Ultrasonic Imaging of Crack Detection in Shafts Using Convolutional Neural Networks and Grid-Wise Classification

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ABSTRACT

We present a data-driven convolutional neural network (CNN) framework for detecting internal cracks in a two-dimensional shaft cross-section using transient elastodynamic wave responses. The model is trained using a grid-wise classification approach, where each element in the domain is labeled as damaged or undamaged. Training data are generated through wave propagation simulations in ANSYS Mechanical, where elliptical cracks of varying sizes, orientations, and positions are randomly introduced. Measured wave signals at the boundary are used as input features, and corresponding damage labels for each grid element of unstructured background mesh are used as output. The CNN learns to predict the probability of damage for each grid element based on wave responses from multiple sensors. The trained model effectively reconstructs internal cracks without prior knowledge of their characteristics. Numerical results on out-of-distribution datasets show that the model can reliably detect cracks in various configurations, indicating its potential for ultrasonic structural health monitoring of complex engineering structures.

INTRODUCTION

Structural health monitoring (SHM) is increasingly employed to assess the integrity and operational safety of components such as shafts, pipes, and turbine blades in various industries. Among various non-destructive evaluation (NDE) techniques, ultrasonic wave-based methods have shown strong potential for detecting internal damage, as they allow for subsurface inspection using boundary-mounted sensors [1]. However, traditional approaches often rely on model-based inversion or manual signal interpretation, which can be time-consuming and sensitive to variations in material properties [2]. While these methods are effective in detecting the presence of damage, they are not

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inherently designed to image internal defects with high spatial resolution. Recently, machine learning techniques have been actively explored for damage detection using wave-based measurements. While promising, many of these methods depend on prior knowledge of damage characteristics, such as their locations or geometries, limiting their generalizability [3–6].

To address these challenges, we adopt an element-wise classification scheme, in which each element in the computational domain is assigned a probability of damage. This enables the detection of damage at arbitrary locations, numbers, and shapes without prior information. Pranto et al. (2023) introduced this concept to homogeneous solids for void detection [7], and Kim et al. (2024) extended it to orthotropic composites for delamination detection [8]. These previous studies adopted a structured background mesh only in a rectangular-shaped domain. In this study, we further advance the approach by applying it to shaft geometries with internal cracks, enabling generalized detection in complex domains by virtue of element-wise classification on an unstructured background mesh.

We present a data-driven convolutional neural network (CNN) framework that uses transient elastodynamic wave responses to detect internal damage. By applying a grid-wise classification method trained on synthetic simulation data, the model achieves high-resolution crack localization without prior knowledge of damage configuration. The framework demonstrates strong generalization across diverse scenarios, showing its potential for real-time SHM applications.

PROBLEM DEFINITION

This study proposes a data-driven CNN framework for identifying and visualizing damage, such as voids, cracks, and corrosion, in shaft structures using elastodynamic wave signals measured at the boundary. The overall methodology is illustrated in Fig. 1. To train the model, synthetic datasets are generated via ANSYS simulations, where randomly distributed cracks are introduced in each iteration. The shaft is discretized into a grid-wise background mesh, and each grid element is labeled as damaged or undamaged.

The CNN is trained using wave responses as input and corresponding damage labels for each grid element as output. It learns to distinguish damaged regions based on the spatial distribution of signals. After training, the model predicts a damage probability for each grid element, which is projected onto the background mesh. Regions with high probabilities form spatial clusters, indicating damage locations.

DATA GENERATION

Domain description

A two-dimensional cross-sectional model of a shaft with an outer diameter of 50 mm and an inner diameter of 32 mm is considered, containing internal cracks. The simulation is conducted under plane-strain conditions, with traction-free inner and outer boundaries and two pinned constraints applied along the bottom edge, as illustrated in Fig. 2(a). The material properties correspond to stainless steel: Young's modulus $E = 193$ GPa, Poisson's ratio $\nu = 0.29$, and density $\rho = 8000 \text{ kg/m}^3$.

