

RESEARCH ARTICLE

Anomaly Detection on Bridges Using Deep Learning With Partial Training

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ABSTRACT Bridges are exposed daily to environmental and operational factors that may cause weariness, fatigue, and damage. Continuous structural health monitoring (SHM) has been crucial to ensuring public safety, preventing accidents, and avert costly damages. In this regard, advances in Machine Learning and Big Data technologies have enabled automated, real-time structural monitoring. However, challenges persist, notably the scarcity of labeled data, rendering supervised learning impractical. Additionally, state-of-the-art methods demand extensive training data to generalize and achieve satisfactory performance, which can be limited in real-world scenarios. This paper presents a novel three-step method supported by advanced Machine Learning and signal processing techniques aimed at detecting anomalous signals. This method is trained solely on structural acceleration signals, eliminating the need for labeled data. Among the contributions of this work, it can be mentioned that a remarkable accuracy in the detection of structural damage was demonstrated quantitatively. (F1 Score of 93%), while requiring significantly less training data volume than alternative methods (less than 25% of the total) and opening up different lines of research.

INDEX TERMS Structural health monitoring, bridges, damage detection, anomaly detection, machine learning, deep learning, unsupervised learning.

I. INTRODUCTION

The bridges constitute a vital component of a country's infrastructure, facilitating the transportation of goods and enhancing connectivity [1]. Given their pivotal role, maintaining their structural integrity is crucial to ensure public safety and, simultaneously, to prevent significant damages whose repair could incur substantial costs [2]. In this context, monitoring the structural health of bridges is paramount, as they can be subject to wear, fatigue, and various forms of damage, emphasizing the significance of continuous inspection. Taking this into account, Structural Health Monitoring (SHM) is crucial for ensuring the safety and longevity of critical infrastructures like bridges by enabling the early detection of anomalies and potential damages.

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In contemporary developments, monitoring has evolved significantly, shifting from reliance on visual inspections alone to increasingly precise methods, utilizing automated and real-time monitoring technologies.

Pattern recognition using artificial intelligence algorithms and the application of signal processing techniques plays a vital role in the SHM process [3], facilitating the accurate analysis of structural responses and the identification of unusual patterns indicative of potential issues. Various techniques have been developed for SHM, including traditional statistical methods, machine learning approaches, and advanced neural network models, each offering unique advantages and limitations. Over the years, several machine learning architectures have been proposed for supervised damage detection. For instance, a combination of Convolutional Neural Networks (CNN) with Gated Recurrent Unit (GRU) is applied in parallel in [4], and hierarchically

in [5]. Furthermore, [6] combines CNNs with Recurrent Neural Networks (RNN) to extract spatial and temporal features from the data. On the other hand, [7] employs Functional Echo State Networks for the extraction and classification of multivariate features. Nevertheless, it is crucial to consider that applying machine learning models in real-life applications often proves impractical under a supervised approach. This is due, on one hand, to the typically time-consuming nature of data labeling. On the other hand, it is often unfeasible to acquire data from various states of damage to feed machine learning algorithms.

In light of these challenges, different techniques have emerged that leverage an unsupervised learning approach, specifically anomaly detection, for structural damage detection. In [8], a neural network-based detection method is proposed for railway bridges. The study in [9] expands this approach by incorporating temperature as an environmental variable. While this approach allows for sensor-level damage detection, it should be noted that both approaches require a manual data labeling process to train the network with various types of trains, which limits their applicability. Moreover, [10] trains a Convolutional Autoencoder to learn to reconstruct signals encoded as images. In line with the above, [11] proposed a method based on artificial neural networks for damage detection using data measured on a vehicle passing over the bridge under evaluation. Although both approaches do not make use of labeled data from different damage states, the techniques applied are not specifically designed to process temporal data, in addition to the fact that they generally require a considerable training data set.

The latter issue, associated with the significant volume of training data required by machine learning models, which may not be readily available in real-world applications [12], [13], [14], [15], is another challenge that needs to be addressed. Several approaches have been employed to tackle this issue. In [16], transfer learning is applied to overcome this obstacle. Essentially, a CNN is trained using data from a laboratory structure, and then this pre-trained model is employed to learn to detect damage using data from a bridge. Although it achieves excellent detection results, it needs to be supported by a supervised approach, which as already mentioned is not feasible in certain real-life cases. Furthermore, in [17], a novel approach known as population-based SHM is utilized. In broad terms, a model is trained considering a population of structures to enhance the information provided by each one. This work explicitly addresses the problem of sparse training data by making use of different structures for the data augmentation process, although it should be mentioned that it is not directly applied to structural damage detection.

Another way in which this problem has been addressed is through the use of exclusively synthetic datasets (generated by simulations) or hybrid datasets (mixing data extracted directly from the structure with data generated by simulations or physical models of the structure). For example, in [18],

the generation of synthetic data through digital twins is studied, which is a rather promising approach but is currently mainly focused on generating data capable of representing general scenarios, rather than trying to reproduce the data of a particular bridge. Furthermore, as mentioned in [19] there are different challenges that currently limit the applicability of this approach in real-world applications. Some of them include data quality (relative to measured data in the structure), test case coverage, uncertainty related to the environment, and so on. However, the trend that mixes data from the structure under study, together with data from computational simulations of the bridge (through a finite element model (FEM), for example) has been intensively studied lately. In [20], the authors adopt a hybrid scheme that uses data from both the actual structure (through installed sensors) FEM. This aims to augment the volume of data input into the model, while also enabling a more accurate representation of changes in structural response induced by environmental or operational variables. Quite an interesting approach, however, obtaining quality data often requires complicated design processes and calibration of a FEM [21]. For more information about hybrid anomaly detection models and their current limitations (using data from both the actual structure and digital models) see [22].

In summary, despite advances in existing SHM techniques, there remain different challenges that need to be addressed together, such as limited accuracy, the need for large volumes of labeled training data, and the difficulty in handling complex temporal dependencies, highlighting the need for improved methods. Accordingly, the three-step method proposed in this paper addresses these shortcomings by integrating advanced machine learning techniques, namely Autoencoders (AE) and long short-term memory (LSTM) networks, into a comprehensive SHM framework. The application of these techniques allows to take better advantage of the temporal information present in the measured bridge signals, thus achieving a better performance when processing time series, while at the same time making better use of a reduced set of training data. This deep learning (DL) model is accompanied by a preprocessing step using signal processing techniques to optimize the results obtained by the model, in addition to an anomaly detection strategy focused on detecting signs of some type of structural damage. This new approach aims for the detection of structural damage by the employment of the vibration signals from the undamaged structure, eliminating the need for labeled data with different damage states.

The main idea of data-driven methods is that they should be as descriptive as possible of the different loading conditions that a structure can go through, so to avoid false detection caused by anomalies in the bridge loading, a database that considers different input load cases should be used. This is why the use of a dataset with these characteristics is necessary. To carry out the experimentation of the proposed approach, the Z24 bridge, a highway structure with a box

girder section that has been extensively studied, has been selected as a case study. The choice of the Z24 bridge is due to its wide acceptance in the scientific community as a reference data set for the validation and evaluation of anomaly detection techniques. This bridge was subjected to different manually induced damage states, providing data for both its intact state and various types of damage that are common in this typology of structures [23]. The availability of these data allows a thorough evaluation of the accuracy and effectiveness of the proposed model under controlled and varied conditions, thus ensuring the relevance and robustness of the results obtained.

The results demonstrate the effectiveness of our approach to accurately detect structural anomalies, with significant improvements over traditional methods in terms of accuracy and computational efficiency, achieving an F1-Score of 93%. Furthermore, it addresses the challenge of limited amount of training data in real-world applications, as this novel three-step method uses less than 25% of the total data volume without sacrificing accuracy, compared to other state-of-the-art algorithms achieving noteworthy results. The results obtained highlight the potential of the proposed method to significantly improve SHM processes, providing safer and more reliable monitoring and maintenance of critical infrastructures. This approach not only contributes to the safety and durability of structures, but also provides a solid foundation for future research. Several lines of research emerge from this work, highlighting additional areas that can be explored and optimized in future studies.

