Impact Location Prediction using Deep learning with the aid of Convolutional Neural Network (CNN)

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Abstract

It has become more important than ever to build highly sustainable systems and structures. One technique to warrant the safety and durability of any structure without over-engineering the components, is to have a continuous health monitoring system that can sense any alarming peripheral impact which could lead to significant damage at later stages of the structure's life. This study aims to predict impact location using piezoelectric sensor data placed symmetrically on the study specimen using Artificial Neural Network (ANN). This can then be implemented in operation in order to, monitor the structural health of static as well as dynamic structures.

Keywords— one, two, three, four, five

1 Introduction

To facilitate sustainability on all fronts, the next generation of machines and structures must be more robust and long-lasting. This can be achieved by a continuous health monitoring system. The prediction of an impact location on a static or a dynamic system by a foreign object constitutes the basic purpose of a structural health monitoring system. The solution to the problem entails obtaining vibrational sensor data that is fed to a computationally intelligent system capable of predicting the site of the impact relative to the system thus, keeping a log of the stresses developed in the structure over the period of its operation due to such impacts. In this research project, we aim to create, compare and identify an optimum computationally intelligent system between Convolutional Neural Network (CNN), Recurrent Neural Network (RNN) and Feed Forward Neural Network (FFNN).

For the purpose of this research project, vibration patterns generated by a controlled impact caused by a steel ball of known size and dropped from a specific height on an aluminium plate was

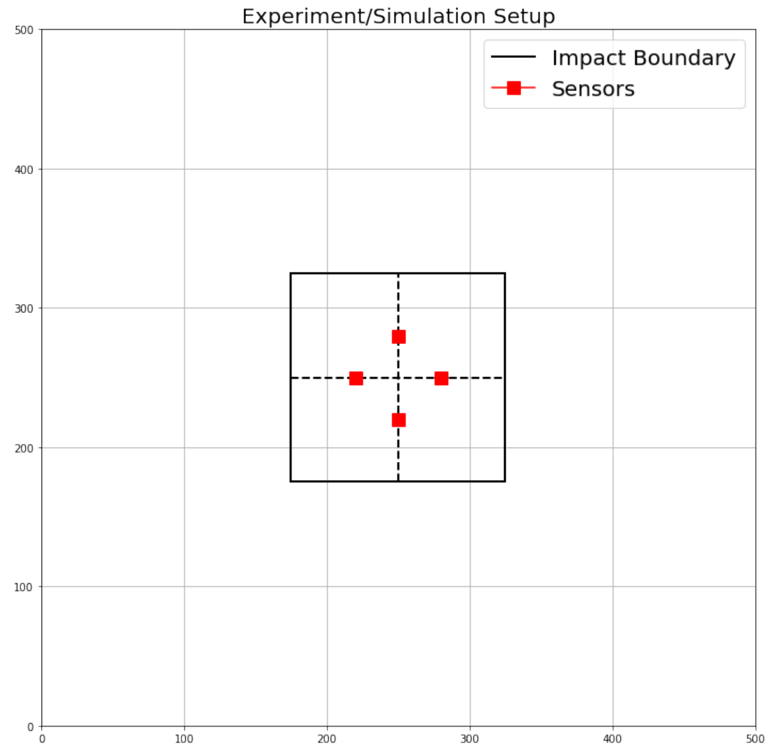

Figure 1: A model of the experiment set-up used for the numerical as well as the experimental data acquisition

recorded using four symmetrically placed piezoelectric transducers (Fig.1). The entire experiment was also simulated to generate numerical data which along with the experimental data was then passed on to the aforementioned Artificial Neural Networks (ANN) for the prediction of impact site using computation intelligence.

