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Original Article

CNN based Crack Detection in Cantilever Beams: A Comprehensive Machine Learning Approach

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Abstract *- Crack detection in cantilever beams is significant, as cracks leads to catastrophic failures of various engineering structures. The method of detecting variation in natural frequencies because of cracks is a well-known method to detect damages. This paper demonstrates how the inspection process for health monitoring can be revolutionized using Machine Learning (ML)- the detection of cracks in cantilever beams using ML algorithms. FEA analysis software ANSYS is used to get the dataset since the correctness of a model heavily relies on the quality and amount of data. An I-section beam is selected for FEA analysis, and the vibrational characteristics of the beam with cracks in different locations are collected to get the dataset for machine learning part. Three regression models, such as multiple linear, random forest and decision tree are developed to predict the crack location from first three mode frequencies. The location of crack from fixed end, as well as beam edge and depth of crack, are predicted. The goodness of fitness of each model is evaluated based on their R-squared value. A deep learning-based regression model was also developed to demonstrate the superior performance of ANNs in structural damage prediction. Subsequently, a Convolutional Neural Network is implemented to detect cracks from images of the beam. The CNN model successfully classified cracked and non-cracked beams with an accuracy of 99% (training) and 98% (validation). The research contributes towards the advancement of smart structural health monitoring systems.*

Keywords *- Crack detection, Machine Learning, Regression model, ANSYS, R^2 score, CNN.*

1. Introduction

Cracks are undesired in any civil/mechanical structures as it leads to catastrophic failures of the structures. The onset of cracks gives an early warning of specimen degradation. If it is possible to detect cracks at the beginning stage as part of periodic maintenance, compensatory actions can be performed to increase their service life. The cracks alter the dynamic behaviour of the structure, and hence, the vibrational response of cantilever beams yields a lot of valid information regarding the presence of damage or cracks, which is essential in condition monitoring of cantilever beams. The possibility of crack detection without dismantling the structure is highly beneficial in structural health inspection, and the vibration-based methodology is widely accepted for crack finding.

This paper demonstrates the prediction of crack location in a cantilever beam using regression algorithms in machine Learning. The cracked cantilever beam is modelled with the help of ANSYS software, and obtained the data set for regression model training is obtained. Cracks are assumed to be in different locations. Natural frequencies of the cantilever beam have been evaluated for different crack dimensions. Then, different machine learning regression models are applied to predict the position of the crack and its details from the first three mode frequencies and also compared the performance of various regression models. An Artificial Neural Network and Convolutional Neural Network based models are also developed in order to classify the cracked and non-cracked beam images.

2. Research Motivation

Structural condition monitoring is a methodology for protecting and ensuring the lifespan of engineering structures, especially in areas of application such as bridges, aggregates for aircraft components, and industrial frameworks. This research is motivated by the necessity for a hybrid method that combines Finite Element Analysis (FEA) and Artificial Intelligence (AI) methods to improve accuracy in crack detection. In this paper, Section 2 gives a literature assessment on the effect of cracks in cantilever beams. Section 3 explains the FEA analysis of an I -section beam using ANSYS software to generate the dataset for Machine Learning part. Section 4

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discusses the regression models for crack prediction and the results. Section 5 and Section 6 explain the implementation of ANN and CNN for crack prediction, respectively.

3. Effect of Cracks in Cantilever Beams - A Literature Review

The cracks change the dynamic behaviour of the beam [1]. The variations in characteristic frequencies because of the cracks are effectively exploited [2, 3] for beam diagnosis. The depth and location of cracks are the utmost characteristics in vibration analysis [4] of cantilever beams in crack prediction. Cracks severely affect the performance of civil structures, as these cracks reduce stiffness.

The change in stiffness brings a reduction in the beam's natural frequency. Frequency-based crack detection [5-9] has thus become a potential approach in damage investigation. The position and depth of the crack also have a substantial effect on the beam's vibrational response. The frequency of the beam is reduced at a higher rate when the crack is near the fixed end.

The literature survey shows many methods to identify cracks in cantilever beams. Stubbs [10] and Chondros [11] analysed the vibration of beams in the presence of cracks using an energy method based on cracked beam theory. AI- and Machine Learning-based crack detection [12-14] is advancing nowadays as it offers distinct advantages. Nagarajan [15] predicted the defect in a cantilever beam with the help of Dynamic Mode Decomposition (DMD) and a classification algorithm in Machine Learning. Pathak [16] used response surface methodology for the analysis of a cracked beam. Kondru [17] and Kumar [18] detected damage in cantilever beams using an Artificial Neural Network.