A. CONTRIBUTIONS OF THE ARTICLE

- **Development of a Hybrid Model for Structural Damage Detection:** This work proposes a novel hybrid model that combines advanced signal processing techniques, specifically a low-pass filter, with DL methods such as AE and LSTM networks. The model enhances the accuracy of unsupervised structural damage detection in bridges.
- **Reduction in Training Data Requirements:** The proposed model achieves high accuracy in structural damage detection with a significantly reduced volume of training data compared to state-of-the-art methods. This feature is particularly valuable in the context of bridge SHM, where training data can be scarce.
- **Quantitative comparison with State-of-the-Art Methods:** A detailed comparative analysis is presented between the proposed model and a state-of-the-art method, highlighting quantitatively the superior performance of the new model in terms of precision and efficiency in structural damage detection using real bridge data.
- **Potential for Future Applications and Extensions:** The developed model and methodology open new avenues for future research and applications across different types of infrastructures. Thus, it is expected to address several challenges related to the application of these techniques in increasingly realistic scenarios,

paving the way for their possible integration into a real surveillance system.

- **Promotion of Machine Learning Techniques in Civil Engineering:** This research underscores the potential and importance of advanced machine learning techniques in the field of civil engineering, advocating for the integration of cutting-edge technology in the management and maintenance of critical infrastructure.

The remainder of the paper is organized as follows: Section II summarizes related work, comparing and classifying existing methods. Section III provides general background on SHM, AE and LSTM networks. Section IV outlines the proposed three-step methodology. In Section V, a comparative study is conducted to showcase the capabilities of this new model in detecting damage using a reduced amount of training data. Finally, Section VI concludes the article, highlighting contributions and suggesting future work.

II. RELATED WORK

This section reviews the related work in the field of SHM, particularly focusing on anomaly detection using DL techniques. The objective is to contextualize the contributions of our proposed method and highlight its novelty.

While the employment of RNN has increased quite a bit lately in the context of bridge SHM, their use has been mainly focused on signal reconstruction. For instance, in [33], LSTM networks are used to predict missing data from faulty sensors. Similarly, [24], [34] uses a comparable approach, considering sensors of different types. Furthermore, in [25], Bi-directional LSTM (Bi-LSTM) networks are utilized and compared with CNNs to demonstrate their superiority in capturing temporal relationships in signals. Additionally, [26] propose a model consisting of a Bi-directional GRU (BiGRU) and an autoregressive component to reconstruct missing data. All of these investigations have demonstrated the ability of recurrent networks to process temporal data, but they do not focus specifically on damage detection, but rather on signal reconstruction.

As previously mentioned, this proposal aims to detect structural damage in an unsupervised manner, making it relevant to review existing anomaly detection approaches. In [27], an AE is used to reconstruct signals from the structure under evaluation, with an ensemble learning strategy to utilize information from multiple sensors for global damage detection. Despite achieving good results, there are two areas for improvement: the architecture is not specifically designed for temporal data, and it demands a high volume of training data for satisfactory outcomes. In contrast, [28] employs a “drive-by” approach, using signals measured from a vehicle crossing the bridge (for more on this technique, see [35]). The authors propose an Adversarial Autoencoder (AAE) model, which integrates AEs with generative adversarial networks to create a generative model. This model, combined with signal processing techniques, calculates a damage index to distinguish between different damage states. Although this

TABLE 1. Related works comparison. - indicates not applicable. X indicates not considered. ✓ indicates fully addressed. ✓* indicates partially addressed.

Reference	Focus on damage detection	Unsupervised approach	Validated with real data	Addresses the problem of limited amount of training data	Presents a quantitative study of damage detection performance
[24] - 2022	X	-	-	-	-
[25] - 2023	X	-	-	-	-
[26] - 2023	X	-	-	-	-
[27] - 2023	✓	✓	✓	X	✓
[28] - 2023	✓	✓	X	✓*	X
[29] - 2018	✓	✓	X	X	✓*
[30] - 2024	✓	✓	X	X	✓
[31] - 2023	✓	X	✓	X	✓
[32] - 2024	✓	✓	✓	X	X
This study - 2024	✓	✓	✓	✓	✓

approach shows improvement over simpler architectures like principal component analysis, AE, and stacked-autoencoders, its validation is exclusively on simulated data and a scaled structure, challenging its comparability with other methods and questioning its applicability to real bridges.

Even though some studies have already employed Long Short-Term Memory Autoencoders (LSTM-AE) modules for SHM anomaly detection, these are mainly focused on an academic context. In [29], the authors apply a deep learning model called Variational Long Short-Term Memory Autoencoders, evaluating its ability to detect anomalies in time series data. Although this work presents an interesting approach, it remains mainly academic, as it exclusively uses synthetic sinusoidal data to evaluate the model. On the other hand, [30] proposes the use of a bidirectional LSTM-AE in combination with a Wavelet decomposition technique to detect and localize damage in composite materials. A notable limitation of this approach is its high sensitivity to signal variations, which can lead to a high false positive rate when applied to real bridge monitoring systems. In addition, the model is validated using two 550 mm × 550 mm carbon fiber plates and a total of 12 piezoceramic transducers, suggesting that the method may work well only with a high sensor density installation, a condition not always feasible when instrumenting a bridge [36].

On the other hand, despite the dataset being nearly thirty years old, it continues to be extensively used by the community to validate emerging proposals over the years, demonstrating the high quality of the data. Among some of the most recent works utilizing the Z24 dataset as a case study, [31] employs a special type of Wavelet transform known as synchrosqueezing transform (SST) in combination with machine learning algorithms to detect and classify structural damage. Although excellent results are achieved, the model relies on a supervised approach, which limits its applicability. Similarly, [32] uses this benchmark with a model that

combines a Convolutional Autoencoder network with a self-attention mechanism. While the study shows that the model can distinguish between signals from the undamaged bridge and those with damage, it does not quantitatively analyze the damage detection results and focuses exclusively on severe damage, making it difficult to compare with other methods.

A comparative analysis of these methods is presented in Table 1, highlighting the strengths and limitations of each approach. Several relevant aspects were considered when comparing the related works in this research. First, we assessed whether the work is specifically focused on damage detection and employs an unsupervised approach. Next, we evaluated if the model validation in the proposed works was conducted using real data extracted from bridges, as demonstrating a model's ability to detect damage in a scaled structure is not equivalent to doing so in a real bridge. Subsequently, we compared the works to determine if they directly address the issue of scarce training data. Finally, we examined whether the works present a quantitative study demonstrating damage detection. This last aspect is critical, as a work might demonstrate its proposal's capability to distinguish between signals from a bridge in good and damaged states but not explicitly and quantitatively present the damage detection results.

In summary, while significant advances have been made in SHM techniques that specifically address various challenges, the current trend focuses on developing models that simultaneously tackle as many of these issues as possible. This approach is particularly relevant for the implementation of algorithms in real-world monitoring contexts, where all these challenges, and possibly additional ones, arise concurrently. Integrating multiple approaches into a single robust and versatile model not only enhances the accuracy and efficiency of structural damage detection but also facilitates the management and maintenance of critical infrastructures in real-world scenarios. Therefore, future research should

focus on creating holistic and adaptive solutions that can be effectively applied in SHM systems for bridges and other infrastructures.

III. BACKGROUND

In the following subsections, a comprehensive overview of the SHM process is presented. The necessary steps for detecting structural damage through a monitoring system are detailed, highlighting the significance of each stage. Additionally, the role of machine learning techniques in this monitoring process is introduced, explaining how these advanced tools enhance the accuracy and efficiency of SHM. Finally, a detailed background on the specific techniques used in the proposed method is provided, emphasizing their characteristics and particularities.

A. OVERVIEW OF STRUCTURAL HEALTH MONITORING

SHM is a vital process for maintaining the safety and integrity of bridges and other critical infrastructure. SHM involves the continuous or periodic collection of data from various sensors installed on structures, followed by data analysis to detect anomalies or damages. The primary goal of SHM is to ensure public safety, prevent catastrophic failures, and minimize maintenance costs. In recent years, advancements in Artificial Intelligence and Machine Learning have revolutionized SHM by enabling automated and real-time monitoring. These techniques have significantly improved the accuracy and efficiency of damage detection.

