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Structural Damage Identification Using One-dimensional Convolutional Neural Network

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Aging transportation infrastructure poses increasing challenges, including higher maintenance costs and uncertainty regarding structural reliability and safety, making early damage detection and risk reduction essential. Structural Health Monitoring (SHM) plays a key role in meeting this need by leveraging sensor data to assess structural conditions and identify potential issues before they escalate. Modern SHM systems increasingly integrate machine learning to analyse complex vibration patterns and extract features that traditional methods may overlook. Convolutional Neural Networks (CNNs), with their ability to automatically learn spatial and temporal features directly from raw data, offer a powerful approach for localizing and quantifying structural damage without requiring preprocessing. This paper presents a CNN-based method for identifying both the location and severity of damage in structural components, evaluated on two distinct datasets to demonstrate its versatility. The first dataset consists of simulated time-domain responses from a bridge structure, while the second contains experimental modal data from a wooden cantilever beam. In both cases, damage is introduced through localized stiffness reductions. Results from the two datasets demonstrate strong predictive accuracy and consistent improvements over conventional artificial neural network models. Future work will explore the integration of Aimed Multilevel Sampling (AMS) to reduce computational effort and further improve prediction robustness.

Keywords: Convolutional neural network, damage detection, structural health monitoring, model updating, dynamic analysis.

1 Introduction

The increasing incidence of failures in ageing transport infrastructure highlights the need for timely and reliable damage detection methods capable of preventing structural degradation and ensuring public safety. Structural Health Monitoring (SHM) has become an essential tool in this regard, enabling continuous or periodic assessment of structural condition through the analysis of dynamic response data (Avci et al. 2021, Gomez et al. 2018). Compared with traditional visual inspections, which are labour-intensive, subjective, and often limited by accessibility issues or the presence of non-structural coverings, vibration-based SHM provides a non-destructive and objective means of detecting damage.

Damage identification approaches within SHM are typically divided into model-based and data-based methods. Model-based strategies rely on inverse analysis, where the parameters of a numerical model are usually constructed using the finite element (FE) method and updated until the simulated response matches the measured response of the damaged structure. Local discrepancies between the updated and reference models indicate potential damage. Data-based methods, in contrast, utilize machine-learning algorithms trained on measured structural states to derive damage directly from sensor data. Because acquiring training data for all relevant damage states is difficult for real bridges in service, hybrid strategies combining FE modelling, experimental data and machine learning are increasingly adopted.

Vibration-based damage detection techniques can be broadly categorized by the type of information extracted from the structural response. One major group relies on modal characteristics such as natural frequencies, mode shapes, curvature modes or modal strain energy, which remain central to SHM research and are widely used in both classical and deep-learning-assisted frameworks (Wang et al. 2024). A second category focuses on signal-processing techniques applied directly to time- or frequency-domain measurements, where wavelet-based analysis, empirical mode decomposition and Hilbert–Huang transforms continue to be effective for extracting local or transient damage features from raw vibration data (Silik et al. 2024). These methods are often integrated with modern machine-learning pipelines to enhance feature extraction and improve damage sensitivity.

Recent developments in deep learning have expanded the possibilities of data-driven SHM, allowing models to automatically learn damage-sensitive features without relying on handcrafted modal or signal-processing indicators. Convolutional Neural Networks (CNNs) have shown strong capabilities for analysing structured data such as vibration time histories, spatially distributed mode shapes or frequency-dependent response patterns (Kiranyaz et al. 2020). Motivated by these advances, this paper proposes a CNN-based framework for identifying the location and severity of structural damage. The method is evaluated using two complementary datasets: simulated time-domain responses of a bridge structure, and experimental modal data obtained from a set of wooden cantilever beams with controlled stiffness reductions. This combined analysis demonstrates the applicability of the approach across different structural scenarios and data types.

