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CWT-CNN-Based Damage Localization in plate like structure

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Abstract

This study proposes a novel hybrid approach integrating Continuous Wavelet Transform (CWT) and Convolutional Neural Networks (CNN) for automated structural damage detection and localization in steel plates. A numerical finite element model of a square steel plate with fixed boundary conditions is developed to obtain the vibration characteristics and mode shapes under intact and damaged conditions. The differences between the first mode shapes of the intact and damaged plates are processed using CWT to extract localized damage-sensitive features at multiple scales. The resulting wavelet representations are converted into images and used as input to a CNN model for automated identification and localization of damaged regions. The results demonstrate that the proposed CWT–CNN framework can effectively distinguish damage locations and provides reliable prediction performance under the considered numerical conditions. The proposed methodology offers a promising and intelligent framework for structural health monitoring, with future scope for validation using experimental and real-time vibration data.

Keywords: CWT, Modal Analysis, CNN, Image processing

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1. Introduction

The purpose of this study is to propose a damage detection system that com-bines CNN and WT to identify, localize, and measure damage. The purpose of the suggested neuro-wavelet technology is to detect minor structural dam-age in steel plates. Damage to the plate structure occurs in various places. Developed algorithm to detection of damage to prevent catastrophic collapse of civil structure by using Wavelet Transform (WT) and Artificial Neural Networks (ANN) [1]. For the first time, a novel method based on the shearlet transform is presented in this work to identify damages. It is compared to the wavelet, Laplacian pyramid, curvelet, and contourlet transformations to identify various kinds of plate structure flaws [2]. Carried out a wavelet transform to find fractures in frame structures, such as beams and plane frames, and found that the chosen wavelets are accurate and that the technique can reliably and simply extract damaged information from response signals. [3]. The one-dimensional continuous wavelet transform is used to examine the beam's estimated mode shapes. The two-dimensional continuous wavelet transform formulation for plate damage detection is introduced. A peak in the spatial variation of the converted response indicates the damage's location [4]. As damage increases in size, the curvature mode forms alter more. The level of damage to the structure may be determined using this information. The displacement mode forms of the two models were obtained by finite element analysis. The curvature mode forms were then computed from the displacement mode shapes using a central difference approximation [5]. Introduces a large-scale road damage dataset with 26,620 annotated images from multiple countries. It aims to create deep learning models that work across different regions for road damage detection and classification [6]. Experiments show that combining data from various countries improves model performance. A detailed analysis was done using data from Japan, India, and the Czech Republic. The dataset attracted 121 teams and demonstrated the research usefulness of GRDDC 2020. It may be expanded to gauge the extent of damage and is open to the public, encouraging outside contributions [7]. A QCNN approach that combines Quantum Computing and Convolutional Neural Networks (CNNs) to detect multiclass damage in RC buildings is proposed using post-earthquake photographs. After being educated on past earthquake data, it showed exceptional accuracy on images of the 2023 Turkey earthquake. While angle encoding was used, future study will focus on deeper layers and more complex quantum encoding. QCNN has promise for broader applications as well as real-time damage detection [8]. A unique active acoustic emission damage detection technology was devised to assess the degree of damage in steel plates. Two novel damage indices were proposed after low- and high-frequency emissions were examined [9]. By applying several single and multiple damage scenarios to a 3D finite element model of a simply supported steel beam and a steel frame of an industrial shed, the viability and performance of the suggested technique were evaluated. The outcomes show how effective and capable the suggested non-destructive technique is for identifying deterioration in these steel frames [10]. Simulations show that the indices remain constant across all noise levels and increase with the depth of damage. Experiments confirmed the approach's accuracy, supporting its use in practical engineering situations [11]. To accurately identify the damage location while dissecting the mode shape changes, the appropriate mother wavelet must be chosen. After a few tries, Paul's mother wave-let is chosen [12]. In order to identify damage in beam and plate structures, wavelet-based methods on mode shapes were introduced. CWTs were found to be more effective than DWTs, with symmetric wavelets and higher vanishing moments improving accuracy; two-dimensional wavelet transforms allow the localisation of even tiny flaws, though the method is still in the early stages of development [13]. Demonstrates how the Wavelet Transform (WT) may be used to analyse non-stationary time series in a variety of domains, such as engineering, finance, geosciences, and medicine. Important issues including the selection of wavelet type, mother wavelet, scale, and the interpretation of decomposed components are covered. [14]. The integration of WT with machine learning has shown promising results, reinforcing WT's value as a powerful tool across diverse scientific and applied domains [15]. Introduces a WT-CNN method that combines 2D wavelet transforms with CNNs to detect damage in laminated composite plates, using FEM-generated signals and optimal wavelets to accurately locate damage while reducing reliance on trial-and-error simulations [16]. The CNN architecture, feature extraction techniques based on 1-D, 2-D, and 3-D CNN models, and multi-feature aggregation techniques are presented. Applications of CNN as a depth feature extractor for identifying and evaluating complex food matrices—such as fruits and vegetables, meat and marine products, cereals and cereal goods, and others—are covered. Additionally, trends for upcoming research on using CNN for food identification and analysis are emphasised, and data sources, model design, and overall performance of CNN with other current approaches are compared [17].