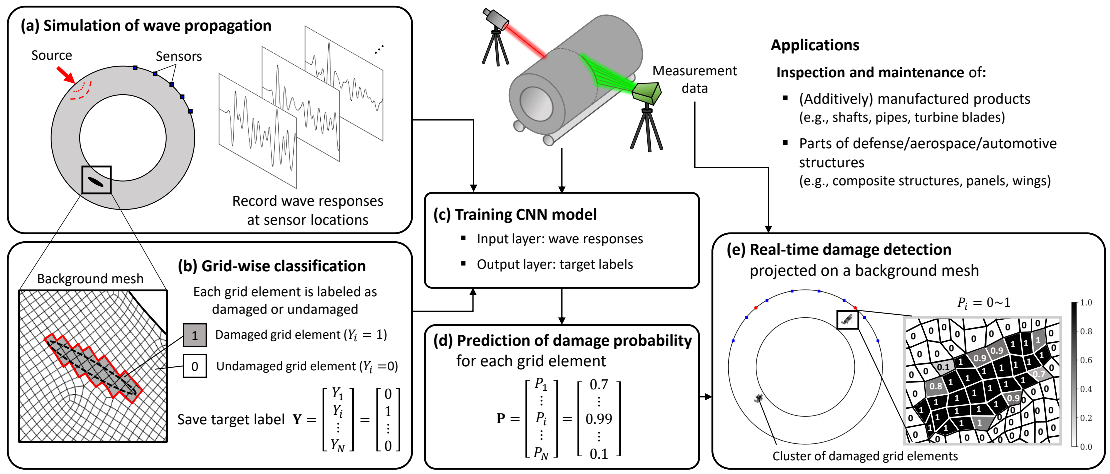

Figure 1. Framework of the proposed CNN-based damage detection using elastodynamic waves and grid-wise classification.

Wave excitation is introduced using a Ricker pulse applied as two point loads on the outer boundary at 50° and 130° , measured counterclockwise from the positive x-axis. The pulse has a central frequency of 200 kHz and a peak amplitude of 1 kN/m. Displacement responses in both x- and y-directions are collected from eight sensors placed at 20° intervals along the outer edge. Wave responses are measured over 300 time steps with a time increment of $\Delta t = 0.1$ µs, yielding a total duration of 30 µs.

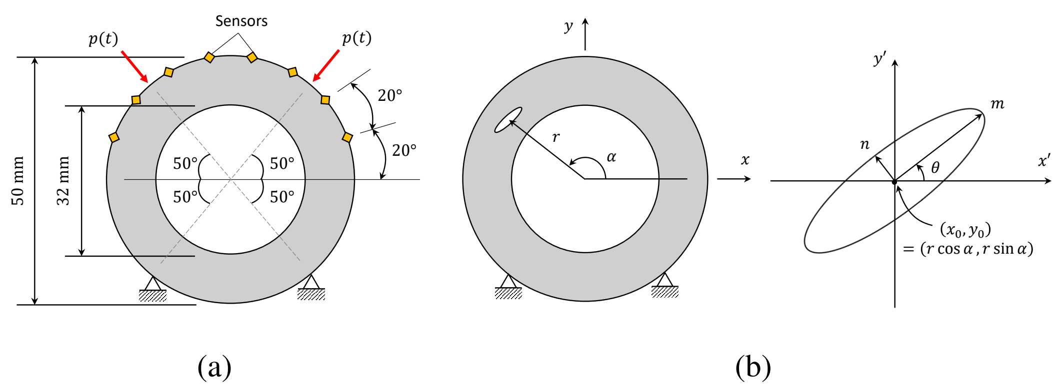

Figure 2. The shaft cross-sectional domain and the parameters of the elliptical crack.

Each simulation includes up to two elliptical cracks. Wave propagation is modeled using ANSYS Mechanical with an unstructured mesh of average element size 0.5 mm. The centers of the cracks are randomly located in the domain using polar coordinates $(x_0, y_0) = (r\cos\alpha, r\sin\alpha)$, where $r \in [16, 25]$ mm and $\alpha \in [0°, 360°]$. The semi-axes m and n are drawn from $[1.5, 2.5]$ mm and $[0.25, 0.3]$ mm, respectively, and the orientation angle θ is uniformly distributed in $[0°, 360°]$.

To validate the accuracy of our forward wave solver, we compare its simulated responses at sensor locations with those from Abaqus/CAE for the same shaft model containing a single crack. The close agreement between the two results confirms the reliability of our solver. We omit to show the comparison for the brevity of the paper.