4. Modal Analysis of Beam using ANSYS

FEA modal analysis is performed to analyse the characteristics of a vibrating structure [19, 20]. In this paper, an I- shaped beam is modelled using ANSYS software.

The beam analysis is performed for different crack locations. The beam's natural frequencies are obtained for various crack depths and locations. I section cantilever beam modelled in ANSYS is shown in Figure 1.

4.1. Specifications of Cantilever Beam Modelled in ANSYS

- Shape: I beam
- Length: 100mm
- Area: 5549.2809mm²
- Material: Steel
- Density: 8000 Kg m-3
- Young's Modulus: 27x109 Pa
- Bulk Modulus: 9x109
- Shear Modulus: 135x108

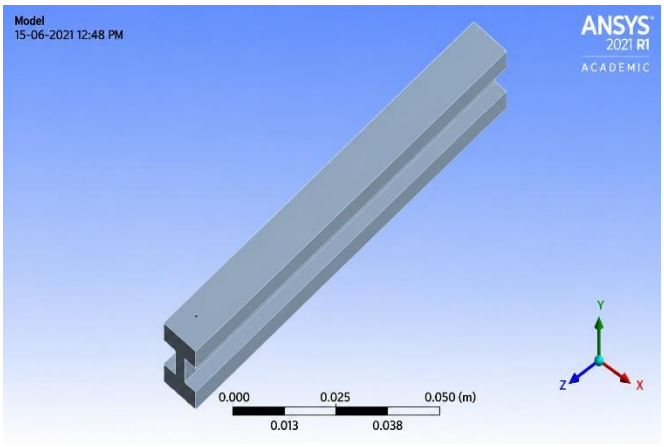


Fig. 1 I section cantilever beam modelled in ANSYS

4.2. Formation of Dataset

The modes of frequency collected from modal analysis of I section Cantilever Beam in ANSYS by varying the position and depth of the crack are given in Table 1. This is used as a dataset for training the regression models in prediction of crack details. In the table, L1 indicates the site of the crack from the fixed end, and L2 is the length from the edge. D is Crack depth, and F1, F2, F3 are the frequencies of the three modes.

5. Implementation of Machine Learning Models

A regression model is implemented to identify the crack location from the beam's first three natural frequencies. Data gained from ANSYS are given to different machine learning regression models, and these models are trained to output the crack details in beams when the first three modes of frequencies are provided. Multiple Linear Regression (MLR), Decision Tree Regression (DTR) and Random Forest Regression (RFR) models are applied for prediction, and the results are compared based on their R2 scores. Regression models rely on statistical techniques to predict an event from a set of inputs.

Multiple Linear Regression (MLR) predicts the result using a number of explanatory variables. Decision Tree Regression (DTR) works in a tree-structured model. An associated decision tree is gradually formed while breaking down the dataset into subsets. DTR performs the prediction by observing the features of an object. Random Forest Regression is capable of making more accurate predictions by using an ensemble learning method that associates predictions from multiple algorithms.

Table 1. Data set for regression model

Sl. NO	L1	L2	D	F1	F2	F3
1	11.46	3.87	2.5	271.72	336.09	1554.5
2	21.46	3.87	2.5	271.73	336.18	1554.3
3	31.46	3.87	2.5	271.75	336.28	1555.4

4	41.46	3.87	2.5	271.76	336.36	1555.8
5	51.46	3.87	2.5	271.78	336.42	1557.5
6	61.46	3.87	2.5	271.8	336.47	1559.3
7	71.46	3.87	2.5	271.82	336.51	1559.5
8	81.46	3.87	2.5	271.85	336.56	1560.6
9	91.46	3.87	2.5	271.89	336.6	1561.4
10	98	5	4.5	272.02	336.77	1562
11	88	5	4.5	271.96	336.68	1561.3
12	78	5	4.5	271.9	336.61	1561.1
13	68	5	4.5	271.85	336.54	1559.9
14	58	5	4.5	271.82	336.47	1558.7
15	48	5	4.5	271.79	336.41	1557.5
16	38	5	4.5	271.77	336.32	1555.4
17	28	5	4.5	271.76	336.23	1556.4
18	18	5	4.5	271.76	336.11	1555.7
19	8	5	4.5	271.76	335.98	1555.2
20	5	2	1.5	271.58	336.15	1558.3
21	15	2	1.5	271.63	336.24	1557.8
22	25	2	1.5	271.67	336.3	1556.4
23	35	2	1.5	271.71	336.35	1556.8
24	45	2	1.5	271.74	336.4	1558.3
25	55	2	1.5	271.77	336.44	1559.3
26	65	2	1.5	271.79	336.47	1560.1
27	75	2	1.5	271.81	336.5	1560.9
28	85	2	1.5	271.83	336.53	1562.1
29	95	2	1.5	271.85	336.55	1561.7