Generally, the SHM process of a bridge, supported by machine learning techniques, consists of the following steps:

- 1) **Data Acquisition:** Various sensors are installed at critical points on the bridge, such as accelerometers, strain gauges, and temperature sensors, among others. These sensors continuously or periodically collect data on vibrations, deformations, temperature, and other structural parameters.
- 2) **Data Transmission:** The data collected by the sensors is transmitted to a central processing unit. This can be done through wired or wireless connections, depending on the bridge’s infrastructure and available technologies. In some cases, the data may be temporarily stored on local devices before being transmitted.
- 3) **Data Processing and Cleaning:** The received data typically contains noise and irrelevant information, making it necessary to process and clean it. This includes noise removal, correction of missing data, and data normalization to ensure consistency and usability for subsequent analysis. Data preprocessing techniques and cleaning algorithms play a crucial role in this stage.
- 4) **Damage Analysis and Detection:** Once the data is cleaned, it is analyzed using machine learning techniques and statistical analysis. Anomaly detection algorithms, such as AEs or RNNs, are applied to identify unusual patterns that may indicate structural damage. These algorithms are trained with historical bridge data and can detect significant deviations

from normal behavior. Finally, the analysis results are interpreted to make informed decisions about the bridge’s condition and necessary maintenance actions.

This comprehensive approach, supported by advanced machine learning techniques, enables precise and efficient monitoring of bridge structural health, contributing to the safety and longevity of these critical infrastructures.

B. MACHINE LEARNING TECHNIQUES

As previously mentioned, the process of damage analysis and detection can be automated through advanced machine learning techniques focused on processing the signals extracted from the bridge. This work employs a technique that combines a neural network architecture known as an Autoencoder with a special type of recurrent network called Long Short-Term Memory. The following subsections introduce the theory behind both techniques.

1) LONG SHORT-TERM MEMORY

In the literature, when dealing with time series data, it has been illustrated that traditional neural networks were unable to handle the complex temporal relationships inherent in the data [37]. Due to this issue, RNN emerged, which has been specifically designed to process sequential data. In such neural networks, the output of previous layers provides information to subsequent layers, as illustrated in Figure 1.

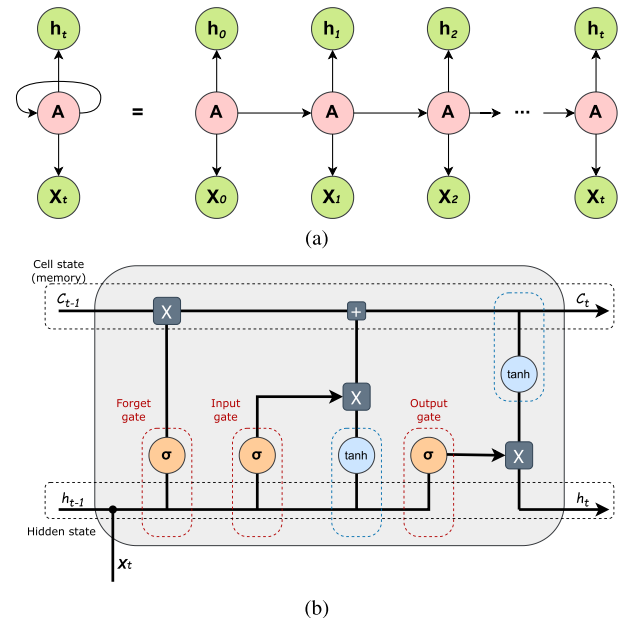


FIGURE 1. (a) RNN structure. (b) LSTM unit structure.

While these types of networks have been applied in various areas [38], [39], [40], [41], they still face challenges in learning long-term relationships present in signals [42]. With this in mind, a new neural network architecture called Long Short-Term Memory is introduced in [43], which was specifically designed to handle these complex long-term relationships. Through a concept known as “gates” (see Figure 1b), LSTMs determine which information to

remember (input gate), what information to forget (forget gate), and what information to use for making predictions (output gate). Assuming we have a time series represented by $x = x_1, x_2, x_3, \dots, x_n$, this process can be summarized with equations 1-6:

$$f_t = \sigma(W_f[h_{t-1}, x_t] + b_f) \quad (1)$$

$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i) \quad (2)$$

$$\tilde{C}_t = \tanh(W_c[h_{t-1}, x_t] + b_c) \quad (3)$$

$$C_t = f_t \cdot C_{t-1} + i_t \cdot \tilde{C}_t \quad (4)$$

$$o_t = \sigma(W_o[h_{t-1}, x_t] + b_o) \quad (5)$$

$$h_t = o_t \cdot \tanh(C_t) \quad (6)$$

where x_t denotes a sample of the signal at time t (defined by the sampling frequency), σ and \tanh correspond to the sigmoidal and hyperbolic tangent functions, respectively. \cdot denotes the dot product. The vectors f_t , i_t , o_t , and C_t represent the activation of the input gate, forget gate, output gate, and memory cell at time t , which have the same dimension as the output factor h_t . Finally, W_f , W_i , W_o , and W_c represent the weight matrices (for each gate and the memory cell), and b_f , b_i , b_o , and b_c represent the biases (also for each gate and the memory cell). Key features of this network include:

- 1) **Handling Temporal Dependencies:** LSTMs can remember information for long periods, making them ideal for time-series analysis.
- 2) **Preventing Vanishing Gradient Problem:** The LSTM architecture includes gates that regulate the flow of information, mitigating issues like the vanishing gradient problem in standard RNNs.

2) AUTO-ENCODERS

On the other hand, AE are a special type of neural network commonly used to reduce data dimensionality. They typically consist of a minimum of three layers (although a multilayer AE can also be implemented), where the first and last layers are the input and output layers, respectively, and always have the same number of neurons. On the other hand, the hidden layer, also known as the bottleneck, is where the AE represents the original data in a lower-dimensional latent space [44]. This process can be expressed in equations 7-9.

$$h = \theta(W_e \cdot x + b_e), \quad (7)$$

$$\hat{x} = g = \phi(W_d \cdot h + b_d), \quad (8)$$

$$L(W_e, W_d) = \frac{1}{N} \sum_{i=1}^N \|x^{(i)} - \hat{x}^{(i)}\|^2 \quad (9)$$

where x_i and \hat{x}_i denote the i -th observation and the i -th reconstruction, respectively. θ and ϕ represent the activation functions of the encoder and decoder, respectively. W_e and W_d correspond to the weights of the encoder and decoder, b_e and b_d represent the biases of the encoder and decoder. Finally, $L(W_e, W_d)$ denotes the reconstruction error (how much the original and reconstructed data differ), considering the weights W_e and W_d . During the training process, the

goal is to minimize this error, indicating that the network is learning to reconstruct the data accurately. Key features of this architecture include:

- 1) **Dimensionality Reduction:** AEs reduce the dimensionality of input data, making it easier to manage and analyze.
- 2) **Anomaly Detection:** By reconstructing input data, AEs can identify anomalies through reconstruction errors, which are significant when the input data deviates from the norm.

3) LONG SHORT-TERM MEMORY AUTOENCODERS

Considering the two aforementioned neural network architectures, a new class of networks, known as Autoencoder with Long-Term Memory Neural Networks, emerges. These networks essentially amalgamate the information compression capabilities (dimensionality reduction) of AE networks with the ability to learn long-term relationships inherent in time series data. In this architecture, a minimum of two LSTM networks is utilized (though more layers can be incorporated). One LSTM network serves as the signal encoder, responsible for reducing dimensionality, while the second LSTM network acts as the decoder, tasked with reconstructing the signal from its compressed representation.

These networks have been previously employed for unsupervised anomaly detection in signals [45], [46]. To achieve this, it is necessary to establish a pre-defined threshold based on the outcomes of the training phase (reconstruction errors). Figure 2 outlines a general topology of such neural networks, depicting the encoding layer that takes input from the temporal sequence and transforms it into a lower-dimensional representation. Subsequently, the decoding layer utilizes this representation to reconstruct the original data.

IV. METHODOLOGY

In the following section, the proposed methodology is presented. Initially, the general three-step framework is outlined, providing an overview of the entire process. Subsequently, each step is explained in detail, highlighting the specific features and particularities that distinguish our approach.

A. GENERAL FRAMEWORK

The design behind the proposed approach is based on the interaction between LSTM networks and AE architectures. In this way, the model is trained to learn how to reconstruct the signals coming from the bridge in a healthy state, considering the temporal relationships in the data. Figure 3 provides a general overview of the proposed process. In essence, a DL architecture is trained to reconstruct signals from the undamaged structure. Subsequently, it can be determined whether a signal s corresponds to a damaged state or not, depending on how challenging it is for the network to reconstruct it.