Previous machine-learning and CNN-based studies have mainly addressed image-based structural damage or composite structures, while limited attention has been given to FEM-generated vibration mode-shape data of isotropic steel plates. Furthermore, the capability of multi-scale CWT images obtained from first mode-shape differences to identify small artificial defects at different locations has not been sufficiently investigated. The influence of an appropriate mother wavelet and the use of spatial wavelet features for automated damage localization also require further study. Therefore, a research gap exists in developing a fully numerical FEM–CWT–CNN framework that can accurately localize and estimate the severity of small defects in steel plates. The present study addresses this gap by transforming simulated mode-shape differences into multi-scale wavelet images and using them to train a CNN for automated damage identification and localization.

This study presents an innovative structural damage detection method that combines the signal-processing capability of wavelet analysis with the pattern-recognition ability of Convolutional Neural Networks (CNNs). The proposed approach focuses on detecting difficult-to-identify damage in steel plates by analyzing vibration-based mode shape differences. The extracted features are transformed into informative images and used to train a CNN model for automated identification of damage location and severity. This innovative strategy improves the precision and effectiveness of structural integrity testing while lowering dependency on traditional manual damage assessment methods. Future research can expand the suggested technique to include experimental and real-time data, offering a viable basis for automated structural health monitoring.

2. Numerical plate modelling

The numerical model consists of a square steel plate measuring 250 mm × 250 mm with a thickness of 2 mm. The material properties adopted for the analysis are presented in Table 1. All four edges of the plate are assumed to be fully fixed. The plate is modeled using finite element analysis software with suitable plate elements and discretized into 672 elements with a mesh size of 20 mm × 20 mm. Modal analysis is performed to obtain the natural frequencies and corresponding mode shapes of the plate under intact and damaged conditions, as illustrated in Figure 1.

Table 1. Material Properties of steel

Properties	Value
Young's Modulus	200 GPa
Poisson's ratio (μ)	0.3
Density (ρ)	7850 kg/m^3

