College of Engineering

Department of Systems Engineering

Interim Report

Structural health monitoring for civil infrastructure using artificial intelligence and digital twin

Student name:	Zhang Peining
Student ID:	57124831
Major:	ITME
Department:	SYE
Project supervisor:	Liu Cheng
Submission date:	19 / 11 / 2024

Table of Contents

The report is expected to be in about 20 pages.

1. Background

Structural Health Monitoring (SHM) has emerged as a pivotal domain within civil engineering, aimed at the early detection of structural defects, real-time monitoring of infrastructure conditions, and the assessment of structural safety. With the aging of infrastructure and increasing environmental challenges, SHM systems are indispensable for ensuring the operational integrity of critical assets, such as bridges, buildings, and dams. By leveraging data collected from a variety of sensors, SHM systems continuously or periodically assess structural conditions, ensuring resilience against external forces and supporting long-term functionality. The integration of advanced monitoring technologies provides a comprehensive view of structural health, offering a reliable foundation for condition-based maintenance strategies[1]. Civil infrastructure, including bridges, dams, and tunnels, represents critical assets that underpin societal functioning. However, these structures are constantly subjected to dynamic loads, environmental stressors, and natural aging processes, which contribute to progressive deterioration[12]. Structural degradation, if undetected, can compromise safety, disrupt operations, and increase the risk of catastrophic failures. Traditional maintenance practices, such as periodic visual inspections and scheduled repairs, have inherent limitations due to their inability to detect concealed damage, high costs, and susceptibility to human error. SHM systems address these challenges by providing continuous, real-time monitoring, ensuring structural integrity, and enhancing maintenance strategies[34][35][36].

One of the critical advantages of SHM lies in its ability to detect early signs of damage, thereby reducing the likelihood of catastrophic failures and extending the lifespan of infrastructure[2]. By collecting real-time data from sensors such as accelerometers, strain gauges, and displacement transducers, SHM systems continuously monitor a structure's behavior and compare it to baseline conditions. Significant deviations from baseline behavior trigger alarms, enabling early diagnosis and preventive maintenance. This proactive approach optimizes maintenance schedules, minimizes operational downtime, and lowers repair costs. Moreover, SHM aligns with sustainability goals by reducing the need for frequent physical inspections and lowering the overall environmental impact of infrastructure maintenance. These systems conserve resources by minimizing physical assessments while providing accurate and reliable data. Additionally, SHM systems play a critical role in ensuring the safety of infrastructure during extreme conditions, such as earthquakes, floods, or high winds, where real-time monitoring is essential for protecting both the structure and its users.

Despite its advantages, traditional SHM methods face several challenges that limit their effectiveness. One major challenge is the vast volume of data generated by modern SHM systems[5]. The extensive sensor networks embedded in structures produce immense datasets, which require efficient processing and analysis to identify potential damage. Traditional techniques often struggle with handling such large datasets and rely heavily on manual intervention, introducing delays, errors, and inefficiencies[3]. Moreover, current SHM systems frequently encounter difficulties in real-time data analysis, hampering timely damage detection and diagnosis. Another critical challenge lies in the complexity and variability of structural behaviors. Structures exhibit unique dynamic responses influenced by factors such as environmental conditions and loading scenarios, making it difficult to detect anomalies without in-depth knowledge of these variables[5]. Additionally, in some cases, SHM systems still require manual inspections to validate automated analysis results, adding further complexity and cost to the maintenance process.

To overcome these challenges, the integration of Digital Twin (DT) technology into SHM represents a transformative advancement. A DT is a virtual replica of a physical asset that evolves alongside its real-world counterpart by integrating real-time sensor data and simulations[3]. In SHM, DTs enhance monitoring capabilities by merging data-driven insights with physics-based models, offering a comprehensive and dynamic representation of structural behavior. During the design phase, DTs enable virtual simulations to predict structural performance under various conditions, facilitating optimal designs prior to construction. In the operational phase, DTs continuously assimilate real-time data from embedded sensors, enabling real-time monitoring, fault diagnosis, and predictive maintenance. This approach not only improves structural reliability and safety but also reduces the frequency of physical inspections, resulting in more cost-effective maintenance. Furthermore, the application of deep learning has the potential to revolutionize SHM by providing sophisticated data analysis techniques capable of handling large datasets and detecting complex patterns in structural behavior[9]. Traditional methods, which often rely on statistical models and rule-based algorithms, struggle to identify subtle or evolving damage. In contrast, deep learning techniques, including Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Transformer-based models, excel in time-series analysis. These models can effectively learn temporal patterns associated with structural changes, enabling automated anomaly detection in real time[10].

2. Literature

SHM methodologies are broadly categorized into Global Methods and Local Methods, each offering distinct approaches tailored to specific monitoring needs. Recent technological advancements, particularly in DT and deep learning, have considerably augmented both categories, enabling enhanced precision and efficiency in monitoring capabilities[1].

2.1. Global Methods in SHM

Global SHM methods aim to detect changes in a structure's overall behavior by analyzing its dynamic characteristics, such as natural frequencies, damping ratios, and mode shapes. These vibration-based techniques utilize data collected from sensors that monitor the structural response to external forces, effectively identifying damage that impacts structural integrity. These methods are typically categorized into data-driven approaches, physics-based models, and hybrid techniques. The advent of DT technology has transformed global SHM by enabling real-time simulations that continuously update using sensor data. When integrated with advanced deep learning models, such as Transformers, DTs enhance the system's ability to process time-series data for detecting anomalies and predicting potential failures[2][3][4].

2.1.1. Data-Driven Methods

Statistical and machine learning techniques play a key role in identifying patterns and anomalies in collected SHM data. Methods such as Principal Component Analysis (PCA), Support Vector Machines (SVMs), and neural networks are widely used to process vibration data for damage detection. Deep learning models, including CNNs, Long Short-Term Memory (LSTM) networks, and Transformers, have significantly advanced data-driven SHM methods. These models excel at extracting hierarchical features and capturing long-range dependencies in structural vibration data, enabling efficient processing of large datasets and real-time damage identification[1][7][13]. For examples, Wang and Cha[17] proposed an unsupervised learning approach using acceleration signals from a laboratory-scale 3D steel bridge. They normalized the response signal vectors and applied Continuous Wavelet Transformation (CWT) and Fast Fourier Transformation (FFT). The transformed data were processed by a two-dimensional (2D) CNN autoencoder to extract key features, while One-Class Support Vector Machines (OC-SVMs) served as novelty detectors for each sensor, helping locate loose-bolt damage based on the highest novelty rates. Similarly, Abdeljaber et al.[13] developed a damage detection framework utilizing output-only acceleration data. They created training datasets for various simulated damage scenarios, such as loose bolts, and trained individual CNNs for each case. The resulting Probability of Damage (PoD) indicator achieved high accuracy with an average error of 0.54% across different damage scenarios. However, practical applications face challenges due to large data requirements for varied damage permutations, as highlighted by Abdeljaber et al.[14]. To address this, a simplified approach was proposed[15], requiring only two damage states—undamaged and fully damaged—though this method provided only a general assessment of structural conditions. Despite the advancements in deep learning-based SHM, current methodologies still struggle to achieve full automation. Replicating human perception through vibration- or vision-based deep learning algorithms remains a significant challenge[18].

