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ORIGINAL

Hybrid weighted sequential learning technique for structural health monitoring using learning approaches

Técnica híbrida de aprendizaje secuencial ponderado para la supervisión de la salud estructural mediante enfoques de aprendizaje

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ABSTRACT

Structural Health Monitoring (SHM) plays a vital role in damage detection, offering significant maintenance and failure prevention benefits. Establishing effective SHM systems for damage identification (DI) traditionally requires extensive experimental datasets collected under varied operating and environmental conditions, which can be resource-intensive. This study introduces a novel approach to SHM by leveraging a Hybrid Weighted Sequential Learning Technique (HWSLT) classifier, which uses Finite Element (FE) computed responses to simulate structural behaviors under both healthy and damaged states. Initially, an optimal FE model representing a healthy, benchmark linear beam structure is developed and updated using experimental validation data. The HWSLT classifier is trained on SHM vibration data generated from this model under simulated load cases with uncertainty. This allows for minimal real-world experimental intervention while ensuring robust damage detection. Results demonstrate that the HWSLT classifier, trained with optimal FE model data, achieves high accuracy in predicting damage states in the benchmark structure, even when mixed with random disturbances. Conversely, data from non-ideal FE models produced unreliable classifications, underscoring the importance of model accuracy. These findings suggest that the integration of ideal FE models and deep learning offers a promising pathway for future SHM applications, with potential for reduced experimental costs and enhanced damage localization capabilities.

Keywords: Structural Health Monitoring; Damage Detection; Deep Learning; Finite Element Analysis; Vibration.

RESUMEN

La monitorización de la salud estructural (SHM) desempeña un papel fundamental en la detección de daños y ofrece importantes ventajas para el mantenimiento y la prevención de fallos. El establecimiento de sistemas SHM eficaces para la identificación de daños (DI) requiere tradicionalmente amplios conjuntos de datos experimentales recogidos en condiciones de funcionamiento y ambientales variadas, lo que puede requerir muchos recursos. Este estudio introduce un enfoque novedoso para la SHM aprovechando un clasificador de técnica de aprendizaje secuencial ponderado híbrido (HWSLT), que utiliza respuestas calculadas de elementos finitos (FE) para simular comportamientos estructurales tanto en estados sanos como dañados. Inicialmente, se desarrolla un modelo de EF óptimo que representa una estructura de viga lineal sana de referencia y se actualiza utilizando datos experimentales de validación. El clasificador HWSLT se entrena con datos de vibración SHM generados a partir de este modelo bajo casos de carga simulados con incertidumbre. Esto permite una intervención experimental mínima en el mundo real a la vez que garantiza una detección robusta de los daños. Los resultados demuestran que el clasificador HWSLT, entrenado con datos óptimos del modelo FE, alcanza una alta precisión en la predicción de estados de daño en la estructura de referencia, incluso cuando se mezcla con perturbaciones aleatorias. Por el contrario, los datos de modelos de EF no ideales produjeron clasificaciones poco fiables, lo que subraya la importancia de la precisión del modelo. Estos resultados sugieren que la integración de modelos FE ideales y el aprendizaje profundo ofrece una vía prometedora para futuras aplicaciones SHM, con potencial para reducir los costes experimentales y mejorar las capacidades de localización de daños.

Palabras clave: Monitorización de la Salud Estructural; Detección de Daños; Aprendizaje Profundo; Análisis de Elementos Finitos; Vibración.

INTRODUCTION

Structural Health Monitoring (SHM) focuses on indirectly detecting structural changes, allowing for maintenance and damage prevention without physical inspection.(1) Similar to Condition Monitoring (CM) in mechanical systems, SHM involves data collection over time, facilitating damage identification through analysis of structural responses.(2,3) SHM has gained prominence due to its potential to reduce maintenance costs and prevent catastrophic failures in both large structures, such as bridges and turbines, and smaller, complex systems, like aircraft components and transmission networks.(4) Typically, SHM systems employ a sensor network to gather acoustic or vibrational data for either on-demand or continuous real-time processing. Through a training phase, models are taught to differentiate between faulty and normal conditions using either supervised or unsupervised learning.(5)