2 Methodology

A convolutional neural network is a type of machine learning model designed to process data with a grid-like structure. For example, image data forms a two-dimensional (2D) grid of pixels, while time series data can be viewed as a one-dimensional (1D) grid of samples taken at regular time intervals. The primary role of a CNN is to perform automatic preprocessing of raw input and extract meaningful features. A typical CNN architecture consists of three main components: a convolutional layer (CL), a pooling or subsampling layer (PL), and a fully connected layer (FCL), as illustrated in Figure 1.

The convolutional layer uses a set of learnable filters (or kernels) that slide across the input. Each filter performs a convolution operation, multiplying its weights with corresponding input values and summing the results. Every filter produces one feature map, and the total number of filters defines the depth of the convolutional layer. The convolutional layer is followed by a subsampling (pooling) layer, which reduces the spatial or temporal dimensions of the feature maps. This improves computational efficiency and makes the extracted features more robust. A commonly used pooling method is max pooling, which selects the maximum value within a specified region of the input and therefore decreases the resolution of the feature maps produced by the previous convolutional layer.

The final component of the network is the classification stage, implemented as a fully connected layer. This layer receives the high-level features extracted by the convolutional and pooling layers and performs the final classification. The classification layer is like classical neural network of multilayer perceptron structure (Yu et al., 2019).

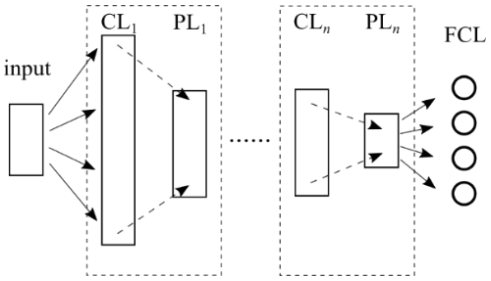

Figure 1. General structure of CNN.

3 Application

This paper presents a one dimenstional CNN-based method for identifying both the location and severity of damage in structural components, evaluated on two distinct datasets to demonstrate its versatility:

3.1 *Riveted truss bridge*

3.1.1 *Description of structure*

The proposed method was applied to a steel railway bridge spanning the Váh River in Trnovec nad Váhom, Slovakia, as shown in Figure 2. The bridge consists of 28 simply supported spans, with 14 spans on each of the two parallel tracks. One track is composed entirely of truss bridges, while the other track contains a combination of truss and box-girder bridges. The total length of the bridge system is 455.8 m. The focus of this study is a single truss-bridge span. The selected span has a length of 31.3 m and is supported by concrete piers, with four spans resting on each pier.

Figure 2. Side view of riveted truss bridge.

3.1.2 *FEM model*

A detailed FEM model of the bridge was created in ANSYS. Most structural components were modelled using shell elements, except for the lateral and transverse bracing, which were represented as beam elements. To better simulate the dynamic response of the structure under train loading, non-load-bearing components such as wooden sleepers and steel rails were also included in the numerical model, implemented as stiffness elements without mass contribution. The structural system was modelled with a fixed bearing at one end and a sliding hinged bearing at the opposite end (modelled as frictionless).

The method was used to identify damage at two different locations, fifth diagonal member marked in light red and eighteenth diagonal member marked in dark red (on the opposite side of the structure), see Figure 3. Damage was simulated by reducing the Young's modulus of selected diagonal members. In the undamaged condition, all members were modelled as steel with an elastic modulus of $E = 210$ GPa, $\rho = 7850\,\mathrm{kg \cdot m^{-3}}$. No structural damping was applied in the transient analysis. For each out of 20 diagonal members, a separate material definition was created, in which the original modulus E was multiplied by a coefficient k, representing the degree of damage. A value of $k = 1$ corresponds to an undamaged member, while $k < 1$ indicates stiffness reduction due to damage. These coefficients $\mathbf{k}$ serve as the design variables in the FE model updating process.

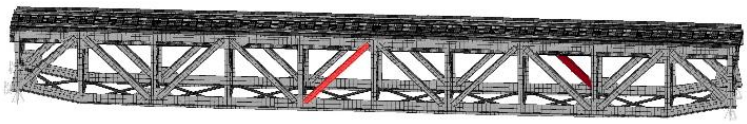

Figure 3. FEM model of the bridge with marked damaged diagonal members.

