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Development of a CNN-based Vibration Data Analysis Framework for Bridge Health Care Monitoring Using SAW Sensors

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1. Introduction

Bridges are designed to withstand different types of loads, including dead, live, environmental, and occasional loads during their service period. Moving vehicles are the main source of the applied live load on bridges[1]. Monitoring bridge health requires mandatory health inspections every 5 years and the inspections conducted from administrative walkways or by hand are difficult in high or unstable locations, and the results are subjective, dependent on the inspector's skill level, and may not capture hidden or progressive damage. To address these challenges, there is a growing interest in implementing Structural Health Monitoring (SHM) as an alternative to traditional inspection methods. SHM involves installing sensors on structures to measure and analyze sound and vibration, enabling the assessment of structural damage, monitoring structural health, and predicting future deterioration [2]. By applying SHM to infrastructure facilities, including bridges managed by municipalities, it becomes possible to monitor their condition, ensure safety, and utilize them effectively. Recent progress in artificial intelligence, especially in deep learning has reached new heights. So, researchers are utilizing different machine learning algorithms such as one class support vector machine, K-means clustering etc. [3] with the combination of SHM data to monitor bridge health. In this study, we focused on developing a convolutional neural network (CNN)-based vibration data analysis framework for bridge health care monitoring using SAW sensors. The framework will leverage the power of CNNs to analyze vibration data collected from bridges and provide insights into their structural health. By leveraging the capabilities of CNNs and utilizing SAW sensors, our proposed CNN-based vibration data analysis framework achieves significantly better performance for bridge health care monitoring compared to the prior methods.

2. Data Simulation

The experimental system **Fig. 1** utilizes aluminum alloy A5052 beams. Vibration induction involves an exciter transforming acceleration into voltage via a geophone. Voltage is then converted to capacitance using a varactor diode, altering SAW wave amplitude for vibration measurement. A multi-function generator (WF1967) generates input signals, while an oscilloscope (Keysight InfiniiVision MSOX4034A) captures SAW sensor reflections. Logging data with a 1 ms sampling interval and 1000 segments for 1-second measurement. In this study, the CNN dataset comprises attenuation coefficients for each frequency at different measurement points. Two sets were created: one without holes (Table 2 in ref. 3)) and one with holes (Table 3 in ref. 3)), each consisting of ten measurements per point.

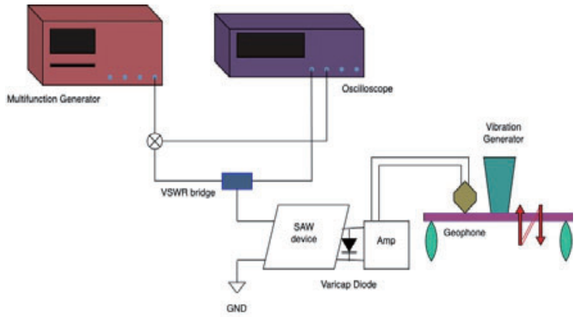

Fig. 1. Vibration Experiment System.

3. Methodology

We have proposed a 1D CNN based framework for classifying the damaged and undamaged aluminum alloy from the simulated SAW data. **Fig. 2** shows the proposed frame work. We performed normalization on the vibration data, and then passed it to our model. The model has two convolutional layers, each layer is followed by a batch normalization and a max pooling layer respectively. Hence, we get the “conv1” and “conv2”, which extracts the useful features from our data. Then the data is flattened using a flatten layer of 448 nodes, followed by two dense layers with Rectified Linear Unit (ReLU) activation function, a dropout layer and finally the output layer of only one node with the sigmoid activation function.

The outcome from the sigmoid activation function is the probability of the aluminum alloy being damaged. If the probability is below 0.5 threshold, we consider it as undamaged one.