Effective SHM design involves three key phases: learning, data collection, and real testing.(6) The data acquisition stage is particularly crucial, as it influences subsequent processes. Structural responses can be simulated using numerical techniques like Finite Element (FE) analysis or collected through sensors. However, empirical data collection can be limited by environmental complexities and practical constraints.(7) Laboratory alternatives or unsupervised learning are often utilized to overcome this limitation.(8,9) With realistic FE models, simulations can emulate various load scenarios and damage types, enabling SHM data generation with minimal experimental intervention.(10)

Machine learning (ML) classifiers, particularly artificial neural networks (ANNs) and support vector machines (SVMs), offer powerful damage detection solutions.(11,12) ANNs, especially Convolutional Neural Networks (CNNs), excel at feature extraction from raw data, reducing the need for manual preprocessing.(13) CNN-based SHM classifiers can handle both supervised and unsupervised detection if provided with accurate input data. We employ CNNs with FE-simulated data to minimize data preprocessing, leveraging optimal FE models fitted to healthy states and adjusted for damaged scenarios. This combination supports efficient damage classification with minimal empirical testing.(14)

Our study uses a benchmark steel beam to validate the CNN-based SHM system. With minimal artificial damage introduced, CNNs trained on FE data detect structural states, assessing damage identification accuracy across binary and multiclass classification tasks. Comparing nominal and optimal FE-trained models emphasizes the importance of model accuracy, with Hybrid Weighted Sequential Learning Technique (HWSLT) classifiers offering promising potential for future SHM tools that integrate supervised DL classifiers with numerically generated data.(15)

This paper is structured as follows: Section 2 reviews key approaches, Section 3 details methodology, Section 4 presents findings, and Section 5 concludes.

Related works

Long-term exposure to external stresses, such as wind, earthquakes, vehicles, environmental vibrations, etc., can cause a variety of problems in building structures. As a result, it may compromise the building's overall security and structural integrity, thereby endangering people and property.(16) Therefore, SHM is crucial regardless of how complex the facility is or how many key components it contains. For example, the proper growth of concrete constructions requires the preservation of solid and long-lasting properties, which are intimately tied to the mortar's composition and ratio.(17) SHM is necessary to evaluate durability by examining vibration, stress, and other relevant factors since a decrease in strength and durability indicates structural instability. As stressed by [18], structural characterization and sensing technologies are essential for detecting potential damage or deterioration in SHM. As said, SHM includes evaluating structural conditions, recognizing various forms of structural degradation, and keeping an eye on operational status. Essentially, SHM's primary goal is to identify, detect, and evaluate the structural operating conditions to facilitate efficient damage detection and condition evaluation. Its core element is Damage Detection (DD), which is the identification, localization, and evaluation of structural damage. Four categories were established for damage identification in the Rytter research.[19] (1) Detection: the process of figuring out whether harm exists. (2) Location: Find the coordinates and location of the damage. (3) Assessment: figuring out how much damage has been done. (4) Repercussions: acquiring precise safety information for the structure in its evaluated level of damage.[20] Identifying the system, evaluating its state, collecting data, and carrying out maintenance are the fundamental elements of structural health monitoring, or SHM. Sensors and sensor data collected during the data-collecting phase are essential components of SHM applications.[21] Contact sensors, such as strain gauges, accelerometers, and fiber optic sensors, as well as non-contact sensors, such as telephones, drones, and high-speed cameras, are used to assess the building's operating state. Following the diagnosis of damage, the status is evaluated by employing data processing methods including machine learning (ML), deep learning (DL), and signal processing techniques to find characteristics linked to damage.[22] The optimal course of action for preserving the structure's service and safety life is finally decided by the evaluation's findings. In the past, visual inspection was the main technique for SHM; however, it had a number of drawbacks, such as poor accuracy, low efficiency, subjectivity, and high labor and time costs. The main structural component is progressively monitored using non-destructive testing (NDT) techniques, such as eddy current, X-ray, magnetic particle inspection, ultrasound, and acoustic emission (AE).[23] The most often used methods at the moment are vibration-based, guided wave (GW)-based, AE-based, and electromechanical impedance (EMI)-based structural health monitoring (SHM) techniques. A popular technique is vibration-based SHM, which looks at the relationship between damage states and vibration characteristics. For SHM, it is often possible to distinguish between model-driven and data-driven DD techniques.[24] The former calibrates a Finite Element Model (FEM) for structural damage analysis using optimization techniques and sensor data. The latter detects structural degradation immediately by using sensor data. Additionally, data-driven methodologies are growing in popularity because of their versatility and capacity to identify structural integrity by extracting damaged properties from sensor data. Consequently, the Gaussian model, ML, and DL have gained popularity as data analysis methods.[25]