2.1.2. Physics model-based methods

Accurate mathematical models are essential for post-processing measured data to predict damage location and severity. Commonly used models include finite difference methods (FDM), finite element methods (FEM), spectral finite element methods (SFEM), and boundary element methods (BEM)[19]. Among these, Finite Element Models (FEMs) are particularly prevalent for simulating the mechanical behavior of structures under various loading conditions[11][12][37][38][39][40]. In SHM studies, a critical aspect of using FEM is the precise modeling of damage, such as cracks. Researchers have developed diverse techniques to simulate defects within the FEM framework. For example, Powar and Ganguli[22] used FEM to model matrix cracks in composite beams, which facilitated the assessment of the performance of a rotating helicopter blade. Similarly, Yang et al.[23] applied FEM to study Lamb wave propagation in composite plates, demonstrating its effectiveness in wave-based damage detection. Crack parameters were also successfully extracted in a study utilizing FEM analysis[20]. Moreover, a novel method employing the Heaviside function was introduced for crack modeling within the FEM framework, offering an innovative approach to damage representation[21].

2.1.3. Hybrid Techniques

The integration of data-driven models with physics-based approaches has gained significant traction, as hybrid methods enhance the robustness and accuracy of damage detection. These approaches combine simulation outputs with real-time sensor data to improve predictive performance. For example, FEM-based models can generate baseline predictions, while deep learning algorithms refine these predictions using feedback from sensors. Lin et al.[16] explored the application of a CNN trained on simulated FEM data of a simply supported beam, considering both noisy and noise-free environments. Their study demonstrated that critical structural features, such as response frequency bands, vibration modes, and their interactions, could be effectively captured by the CNN using sensor data. Additionally, a novel framework called DeepSHM was developed, leveraging data augmentation of sensor signal responses obtained from FEM simulations. This framework provides a generalized methodology by feeding augmented data into a CNN for training, enabling the extraction of neural weights[24].

2.2. Local Methods in SHM

Local SHM methods focus on specific components or areas of a structure to identify and evaluate damage. These techniques often involve detailed assessments or Non-Destructive Testing (NDT) methods to detect localized issues, such as cracks, corrosion, or material degradation. Unlike global SHM methods, local approaches are highly targeted, frequently leveraging insights from global analyses to pinpoint potential damage zones. DT technology enhances local SHM by providing precise simulations of localized damage. DTs utilize real-time data integrated with multi-physics finite element models (FEM) to analyze stress, strain, and displacement in critical areas. For instance, a DT can simulate interactions between piezoelectric sensors and the structure to identify micro-cracks in real time[13]. By combining DT technology with deep learning, local SHM methods gain improved interpretability and accuracy, supporting targeted repair strategies and reducing inspection expenses.

2.2.1. Non-Destructive Testing Techniques

Traditional NDT techniques, such as ultrasonic testing and thermography, are integral to local SHM[41][42][43][44][45]. Ultrasonic Testin uses high-frequency sound waves to identify subsurface defects like cracks and voids. Ultrasonic guided waves (UGWs) are widely applied in health prognosis through various probing techniques, including contact, semi-contact, and non-contact approaches. In the contact method, acoustic sensors—often bonded to or embedded within structural surfaces—are employed to excite and detect acoustic waves[25]. These sensors are crafted from materials responsive to electrical or magnetic stimuli, generating strain upon excitation. Common transducer materials include piezoelectric polymers (PVDF), piezoelectric ceramics (PZT), electrostrictive ceramics (PMN), and magnetostrictive materials (Terfenol-D). Thermograph employs infrared imaging to detect temperature variations that indicate structural damage. Miao et al.[26] introduced an innovative electromagnetic thermography approach for subsurface defect detection. By leveraging radiation parameters and the thermophysical properties of the medium, this method demonstrated superior performance in identifying natural subsurface cracks.

2.2.2. Enhancing Local Methods with Deep Learning

Deep learning has significantly enhanced the efficiency and precision of local SHM methods. CNNs are widely used to process image-based NDT data, such as radiographic or thermographic images, enabling automated defect classification. Transformer-based Models excel in capturing contextual relationships within complex datasets, further improving the accuracy of defect identification and localization. By reducing the dependence on manual inspections, these advancements enhance the scalability of local SHM techniques. For example, Ali and Cha[27] developed a method combining passive thermography with a Deep Inception Neural Network (DINN) to identify and localize internal defects in steel bridge components. Arbaoui et al.[28] applied CNN architectures, including AlexNet and ResNet50, to detect cracks in concrete structures by integrating ultrasonic testing with multiresolution analysis. Han et al.[29] proposed a 2D CNN model to detect crack signals in concrete structures using acoustic emission data.

3. Problem Statement

While DT technology holds great promise for SHM, challenges like environmental noise, measurement errors, and computational constraints limit its accuracy and real-time applicability. Effective models are needed to process complex datasets and address these limitations. This project aims to develop a high-performance hybrid machine-learning model for bridge health monitoring, leveraging DT-generated data. By integrating 1-D CNN and LSTM architectures and employing techniques like Bayesian optimization, the model seeks to enhance damage detection accuracy, address overfitting, and enable cost-effective, proactive maintenance strategies.

4. Proposed methodology

In this project, a large set of numerical models mimicking real bridge structures were created using DT technology. These models were then used to train a hybrid CNN-LSTM model. A portion of the simulated data was employed to fine-tune the model through Bayesian Optimization, optimizing the hyperparameters. The remaining data was used to assess the model's performance. The implementation process is shown in Fig. 1.

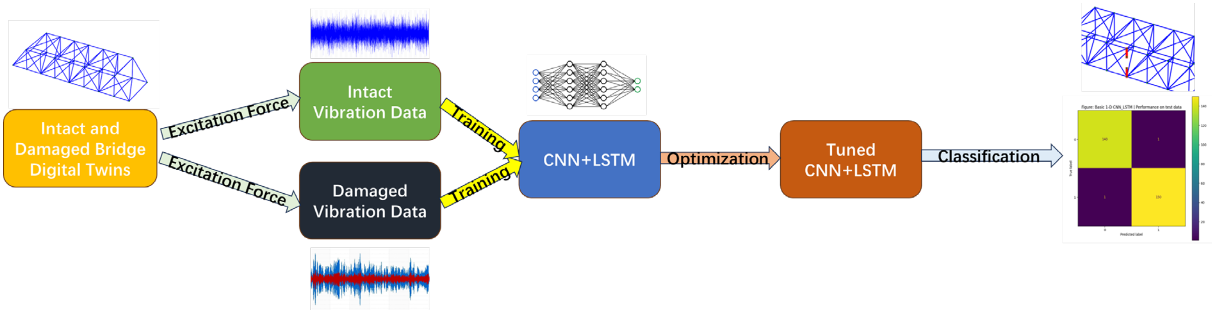

Fig. 1. Overview of method implementation.