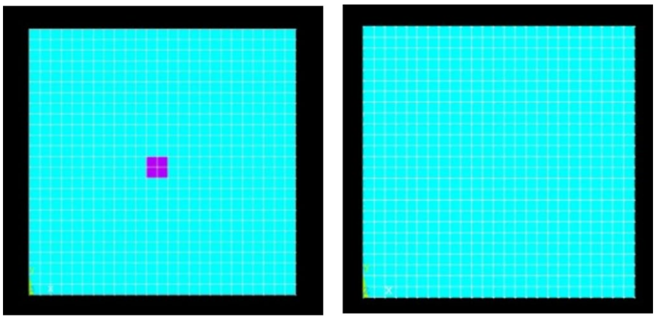

Figure 1. Square plate modelled with defect and without defect

To investigate the capability of the proposed damage detection approach, artificial damage is introduced at five different locations: the centre, top-left, top-right, bottom-left, and bottom-right regions of the plate. The damaged regions are represented by a local reduction in plate thickness over a rectangular area of 40 mm × 40 mm. The difference between the intact and damaged conditions is obtained by subtracting the nodal displacement values of the first mode shape. The resulting mode-shape difference is then processed using the Continuous Wavelet Transform (CWT) to identify localized changes associated with damage. An appropriate mother wavelet is selected to achieve effective decomposition and enhanced localization of the damage-related features. The resulting wavelet coefficients, together with their corresponding spatial coordinates, are subsequently used as input features for training the neural network model to determine the damage location and severity.

3. Continuous Wavelet transformation

3.1. Formulation

A mother wavelet function $\psi(x)$ creates a wavelet family $\psi_{u,s}(x)$.

$$\psi_{us}(x) = \frac{1}{\sqrt{s}}\psi\frac{(x-u)}{s} \quad (1)$$

where s and u are scale and position, respectively.

The deflection of the plate as a one-dimensional signal f(x), the CWT defined by:

$$Wf(u,s) = \frac{1}{\sqrt{s}}\int_{-\infty}^{+\infty} f(x)\psi\left(\frac{x-U}{s}\right)dx \quad (2)$$

where $Wf(u,s)$ is wavelet coefficient of the wavelet $\psi_{u,s}(x)$. The n vanishing moment of a wavelet is vital in detecting singularity of signals, which is based on the equation:

$$\int_{-\infty}^{+\infty} f x^k \psi(x)\,dx = 0, k = 0,1,2,3 \ldots, n-1 \quad (3)$$

Rewriting the above equation gives:

$$Wf(u,s) = \frac{1}{\sqrt{s}}\int_{-\infty}^{+\infty} f\left((x)\psi\left(\frac{-(u-x)}{s}\right)\right)dx = \frac{1}{\sqrt{s}} f * \psi\left(\frac{-u}{s}\right) = f * \bar{\psi}_s(u) \quad (4)$$

and

$$\bar{\psi}_s(u) = \frac{1}{\sqrt{s}}\psi\left(\frac{-x}{s}\right) \quad (5)$$

Re-writing as the nth order derivation of a smooth function $\theta(x)$ [4]:

$$Wf(U,s) = \frac{s^n}{\sqrt{5}}\int_{-\infty}^{+\infty} f(x)\frac{d^n}{dx^n}\theta\left(\frac{x-u}{s}\right)dx = \frac{s^n}{\sqrt{s}}\frac{d^n}{dx^n}\int_{-\infty}^{+\infty} f(x)\theta\left(\frac{-(U-x)}{s}\right)dx \quad (6)$$

$$\bar{\theta}_s(x) = \frac{1}{\sqrt{s}}\theta\left(\frac{-x}{s}\right) \quad (7)$$

where $f * \bar{\theta}_s$ is convolution. In two-dimensional CWT, the function $f(x, y)$ is given in [13] as:

$$W^i f(u,v,s) = \frac{1}{s} f * \psi^i\left(\frac{-u}{s},\frac{-v}{s}\right) = f * \bar{\Psi}_s(u,v), i = 1,2 \quad (8)$$

The horizontal $\psi^1(x,y)$ and vertical $\psi^2(x,y)$ wavelets are constructed with separable products of scaling $\emptyset$ and wavelet function

$$\psi^1(x,y) = \emptyset\cdot(x)\psi(y)\ \psi^2(x,y) = \psi\cdot(x)\emptyset\cdot(y) \quad (9)$$

3.2 Procedure of Continuous Wavelet Transform technique:

The methodology employs mode shape data derived from modal analysis of a square steel plate under both healthy and damaged conditions. These datasets are generated using a finite element simulation. The plate, constructed from steel, is constrained along all four edges to replicate fixed boundary conditions. This configuration makes it possible to extract mode shape differences, which are essential input characteristics for wavelet processing and damage detection using neural networks.