3.1.3 Input data and CNN architecture

The input to the CNN consists of the displacement time history recorded at a single monitoring point located at the mid-span of the structure, in all three orthogonal directions (x, y, z). The structure was subjected to an impulse load of 100 N applied in the vertical direction (F_z) at mid-span of the structure. The analysis started from a zero-displacement, zero-velocity initial condition, and gravity effects were not included. The signals are recorded over 2 s with a time step of 0.01 s, so each direction provides 200 samples. The three directional signals are concatenated into a single input vector of size 600 × 1. The first convolutional layer applies 32 filters with kernel size 3 and stride 1, using padding to preserve the input length, resulting in 32 feature maps of size 600 × 1. The resulting feature maps are downsampled by max-pooling, reducing their size to 300 × 1. A second convolutional layer with 64 filters (kernel size 3 and padding) produces 64 feature maps of size 300 × 1, followed by another max-pooling step, reducing the size to 150 × 1. The 64 feature maps are then flattened into a 9600-element vector, which feeds into a fully connected layer with 64 neurons. The output layer contains 20 neurons, corresponding to the number of predicted diagonal parameters. The CNN architecture used for the riveted truss bridge is shown in Figure 4. The CNN was trained using 600 dynamical simulations computed with the full transient (implicit Newmark) method, using randomly generated inputs covering the full design space, with member stiffness coefficients uniformly sampled between 0.85 and 1.05.

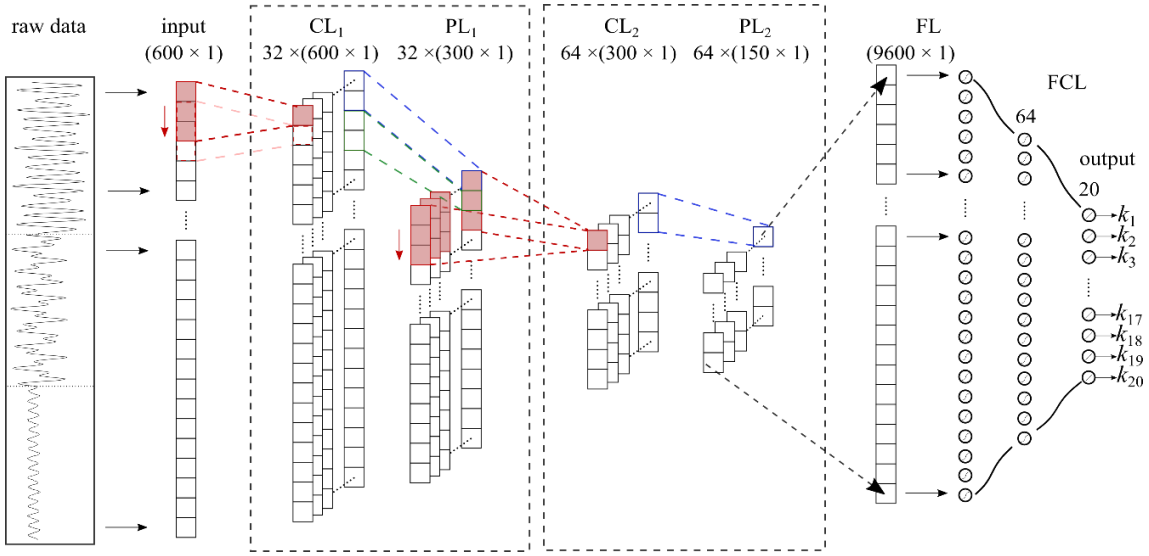

Figure 4. Scheme of architecture of CNN for riveted truss bridge.

3.1.4 Results

The results of the riveted truss bridge are shown in Figure 5 below, where the red column represents fifth damaged member ($k_5 = 0.95$), the dark red is eighteenth damaged member ($k_{18} = 0.9$) and other columns are in white and should be equal to 1, as undamaged. The results show that the damaged elements were successfully localised, and that the extent of the damage was determined with sufficient accuracy.