4.1. Data from DT bridge model

In this project, two numerical bridge models—one healthy and one damaged—were established using DT technology. The dimensions of the models are as follows: length = 2.4 m, width = 0.3 m, and height = 0.3 m. The modeling parameters for these numerical bridge models are provided in Table 1. The four random factors used in the numerical modeling were set as follows (based on the ABAQUS platform, SIMULIA Inc., Providence, RI, USA):

1. The numerical models were randomly scaled by ±15% from a physical bridge model, as outlined in[10].
2. A 1000 N excitation force was applied through random amplitude curves along the y-axis. The excitation point was randomly selected from one of the 32 points in the healthy truss model (green points in Fig. 2) and 34 points in the damaged truss model (green points in Fig. 3).
3. The random excitation forces were generated using the "randbetween" function in Excel, with a total of 34 values applied to nodes in both models.

4. The excitation force was applied for 4 seconds on each node, and acceleration data in the x, y, and z directions were collected. The time step for data collection was 0.002 seconds, resulting in 2001 data points for each node.

Fig. 2 and Fig. 3 show the locations of the sampling points in the numerical models: 32 points in the healthy model and 34 in the damaged model. However, after visualizing the collected data, I observed that some data points might mislead the model's prediction results. I manually removed these points, and further work will be needed to identify and remove other misleading data. This will be discussed in the Next Steps section.

For the healthy model, 27 nodes were selected as useful data points. When a random excitation force was applied to a node, I collected the vibration signals from all 27 nodes. After applying the excitation force to all 27 nodes, I collected a total of 27x27 sets of healthy data, with each set having a size of (2001, 3), where 2001 is the number of time steps and 3 represents the vibration signals in the x, y, and z directions. Similarly, for the damaged model, flat steel bars were damaged between nodes 20 and 24. I selected the same 27 points, resulting in 27x27 sets of damaged data, each with a size of (2001, 3). Thus, my dataset size is (2x27x27, 2001, 3).

Table 1. The modeling parameters by ABAQUS.

Elastic modulus	Poisson's ratio	Mass density	Modal damping ratio	Meshed with
210 GPa	0.3	7,8000 kg/m^3	0.03	Beam elements (B31 type)

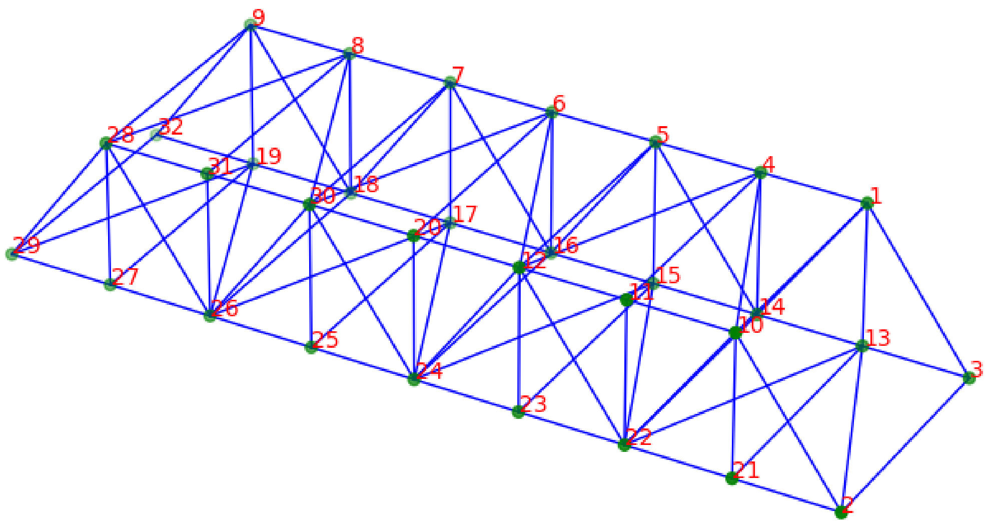

Fig. 2. Layout of the health truss model.

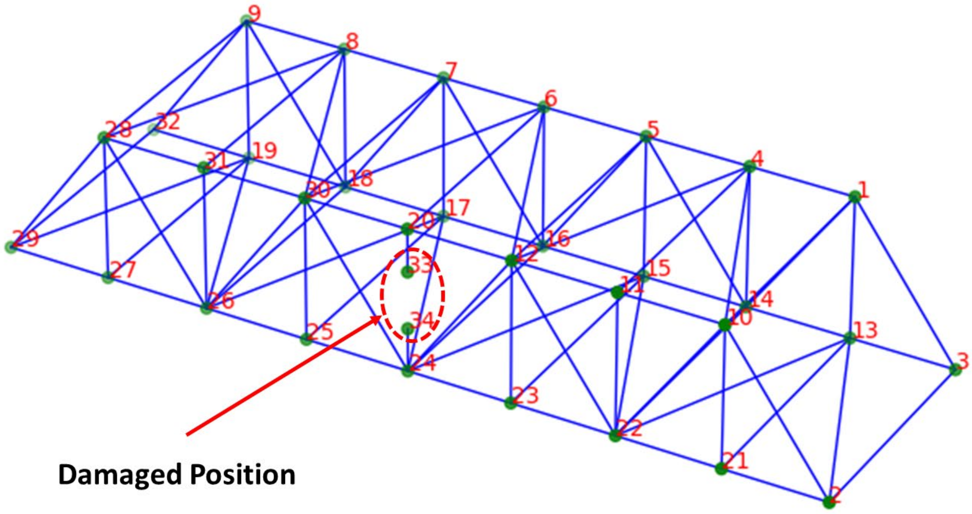

Fig. 3. Layout of the damaged truss model.

4.2. 1-D CNN and LSTM

One-Dimensional Convolutional Neural Networks (1D CNNs) are a specialized form of traditional 2D CNNs, designed for processing sequential or one-dimensional data. A key advantage of 1D CNNs is their computational efficiency, with a complexity of O(NK) compared to $O(N^2K^2)$ for 2D CNNs of equivalent dimensions[30]. Typically, 1D CNNs use more compact architectures, featuring 1-2 hidden layers and fewer than 10K parameters, in contrast to 2D CNNs, which often require millions of parameters. The structure of a 1D CNN is shown in Fig. 4. This streamlined design makes 1D CNNs particularly suitable for real-time applications and resource-constrained environments, as they can be trained and deployed on standard CPUs without the need for specialized hardware like GPU farms. Their applications extend across various fields, including signal processing, sensor data analysis, time series forecasting, and mobile computing. The combination of reduced computational requirements, simpler implementation, and effective performance makes 1D CNNs ideal for mobile devices, IoT applications, and other scenarios that require processing efficiency and real-time performance[31].