This approach can be essentially defined by three main steps. Initially, a preprocessing strategy is employed to prepare the data and facilitate subsequent analysis. Next, the

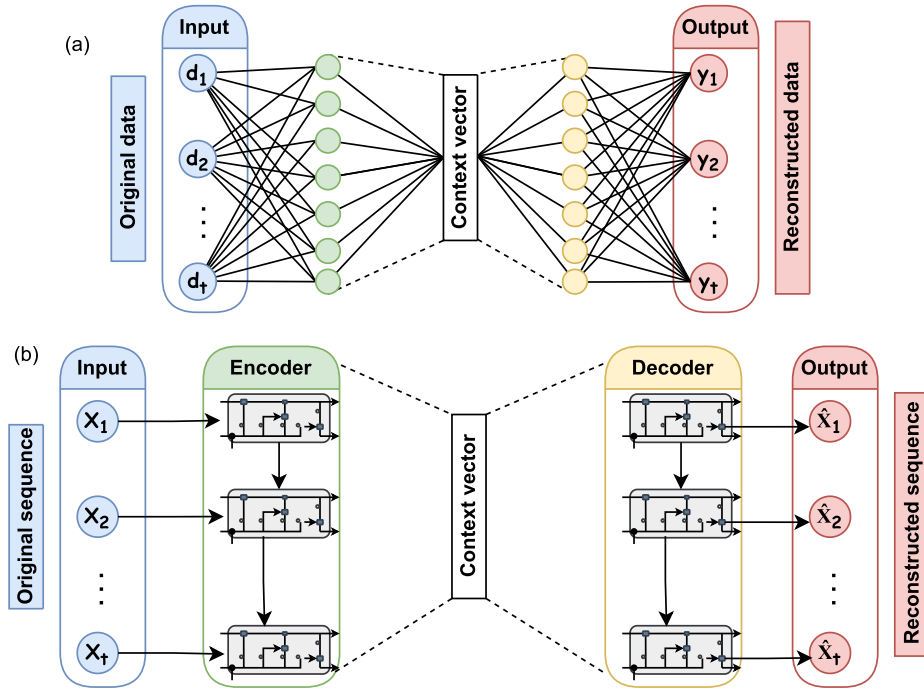


FIGURE 2. (a) AE architecture for data reconstruction, (b) LSTM-AE architecture for signal reconstruction.

previously mentioned reconstruction model is implemented to learn the bridge’s dynamics. Finally, a damage detection strategy is defined, which uses the reconstruction errors from the model to determine if a signal should be labeled as anomalous. The following subsections will provide a detailed description of each specific step.

B. PREPROCESSING STRATEGY

To optimize the results obtained by this new method, several preprocessing steps are required before moving on to the training stage. The first strategy involves applying a low-pass filter to eliminate high-frequency noise, which can potentially degrade the algorithm’s performance in reconstructing signals [25]. The filter’s cutoff frequency should be defined based on the characteristics of the bridge under evaluation to avoid losing crucial structural information. As a second step, a data normalization process is performed. The data normalization range may vary depending on the activation function used. In this particular model, normalization was conducted within the range of $[-1, 1]$.

Finally, the original signal obtained by the sensors (which has already been processed in the previous steps) is divided into N micro-sequences of a certain temporal length (up to 10 seconds, depending on the case). This segmentation into shorter sequences reduces the complexity of the temporal relationships that the network needs to learn. Additionally, dividing the original signal into more segments provides the network with a larger number of training samples. The length of these micro-sequences is a parameter that must be optimized during the training process to enhance the network’s performance.

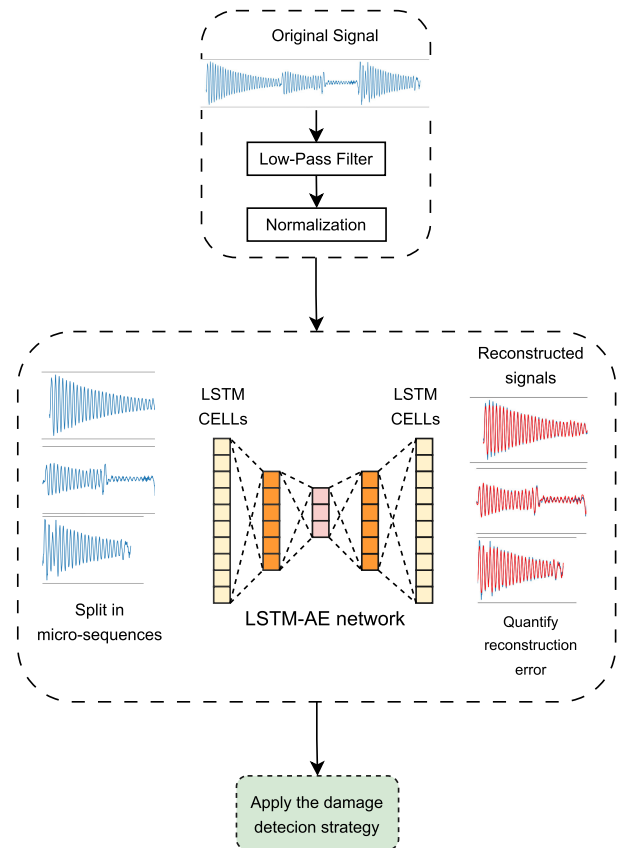


FIGURE 3. General three-step framework proposed using the LSTM-AE architecture.

C. RECONSTRUCTION MODEL

While errors will inevitably occur when decoding data from a lower-dimensional space, the fundamental idea behind

this model is to minimize reconstruction errors as much as possible. Thus, if the error increases when evaluating a signal corresponding to a damaged state, the majority of the reconstruction error will likely be attributed to actual changes in the structure’s vibration pattern due to damage. This approach makes it easier to detect anomalous signals. To achieve this, the LSTM-AE deep learning architecture is employed, combining the reconstruction capabilities of AE with the ability to learn temporal relationships from LSTM networks [47]. This model is exclusively trained with vibration signals from the structurally sound state. The goal is to adapt the network parameters to minimize the difference between the original and reconstructed signals, quantified using a reconstruction loss metric.

The Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE) are widely used metrics for evaluating the accuracy of predictive models. MAE measures the average magnitude of errors in a set of predictions, without considering their direction, and is given by the formula 10. MSE, defined by 11, penalizes larger errors more significantly due to squaring the error term, thus providing a more sensitive measure of error magnitude. RMSE, calculated as 12, provides an error metric that is in the same units as the original data, offering a more interpretable measure of predictive accuracy. These metrics provide a comprehensive assessment of model performance, balancing sensitivity to large errors and overall prediction accuracy.

$$MAE = \frac{1}{N} \sum_{i=1}^N |x^{(i)} - \hat{x}^{(i)}|, \quad (10)$$

$$MSE = \frac{1}{N} \sum_{i=1}^N (x^{(i)} - \hat{x}^{(i)})^2, \quad (11)$$

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (x^{(i)} - \hat{x}^{(i)})^2} \quad (12)$$

D. DAMAGE DETECTION

A quite interesting approach to detecting structural damage using anomalous signals is presented in [10]. This method aims to reduce false positives by basing the decision on whether or not a sequence corresponds to a damaged state by considering subsequent sequences (not just the sequence itself), forming macro-sequences, and providing a broader perspective of the signal behavior. Thus, if a pre-established threshold of damaged sequences is not exceeded within a macro-sequence, it is not classified as damaged.

In this work, a quite similar process is undertaken, which is expressed in the algorithm 1. For each of the N micro-sequences processed by the network, the reconstruction error metric is calculated, resulting in a vector E of length N , where the i -th element represents the reconstruction error for the i -th micro-sequence (line 2). Each element of vector E is then compared with a preset threshold T_{micro} (line 5). If the reconstruction error of the i -th element exceeds the threshold,

the i -th micro-sequence is labeled as 1; otherwise, it is labeled as 0 (lines 6 and 8). This process produces the vector L_{micro} of length N , containing the labels for each micro-sequence. Next, the labels in L_{micro} are grouped into macro-sequences, where each macro-sequence is represented by M contiguous micro-sequences, resulting in the vector L_{macro} (line 12).

