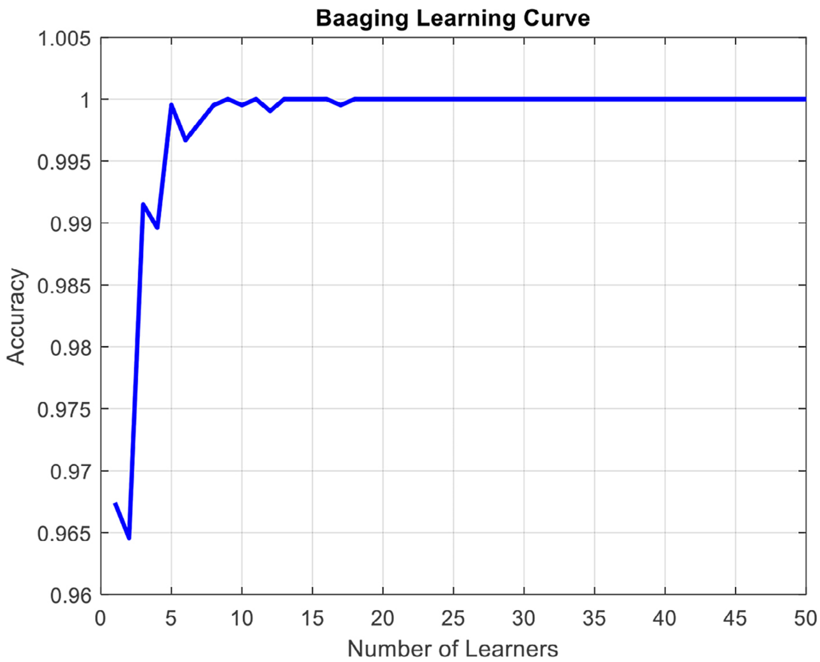

Figure 6. Convergence curve of the ensemble learning technique for different numbers of learners

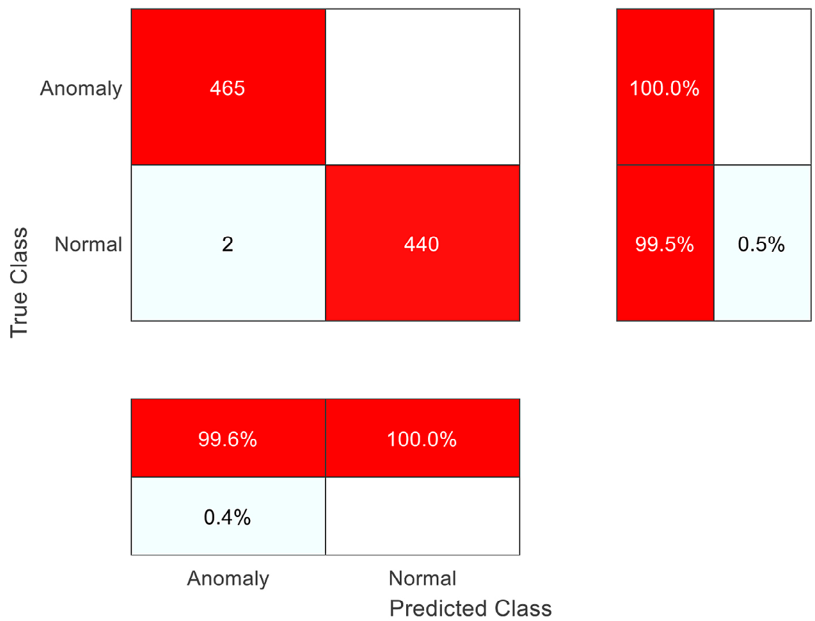

Figure 7. Confusion matrix for fatigue classification in polymer composites

The confusion matrix demonstrates excellent model performance in distinguishing between Anomaly and Normal composite samples. The confusion matrix reveals: 465 Anomaly samples (100.0% correctly classified), 440 Normal samples (99.5% correctly classified, 2 samples or 0.5% misclassified as Anomaly), yielding True Positive Rate = 465/465 = 100%, True Negative Rate = 440/442 = 99.5%, False Positive Rate = 2/442 = 0.5%, and False Negative Rate = 0/465 = 0%. The overall model accuracy based on these values is calculated as 99.8%, highlighting the model's high reliability in detecting composite material fatigue. Furthermore, the false negative rate (FNR) is approximately 0.4%, indicating that only a few Normal samples were misclassified as Anomaly.