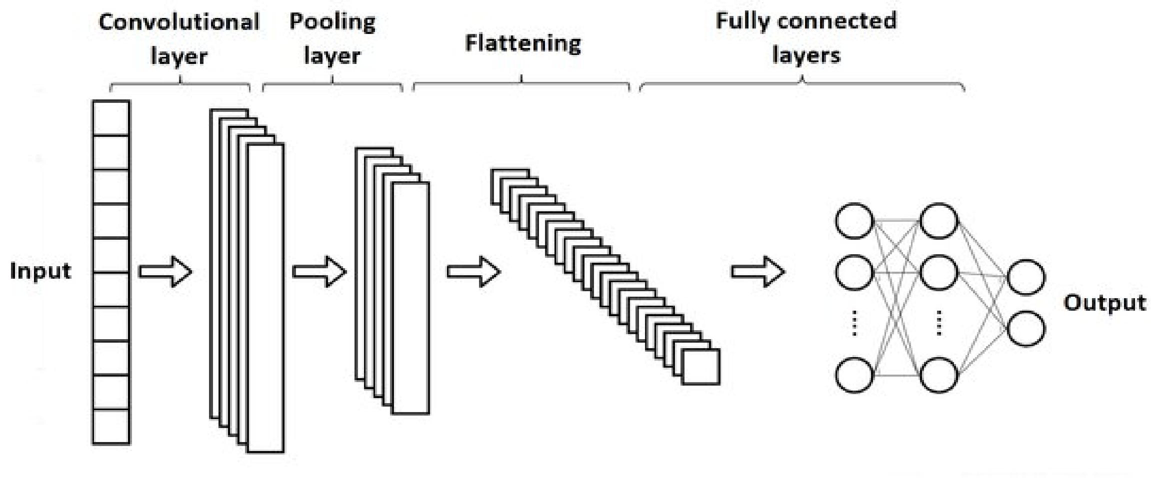

Fig. 4. The structure of 1-D CNN[32].

CNN architecture is based on two primary components: convolution and pooling layers. In a 1D CNN, the convolution operation for single-channel data can be mathematically represented as:[33]

$$F(i) = \sum_{n=1}^{\vartheta_k} S(i+n)K(n)$$

This operation involves the filter sliding across the input signal, computing the sum of element-wise multiplications between the filter coefficients and the corresponding input values at each position. For multi-channel data, the convolution operation is applied simultaneously across all channels, with the results being aggregated. The movement of the filter across the input is controlled by the stride parameter, which defines the step size between consecutive filter positions. Following the convolution layer, a pooling layer is generally applied to reduce the dimensionality of the feature maps while retaining important information. Max pooling is a common approach, which halves the feature map size by selecting the maximum value within each pooling window. To introduce non-linearity, activation functions like the Rectified Linear Unit (ReLU) are used. ReLU is effective due to its computational efficiency and its ability to mitigate the vanishing gradient problem. The ReLU function is defined as:

$$ReLU(x) \ = \ max(0, x)$$

where x is the input value.

LSTM networks are built around specialized memory units called cells. Each cell manages both a cell state and a hidden state, which propagate through the network. The cell state serves as the main information pathway, allowing data to flow with minimal modification through controlled gates. The structure of the LSTM used in this study is shown in Fig. 5.

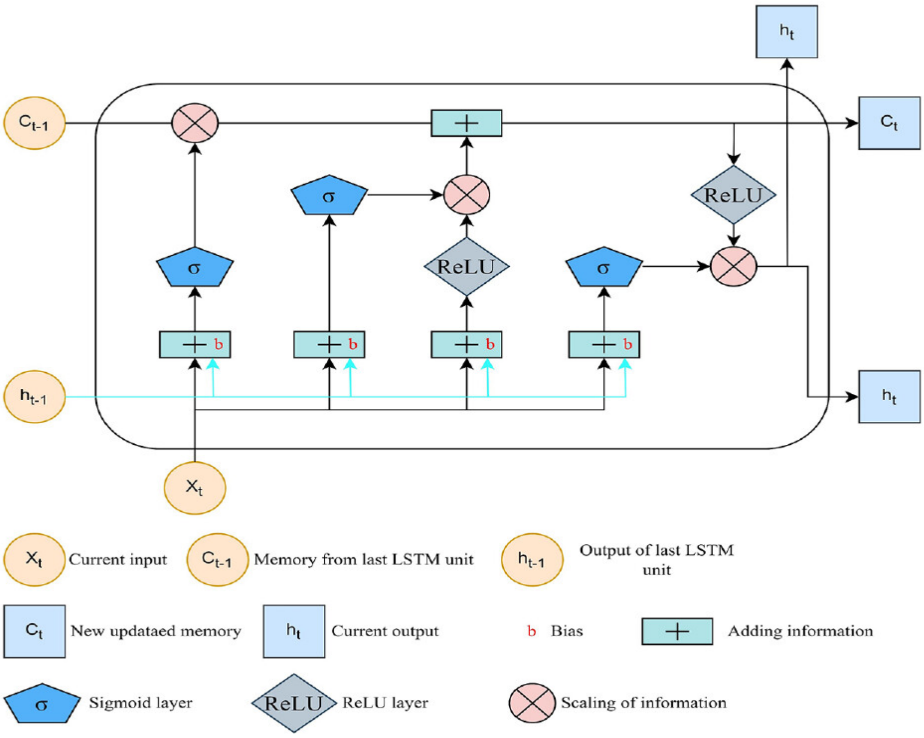

Fig. 5. The structure of LSTM[32].

LSTM operation involves three main phases: First, the forget gate:

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

determines which information should be discarded from the previous state. The second phase is the memory update, which combines an input gate:

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

with candidate values:

$$N_t = ReLU(W_n[h_{t-1}, X_t] + b_n)$$

to update the cell state:

$$C_t = C_{t-1}f_t + N_t i_t$$

The final phase generates the cell's output via the output gate:

$$O_t = \sigma(W_o[h_{t-1}, X_t] + b_o)$$

and the final computation:

$$h_t = O_t * ReLU(C_t)$$

While traditional LSTMs typically use the tanh activation function, this architecture utilizes ReLU, which provides advantages such as improved handling of long-term dependencies, reduced vanishing gradient issues, faster convergence during training, and lower computational overhead. These benefits ultimately enhance the network's performance in sequential data processing tasks.

In this project, the 1-D CNN-LSTM model was employed to classify the damage scenarios of the bridge model. The structure of the 1-D CNN-LSTM network, as depicted in Fig. 6, consisted of four convolutional layers, two pooling layers, two LSTM layers, and one fully connected layer. The collected vibration signals (acceleration) served as the input to the model, while the damage scenarios of the bridge model were used as the output, with intact structures labeled as 0 and damaged structures labeled as 1. To preprocess the data, the acceleration signals in three directions (x, y, and z) were normalized using standardization, ensuring that each component had a mean of 0 and a standard deviation of 1. The dataset was split into training, validation, and test sets with proportions of 60%, 20%, and 20%, respectively. The model was trained using the Adam optimizer with an initial learning rate of 0.001 and a batch size of 32. Cross-Entropy Loss was employed as the loss function to calculate the difference between the predicted logits and the true labels. A learning rate scheduler, ReduceLROnPlateau, monitored the validation loss during training and reduced the learning rate by a factor of 0.1 if no improvement was observed for 7 consecutive epochs. The training process involved processing the normalized vibration data through the 1-D CNN layers to extract spatial features, followed by the LSTM layers to capture temporal dependencies. Finally, the output was passed through a fully connected layer to classify the scenarios into intact or damaged categories. This workflow facilitated effective classification of the bridge model's damage scenarios.