5.1. Results of Regression Models

Three regression models, such as multiple linear, Random Forest, and Decision Tree, are trained with the data set obtained from ANSYS. After training, these models are used to predict the crack details, such as the location of the crack from fixed (L1, Location of crack from edge, L2 and Depth of crack, D are predicted.

The results of prediction using Multiple Linear Regression, Random Forest, and Decision Tree are listed in Tables 2 to 4.

Table 2. Multiple Linear Regression model predictions

Parameter in mm	Actual Value	Predicted Value
L1	31.46	29.537
L1	45	48.25
L1	65	64.07
L2	2	2.8413
L2	3.87	4.2959
L2	5	3.8361
D	1.5	2.0138
D	2.5	3.3283
D	4.5	3.194

Table 3. Decision tree regression model predictions

Parameter in mm	Actual Value	Predicted Value
L1	31.46	25
L1	45	61.46
L1	65	51.46
L2	2	2
L2	3.87	5
L2	5	3.87
D	1.5	2.5
D	2.5	4.5
D	4.5	2.5

Table 4. Random Forest regression model predictions

Parameter in mm	Actual Value	Predicted Value
L1	31.46	27.4
L1	45	48.776
L1	65	66.83
L2	2	3.08
L2	3.87	4.661
L2	5	3.309
D	1.5	2.4
D	2.5	4.1
D	4.5	2.5

The location of cracks such as L1 and L2, as well as crack depth D predicted by three regression models are compared in Figures 2-4.