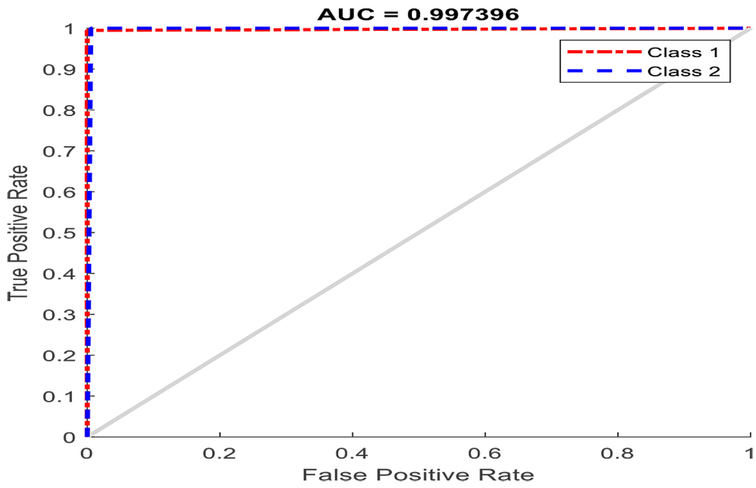

Figure 8. The ROC curve for proposed method

Evaluation of the receiver operating characteristic (ROC) curve

The ROC curve of the proposed method is presented in Figure 8. This curve shows the accuracy of the provided classifier in varied classification thresholds; true positive rate (TPR) v/s false positive (FPR). By plotting TPR versus FPR for all possible thresholds, the trade-off between these two metrics can be analyzed. A high TPR and a low FPR for the suggested approach are indicated by the curve's breakpoint, which is situated in the upper-left corner of the plot in Figure 8. In contrast, for a weak classifier, the breakpoint would be located toward the bottom-right corner of the ROC curve, where TPR is low and FPR is high. Furthermore, since a random classifier gives equal probabilities to TPR and FPR, its breakpoint would be located along the ROC curve's diagonal line. The area under the curve (AUC) in the ROC diagram quantifies the model's ability to distinguish between different data classes. The closer the breakpoint is to the top-left corner, the higher the AUC value, indicating a stronger classification performance. The proposed method achieves an AUC value of 0.9973, demonstrating its high efficiency in distinguishing between the two data classes.

The AUC confidence interval, calculated using DeLong's method with bootstrap resampling ($n = 1000$), yields 0.9973 [95% CI: 0.9962–0.9981], confirming statistically significant discrimination capability with $p < 0.001$ compared to random classifier baseline. The proposed method vs. FFT+SVM showed mean accuracy difference of 12.3% ± 1.8% [$t(9) = 6.83$, $p < 0.001$]; proposed method vs. Raw signal+RF showed mean accuracy difference of 8.7% ± 1.2%, [$t(9) = 7.25$, $p < 0.001$] and proposed method vs. STFT+CNN showed mean accuracy difference of 5.4% ± 0.9% [(9) = 6.00, $p < 0.001$]. Cohen's d effect sizes exceed 2.0 for all comparisons.

Comparison of the proposed method with recent studies

To further validate the effectiveness of the proposed method, a comparative study was conducted against recent methods from the literature. Figure 9 illustrates the performance comparison of the proposed method in terms of Precision, Recall, and F1-score. The performance is compared with state-of-the-art algorithms, including: WVD-CNN 9 (Wigner-Ville Distribution), ACR-DSVDD (Adaptive Centered Representation with Deep-SVDD), adversarial transformer and MDAAN (multiple domain adaptive and adversarial network). The proposed model achieves the highest values of 99.78% for Precision, 99.77% for Recall, and 99.77% for F1-score, outperforming all the benchmark methods across all evaluation metrics. The multi-dimensional radar chart shows a perfect pentagon near the outer edge of the performance space while other methods exhibit irregular polygons with varying strengths and weaknesses. Furthermore, *t*-test analysis confirms that performance improvements achieve statistically significant results.