Grid-wise classification

To localize internal damage within the structure, we adopt a grid-wise classification method based on unstructured background mesh that discretizes the computational domain. Each element in the mesh is assigned a binary label indicating whether it is damaged or not: $Y_i = 1$ if the i-th grid element contains damage, and $Y_i = 0$ otherwise, as illustrated in Fig. 3. These grid element-wise labels, differently produced for each damage profile in each training data, are used as the output features for training the CNN. After training, the CNN predicts the probability of damage for each grid element based on the measured wave responses. These predicted probabilities are then visualized onto the background mesh, enabling spatial imaging of internal damage within the domain.

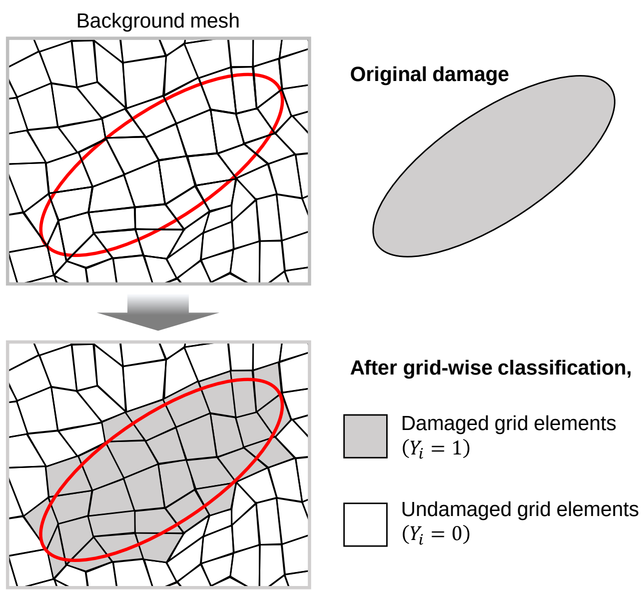

Figure 3. An illustration of the grid-wise classification of damaged and undamaged grid elements in an unstructured background mesh.

Data preparation

To ensure stable training and consistent interpretation, the displacement responses were normalized to the range of $[-0.5, 0.5]$ using training set statistics. A total of 8,000 datasets were generated, equally divided between cases with one and two cracks. The data were split into training (80%), validation (10%), and test (10%) sets, maintaining a balanced distribution. The CNN was trained using the training set, validated on unseen samples, and evaluated using the test set.

CONVOLUTIONAL NEURAL NETWORK (CNN)

CNN architecture

In this study, we employ a convolutional neural network (CNN), illustrated in Fig. 4, to detect damage within the cross-section of the shaft domain using wave measurement data. The network consists of five one-dimensional (1D) convolutional layers, each accompanied by a batch normalization layer to enhance training stability [9]. Each of these layers is paired with a batch normalization layer and a max-pooling operation and utilizes multiple filters with Leaky Rectified Linear Unit (LeakyReLU) activation functions. The output from the final convolutional stage is flattened and passed through a fully connected layer with a sigmoid activation function, generating a binary probabilistic output for each grid element, where the predicted values range between "0" to "1". By projecting the predicted probability P_i at the i-th grid element onto the background mesh, the model maps and predicts the damage profile within the domain.