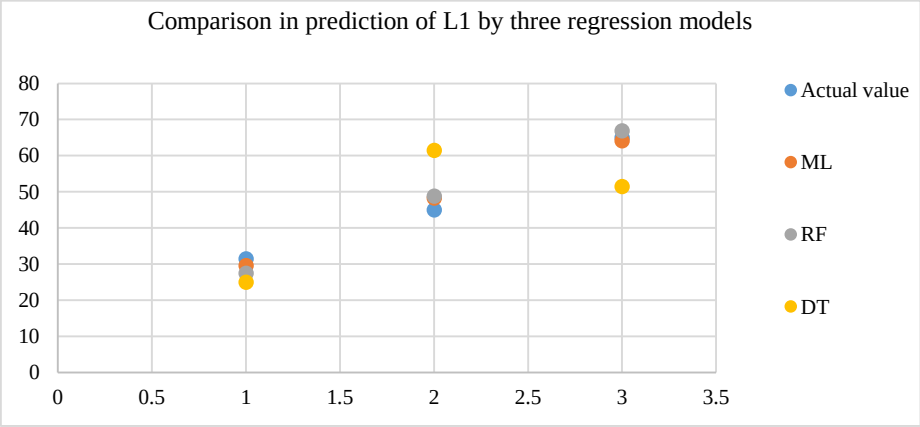


Fig. 2 Comparison of regression models in prediction of L1

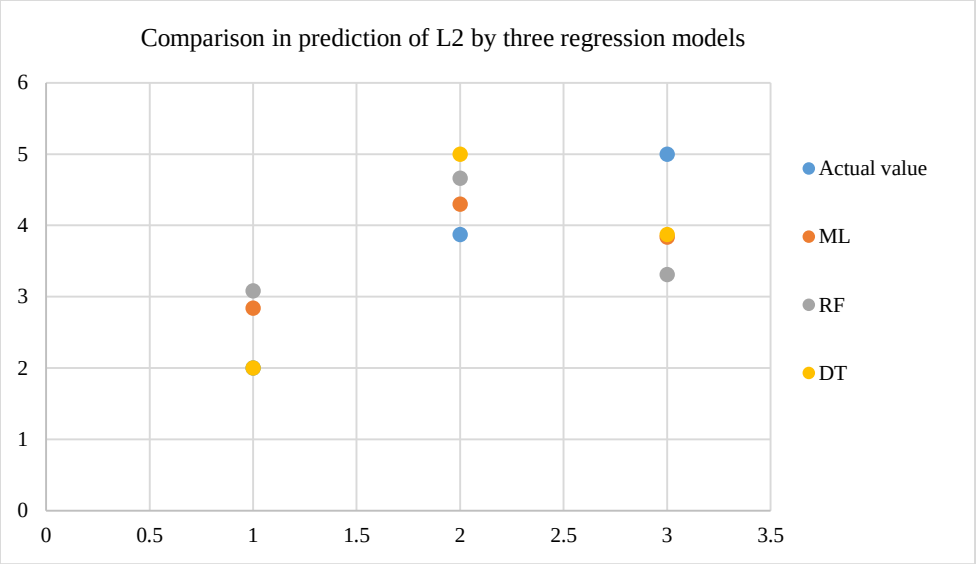


Fig. 3 Comparison in prediction of L2

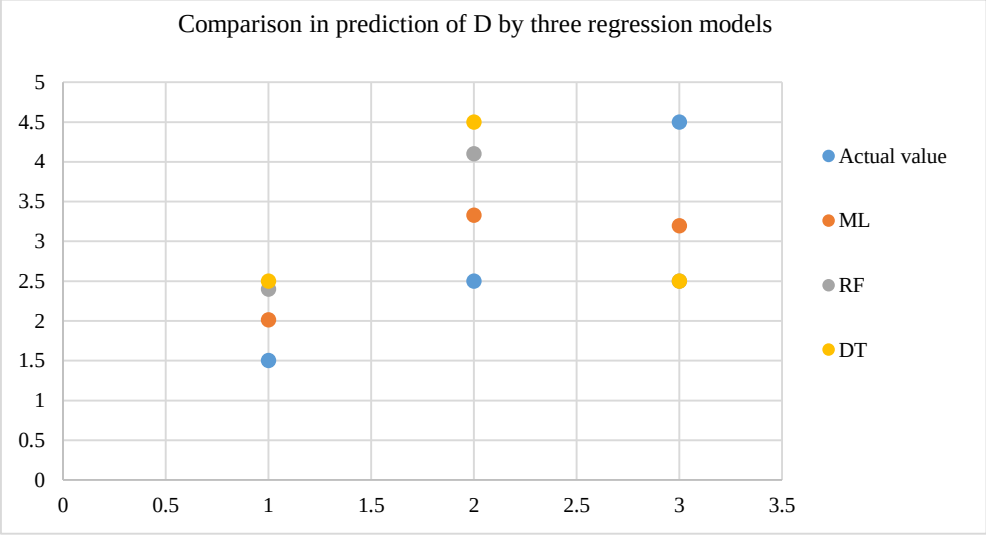


Fig. 4 Comparison in prediction of D

5.2. Model Performance Comparison

The goodness of fit of various models can be evaluated based on R squared values. R squared is somewhere between zero and one. The R squared values of different regression models in prediction of the crack information are given in Table 5.

Table 5. R^2 scores of regression models in predicting crack details

Regression Models	L1(R^2)	L2(R^2)	D(R^2)	Overall performance
Multiple Linear	0.91	0.62	0.47	Good
Decision Tree	0.89	-0.46	-0.29	Poor
Random Forest	0.94	0.22	-0.18	Excellent for L1

Table 5 shows that the Random Forest Regression Model predicts the location of cracks from the fixed end more efficiently than the other two models, whereas the Multiple Linear Regression Model predicts other crack details such as depth and location from the edge of the beam more effectively.

6. Artificial Neural Network

6.1. (ANN) Implementation

ANNs have been considered as an influential tool for crack detection across various structural applications and have significantly enhanced the identification of cracks in materials such as road pavements and structural beams. The ANN model for crack detection was implemented with the following characteristics:

- An input layer of 3 neurons (F1, F2, F3)
- Hidden Layers are of multiple layers with optimized neuron counts.
- The output Layer consists of two neurons for L and D.
- A sigmoid activation function is used, and the Backpropagation algorithm is used as the training algorithm.

Mean Squared Error, Root Mean Squared Error, and the Coefficient of Determination were the metrics used to evaluate the model. MSE of 0.0000312, RMSE of 0.000111 and R^2 of 1 show the superior performance of the ANN model. These results demonstrate the exceptional capability of ANNs in crack parameter prediction, achieving near-perfect accuracy for the given dataset.