SHM is also included in the vibration-based and image-based DL techniques. Image processing methods including segmentation, classification, and identification are made possible by the use of deep learning to extract features from images of structural surface damage. The photos are then separated into two groups: damaged and undamaged. Additionally, the location and coordinates of the affected area have been determined. The last method uses pixel-level segmentation to categorize picture pixels as intact or degraded. Convolutional Neural Networks (CNNs) are the most widely used deep learning (DL) method for detecting damage in structural surface pictures. CNN may be used for tasks including object identification, image classification, and semantic segmentation. Two-Dimensional Convolutional Neural Networks (2D-CNN), Mask Region-Based Convolutional Neural Networks (Mask R-CNN), Fully Convolutional Networks (FCN), Region-based Convolutional Neural Networks (R-CNN), U-Net, and Look Only Once (YOLO) are a few of the CNN algorithms that are commonly used for this purpose.[26,27] The author in [28] classified the nuts, nut holes, and bolts on the steel bridge using convolutional neural networks (CNN) using pooling and convolution techniques after assessing the bridge picture using the sliding window methodology. In order to quantify cracks, the author used edge detection techniques to extract cracking outlines and boundary frame selection in combination with YOLOv4 to identify bridge fractures.[29] To generate an iterative loop U-Net that can accurately identify fracture forms, they divide pictures between pixels that have cracks and those that do not. In images of infrastructures including dams, frame buildings, bridges, tunnels, and more, our deep learning system can identify structural abnormalities like cracks, rebar surface flaws, bolt loosening, voids, displacement, delamination and reinforcement exposure. A number of studies have shown this capacity.[30]

The objective of this study is to develop an efficient Structural Health Monitoring (SHM) framework that integrates optimal Finite Element (FE) models with deep learning classifiers, specifically a Hybrid Weighted Sequential Learning Technique (HWSLT). This framework aims to minimize experimental interventions by leveraging FE-simulated data to train convolutional neural network (CNN)-based classifiers, ensuring accurate and reliable damage detection in structural systems. By testing on a benchmark structure with simulated damage scenarios, this study seeks to demonstrate the potential of a numerically driven SHM approach, advancing future applications of SHM in complex environments while reducing dependency on costly experimental data collection.

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METHOD

The objective of this study is to develop an efficient Structural Health Monitoring (SHM) framework by integrating Finite Element (FE) models with deep learning classifiers, specifically a Hybrid Weighted Sequential Learning Technique (HWSLT), for accurate damage detection. This applied research leverages FE-simulated structural response data to train convolutional neural networks (CNNs), enabling automated feature extraction with minimal manual preprocessing and reliable classification of structural states. Statistical analysis is conducted through accuracy, precision, and recall metrics to evaluate classifier performance, with comparative analysis of nominal and optimized FE models validating the framework's robustness across different damage scenarios. The study involves no human or animal subjects; ethical considerations include maintaining data integrity, transparent modeling practices, and result reproducibility to ensure applicability in structural safety and SHM advancements.

Dataset

A variety of random signals with different signal-to-noise ratios (SNR) were added to the experimental function of the architecture. This approach used measurement noise instead of actual empirical information to evaluate the impact of sensor accurateness on the efficacy of the developed methodology. Further details are provided in the next sections. With an evenly distributed floor mass of $m = 620$, tones, the hypothetical eight-story shear building under examination has a uniform inter-story rigidity of $k^{sh}=10^6$ kN/m.

Prediction

The simulated ideal FE information is sent into the convolutional neural network for learning at the next step of the suggested SHM approach. Only supervised learning that applies DI to the structure of interest will be used in this research. The Hybrid Weighted Sequential Learning Technique (HWSLT) classifier designs allows the prediction of SHM. The dataset is partitioned into learning and verification portions at the learning stage, and our general goal is a high learning testing precision. For the actual testing that comes at the final process, this is the only proof that the artificial neural network has mastered the task effectively. More load cases required the FE model if the data is not sufficiently even or if substantial deviation is measured throughout feature learning.