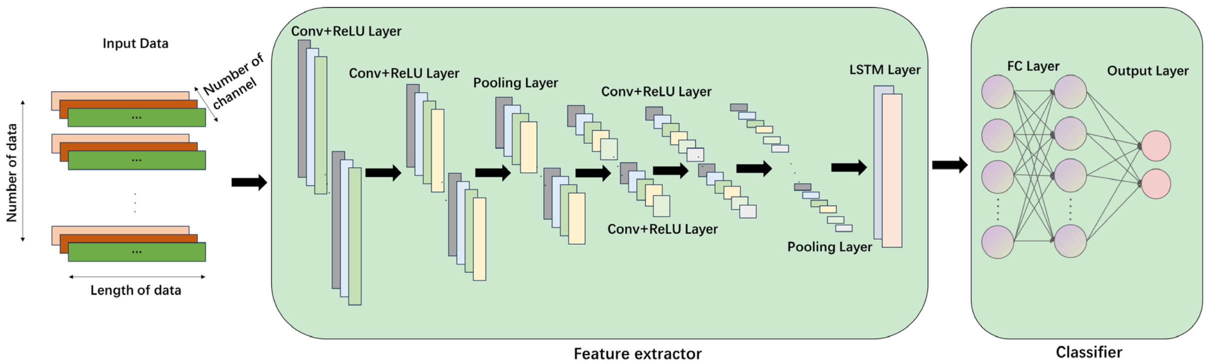

Fig. 6 Structure of the deep learning model.

The optimal architecture of the network was determined using Bayesian optimization. The Tree-structured Parzen Estimators (TPE), a robust hyperparameter optimization technique within the sequential model-based optimization (SMBO) framework, was employed to identify the most effective network configuration. Unlike conventional methods that directly model $P(y|x)$, TPE builds a probabilistic model by estimating $P(x|y)$ and $P(y)$, where x represents the hyperparameters and y denotes the objective function value. The algorithm divides the observed performance metrics into two probability densities: $l(x)$ for superior performances below a threshold y^* (determined by the γ-quantile of observations) and $g(x)$ for inferior performances. This relationship can be expressed as:

$$P(x|y) = \begin{cases} l(x), & for\ y < y^* \\ g(x), & for\ y \geq y^* \end{cases}$$

The optimization process maximizes the Expected Improvement (EI), defined as:

$$EI(x) = \frac{\gamma l(x) - g(x)(1-\gamma)}{\gamma l(x) + g(x)(1-\gamma)}$$

where γ represents the proportion of observations in $l(x)$. Both probability densities are modeled using Gaussian kernel density estimation, allowing for efficient handling of diverse hyperparameter types. The hierarchical structure and computational efficiency of this methodology made it particularly suitable for optimizing the network's architecture, with the final configuration chosen based on the minimum validation error.

5. Preliminary results

This section presents the preliminary detection results of the proposed method, divided into two parts: (1) the pre-trained CNN, developed using DT models (numerical models) with strong compatibility, and (2) the application of the Bayesian optimization algorithm to identify the most suitable model structure.

5.1. 1-D CNN and LSTM trained by using DT models

Initially, the training samples obtained from the numerical models described in Section 3.1 (generated using DT technology) were used to train the 1-D CNN and LSTM. When using only the Y-axis vibration data, the training and validation processes (including accuracy and loss values) are shown in Fig. 7. The best model achieved a validation loss of 0.0052 and 100% accuracy. When evaluated on test data, as shown in Fig. 8 and Table 2, it achieved 99.32% across all metrics - accuracy, precision, recall, and F1 score, as evidenced by both the confusion matrix and evaluation metrics. These exceptional results demonstrate that using Y-axis vibration data alone is highly effective for this classification task.

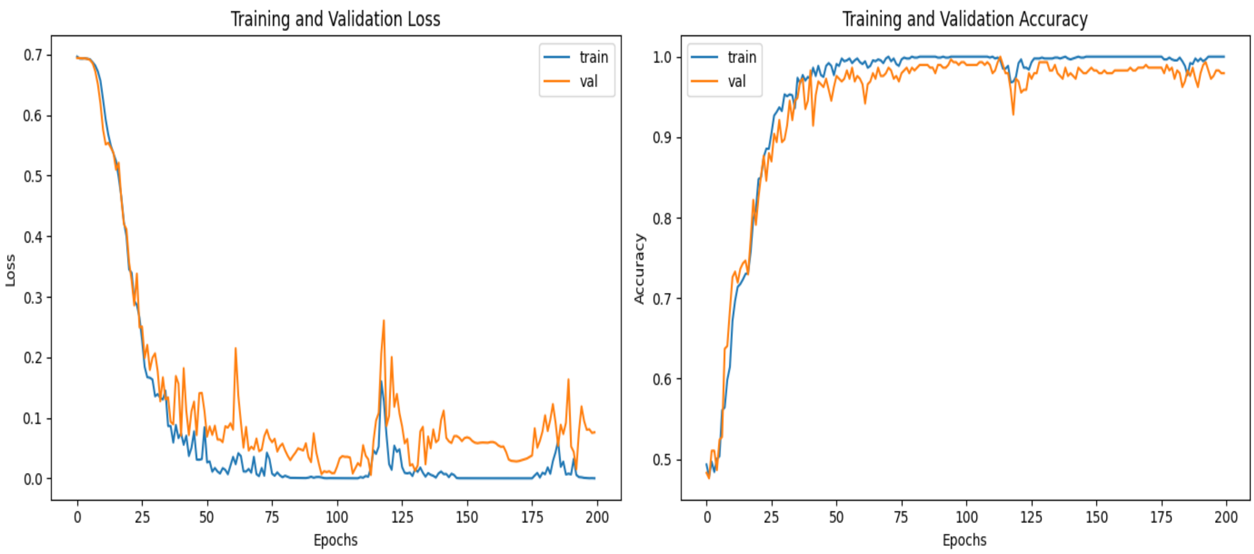

Fig. 7. Training and validation process for the Y-axis vibration signal.

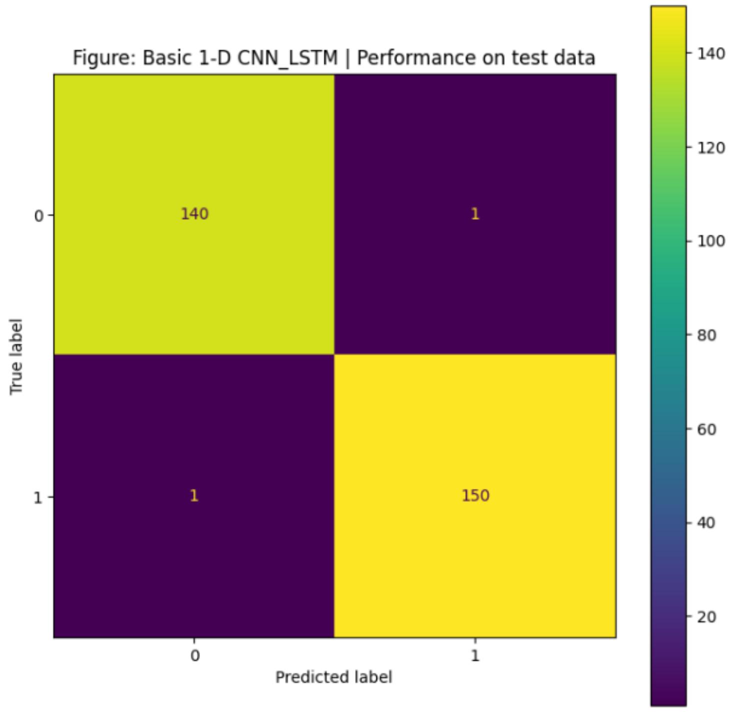

Fig. 8. Confusion matrix of the testing data for the Y-axis vibration signal.