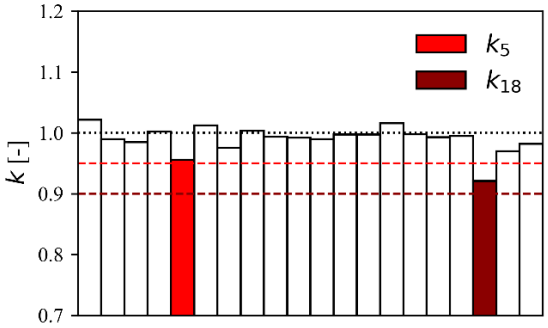

Figure 5. Stiffness scheme of diagonal members with marked damage.

3.2 *Cantilever wooden beam*

3.2.1 *Description of structure*

The experimental campaign was carried out on ash-wood cantilever beams with a length of 1.0 m and a rectangular cross-section of 30 × 7 mm. A 100 mm clamping region created an effective cantilever length of 0.9 m. Before testing, all specimens were weighed and measured, and their Young's modulus was estimated from the measured natural frequencies using Euler–Bernoulli beam theory. The average value obtained was 15.5 GPa with a coefficient of variation of 0.10.

Dynamic measurements were performed using five Brüel & Kjær 4508 B 001 accelerometers connected to a 3560 B 140 analyzer. The sensors were positioned along the beam at 180 mm intervals from the free end. The test configuration is shown in Figure 6. Acceleration time series of approximately 10 s were recorded at 4096 Hz. Excitation was provided by a repeatable single impact from a 0.25 g plastic spherical projectile dropped from 32 cm, ensuring clean modal responses without multiple contacts. After the initial undamaged tests, each beam was locally cut at mid-span to introduce a controlled stiffness reduction, and the measurements were repeated to assess the influence of damage on the modal properties (Lehký and Frantík 2009).

Figure 6. Test configuration and realization of beam's fixed support.

3.2.2 *FEM model*

A finite element model of the cantilever beam was developed in ANSYS using beam elements. The model geometry, boundary conditions, and material properties were defined to match the experimental specimen. The effective 0.9 m cantilever length was discretized into fifteen equal elements (see Figure 7) to allow localized stiffness reductions to be represented by assigning each element an independent Young's modulus.

Damage was simulated by reducing the Young's modulus of selected elements using a coefficient k, where $k = 1$ corresponds to the undamaged state and $k < 1$ represents stiffness loss, as in the previous case. This approach replicates the experimentally introduced mid-span cut, which produced a local reduction in bending stiffness. Concentrated masses corresponding to the accelerometers were added at the respective nodes, as shown in Figure 7. The resulting model was used to compute modal properties for both undamaged and damaged configurations, providing numerical reference data for comparison with the experimental measurements.

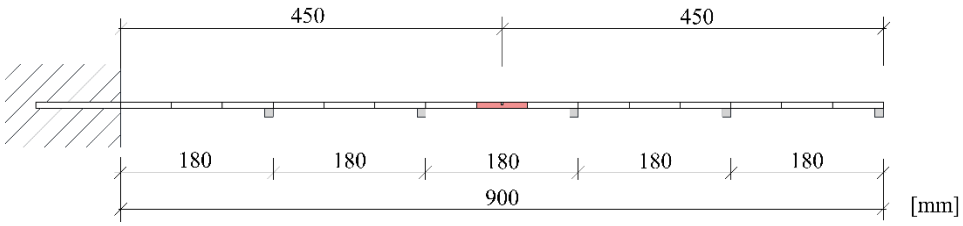

Figure 7. Scheme of cantilever beam with marked cut middle section and accelerometers.

3.2.3 Input data and CNN architecture

The input to the CNN for the wooden cantilever beam is based on experimentally obtained modal parameters. The first half of the input vector contains the relative differences between simulated and experimental mode shapes, while the second half contains the relative differences between simulated and experimental natural frequencies. These modal quantities are arranged into a 1D input vector of size 50 × 1.