7. CNN for Crack Detection

This paper also presents the more effective use of Deep Learning with CNN for crack detection in civil structures. It highlights several key differences between CNN and traditional methods for crack detection. CNN shows superior accuracy in surface crack detection compared to traditional methods. CNNs are designed to handle diverse conditions involving complex patterns and variations in images.

This paper demonstrates that the CNN-based model can efficiently manage complexities that traditional approaches cannot solve effectively. CNNs can extract relevant features from images during the training process, which enables them to classify in an efficient way. A dataset of 6312 images for training and 1440 images for testing was collected to implement the CNN model. The dataset consists of cracked and non-cracked images. A CNN model was trained using TensorFlow to classify and detect cracks in the collected dataset. The model was designed to extract essential crack features, allowing for accurate classification.

7.1. CNN Model Training & Development

Figure 5 shows the flow chart for detecting cracks using CNN:

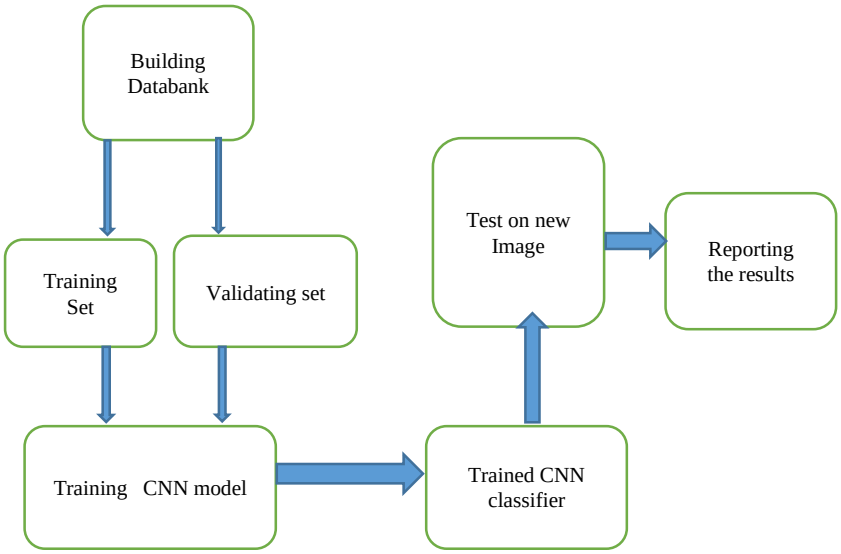


Fig. 5 Block diagram of CNN implementation

The architecture of the CNN model was designed as follows:

- Input Layer: Images of size 64 × 64 × 3 (RGB channels).
- Convolutional Layers: Two Conv2D layers with 32 filters, followed by ReLU activation functions.
- Pooling Layers: A MaxPooling2D layer (2×2) to decrease dimensionality while retaining critical features.
- Fully Connected Layer: A dense layer having 128 neurons and ReLU activation to acquire complex feature representations.
- Output Layer: A sigmoid-activated neuron to classify images as either cracked or uncracked.
- Training Parameters: Adam optimizer with Binary Cross-Entropy

7.2. Results and Discussions of CNN Model

The performance of the developed CNN model was validated using cracked and non-cracked images. The model was able to gain 99% training and 98% validation accuracies in 10 epochs. Figures 6 & 7 show the accuracy as well as the loss obtained by the CNN model during training and validation. The confusion matrix is shown in Figure 8.

The CNN model is able to classify the images depending on the presence of cracks accurately. The samples of the uploaded image and the classification by the developed CNN are shown in Figures 9(a)-9(h). These results ensure that CNNs need less computation and make CNNs an efficient image recognition method that is deployed for crack detection.