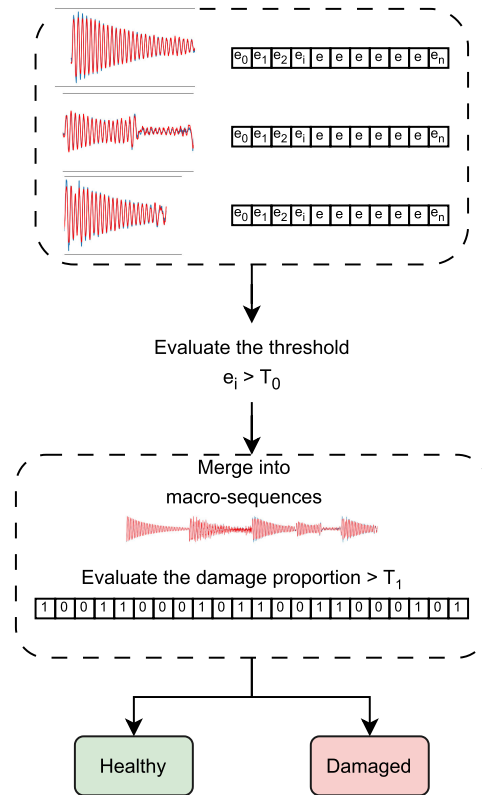


FIGURE 4. Damage detection strategy.

For each macro-sequence, the proportion of micro-sequences labeled as anomalous is calculated, yielding a value in the range [0, 1] (line 16). This proportion is then compared with a preset threshold T_{macro} (line 17). If the proportion exceeds the threshold, the macro-sequence (and all its constituent micro-sequences) is labeled as anomalous (line 18).

This method employs two thresholds in the damage detection strategy. The T_{micro} threshold can be set as a percentage between 90% and 99% of the error during the training phase, requiring only healthy bridge signals for calibration. On the other hand, the T_{macro} threshold typically yields good values within the range of 0.4 to 0.6. The optimal value for T_{macro} can be fine-tuned based on simulations of the bridge under various conditions.

V. COMPARATIVE ANALYSIS

The following section presents a comprehensive comparative analysis that demonstrates the capabilities of the proposed method for detecting structural damage. First, the case study used in this work, a highway bridge widely studied by the scientific community, is described. Next, the selection process of the training and test data sets is detailed. Then, the steps performed in the training process are explained,

Algorithm 1 Pseudocode of the Damage Detection Strategy

```

1:  $S_{micro} \leftarrow$  microsequences
2:  $E \leftarrow compute\_error(S_{micro})$ 
3:
4: for  $i \leftarrow 1$  to  $N$  do
5:   if  $E[i] > T_{micro}$  then
6:      $L_{micro}[i] \leftarrow 1$ 
7:   else
8:      $L_{micro}[i] \leftarrow 0$ 
9:   end if
10: end for
11:
12:  $L_{macro} \leftarrow groupmacros(L_{micro}, M)$ 
13:  $N_{macro} \leftarrow length(L_{macro})$ 
14:
15: for  $i \leftarrow 1$  to  $N_{macro}$  do
16:    $p_{damaged} \leftarrow \frac{1}{M} \sum_{j=1}^M L_{macro}[i, j]$ 
17:   if  $p_{damaged} > T_{macro}$  then
18:      $damaged\_macros[i] \leftarrow 1$ 
19:   else
20:      $damaged\_macros[i] \leftarrow 0$ 
21:   end if
22: end for

```

along with the optimization of the model hyper-parameters. Subsequently, the state-of-the-art method selected to compare the performance of our proposal is presented, specifying the parameters used. Finally, the results of the damage detection process are presented, highlighting the performance of both methods during training and testing, and underlining the improvements of the proposed method in the detection of anomalies related to structural damage.

A. STUDY CASE DESCRIPTION

The Z24 bridge was a Swiss highway box girder bridge built mainly with prestressed concrete. It had a total length of 60 meters, which housed three spans and two lanes. It connected Koppigen and Utzenstorf and was inaugurated in 1963. Active for 35 years, the bridge was demolished in 1998 to make way for a wider bridge accommodating a new railway track. Before demolition, the bridge underwent a year-long monitoring process as part of the SIMCES project (System Identification to Monitor Civil Engineering Structures) [48]. The aim was to investigate the influence of environmental variations (temperature, air humidity, rain presence, wind speed, and direction) on the bridge's dynamics [49]. In the last month before demolition (August 4th to September 9th), various interventions were performed on the bridge to induce distinct damage states, thereby capturing dynamic response data [50]. Among the induced damage states were pier settlement, pier uplift (foundation tilting), concrete spalling in the soffit, and tendon breakage, among others.

Regarding the instrumentation system, an extensive setup was implemented with significant emphasis on monitoring

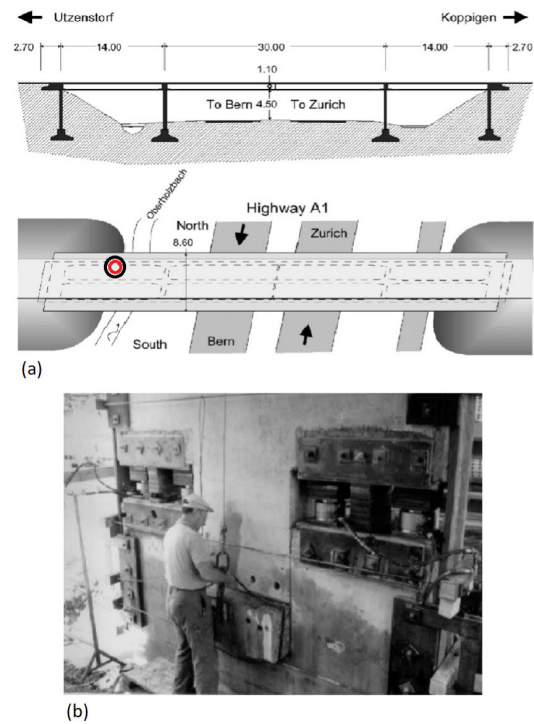


FIGURE 5. (a) Top view and cross section of the Z-24 Bridge, with the sensor selected, (b) Settlement of pier scenario (Extracted from [51]).

the thermal condition of the bridge and its surroundings. This translated to 12 sensors measuring ground temperature (near the piers), and an additional 8 sensors mounted on the bridge. Furthermore, 5 sensors recorded atmospheric conditions, and a total of 16 acceleration sensors with a sampling frequency of 100Hz were distributed across different parts of the bridge to measure dynamic responses. Among the 16 acceleration sensors, several exhibited failures during the data collection period, while others began to produce corrupt and unreliable data, which were subsequently excluded. Only 8 sensors remained operational until the conclusion of the project, and were utilized to construct the database. It is worth noting that, to avoid extending this work excessively, only one accelerometer was considered for the comparative study (see Figure 5).

One of the main objectives pursued in this project was to obtain a data set of bridge dynamics under operating conditions as standardized as possible, so for the long-term monitoring process of the Z24 bridge, acceleration data were obtained mainly from environmental vibrations. These vibrations included those caused by traffic and natural environmental conditions, such as wind. This allowed a continuous assessment of the dynamic behavior of the bridge under normal operating conditions, providing a solid basis for damage detection and analysis of its structural behavior.

B. DATA SELECTION

Since we aim to compare the algorithm's ability to detect structural damage using a smaller amount of training data, two separate cases need to be defined. The first training

TABLE 2. Overview of progressive damage test escenarios, extracted from [52].

No.	Date (1998)	Scenario
1	01/08	Undamaged condition
2	10/08	Lowering of pier, 20mm
3	12/08	Lowering of pier, 40mm
4	17/08	Lowering of pier, 80mm
5	18/08	Lowering of pier, 95mm
6	19/08	Tilt of foundation
7	25/08	Spalling of concrete, 12m2
8	26/08	Spalling of concrete, 24m2
9	27/08	Landslide at abutment
10	31/08	Failure of concrete hinge

dataset (referred to as case 1 or FT, for full training) considers the entire month of March 1998. Meanwhile, the second dataset (referred to as case 2 or PT, for partial training) includes only the first week of March 1998. Given that data were measured every hour for eleven minutes, case 1 would encompass approximately 7,920 minutes in total. In contrast, case 2 only considers a total of 1,848 minutes, equivalent to less than 25% of the data in case 1. In both cases, one week's worth of data (first week of April 1998) was used as a validation set.