Testing and evaluation

The suggested SHM approach moves on to actual testing, which incorporates actual damage conditions next to the HWSLT have been effectively trained. For representative assessments, a sufficient number of actual measurements have to be taken for every case. Following that, the signals are fed into FE-trained HWSLT, which identify potential actual standard states. The accuracy of classification is typically the first criterion used to evaluate DI systems. Recall and precision values, as well as potential classifier biases, are additional metrics that are utilized as standards in DL applications and include useful data in addition to classification accuracy. The level of the testing conducted at the HWSLT learning reflects actual testing accuracy and how well it may serve as a reliable predictor for issues of a similar nature in future phases can also be investigated.

LSTM

One kind of network that provides data persistence simpler is LSTM because it can handle huge parameter sizes and employ nonlinear activation functions in each layer related to SHM, it is especially well-suited for managing enormous quantities of data. By analyzing individual SHM data points and complete data sequences, LSTM, in contrast to the original RNN, resolves the vanishing gradient problem. It also captures nonlinear trends in the data and retains historical information for a long time. LSTMs can learn from long-term dependencies and alter their cell state and other gates. There were several hidden layers present in the architecture of LSTM. The framework becomes increasingly intricate and appropriately categorized as a deep learning technique when LSTM hidden layers are added. Figure 1 shows the input gate, forget gate, output gate, and self-circulation neuron, which are the four primary parts of an LSTM memory cell. An input gate allows memory cells to exchange information to each other and to their neighbors. The input gate decides whether a signal that arrives can alter the memory cell's configuration. However, depending on whether the other memory cell condition is flexible, the output gate could control the memory cell state. Additionally, the forget gate has the option to retain or delete the prior state. We employed a 3-layered weighted LSTM design in this investigation.

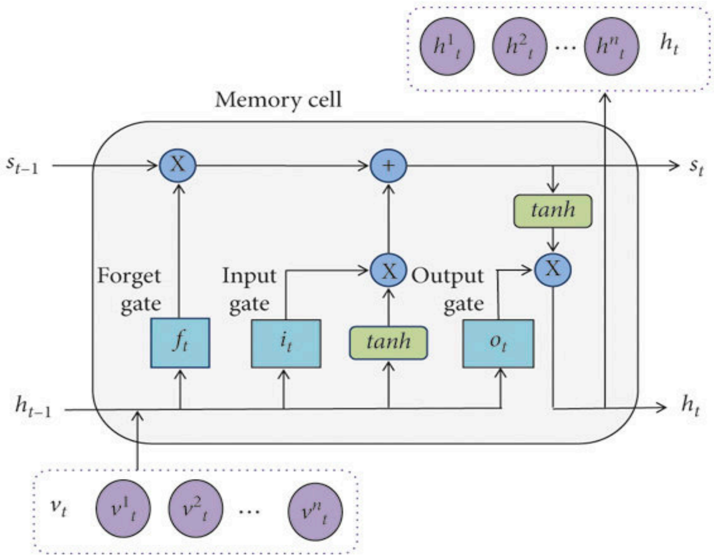

Figure 1. Traditional LSTM model

The activation function present in the 32 cells was included in both the first and second hidden layers. This solves the issue of vanishing gradients, where output recognition reliability and efficacy are at their highest. 32 cells in the third layer use the sigmoid activation function to forecast the output's possibility. One fully connected neuron makes up the output layer. Figure 2 shows the framework's specification. The neural network was configured using the "keras" repository and a collection of functions called LSTM, Sequential, and Dense. The following hyper-parameters were used in the model's construction: Batch size = 30 (samples count per gradient update); epochs = 500 (epochs count for the methods training); units = 32 (dimensionality of the output space). Adaptive Moment Estimation (Adam), an optimization approach that is successful in reality, was employed with a learning rate, which is equal to 0,001. To avoid over-fitting, early termination was employed as a form of regularization.