2 Methods

For this study regression models were built to predict the X and Y coordinates of the impact locations with respect to the center of the array of the four piezoelectric transducers using FFNN, RNN and CNN. Models were compared on prediction accuracy and variation of each model by training them on numerically simulated and experimental data. All the three architectures were tested on a prediction dataset where the impact coordinates were initially unknown and were made available later for validation purposes. The best suited neural network was then further extended to predict the X and Y position using independent networks as well as using a single neural network model. Further optimisation of the selected model was performed by balancing the data in each quadrant for training the neural network.

2.1 Data preprocessing

The data received from the sensors needed to be preprocessed to remove noise and extract relevant data corresponding to the impact. The sensor data was cut at 50 points before and 300 points

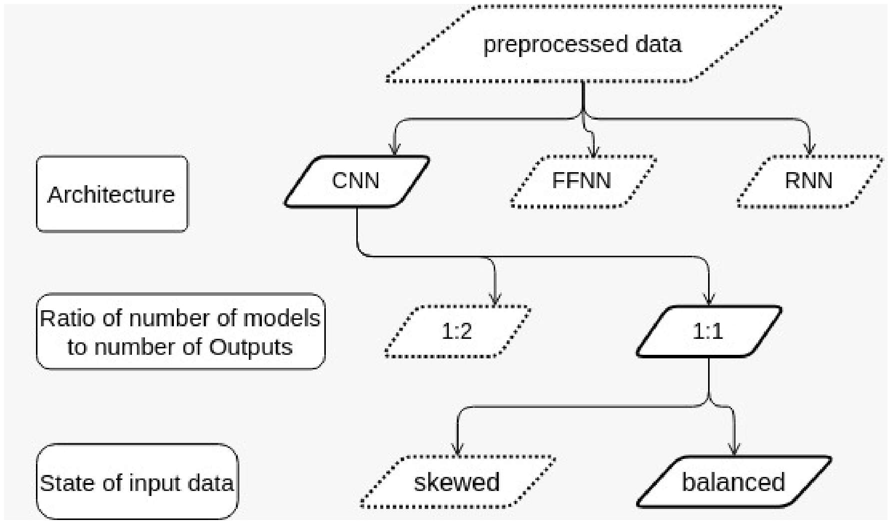

Figure 2: The work-flow in this report

after the highest peak. The highest peak was considered as this is the point at which the impact vibration reaches the sensor. The isolated data was then normalised and further reduced to zero after the highest peak point. The data was finally filtered using a ***Savitzky-Golay*** filter to remove noise from the processed data. These preprocessed data were then restructured to suit the input of each neural network.

2.2 Comparison of the Architecture

Convolutional Neural Network (CNN) with 3 convolution layers with 16, 32 and 64 filters respectively. The first layer is activated using a ReLU function, whereas the next two layer are activated using linear function. 1D convolution layers are used for our project, as each sensor produces a one dimensional time series data, and each sensor data is treated as a channel for the given impact data. The final convoluted data is passed to a dense hidden layer with 128 neurons which is then output into 2 neurons one each for X and Y coordinate of the received data. A dropout layer and callback functions (similar to FFNN) are introduced into the model in order to avoid an overfit regression model.

Feed Forward Neural Network (FFNN) contains of 4 layers with 2 hidden layers, the first layer has 1000 neurons and the following hidden layer contains 326 neurons which was then output into 2 neurons each for predicting the X and Y coordinates for the provided input data. The hidden layers were activated using a ***Rectified Linear Unit (ReLU)*** function. Callback function was used to monitor the mean squared error (**MSE**) of the model with a patience of 5 in order to prevent overfitting of the model.

Recurrent Neural Network (RNN) Requires some additional preprocessing in order to input the time series in the optimal format. 1 recurrent layer with the LSTM cell type is used which has a state size of 256 and the weights initializer set to ***HeUniform***. The layers are bidirectional so that the time series can be read both, forwards and backwards. This is followed by 3 dense layers with the tanh activation function whereas a sigmoid activation function has been used for the recurrent layer. Callback functions similar to FFNN have been used.