C. TRAINING PROCESS

As previously mentioned, a component of the data preparation process involves applying a low-pass filter. This is done to mitigate the impact of high-frequency noise on the model's performance when reconstructing signals. Drawing upon findings presented in [50] and [53], a filter with a cutoff frequency of 18Hz is applied, ensuring that information about the first 9 modal shapes of the Z24 bridge is retained. Figure 6 illustrates the applied filter alongside a sample of the original signal and the signal post-filtering. Additionally, in Figure 7, the Fourier transform of both the original and filtered signals is depicted. As will be seen later, a slight improvement in the training process was achieved after applying the filter.

To optimize the results obtained by this neural network architecture, the training process was conducted with various topologies and different parameters. This was done to explore the model's sensitivity and highlight its learning capabilities in signal reconstruction. Experimental tests were conducted to examine the influence of signal length on the network reconstruction process. A basic network topology was established, while the number of samples per sequence was systematically varied. As illustrated in Figure 8, this parameter exhibits a notable impact. As the length of sequences increases, the network's ability to capture long-term temporal relationships diminishes, underscoring the importance of maintaining this parameter at lower values to achieve optimal outcomes.

On the other hand, another critical parameter for optimizing the LSTM-AE results is its topology. Four architectures

were trained using the same dataset with a fixed number of epochs, varying primarily the number of neurons per LSTM layer. As depicted in Figure 9, noticeable improvements in reconstruction error cease after reaching 64 neurons. Moreover, Table 3 illustrates that as the number of neurons increases, so does the required training time due to the higher number of parameters to update at each step. Consequently, selecting a neuron count that balances training time while maintaining satisfactory performance becomes crucial.

Finally, a dynamic learning rate update strategy was incorporated. This strategy automatically adjusts the learning rate if the algorithm stagnates. The *Patience* parameter indicates the number of epochs that must pass without improvement in the optimization metric (reconstruction error) before updating the learning rate using the established *Updatefactor*. This strategy enables a faster initial decrease of the loss function by employing a higher learning rate. As the training process progresses and more promising regions are discovered, the gradient optimization algorithm converges more finely through the reduction of the learning rate. After completing this hyperparameter tuning process, the topology described in Table 5 was selected.

D. METHOD COMPARED

To test the detection capabilities of this new method under conditions of limited training data, it was decided to compare it with the AE-based method proposed in [27], for various reasons. Firstly, it is more interesting to use contemporary state-of-the-art methods for such comparisons. Secondly, considering the excellent results it achieved, it sets a rather ambitious benchmark to reach. Lastly, this method also employs a similar approach to the one proposed in [10] when evaluating macro-sequences, making it suitable for comparison. Table 4 presents the parameters used in the training process.

E. DAMAGE DETECTION RESULTS

To validate the proposed method, this study used both data from the bridge in good condition and data from the damaged bridge as the test set. The first two weeks of July 1998 were used for the former, while the data for the damaged structure was selected from August 10 to 25, 1998. These signals mainly correspond to damage types such as lowering of pier, tilt of foundation and spalling of concrete.

The network topology used, along with the parameters of the training process, can be found in Table 5. Here, you can also observe the number of parameters to be optimized during the training period. On the other hand, in Figure 10, you can see the convergence curves of the AE model using data from both case 1 and case 2, in addition to the LSTM-AE model only in case 2. From here, it can be noted that this new model is capable of achieving lower MSE values during the training process, indicating better performance in reconstructing vibration signals. On the other hand, it is confirmed that the LSTM-AE network performs better after filtering the high-frequency noise from

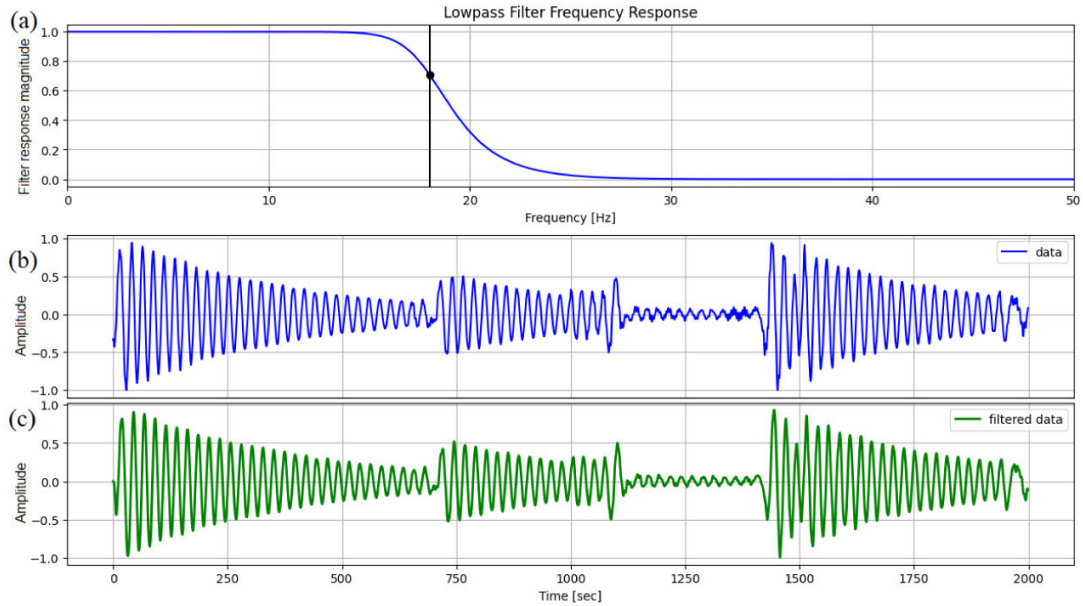


FIGURE 6. (a) Low-pass filter applied. (b) Original signal sample. (c) Filtered signal sample.

TABLE 3. Comparison of tested topologies.

Network	Layers	N. Neurons	Training Time (seg)	MSE
1	LSTM	32	718.6726	5.6031e-04
	RepeatedVector	-		
	LSTM	32		
	TimeDistributed	-		
2	LSTM	64	773.3910	6.4635e-05
	RepeatedVector	-		
	LSTM	64		
	TimeDistributed	-		
3	LSTM	128	1010.7302	3.8565e-05
	RepeatedVector	-		
	LSTM	128		
	TimeDistributed	-		
4	LSTM	256	1046.9695	3.4260e-05
	RepeatedVector	-		
	LSTM	256		
	TimeDistributed	-		

TABLE 4. Parameters of the AE proposed in [27], used in this study.

AE Parameter	Value used
Input size (sequence length)	1000
Number of hidden layers	3
Neurons per layer	[256, 128, 256]
Number of epochs	30
Batch size	64

the data, as the training error decreased from $9.8735e^{-5}$ to $1.7595e^{-5}$, considering the aforementioned cutoff frequency. Considering the convergence curves, the first improvements

in terms of the LSTM-AE network compared to the basic AE architecture are already evident.

In Figure 11, examples of two sequences reconstructed by the trained LSTM-AE network can be seen. In 11.a, there is an arbitrary sequence corresponding to the set of signals from the undamaged bridge. It can be observed that the network reconstructs the sequence quite well, resulting in a relatively low reconstruction error. On the other hand, in 11.b, a sequence from the set of signals from the damaged bridge is shown. Here, it is evident that the network struggled to reconstruct this signal, leading to a significantly higher reconstruction error. It is worth noting that a sequence was selected where the network performed particularly poorly in

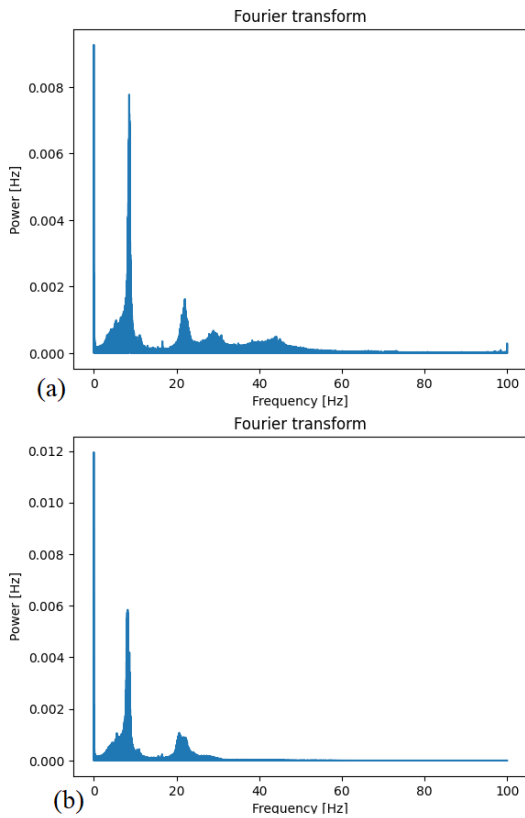


FIGURE 7. (a) Fourier transform of the original signal. (b) Fourier transform of the filtered signal.