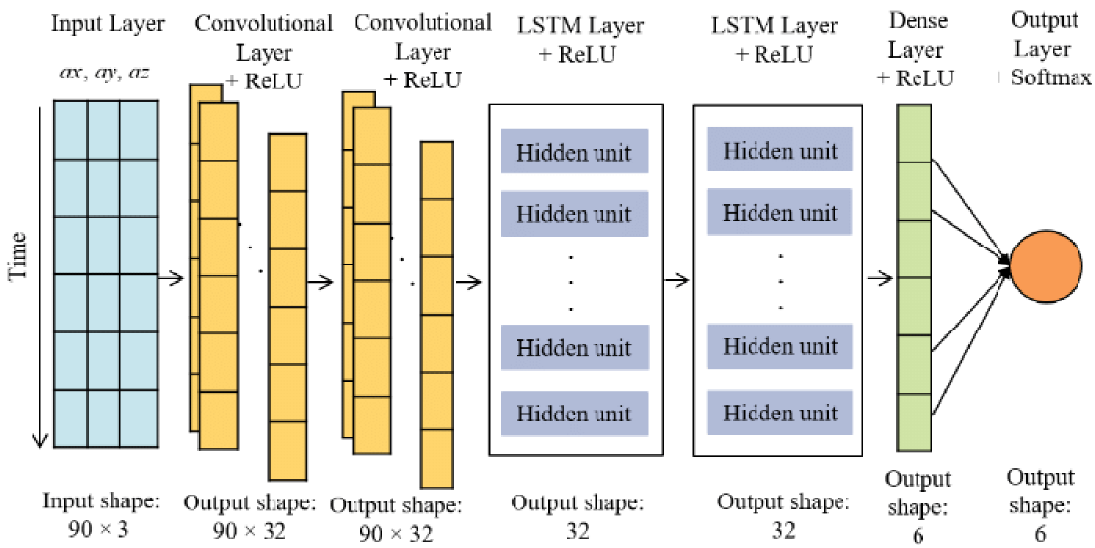

Figure 2. Hybrid model

Hybrid model

A class of DL techniques called Convolution Neural Networks (CNNs) was created especially to handle data with grid-like arrangements, like photographic images. As shown in figure 2, convolution, pooling, and a fully connected layer are the three primary parts of a CNN. Feature extraction is done in the pooling and convolution layers. The fully connected layer then maps the retrieved features into the final results, which could include classification. Digital images' values for pixels can be shown as 2-D grids known as matrices. For extracting the image features this research implements kernel, which is a supplementary grid parameter. The efficiency of the entire image learning procedure is derived from the features of the images that are determined by the "kernel". By implementing an integrated CNN-LSTM deep learning approach, this study offers a novel method for predicting temperature time series information. A series of historical data points is used to predict the following series of further data points in the prediction process, which operates as a sequence-sequence learning methodology. The numbers for the next 6-month timeframe are predicted using the previous 12-month records. The model gains insight into the expected patterns on the test dataset that have not been seen before. Trends and seasonality are both well-represented in the framework. For CNN operations on 1-D time sequence information, the first step entails performing matrix operations using a 3-D array structure. Furthermore, the CNN layer performs a convolution operation on the time series data once it has been processed as a 3-D array. Conv1D is used to execute calculations on the CNN layer, yielding the feature map. The recurrent layer's LSTM cells are then linked to learn the time series data. Without requiring extensive fine-tuning, the design of the framework has the capacity to learn the seasonality and pattern of the series automatically. Figure 2 shows the schematic depiction of the proposed concept. First, the data is resized and reshaped to meet the sequential system's 3-D input demands. For a basic univariate approach, the input shape would include only one feature. Additionally, we decided on a kernel size of 5. Six output numbers are generated by the dense layer. A thorough model summary can be found. The size of the batch input is 16. Ultimately, the model outputs the loss after being fitted for 200 epochs. Adam optimization and the mean squared error loss function were applied. Through the processes of data selection, extraction, and preparation, a high-quality fundamental training dataset is obtained, which enables the effectiveness of the technique for temperature prediction. Performing a transfer test and identifying the missing values in the adopted dataset are included in the following steps. The model is obtained by monitoring and identifying the optimal hyper-parameters for the suggested model.