In this work, the mode shape differences between the injured and undamaged states are broken down using the Continuous Wavelet Transform (CWT). The wavelet transform is very useful for identifying localised changes in structural responses because it gives localisation in both the time and frequency domains, in contrast to the Fourier transform, which only provides localisation in the frequency domain. CWT can efficiently detect and locate structural deterioration by evaluating localized data, such as displacement. However, choosing a suitable mother wavelet, which usually requires repetitive trial-and-error processes, is one of the primary difficulties in performing wavelet-based analysis. By using CWT to break down the mode shape discrepancies, important information about the existence and location of structural damage is revealed. The different stage in damage detection using wavelet transformation is given in Figure 2.

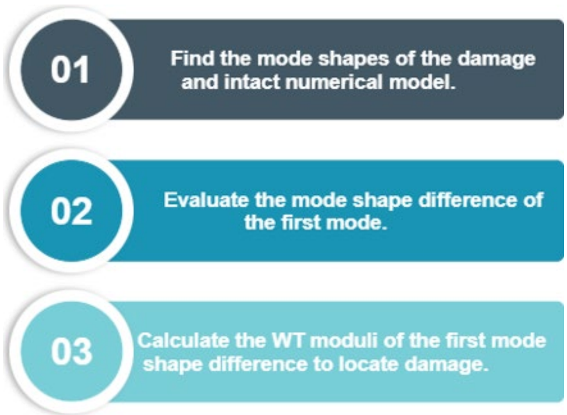

Figure 2. CWT process flow

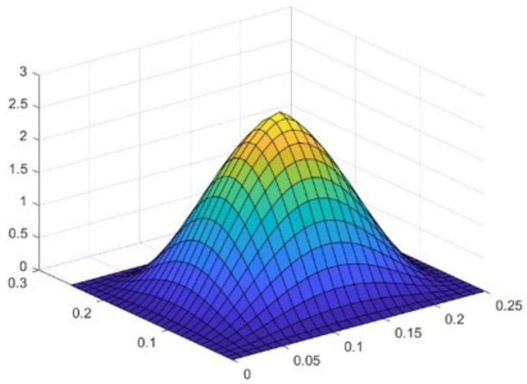

Figure 3: Mode shape the plate

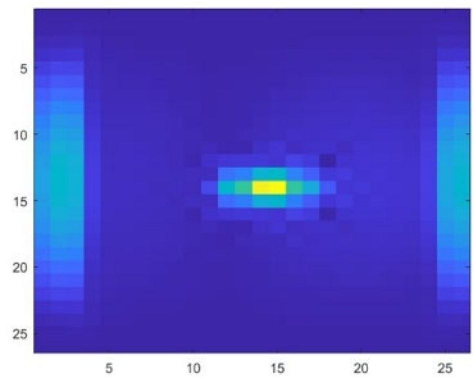

Figure 4. Mode shape after wavelet transform

To ensure uniformity in boundary conditions and normalisation, modal analyses are first carried out on both the undamaged and damaged numerical models in order to extract their corresponding mode forms. Since lower modes are usually more sensitive to changes in global stiffness brought on by damage, the difference between the first-mode forms of the intact and damaged models is next assessed. Lastly, the first-mode shape difference's wavelet transform (WT) modulus is calculated, which amplifies singularities and sudden changes in the modal response to allow for the spatial localisation of damage. Peaks in the WT modulus indicate regions of stiffness discontinuity, thereby providing an effective and sensitive means for damage detection and localization In this study, MATLAB is utilized to perform the Continuous Wavelet Transform (CWT) analysis. Figure 3 presents the first mode shape of the numerically modelled square steel plate, with all edges subjected to fixed boundary conditions. The difference in nodal displacements between the damaged and intact plates for the first mode shape is used as input to the CWT module in MATLAB. This wavelet-based processing enables enhanced visualization of localized structural variations. As illustrated in Figure 4, the resulting wavelet coefficients clearly reveal the damaged location on the plate surface.