Table 2. Evaluation metrics of the testing data for the Y-axis vibration signal.

Accuracy	Precision	Recall	F1-Score
99.32%	99.32%	99.32%	99.32%

Additionally, the model was trained using all three axes of vibration data (X, Y, and Z). The training and validation results (accuracy and loss values) are shown in Fig. 9. The best model achieved a validation loss of 0.5583 and accuracy of 84.36%. Based on the test data results shown in Fig. 10 and Table 3, the model achieved an accuracy of 76.03%, with a precision of 76.75%, recall of 76.03%, and F1 score of 75.95%, as demonstrated by the confusion matrix and evaluation metrics. However, these performance indicators suggest the model may be overfitting to the training data, indicating that modifications to the model's architecture should be considered to improve its generalization capabilities.

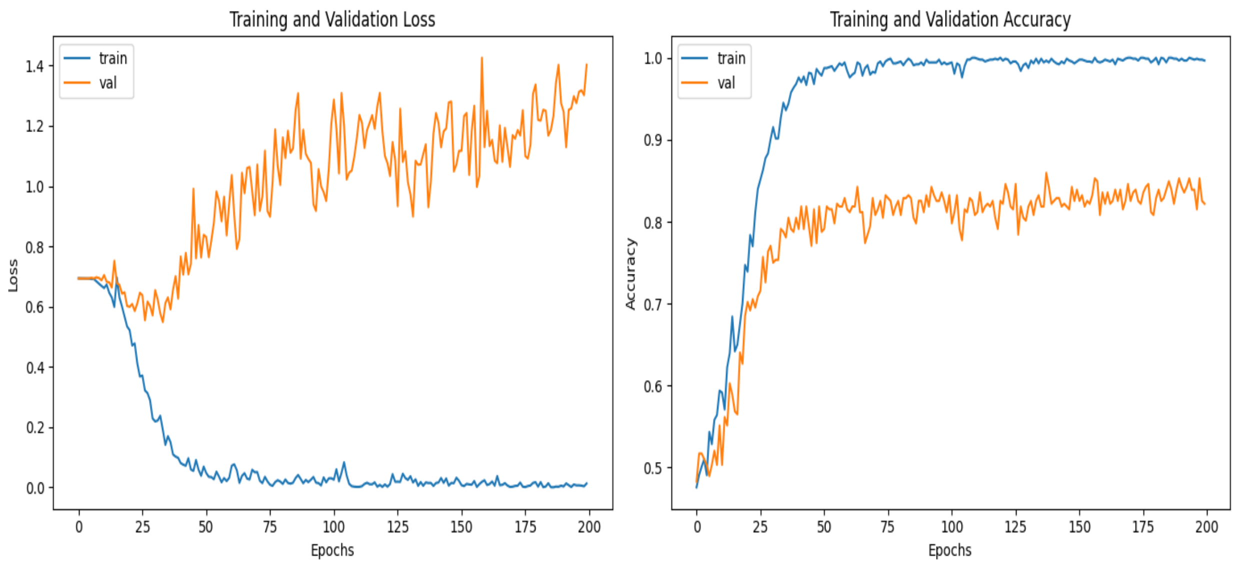

Fig. 9. Training and validation process for all three axis vibration signals.

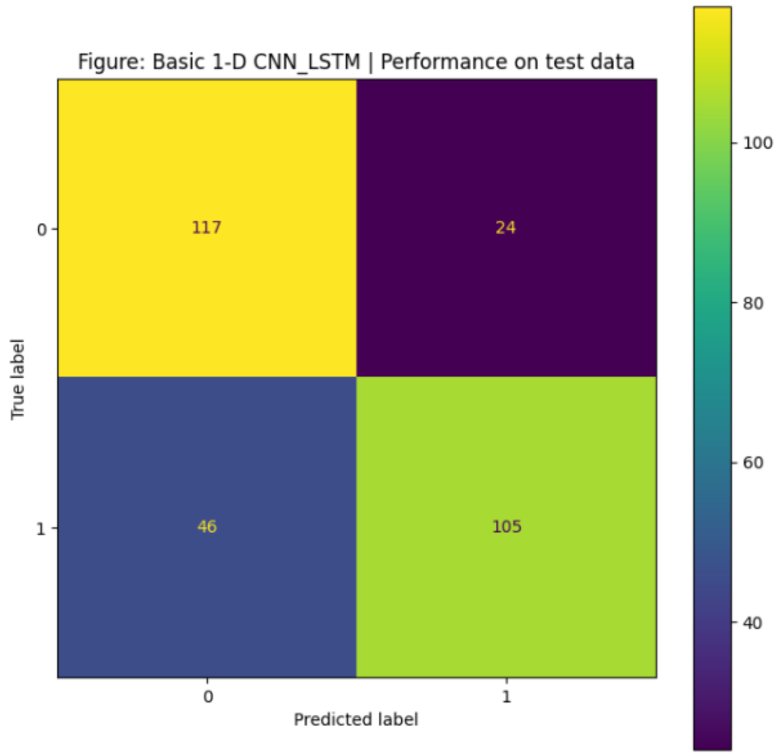

Fig. 10. Confusion matrix of the testing data for all three axis vibration signals.

Table 3. Evaluation metrics of the testing data for all three axis vibration signals.

Accuracy	Precision	Recall	F1-Score
76.03%	76.75%	76.03%	75.95%

5.2. model structure optimization

Based on the Fig. 9 above, the training and validation process for all three-axis vibration signals shows signs of overfitting. Since Bayesian optimization updates the best weights based on the lowest validation loss, the model structure does not perform well due to this overfitting. Therefore, future work is required to address the overfitting issue and further optimize the model structure.

6. Next steps

6.1. Data sampling

In this project, 27 sampling points were initially selected for each numerical bridge model to collect vibration data for health monitoring. However, it may not be necessary to gather acceleration signals from all the sampling points. Redundant data collection can result in higher sampling costs, both in terms of time and resources. Additionally, manually selecting and combining these sampling points is a time-consuming and impractical task, especially when working with large-scale structures. Given these challenges, optimizing the sampling process becomes crucial to ensure that the collected data is both sufficient and cost-effective.