2.3 Singular model compared to distributed models

CNN provided the best results with minimal variation. This can be attributed to the pattern and feature recognition capability of the CNNs. The CNN architecture was further extended to predict X and Y position of impact location via a single NN model as well as independently using individual NN models, the most suited of which was further optimised. Both the models to independently predict X and Y coordinates had 2,3 and 4 one dimensional filters in the 3 convolution layers used in them, which was then connected to a dense layer with 16 neurons, that further connects to a single output neuron to predict the corresponding impact location coordinate. Though, the model for X uses a kernel window of size (9,) in the first convolution layer, as opposed to the model for Y using a kernel window of (8,) at the same position. On the other hand, prediction using single NN model had the similar structure as used initially while comparing with the FFNN and RNN models.

2.4 Robustness check

The selected model was further optimised by balancing data in each quadrant to be used for the training of the neural network. A total of 1024 data files (256 data files corresponding to each quadrant) were available for the training of the NN. Balancing the data helped in reducing the bias of the model towards a specific quadrant. Such that, it had a fairly constant mean absolute error over all the four quadrants under study.

3 Results

Mean absolute error (MAE) is selected as a comparison criteria for our study. In CNN, the model was able to predict the impact location with a fairly low MAE, as compared to FFNN and RNN. RNN on the other hand had a complex structure, resulting in longer training times. Even then the MAE for RNN was more than double of the other two NN models used in this study. CNN and FFNN had similar MAE values and so to further compare these two models the mean squared error (MSE) and root mean squaed error (RMSE) were also calculated. The RMSE value indicate the variation of the model. Based on the results of FFNN and CNN it was observed that FFNN had a higher variance as compared with CNN. The results of MAE, MSE and RMSE for all the three NN models are tabulated in the table below.

NN Model	**MSE**	**MAE**	**RMSE**
Feed Forward Neural Network	470.5735	15.5867	21.6927
Convolutional Neural Network	234.6247	10.3214	15.3174
Recurrent Neural Network	1079.8892	25.7841	32.8616

Table 1: NN Architecture Comparison

The variation in the prediction of the impact location as compared to the desired location with the CNN can be seen in the graph plotted below, which plots the desired and predicted coordinates for X and Y independently. Both the graphs are closely overlapping indicating a high accuracy of impact location prediction using our selected CNN model.

Comparison between models for single output and multiple outputs <insert Graphs for CNN single model and double output model>

Check for robustness by skewing and balancing the data

Degree of Skewness	0%***(Balanced Data)***	75%***(Trained on*** $Q2$ ***Data)***	50%***(Trained on*** $Q2$ ***and*** $Q4$ ***Data)***
MSE	234.62	500.96	396.34
MAE	10.32	18.53	15.06

Table 2: Model comparison for completely balanced and skewed data

4 Discussion

The results of this study reveals that CNN can be used to predict impact location by measuring the impact vibrations using piezoelectric transducers. CNNs are the best suited NN use with such vibrational data as it is capable of recognizing patterns from the data received from the sensor. As well as it is able to neglect noise in the data passed to it making it more suitable for use in operation, as it would require minimal to no data pre processing. Additionally this impact vibration data can also be extended to calculate the intensity of impact, which when coupled with the impact location co-ordinate can be further used to calculate stresses generated and stored in the structure over the period of its operation. This would help to continuously monitor the structural health of the system. Thus, enabling us to take preventive measures as soon as an alarm is triggered as a result of detection of deterioration in the structural health/integrity of the system.

5 Conclusion

The study carried out here shows the best fit deep learning model for the prediction of impact position from the sensor data corresponding to it. A CNN using single NN model to predict both the X and Y co-ordinate is the best fit ANN for such use case scenario. This is further optimised by training the data on balanced data in order to reduce the bias of the model towards any given quadrant. The robustness of the model is checked by training it with data containing no data from any one of the quadrant. From the robustness check it is observed that even when the network is trained with data from only one quadrant, it is still able to predict the impact position with an RMSE of $19.585mm$ indicating a low variance.

References

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