The input vector is processed by a convolutional layer containing 32 filters with kernel size 3, which extracts local patterns from the modal-parameter sequence. The resulting feature maps are flattened and passed to a fully connected layer with 32 neurons. The output layer contains 15 neurons, corresponding to the number of sections identified for this structure. The CNN architecture used for the wooden beam case is illustrated in Figure 8.

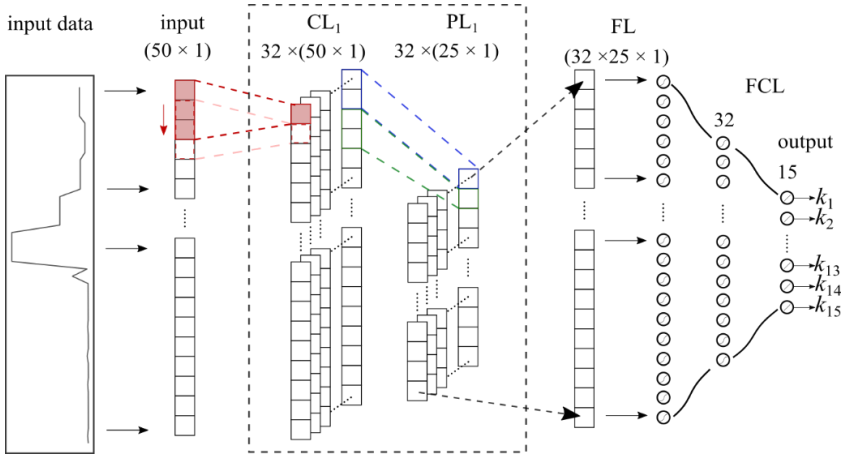

Figure 8. Scheme of architecture of CNN for wooden cantilever beam.

To train the CNN, 85 simulations, i.e., 85 models for numerical modal analyses were generated in which stiffness was varied only in a predefined subset of five sections (2, 5, 8, 11, 14). In each simulation, only one of these sections was assigned a reduced stiffness, sampled independently from the interval 0.3–1.1, while all remaining sections were kept at the undamaged value of 1.0. This design ensured that the network learned to identify isolated local stiffness reductions without the confounding effects of multiple simultaneous damage locations.

3.2.4 Results

Figure 9 shows the predicted stiffness parameters for the cantilever beam. Most sections remain close to the undamaged reference value of approximately 1.0, while a clear reduction appears in the middle region. The lowest predicted value occurs at element 8, which corresponds exactly to the location where the beam was physically cut during the experiment.

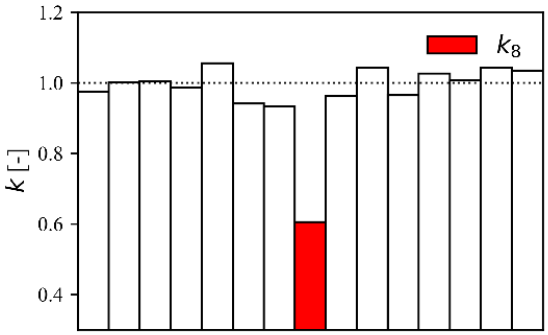

Figure 9. Stiffness scheme of sections with marked cut section.

4 Conclusion

This paper demonstrated the applicability of convolutional neural networks for detecting localized stiffness reductions in two different structural systems: a riveted truss bridge using simulated responses in the time domain and a wooden cantilever beam using experimentally measured modal data. Thus, the input data formats differed significantly—in the first case it was a time-series record of displacement, and in the second, modal parameters. The results show that CNN successfully identified the location of damage in both structures.

The findings suggest that CNN-based models can extract relevant damage features from relatively compact modal or time series datasets, making them suitable for practical applications involving different levels of measurement availability. Future work will focus on integrating aimed multilevel sampling optimization method (AMS) to reduce computational demands during training and further increase robustness and generalization for more complex structural configurations. This synergy of metaheuristic optimization with machine learning method has proven its effectiveness in identifying damage using frequency-domain data, as presented in paper Šplíchal et al. (2025).

Acknowledgments

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