4. Convolutional Neural Network - CNN

CNN is a deep learning model specially designed for processing visual data like image and videos. Based on the project CNN is a useful model as it helps in detecting or recognizing spatial patterns such as textures, edges, shapes and objects in the given image data. It is also efficient for smaller datasets. Displacement mode shapes and wavelet processed healthy and defect images are trained to CNN will be able to automatically learn and extract patterns without needing manual feature engineering, making it ideal for this task. In the code using the TensorFlow the labelled dataset which contains wavelet images of the defective steels are loaded and are pre-processed. In preprocessing the images are resized to a specific size, converted into batches and encoded for multi-class classification.

4.1 CNN Model Architecture

The CNN comprises of three convolutional layers with increasing filter sizes which helps in detecting edges, spots, textures and complex damages like cracks or combined patterns across different locations of the steel plate.

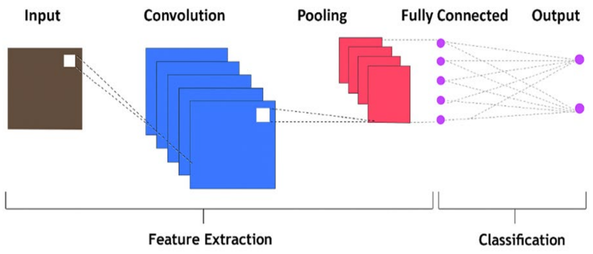

Figure 5. The Architecture of CNN

Max Pooling layers which help in retaining important features which discard irrelevant details. It helps the network to be more robust to small shifts and noise in the image, as damage may vary in position. Pooling helps the model remain accurate even if the defect happens in different sizes. The architecture of the CNN model is illustrated in Figure 5, which shows the sequential arrangement of layers from input to output. A Flatten layer followed by a 128-neuron dense layer with dropout. Flatten layer converts the two-dimensional output from convolutional layers into one-dimensional vector then this one-dimensional vector is needed to pass data to fully connected layers that make classification decisions. Dense layer helps the model to decide on which position the defect is present or the image has no defect. Finally, in the model to measure confidence in the prediction of the unseen image the SoftMax activation was used for the output.

5. Results and discussions

For the unseen steel plate wavelet image to be predicted, the image was classified using the CNN model, and the model's performance was assessed using a confusion matrix and classification report, confirming high accuracy as 0.98. The steel plate wavelet image Shown in Figure 6a was first converted from BGR image to Lab color space to enhance feature representation. The quadrant of the image with the highest impact area was identified and visualized through a heatmap and defect mask overlay, highlighting the predicted damage location with high confidence Figure 6b. Additionally, the training and validation curves of the CNN model demonstrate strong convergence, indicating effective learning and minimal overfitting Figure 7.

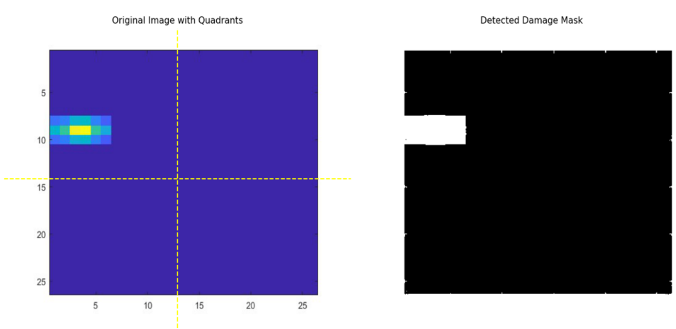

Figure 6. a) Defect Localization using wavelet.
b) Defect localization through CNN