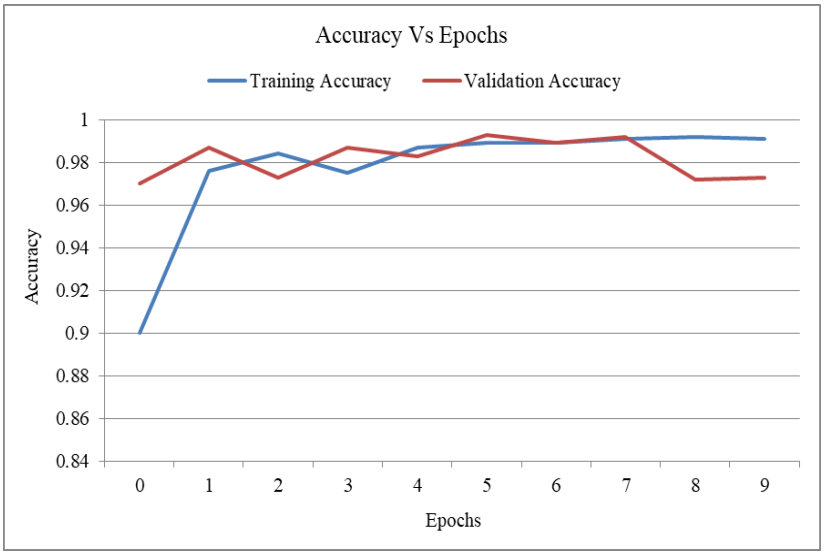


Fig. 6 Accuracy of ML model

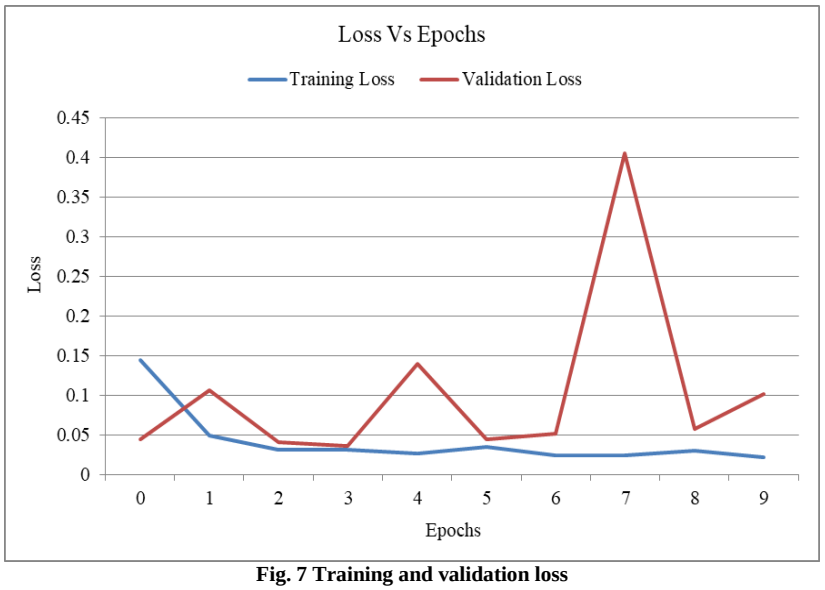


Fig. 7 Training and validation loss

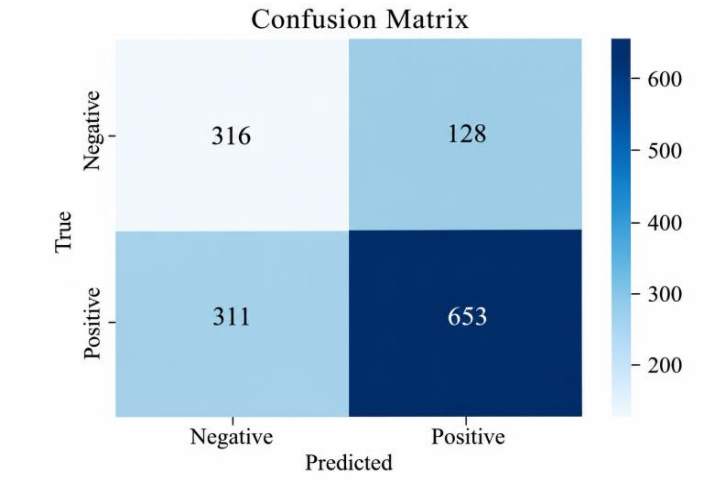


Fig. 8 Confusion matrix


no crack

(a)


no crack

(b)