To address this issue, the Bayesian optimization algorithm will be employed to determine the optimal locations and number of sampling points for the model. This algorithm will help identify the most informative points, reducing the number of data collection points while still maintaining high accuracy in the classification of damage scenarios. By using Bayesian optimization, I can efficiently explore the vast space of possible combinations of sampling points, leveraging past observations to identify the best configuration. This method not only minimizes the data collection cost but also enhances the overall performance and reliability of the monitoring system.

6.2. Structure optimization

As discussed in Section 4.1, the current model is experiencing overfitting, which hampers its ability to generalize to new, unseen data. Overfitting occurs when the model becomes too complex and fits too closely to the training data, capturing noise or random fluctuations rather than the underlying patterns. This leads to poor performance on the testing data, as the model struggles to make accurate predictions on unseen samples.

To resolve this issue, specific techniques will be applied to reduce overfitting. These techniques may include regularization methods, such as L1 or L2 regularization, dropout layers, or reducing the complexity of the model by limiting the number of layers or neurons in the network. Furthermore, cross-validation will be employed to evaluate the model's performance on different subsets of the data, ensuring that the model is not overly fitted to any particular portion of the dataset.

Once the overfitting issue is addressed, the next step will be to optimize the model’s hyperparameters. Hyperparameter optimization is critical for improving model performance, as it involves tuning the settings that govern the learning process, such as the learning rate, batch size, and the number of hidden layers. Advanced optimization techniques, such as grid search or random search, can be used to identify the hyperparameter values that lead to the best performance on validation data. By finetuning the model’s hyperparameters, I aim to achieve a more accurate, efficient, and robust model for bridge health monitoring.

6.3. Model Comparison

To further enhance the model's performance, alternative pretrained models or different machine learning approaches will be explored. Pretrained models, which have been trained on large datasets and can be fine-tuned for specific tasks, may offer a better starting point for classification tasks compared to training a model from scratch. These models have the advantage of leveraging prior knowledge learned from similar problems, potentially improving generalization and reducing training time.

In addition to pretrained models, other machine learning approaches, such as support vector machines, decision trees, or ensemble methods, will also be considered to assess whether they could yield better results for solving this classification problem. By comparing the performance of different models, I can determine the most effective approach for predicting damage scenarios in bridge structures and ensure that the selected model offers the best trade-off between accuracy, computational efficiency, and ease of deployment.

Reference

[1] Cha, Y. J., Ali, R., Lewis, J., & Büyüköztürk, O. (2024). Deep learning-based structural health monitoring. *Automation in Construction*, *161*, 105328.

[2] Tuegel, E. (2012, April). The airframe digital twin: some challenges to realization. In *53rd AIAA/ASME/ASCE/AHS/ASC structures, structural dynamics and materials conference 20th AIAA/ASME/AHS adaptive structures conference 14th AIAA* (p. 1812).

[3] Grieves, M., & Vickers, J. (2017). Digital twin: Mitigating unpredictable, undesirable emergent behavior in complex systems. *Transdisciplinary perspectives on complex systems: New findings and approaches*, 85-113.

[4] Niederer, S. A., Sacks, M. S., Girolami, M., & Willcox, K. (2021). Scaling digital twins from the artisanal to the industrial. *Nature Computational Science*, *1*(5), 313-320.

[5] Ye, Y., Yang, Q., Yang, F., Huo, Y., & Meng, S. (2020). Digital twin for the structural health management of reusable spacecraft: a case study. *Engineering Fracture Mechanics*, *234*, 107076.

[6] Podskarbi, M., & Knezevic, D. J. (2020, May). Digital twin for operations-present applications and future digital thread. In *Offshore Technology Conference* (p. D031S037R006). OTC.

[7] Parida, L., & Moharana, S. (2023). A comprehensive review on piezo impedance based multi sensing technique. *Results in Engineering*, *18*, 101093.

[8] Sun, Z., Chen, T., Meng, X., Bao, Y., Hu, L., & Zhao, R. (2023). A critical review for trustworthy and explainable structural health monitoring and risk prognosis of bridges with human-in-the-loop. *Sustainability*, *15*(8), 6389.

[9] Bao, Y., Chen, Z., Wei, S., Xu, Y., Tang, Z., & Li, H. (2019). The state of the art of data science and engineering in structural health monitoring. *Engineering*, *5*(2), 234-242.

[10] Teng, S., Chen, X., Chen, G., & Cheng, L. (2023). Structural damage detection based on transfer learning strategy using digital twins of bridges. *Mechanical Systems and Signal Processing*, *191*, 110160.

[11] Liu, C., Xu, X., Wu, J., Zhu, H., & Wang, C. (2023). Deep transfer learning-based damage detection of composite structures by fusing monitoring data with physical mechanism. *Engineering Applications of Artificial Intelligence*, *123*, 106245.

[12] Tavana, N. R., & Dinavahi, V. (2016). Real-time nonlinear magnetic equivalent circuit model of induction machine on FPGA for hardware-in-the-loop simulation. *IEEE Transactions on Energy Conversion*, *31*(2), 520-530.

[13] Abdeljaber, O., Avci, O., Kiranyaz, S., Gabbouj, M., & Inman, D. J. (2017). Real-time vibration-based structural damage detection using one-dimensional convolutional neural networks. *Journal of sound and vibration*, *388*, 154-170.

[14] Avci, O., Abdeljaber, O., Kiranyaz, S., Hussein, M., & Inman, D. J. (2018). Wireless and real-time structural damage detection: A novel decentralized method for wireless sensor networks. *Journal of Sound and Vibration*, *424*, 158-172.

[15] Abdeljaber, O., Avci, O., Kiranyaz, M. S., Boashash, B., Sodano, H., & Inman, D. J. (2018). 1-D CNNs for structural damage detection: Verification on a structural health monitoring benchmark data. *Neurocomputing*, *275*, 1308-1317.

[16] Lin, Y. Z., Nie, Z. H., & Ma, H. W. (2017). Structural damage detection with automatic feature-extraction through deep learning. *Computer-Aided Civil and Infrastructure Engineering*, *32*(12), 1025-1046.

[17] Wang, Z., & Cha, Y. J. (2018, March). Automated damage-sensitive feature extraction using unsupervised convolutional neural networks. In *Sensors and Smart Structures Technologies for Civil, Mechanical, and Aerospace Systems 2018* (Vol. 10598, pp. 380-386). SPIE.

[18] Zhang, T., Biswal, S., & Wang, Y. (2020). SHMnet: Condition assessment of bolted connection with beyond human-level performance. *Structural Health Monitoring*, *19*(4), 1188-1201.

[19] Gopalakrishnan, S., Ruzzene, M., Hanagud, S., Gopalakrishnan, S., Ruzzene, M., & Hanagud, S. (2011). Application of the finite element method in shm. *Computational Techniques for Structural Health Monitoring*, 157-175.

[20] Dado, M. H., & Shpli, O. A. (2003). Crack parameter estimation in structures using finite element modeling. *International Journal of solids and structures*, *40*(20), 5389-5406.

[21] Ghoshal, A., Kim, H. S., Kim, J., Choi, S. B., Prosser, W. H., & Tai, H. (2006). Modeling delamination in composite structures by incorporating the Fermi–Dirac distribution function and hybrid damage indicators. *Finite elements in analysis and design*, *42*(8-9), 715-725.