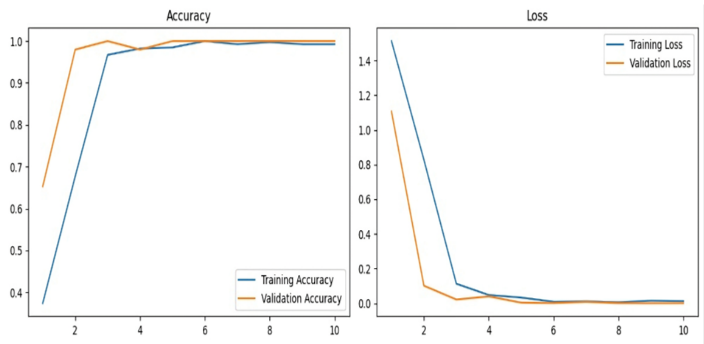

Figure 7. Model Training Metrics

The CNN-generated feature maps were analyzed after classification to visualize the spatial patterns that were learned to correspond to damage zones. Figure 6 illustrates how these patterns were superimposed on the original image to create a map that identified areas of concern by clearly displaying the regions of highest activation. The damaged areas were then separated from the background by employing a suitable thresholding technique to create binary defect masks from the activation maps. This procedure improves the model's interpretability by clearly separating the zones that are flawed and those that are not. Additionally, the CNN's localization capacity can be intuitively validated by superimposing the predicted masks on the original image. A single faulty region is precisely located in Figure 8, demonstrating the efficacy of this technique.

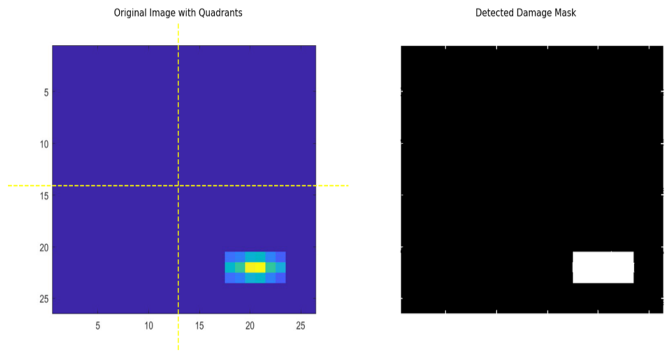

Figure 8. Right Bottom defects on the steel plate

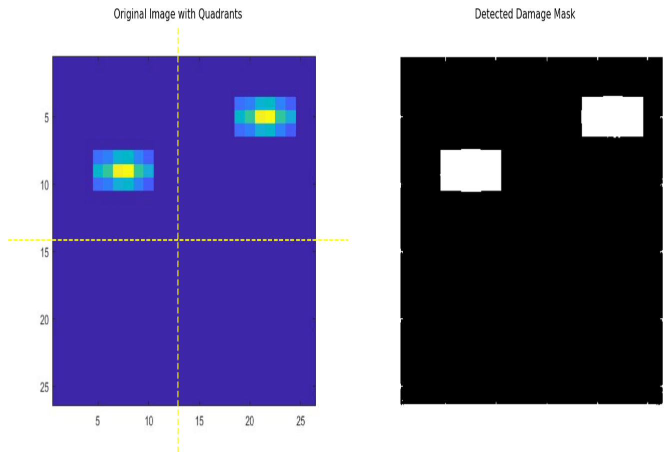

Figure 9. Multiple defects on the steel plate

6. Conclusion

This paper presents an efficient hybrid framework for automatic damage detection and localisation in steel plate structures that combines Convolutional Neural Networks (CNN) and Continuous Wavelet Transform (CWT). The suggested method makes use of CNN's capacity to recognise patterns and CWT's sensitivity to localised changes in mode-shape disparities to precisely locate damage. An effective end-to-end framework for structural health monitoring is established using numerical simulations using ANSYS, wavelet-based picture creation in MATLAB, and CNN training in TensorFlow. The outcomes validate the promise of the suggested approach for early-stage structural damage assessment by showing excellent prediction accuracy, efficient feature extraction, and dependable model convergence. To increase the methodology's generalisation and practical application, it will be expanded to include experimental and real-time vibration data, various structural geometries, a range of damage sizes and severities, and many forms of damage. Its potential for predictive maintenance and structural safety assurance will be further enhanced by integration with real-time structural health monitoring systems and validation under practical environmental and operational situations.

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