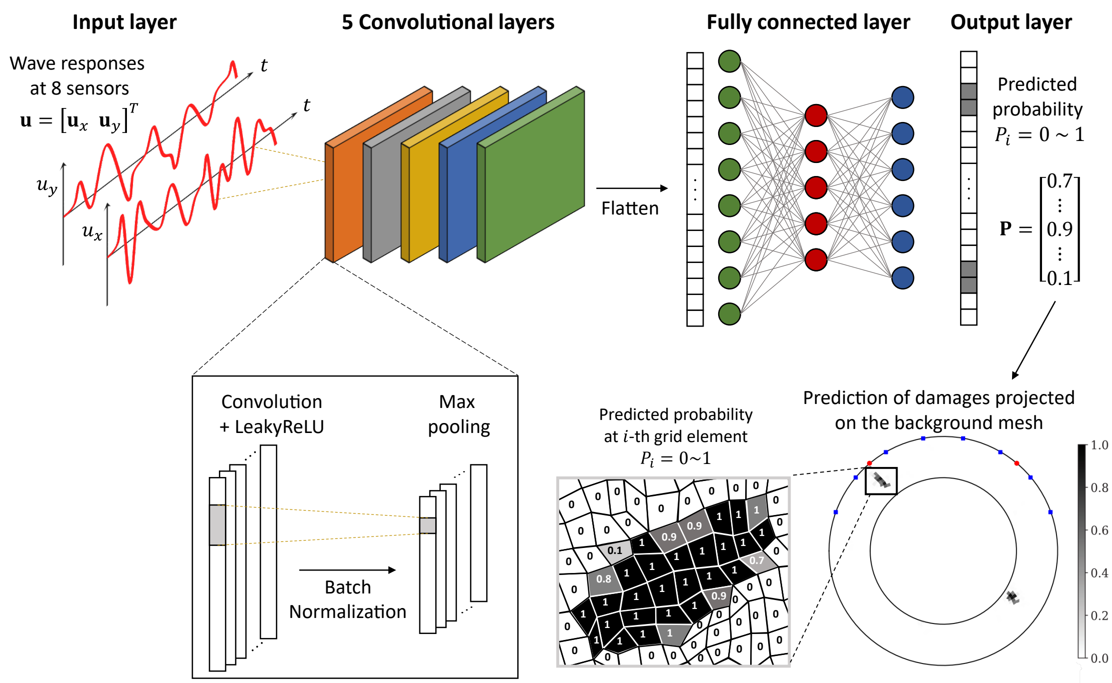

Figure 4. CNN Architecture.

We employ the "binary cross-entropy" loss function to compute the loss between the predicted and target outputs in the grid elements of the background mesh, as expressed in Eq. (1).

$$\mathcal{L} = -\frac{1}{N^t}\sum_{i=1}^{N^t}\left(\frac{1}{N^e}\sum_{i=1}^{N^e} Y_i \log(P_i) + (1-Y_i)\log(1-P_i)\right), \tag{1}$$

where Y_i denotes the target label for the i-th grid element, where "1" and "0" represent damaged and undamaged grid elements, respectively, and P_i is the predicted probability that the i-th grid element is damaged, with values ranging from "0" to "1". N^e and N^t denote the total number of grid elements and training datasets, respectively.

We use the Hyperband algorithm from the KerasTuner library to efficiently search for hyperparameters that minimize the loss function and improve model performance.

Evaluation metrics

To assess the performance of the CNN predictions, the following evaluation metrics are used:

$$\mathit{Accuracy} = \frac{\mathit{TP} + \mathit{TN}}{\mathit{TP} + \mathit{FN} + \mathit{TN} + \mathit{FP}} \times 100\ (\%), \tag{2a}$$

$$\mathit{Precision} = \frac{\mathit{TP}}{\mathit{TP} + \mathit{FP}} \times 100\ (\%), \tag{2b}$$

$$\mathit{Recall} = \frac{\mathit{TP}}{\mathit{TP} + \mathit{FN}} \times 100\ (\%), \tag{2c}$$

$$\mathit{F1\text{-}score} = \frac{2 \times \mathit{Precision} \times \mathit{Recall}}{\mathit{Precision} + \mathit{Recall}} \times 100\ (\%), \tag{2d}$$

where *TP*, *TN*, *FP*, and *FN* denote the counts of true-positive, true-negative, false-positive, and false-negative classifications. Damaged grid elements correctly identified as damaged are counted as *TP*, while those incorrectly identified as undamaged are counted as *FN*. Similarly, undamaged grid elements correctly classified as undamaged are counted as *TN*, and those misclassified as damaged are counted as *FP*.

Due to the class imbalance in the dataset, *Accuracy* is less informative and often yields overly optimistic results. Therefore, the *F1-score* is used as the primary evaluation metric, as it balances *Precision* and *Recall* and more accurately reflects the model's performance in detecting damage.

To identify the optimal hyperparameters, we conduct an extensive search across a wide range of possible values. This process aimed to find parameters that performed best on validation data. This step is crucial for achieving optimal results. The hyperparameter search focuses on minimizing the binary cross-entropy loss function rather than relying on evaluation metrics.