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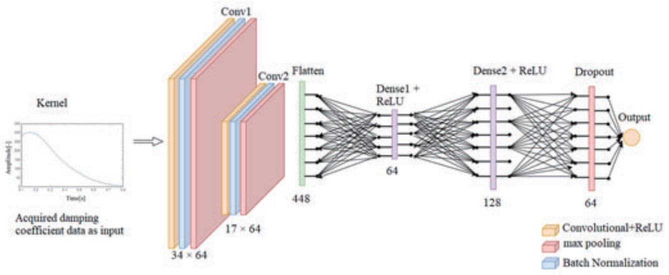

Fig. 2. Our proposed CNN-based framework.

5. Experimental Results and discussion

We have conducted our experiment with a total number of 2000 simulated data. We divided the dataset into training data and test data with a ratio of 80:20, which gave us 1600 observations for training the model and 400 for testing. We used the standard classification metrices to evaluate our results, which include precision, recall, f1 score and support. We have also used confusion matrix to have a detailed vision of the true positive, false positive, true negative and false negative outcomes. Finally, using the same confusion matrix, we calculated our proposed model's accuracy score.

Table 1 provides a comprehensive classification report for our proposed method's experimental results. The table includes essential metrics such as Precision, Recall, F1 Score, and Support, offering a clear overview of the model's classification performance. With high scores of 0.99 for Precision, Recall, and F1 Score in both Damaged and Undamaged classes, the model demonstrates consistent and accurate identification of instances. The Support values of 199 for Damaged and 201 for Undamaged instances indicate the dataset's distribution. Overall, the table confirms the model's strong classification capabilities and its ability to effectively distinguish between different classes.
The confusion matrix in **Fig. 4** indicates that a total of 198 damaged observations were predicted correctly, while 1 observation that was actually damaged was predicted as the undamaged class. On the other hand, there are a total of 3 incorrect predictions for undamaged observations, and our CNN model made 198 correct predictions for undamaged observations. The confusion matrix also reflects the accuracy of our model, which stands at 99%.

Table 1. Classification report of proposed method.

Class	*Precision*	*Recall*	*F1 Score*	*Support*
Damaged	0.99	0.99	0.99	199
Undamaged	0.99	0.99	0.99	201

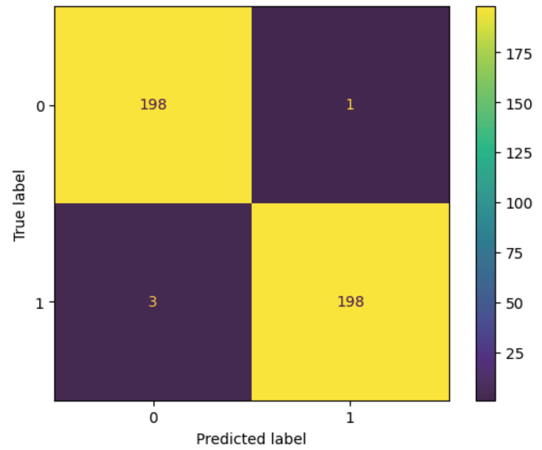

Fig. 4. Confusion Matrix of experimental results.

6. Conclusions

The CNN-based vibration data analysis framework developed in this research, using SAW sensors for bridge health care monitoring, has shown remarkable accuracy in detecting potential structural damage. Leveraging CNN and SAW sensors, our framework achieved an accuracy score of 0.99, surpassing the performance of previous methods, such as the OCSVM-based approach. This achievement highlights the potential of our framework for real-world bridge health care monitoring scenarios.

By combining CNNs with SAW sensors, this research showcases the significant impact of machine learning and sensor technology on infrastructure maintenance and safety. The innovative integration of these technologies holds the potential to transform the industry, ensuring the longevity and resilience of critical infrastructure systems. Our next steps involve testing our vibration data analysis framework on real bridges to assess its real-life performance and enhance its accuracy. We also aim to utilize Transfer Learning to further optimize our CNN model by leveraging existing knowledge for improved efficiency and effectiveness.

References

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