Numerical results and discussion

The numerical discussion presents the numerical findings of the hybrid weighted sequential learning technique (HWSLT) and the learning data production stage. To demonstrate the possible performance improvement of the most favorable FE data on identifying the observed states, frameworks are trained on FE-produced information in 2 scenarios: i) optimal FE and ii) nominal FE-produced data. This section also presents the forecasting of experimental states, where class scores are computed using FE-trained HWSLT using actual measured input. The learning outcomes and empirical validations obtained from "multi-head" and "single-head" one-dimensional convolutional neural networks with Grid-Search-tuned parameters are displayed. Results are shown for the binary DI issue, which involves separating the Healthy from Damage 1 and Damage 2 beam states. Table 1 displays the HWSLT learning outcomes for the data obtained from the nominal and optimal FE. The algorithms have effectively learned the FE task, as seen by the values, which show a significant learning accuracy in validation for all cases. It is hoped that the networks trained using FE would also generalize effectively on actual measurements. Moving on to the empirical verification, Fig 2 displays the trained network forecasting class scores based on the learning data from the FE structure. The following is how all of the inputs for the class forecasting values are obtained from set 14 to set 16. The class forecasting values for inputs provided from the empirical observations set 14, which represents the Healthy benchmark states, are displayed in the top portion of the charts. The bottom plots, which are equally selected from experimental sets display class predictions based on the damaged benchmark state data. The network kind "single" or "multi-head" is employed to separate the left and right outcomes, respectively. The class threshold for the network prediction scores is 0,5, and the scores range from 0 to 1. The network uses red for the damaged class score and blue for the Healthy class score. In the network results, the total columns are always 1. The confusion matrices in figure 3 summarize the whole prediction of class scores for 10 experimental inputs, excluding the displayed 20 measurements. The matrices show the same correlation between class predictions and inputs as shown in figure 4. Set 14 provides 100 inputs corresponding to the healthy class targets, whereas sets 15 and 16 facilitate 50 measurements each belonging to the damaged class targets. The following is an explanation of the confusion matrices' components. While off-diagonal components always display misclassified cases, diagonal components display the number of accurately categorized cases (in conjunction with their proportion).

Table 1. HWSLT parameters

Layers	Output	Parameters
Conv_1D	(-,8,6)	36
LSTM	(-,8,6)	312
LSTM_1	(-,6)	312
Dense	(-,6)	42

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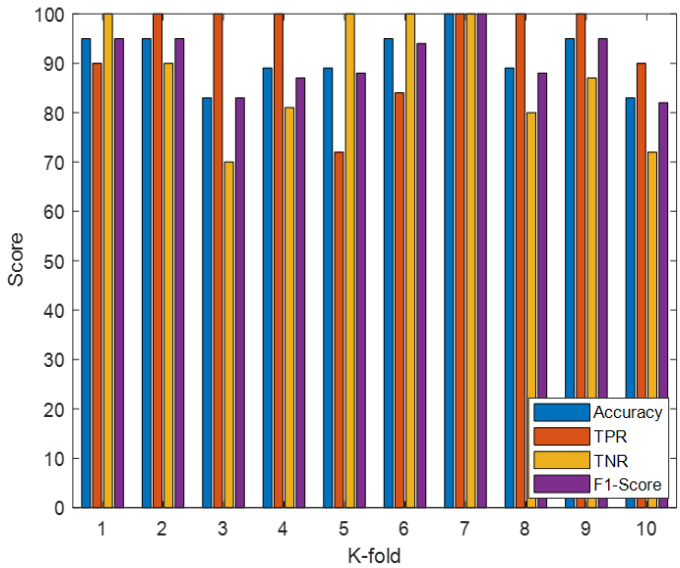