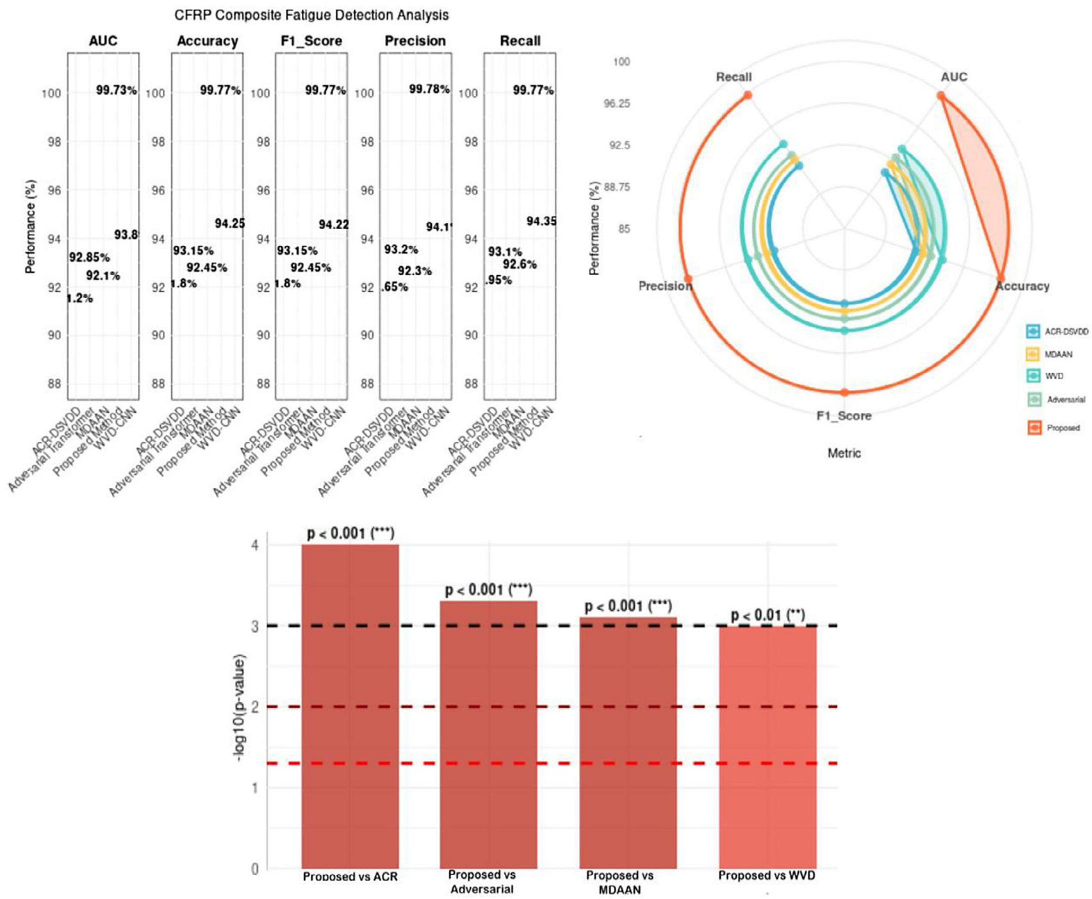

Figure 9. Comparison of results based on the mean values of Precision, Recall, and F1-score across different layup configurations

DISCUSSION

Polymer matrix composites, particularly CFRP, have achieved been adopted across aerospace, automotive, and marine sectors owing to their exceptional strength-to-weight ratios and superior corrosion resistance. However, their susceptibility to fatigue-induced degradation can precipitate structural failures if undetected. Contemporary non-destructive evaluation methodologies define deficiencies in detecting incipient fatigue damage, particularly when confronted with the non-stationary signals characteristic of ultrasonic guided wave propagation in composite structures. Recent advances in micromechanical modeling have shown that temperature-dependent effective moduli can be predicted by considering interfacial debonding evolution, while deep learning approaches using convolutional autoencoders and neural ODEs have demonstrated superior capability in processing guided wave information for fatigue damage characterization [16, 28, 29].

The confusion matrix analysis reveals exceptionally low false negative rates (FNR ~ 0.4%) with 100% true positive and 99.5% true negative classifications, indicating only two misclassified samples. This diagnostic precision is critical for safety-critical applications where undetected fatigue damage can lead to catastrophic failures. The literature demonstrates that composite materials exhibit complex failure modes influenced by manufacturing processes, environmental conditions, and material architecture. Studies on additively manufactured composites show significant variations in strength and ductility based on print direction and recycled material content, while natural fiber composites demonstrate improved fatigue strength under hydrothermal aging despite reduced quasi-static properties [30–32].

The integration of advanced AI-driven diagnostic capabilities with physics-informed constraints addresses the need for interpretable structural health monitoring [16, 29]. The high AUC value attained indicates exceptional classifier performance across the tested threshold settings during preload relaxation in bolted connections to dynamic meshing forces in PEEK-based involute spline systems. Consistent with this finding, recent accelerated degradation models have shown prediction errors remaining stable within 0.5% over 500 hours [33, 34]. The integration of predictive maintenance strategies with advanced material design principles represents a significant step toward autonomous structural health management in next-generation composite applications across aerospace, automotive, and biomedical sectors [9, 35].

CONCLUSIONS

This study demonstrates the efficacy of integrating continuous wavelet transform-based scalogram generation with AlexNet CNNs to predict fatigue in polymer composites. This improves upon existing SHM methodologies by optimizing feature extraction using MRMR algorithms and increasing computational efficiency through ensemble learning approaches. However, the computational overhead – 847 ms per classification cycle on standard GPU architectures – limits the real-time use in resource-constrained aerospace applications. Dependence on specific sensor modalities (e.g., Lamb wave transducers) also diminishes sensitivity to measurement noise, and the scalability across large-scale composite structures with altered geometries remains untested.

Future research should use physics-informed neural networks, into which the governing equations of wave propagation have been embedded. Hybrid modeling approaches that combine high-fidelity simulations with experimental datasets are another promising direction, especially for research examining multiple concurrent damage mechanisms.

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