NUMERICAL RESULTS

To evaluate the generalization performance of the proposed CNN-based damage detection framework, we present results on out-of-distribution (OOD) datasets. These test cases involve crack configurations not seen during training and demonstrate the model's ability to detect damage in previously unseen structural scenarios.

Specifically, the test cases include: internal and external surface cracks (Example 1), a single internal corrosion (Example 2), and two radial cracks (Example 3). Figure 5 illustrates the model's predictions for various OOD crack configurations, showing its ability to localize damage under diverse structural conditions. Table I summarizes the corresponding performance of the CNN using evaluation metrics.

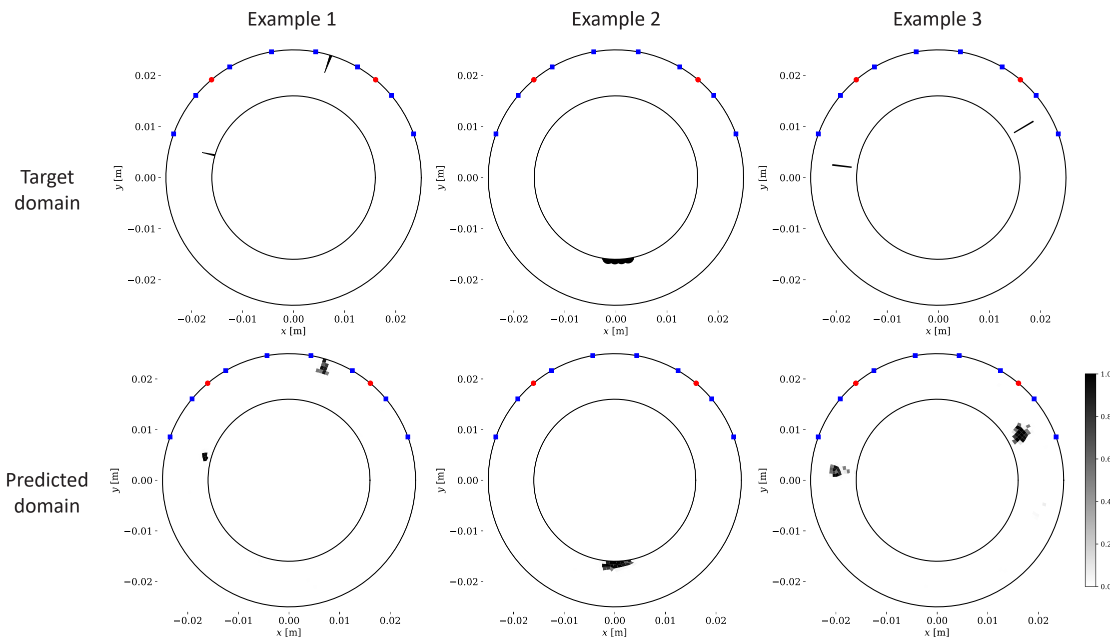

Figure 5. Target and predicted domains on OOD datasets.

TABLE I. Evaluation metrics of the CNN on OOD datasets with various damage configurations.

Examples	Targeted cracks	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
1	Internal and external surface cracks	99.55	60.16	43.40	50.42
2	Single internal corrosion	99.54	62.17	53.20	57.34
3	Two radial cracks	99.31	43.86	52.09	50.43

CONCLUSIONS

In this paper, we propose a convolutional neural network (CNN)-based framework for detecting and imaging damages in shaft structures using elastodynamic wave responses. The model is trained using a grid-wise classification approach leveraging unstructured background mesh, allowing it to identify damage at the grid element level with high spatial resolution. Synthetic training data are generated through wave propagation simulations with randomly distributed cracks, enabling the model to learn diverse damage patterns without prior knowledge.

The proposed method demonstrated strong generalization performance on OOD datasets, accurately predicting crack locations even under previously unseen damage configurations. This demonstrates that the proposed method can generalize well to various damage configurations, including those not seen during training. Its ability to reliably predict internal cracks using only boundary wave data suggests it can be a useful tool for structural health monitoring tasks in real-world shaft components and similar geometries.

Future work will focus on expanding the framework to three-dimensional domains, incorporating experimental data, and optimizing model efficiency for deployment in real-time monitoring systems.

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