Figure 3. Evaluation metrics with kernel weight

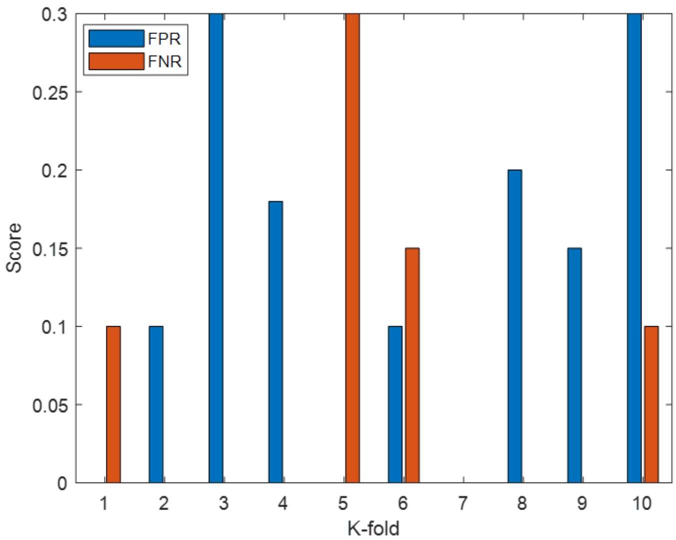

Figure 4. FPR and FNR evaluation

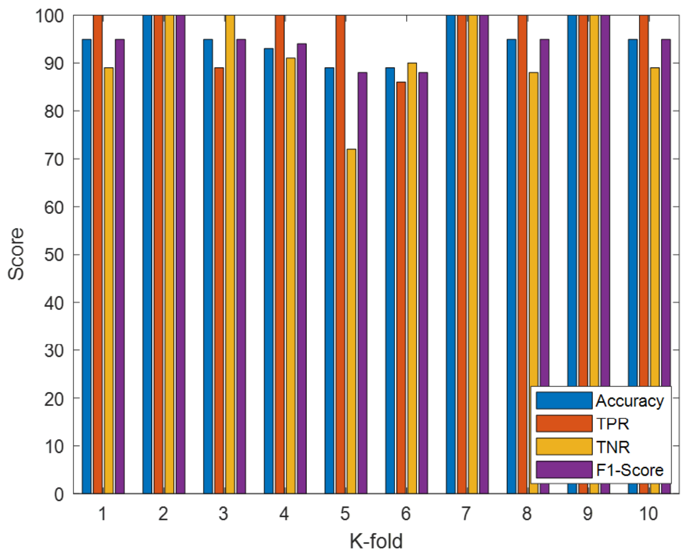

Figure 5. Evaluation metrics with successive iterations

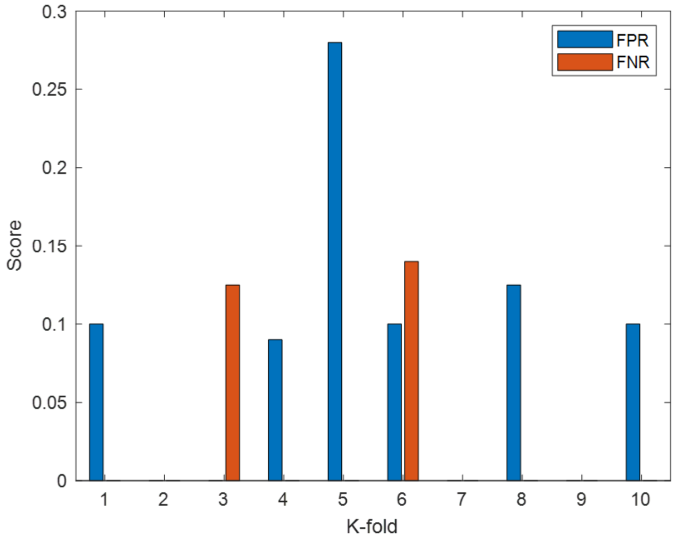

Figure 6. FPR and FNR evaluation with successive iterations

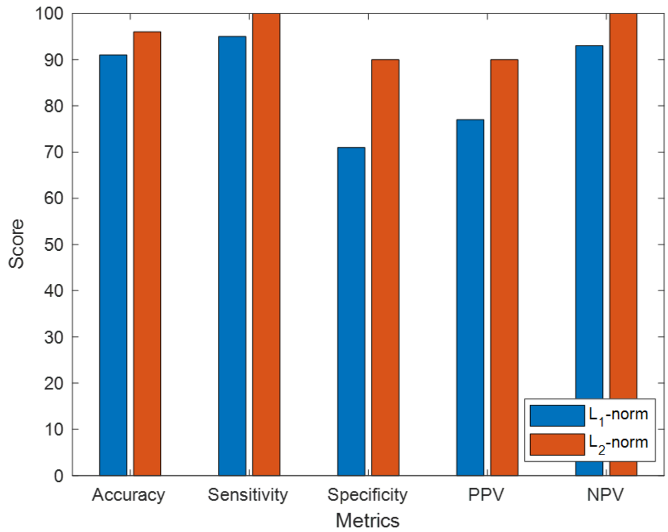

Figure 7. Comparative analysis based on conventional approaches

The average precision and damage are displayed that are arranged diagonally. The accuracy and false prediction rates are displayed. Recall and FN rates are displayed. As anticipated, the “single-head” systems trained by the conventional set obtained the lowest scores, while the “multi-headed” systems trained by the best possible FE feature set scored the highest. The latter generated forecasts were skewed heavily in favor of the Healthy class. For this binary issue an optimal technique proved to be more significant than adopting a “multi-head” design. The “single-head” system outperformed the “multi-headed” network by a slight margin. Even when trained using nominal FE-derived datasets, the “multi-headed” DL classifier was still able to produce satisfactory results, with the lowest accuracy of 67 %. It must be emphasized once more that the combination of random base excitations and the minor damage magnitudes applied to the benchmark create a challenging problem. In contrast to the inaccurate outcomes obtained when single filter learners were employed, the multiple filter length structure demonstrated that it was learning enough appropriate characteristics regardless of nominal FE data. Additionally, the researcher should be informed that the experimental forecasting accuracy and the network learning reliability for validation differ. The superior learning accuracy of 93 percent, particularly for the “single-head” system trained using nominal FE data, indicates that it has mastered the FE task effectively; nevertheless, this is not at all represented in the actual setup. Therefore, the difference between simulated and actual responses can be reduced by using an optimal FE technique and wider DL properties by varying the filter sizes.