[22] Pawar, P. M., & Ganguli, R. (2005). On the effect of matrix cracks in composite helicopter rotor blade. *Composites Science and Technology*, *65*(3-4), 581-594.

[23] Yang, C., Ye, L., Su, Z., & Bannister, M. (2006). Some aspects of numerical simulation for Lamb wave propagation in composite laminates. *Composite structures*, *75*(1-4), 267-275.

[24] Ewald, V., Groves, R. M., & Benedictus, R. (2019, March). DeepSHM: A deep learning approach for structural health monitoring based on guided Lamb wave technique. In *Sensors and Smart Structures Technologies for Civil, Mechanical, and Aerospace Systems 2019* (Vol. 10970, pp. 84-99). SPIE.

[25] Rizzo, P., Cammarata, M., Bartoli, I., Di Scalea, F. L., Salamone, S., Coccia, S., & Phillips, R. (2010). Ultrasonic guided waves-based monitoring of rail head: laboratory and field tests. *Advances in civil engineering*, *2010*(1), 291293.

[26] Miao, L., Gao, B., Li, H., Lu, X., Liu, L., Woo, W. L., & Wu, J. (2023). Novel interventional electromagnetic thermography for subsurface defect detection. *International Journal of Thermal Sciences*, *184*, 107960.

[27] Ali, R., & Cha, Y. J. (2019). Subsurface damage detection of a steel bridge using deep learning and uncooled micro-bolometer. *Construction and Building Materials*, *226*, 376-387.

[28] Arbaoui, A., Ouahabi, A., Jacques, S., & Hamiane, M. (2021). Concrete cracks detection and monitoring using deep learning-based multiresolution analysis. *Electronics*, *10*(15), 1772.

[29] Han, G., Kim, Y. M., Kim, H., Oh, T. M., Song, K. I., Kim, A., ... & Kwon, T. H. (2021). Auto-detection of acoustic emission signals from cracking of concrete structures using convolutional neural networks: Upscaling from specimen. *Expert Systems with Applications*, *186*, 115863.

[30] Kiranyaz, S., Ince, T., Hamila, R., & Gabbouj, M. (2015, August). Convolutional neural networks for patient-specific ECG classification. In *2015 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)* (pp. 2608-2611). IEEE.

[31] Kiranyaz, S., Avci, O., Abdeljaber, O., Ince, T., Gabbouj, M., & Inman, D. J. (2021). 1D convolutional neural networks and applications: A survey. *Mechanical systems and signal processing*, *151*, 107398.

[32] Serghini, O., Semlali, H., Maali, A., Ghammaz, A., & Serrano, S. (2023). 1-D Convolutional Neural Network-Based Models for Cooperative Spectrum Sensing. *Future Internet*, *16*(1), 14.

[33] Lin, Y. Z., Nie, Z. H., & Ma, H. W. (2017). Structural damage detection with automatic feature-extraction through deep learning. *Computer-Aided Civil and Infrastructure Engineering*, *32*(12), 1025-1046.

[34] Jia, J., & Li, Y. (2023). Deep learning for structural health monitoring: Data, algorithms, applications, challenges, and trends. *Sensors*, *23*(21), 8824.

[35] Rosso, M. M., Cucuzza, R., Marano, G. C., Aloisio, A., & Cirrincione, G. (2022). Review on deep learning in structural health monitoring. In *Bridge Safety, Maintenance, Management, Life-Cycle, Resilience and Sustainability* (pp. 309-315). CRC Press.

[36] Dang, H. V., Tran-Ngoc, H., Nguyen, T. V., Bui-Tien, T., De Roeck, G., & Nguyen, H. X. (2020). Data-driven structural health monitoring using feature fusion and hybrid deep learning. *IEEE Transactions on Automation Science and Engineering*, *18*(4), 2087-2103.

[37] Fang, X., Li, H., Zhang, S. R., Wang, X. H., Wang, C., & Luo, X. C. (2023). A combined finite element and deep learning network for structural dynamic response estimation on concrete gravity dam subjected to blast loads. *Defence Technology*, *24*, 298-313.

[38] Pathirage, C. S. N., Li, J., Li, L., Hao, H., Liu, W., & Ni, P. (2018). Structural damage identification based on autoencoder neural networks and deep learning. *Engineering structures*, *172*, 13-28.

[39] Hashemi, A., Jang, J., & Beheshti, J. (2023). A machine learning-based surrogate finite element model for estimating dynamic response of mechanical systems. *IEEE Access*, *11*, 54509-54525.

[40] Kosova, F., Altay, Ö., & Ünver, H. Ö. (2024). Structural health monitoring in aviation: a comprehensive review and future directions for machine learning. *Nondestructive Testing and Evaluation*, 1-60.

[41] Capozzoli, L., & Rizzo, E. (2017). Combined NDT techniques in civil engineering applications: Laboratory and real test. *Construction and Building Materials*, *154*, 1139-1150.

[42] Rhazi, J. (2000). NDT in civil engineering: The case of concrete bridge decks. *CSNDT JOURNAL*, *21*(5), 18-25.

[43] McCann, D. M., & Forde, M. C. (2001). Review of NDT methods in the assessment of concrete and masonry structures. *Ndt & E International*, *34*(2), 71-84.

[44] Wiggenhauser, H., & Taffe, A. (2012, April). NDT in civil engineering: research, application, validation and training. In *18th World Conference on Nondestructive Testing*.

[45] Foucher, F., Fernandez, R., Algernon, D., Leberre, S., Leymarie, N., & Dorval, V. (2022, August). Application of simulation software for NDT for civil engineering. In *NDT-CE 2022-The International Symposium on Nondestructive Testing in Civil Engineering* (Vol. 27, No. 9).

[46] Nguyen, D. C., Salamak, M., Katunin, A., Poprawa, G., & Gerges, M. (2024). Vibration-based SHM of railway steel arch bridge with orbit-shaped image and wavelet-integrated CNN classification. *Engineering Structures*, *315*, 118431.

[47] Avci, O., Abdeljaber, O., Kiranyaz, S., & Inman, D. (2017). Structural damage detection in real time: implementation of 1D convolutional neural networks for SHM applications. In *Structural Health Monitoring & Damage Detection, Volume 7: Proceedings of the 35th IMAC, A Conference and Exposition on Structural Dynamics 2017* (pp. 49-54). Springer International Publishing.

[48] Duan, Y., Chen, Q., Zhang, H., Yun, C. B., Wu, S., & Zhu, Q. (2019). CNN-based damage identification method of tied-arch bridge using spatial-spectral information. *Smart Struct. Syst*, *23*(5), 507-520.

[49] Zhang, X., & Zhou, W. (2023). Structural Vibration Data Anomaly Detection Based on Multiple Feature Information Using CNN-LSTM Model. *Structural Control and Health Monitoring*, *2023*(1), 3906180.

[50] Huang, L., Hong, X., Yang, Z., Liu, Y., & Zhang, B. (2022). CNN-LSTM network-based damage detection approach for copper pipeline using laser ultrasonic scanning. *Ultrasonics*, *121*, 106685.