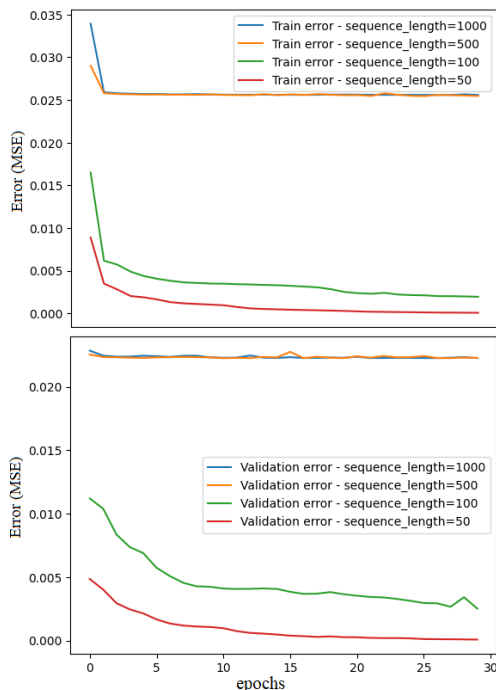


FIGURE 8. Training curves (train loss and validation loss) considering different sequences length.

terms of the reconstruction metric for illustrative purposes. However, the difference between healthy and damaged signals is not always as pronounced.

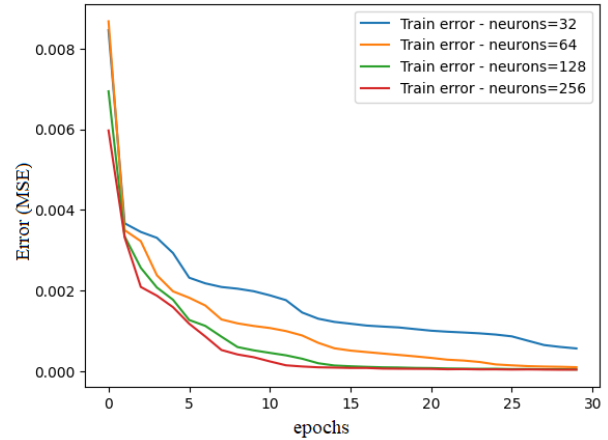


FIGURE 9. Train loss evolution considering different numbers of neurons in the LSTM layers.

TABLE 5. Topology and parameters of the LSTM-AE.

Layer (type)	Output Shape	Params #
LSTM	(None, 50, 64)	16.896
RepeatedVector	(None, 50, 64)	0
LSTM	(None, 50, 64)	33.024
TimeDistributed	(None, 50, 1)	65
Parameter	Value	
Epochs	30	
Learning rate	1e-3	
Optimizer	Adam	
Lr update strategy	On Plateau	
Patience	5	
Update factor	0.9	
Batch size	64	

To evaluate the ability to detect anomalous signals related to some structural damage, the F1-score and Area Under the Receiver Operating Characteristic Curve (AUC-ROC) metrics were used. The F1-score and the AUC-ROC are essential metrics for evaluating the performance of classification models. The F1-score is the harmonic mean of precision and recall, providing a single metric that balances both false positives and false negatives. The AUC-ROC quantifies the overall ability of the model to discriminate between positive and negative classes across all possible classification thresholds. The ROC curve plots the true positive rate against the false positive rate, and the AUC represents the probability that a randomly chosen positive instance is ranked higher than a randomly chosen negative instance. The AUC value ranges from 0 to 1, with a value of 0.5 indicating no discriminative power, and a value of 1 representing perfect classification. These metrics are particularly useful in scenarios with imbalanced class distributions and for comparing different models regardless of their specific classification thresholds.

Besides, to enhance the comparison of this new method with the state-of-the-art methods used in the validation, a verification process is conducted using statistical tests.

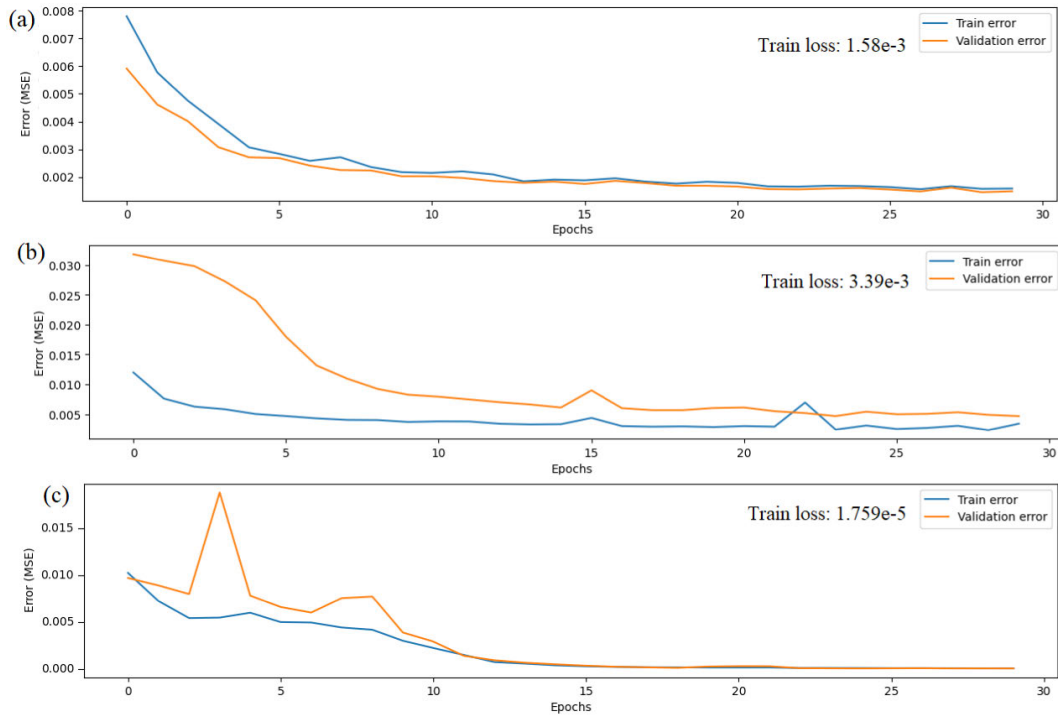


FIGURE 10. Training curves. (a) AE (Fully trained), (b) AE (Partially trained), (c) LSTM-AE (Partially trained).

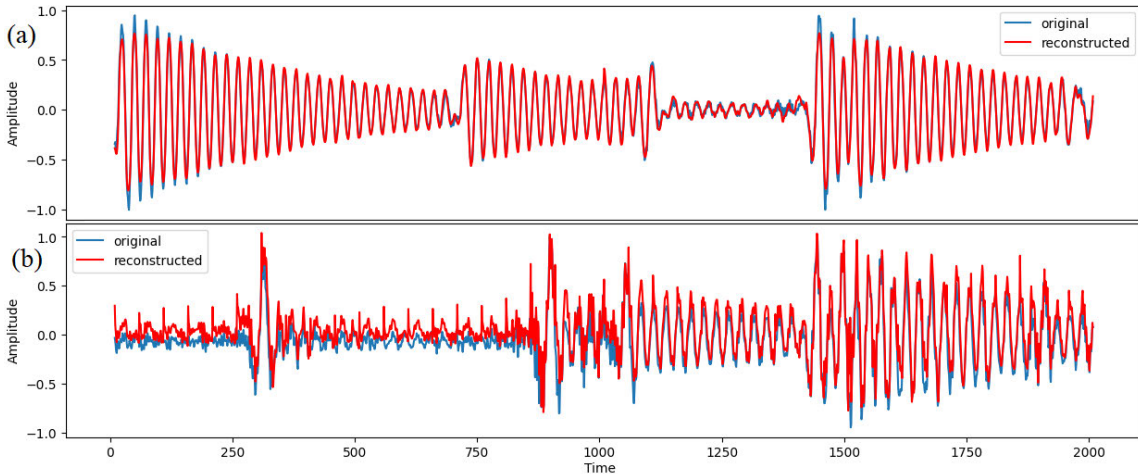


FIGURE 11. (a) Reconstructed signal of a healthy state. (b) Reconstructed signal from a damaged state.