The learning and experimental validations from the “multi-headed” one-dimensional convolutional neural networks with grid-search-tuned parameters for the multiclass DI issue are presented. In this instance, the aim is to split the three benchmark states: Damaged 1, Healthy, and Damaged 2 into a corresponding three-class problem following the FE training process. With CNN algorithms having poorer learning accuracy for validation on the FE-generated datasets, the computed values demonstrate that the multiclass DI is more highly required than the binary of paragraph 6,3. Except for the ideal FE dataset “single-head” convolutional neural network, validation accuracies of almost 80 % are noted, indicating that systems have sufficiently learned the task and may be able to solve the problem effectively. This time, the experimental data sets are the complete sets (14 to 16) that include 100 measurements of every benchmark state. By the FE model learning data extraction, figure 3 to figure 7 display the class identification values from the pre-trained CNN on the measurements. Class scores using Healthy benchmark research sources (set 14) are displayed in the top charts. The class identification outcomes based on Damage 1 (set 15) and Damage 2 (set 16) experimental inputs are shown in the center and bottom charts, respectively. The single-head and multi-head network forecasts are displayed respectively. This time, the class value falls between 0 and 1, but the overall average of the three classes equals 1. The highest score is used to identify the class. The same format is used to present the findings in the matrices. With 83,3 % global accuracy, the “multi-headed” network that was trained using the ideally FE extracted set can record the best predictions once more. With incorrect Damage 2 forecasts of 16 % in the Healthy benchmark measures and 29 % in the Damage 2 observations, it seems to be the most challenging and hard to differentiate between the Healthy and Damage 2 states. On the other hand, Damage 1 measures seem to be accurately anticipated, with a 96 % TP rate. The prediction image is significantly different for the “multi-headed” network trained using the nominal FE-derived data set. Although the levels of Damage 1 are recognized with 100 % accuracy, the system is unable to differentiate states to a satisfactory degree, and its overall accuracy on the experimental data is 65,3 %. Healthy measurements have a 56 % erroneous Damage 1 prediction rate, whereas Damage 1 measurements contain a 31 % false rate for Healthy forecasts. In contrast, single-head systems performed poorly in every scenario for both FE data sets. The researcher could additionally observe that the “single-head” systems struggled to make a definitive class prediction, with computed scores typically falling below 0,5. Therefore, it seems that the multiclass DI requires both excellent FE data and a “multi-headed” design. Lastly, discrepancies between the actual prediction values and the validation values for FE data learning show that only “multi-head” systems trained with an ideal FE data set can generalize accurately on experimental observations. When trained using the nominal FE data set, the “single-head” networks in particular displayed a high degree of discrepancy between learning and empirical validation results. It is additionally demonstrated that understanding the simulated FE issue does not guarantee successful standardization in the actual experiment.

CONCLUSION

The HWSLT-based deep learning classifiers, trained solely on numerically generated structural data, have demonstrated promising results for damage identification in Structural Health Monitoring (SHM). By leveraging simulated data and limiting experimental data requirements to the creation of an ideal benchmark model representing the healthy structure, this approach effectively models various damage scenarios. Real-world applicability of the HWSLT model is validated through experimental measurements on benchmark setups for binary and multiclass classifications, confirming its reliability. The integration of HWSLT learning with distinct data production processes has yielded significant performance improvements, with HWSLT models trained on simulated data from optimized finite element (FE) models surpassing conventional feature-based models in prediction accuracy. Despite the upfront costs of updating the FE model in healthy states, this investment enhances overall SHM system accuracy and reliability. However, discrepancies between HWSLT validation and experimental predictions underscore the need for continued experimental validations, as simulated data alone cannot ensure real-world accuracy. Future research will explore accuracy metrics of the proposed SHM method across diverse structures, uncertainty simulations, and experimental validations, with plans to test larger benchmark structures to further refine this innovative SHM approach.

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CONFLICT OF INTEREST

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