no crack

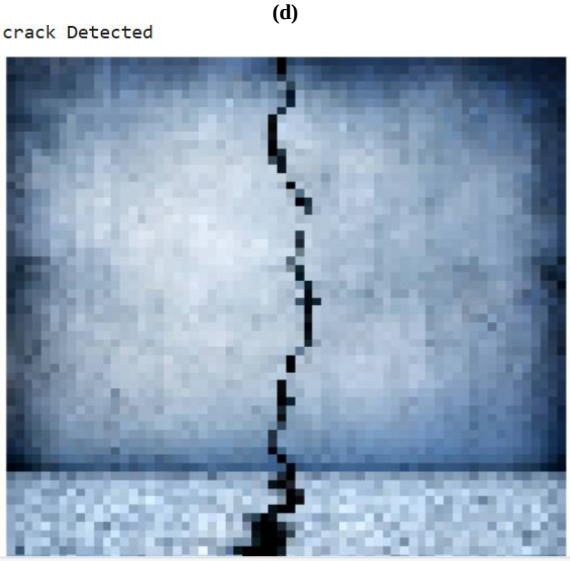
(c)


no crack

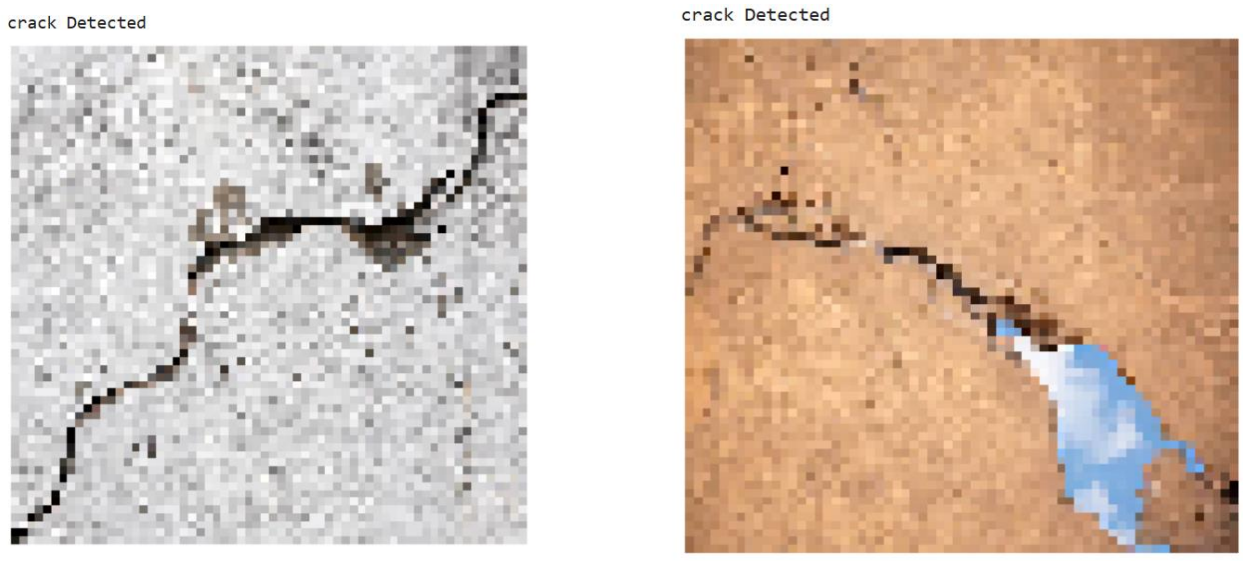
(d)


crack Detected

(e)


crack Detected

(f)



(g) (h)

Fig. 9 Samples of classified images by CNN model

8. Conclusion

Early identification of cracks in cantilever beams is significant because catastrophic failures can be avoided to a certain extent by handling the detected cracks very seriously. An attempt to predict the location of cracks using regression models in machine learning is presented in this paper. It is seen that, by feeding the models with characteristic frequencies of the beam, the crack location and depth can be predicted.

This research successfully demonstrated ML-based crack detection in cantilever beams, yielding several important findings:

Frequency-based crack detection is highly effective: The first three natural frequency modes provide sufficient information for accurate crack parameter prediction.

Model performance varies by parameter: Different regression models excel at predicting specific crack characteristics, with Random Forest achieving $R^2 = 0.94$ for location prediction from the fixed. Deep learning provides higher capabilities: This paper validates that ANN can provide a better solution in structural health monitoring. CNN is extremely superior in classification: CNN can classify cracked and non-cracked beams, providing significant contributions in damage detection.

Thus, this paper establishes a validation for advanced AI-driven structural health monitoring systems, contributing to safer and more reliable engineering structures.

Conflicts of Interest

"The authors declare that there is no conflict of interest regarding the publication of this paper."

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