These tests, based on a significance level, allow the hypothesis to be validated or rejected. The procedure unfolds as follows: initial samples underwent a scrutiny for normality through the Kolmogorov-Smirnov Lilliefors test, which, upon failing (p -values > 0.05), led to the subsequent application of the non-parametric Mann-Whitney test to assess the performance disparity between AE and LSTM-AE outcomes. Two pivotal hypotheses merit consideration:

$$H_0 : \mu_{AE} = \mu_{LSTM_{AE}} \quad (13)$$

$$H_1 : \mu_{LSTM_{AE}} \neq \mu_{AE} \quad (14)$$

Here, μ_{AE} and $\mu_{LSTM_{AE}}$ represent the median fitness values corresponding to AE and the proposed LSTM-AE,

TABLE 6. Results comparing. FT: Full trained - PT: Partially trained.

Model	LSTM-AE (PT)		AE (FT)		AE (PT)	
Metric	F1	AUC	F1	AUC	F1	AUC
Value	0.9377	0.9371	0.8883	0.8931	0.7975	0.8002

respectively. It is crucial to note that the significance level is set at 0.05, implying that values smaller than 0.05 reject the assumption of H_0 .

Accordingly, Table 6 delineates the comparison between the two implementations, with statistically significant winners highlighted in bold. Note that in the case where the full training set was available, the AE model performed quite competitively compared to LSTM-AE. However, for a fair

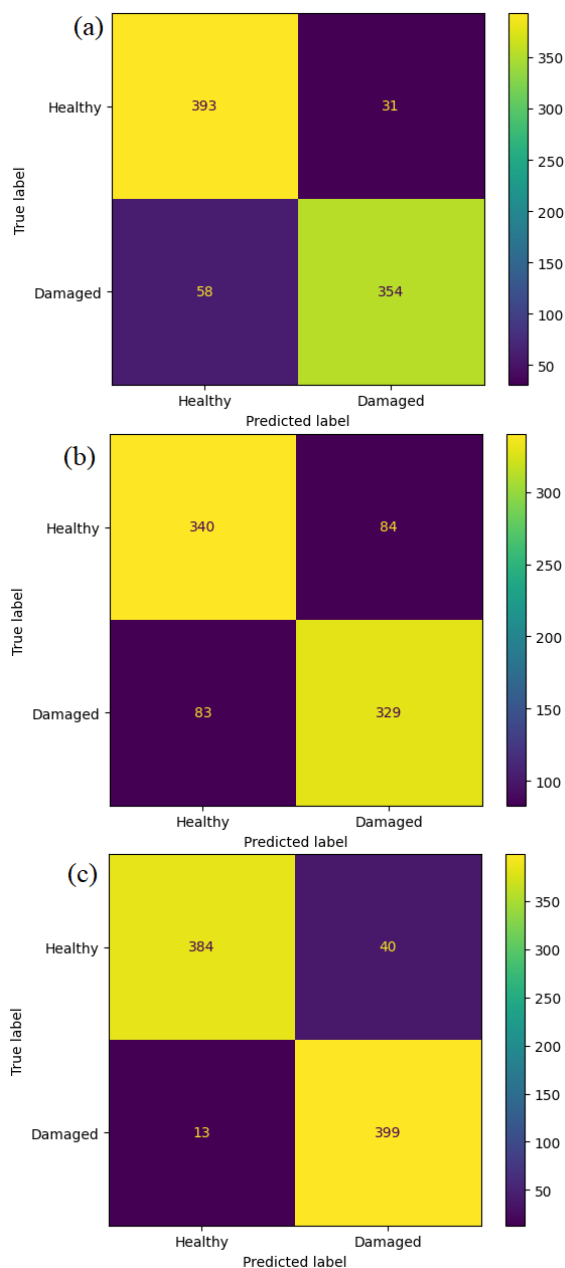


FIGURE 12. (a) AE (Fully trained) confusion matrix. (b) AE (Partially trained) confusion matrix. (c) LSTM-AE (Partially trained) confusion matrix.

comparison, LSTM-AE should be compared with the AE model in case 2 (with a fraction of the total training volume). Here, the detrimental effects of having less training data are evident, as the AE model completely deteriorates and fails to generalize correctly. On the other hand, the LSTM-AE model is capable of learning to reconstruct vibration signals using less than 25% of the total training data. Figure 12 presents the confusion matrices, providing a clearer view of this difference.

An important point to note is that the proposed LSTM-AE model imposes a significantly higher time burden compared to the simple AE network. This increase in processing time

primarily stems from the complexity of more advanced models, which involve a greater number of layers and/or neurons per layer, requiring additional processing and memory due to the increased number of parameters to optimize. This can substantially increase the prediction time, leading to longer training and reconstruction times as well. Such considerations are crucial, as they may pose limitations on the real-time implementation of the model within a SHM system, particularly considering that the data acquisition rate (sensor data) may outpace the detection results.

VI. CONCLUSION

In this study, a new algorithm based on deep learning techniques was proposed for structural damage detection. The accuracy and precision of this method were validated using data from a real box-girder bridge, yielding excellent results. Furthermore, among the contributions of this work, it should be mentioned that it was demonstrated that this novel three-step method does not require labeled data to detect anomalous signals indicating structural damage. Additionally, the algorithm was shown to use a smaller training data volume compared to other state-of-the-art methods, without sacrificing accuracy, as competitive results were still achieved. Also, a quantitative study was performed using data from real bridges to demonstrate the capabilities of this approach to detect anomalies that indicate structural damage.

To the best of our knowledge, as of the current date of this article, this is one of the first work which proposes a design based on the interaction LSTM-AE as an architecture for structural damage detection in bridges. This architecture proved to be more suitable for reconstructing vibration signals compared to other state-of-the-art methods. This is mainly because they are designed to process time series data.

Regarding to the future lines of research that emerge from this work, the following can be mentioned:

- **Damage localization:** While the detection capability of this new method was demonstrated, the ability to locate structural damage was not investigated. Since an LSTM-AE is trained for each sensor, detection errors may be higher in sensors closer to the specific failure.
- **Environmental variables:** The effects of temperature on the performance of this model were not studied either, which could be interesting as some environmental variables have been shown to influence certain behaviors of structural response [54], [55].
- **Thresholds selection:** Another aspect worth considering for future work is the selection of appropriate values for the thresholds T_{micro} and T_{macro} . These parameters are critical for the model to achieve good results, and further research on the selection and optimization process should be conducted. It might also be considered to automate this selection process and adapt it alongside changes in the dynamic responses of the bridge. This would allow updating these values depending on how the bridge's health evolves throughout its lifecycle, thus enabling a more robust and dynamic model.

- Hyperparameter tuning: Considering the results obtained from the hyperparameter optimization process, the significant sensitivity of this model was evident. Incorrect selection of a parameter may result in the model's inability to generalize the reconstruction of vibration signals from the bridge in good condition, leading to poor performance in unsupervised damage detection. Therefore, more time and effort need to be invested in designing strategies to optimize these network parameters and enhance the obtained results.
- Contemporary models: As seen in this study, the combination of LSTM with AE yielded superior results compared to the state-of-the-art method. This underscores the importance of investigating the applicability of emerging models, which exhibit greater capability to handle temporal data, thus potentially enhancing the obtained outcomes. Among these models, it would be worthwhile to explore the applicability of Large Language Models (LLMs) and transformers, which have demonstrated excellent ability to capture temporal relationships present in the data.

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