Weak Adhesion Detection using Lamb Waves and Artificial Neural Networks

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Introduction

Although the aeronautical industry utilizes state of the art materials and production techniques, adhesive-based primary structures still have limited application due to the inexistence of reliable nondestructive monitoring methods for damage detection [1,2].

This work presents a novel technique for identifying the existence of weak adhesion in an adhesive bond layer by employing Lamb waves (LW) in conjunction with machine learning algorithms.

Experimental Methodology

Finite element models were used in order to create the required dataset to apply the machine learning algorithms. The model was created with two aluminum sheets with 150 x 150 x 2 mm and an overlap of 25 x 150 mm. A mesh size of 1.5 mm was chosen. The adhesive simulated was Nagase T-836/R-810 with a layer of 0.2 mm and the sensor/actuator were placed along the longitudinal line, centered at a distance of 30 mm from the edge of each substrate, shown as red dots in Fig. 1. The weak adhesion was simulated by altering the interface force between the adhesive and substrates. The LW, which are a form of guided waves, were generated using a Hann windowed force pulse with a frequency of 100 kHz applied on the horizontal surface of the plate (at the actuator location). The time-series of the amplitude of vibration at the sensor location was measured.

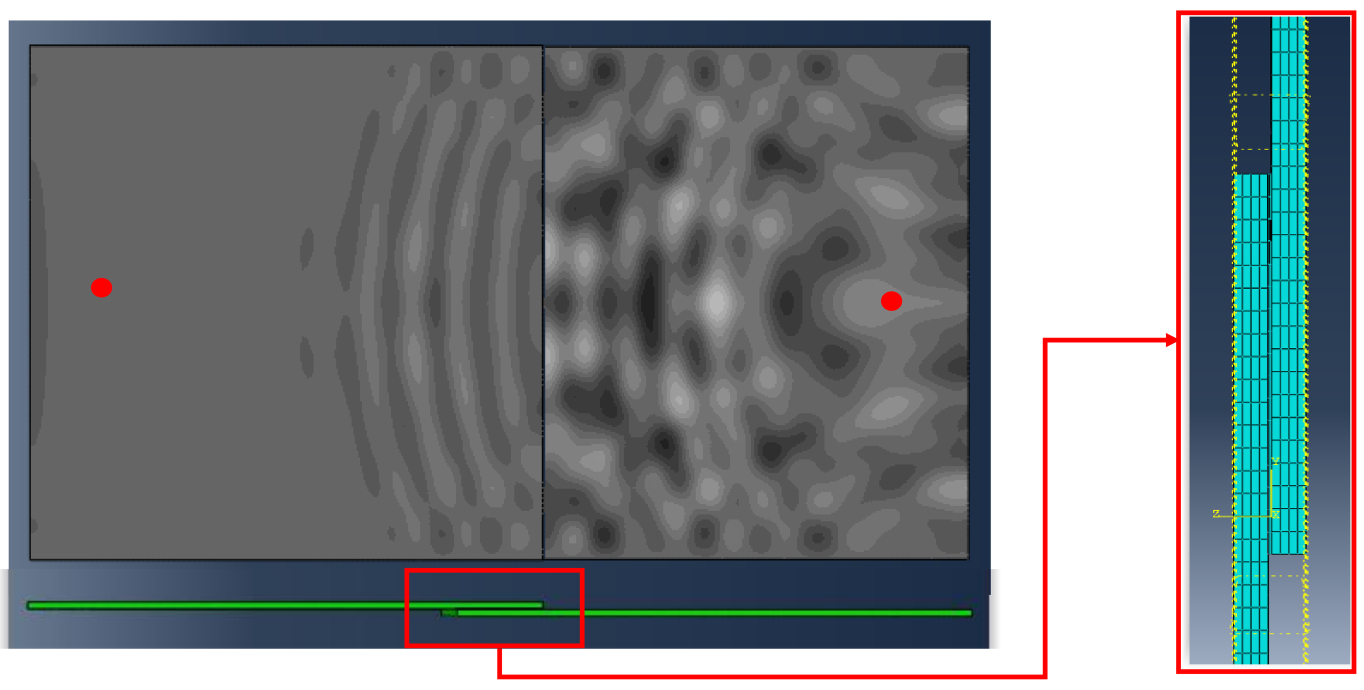

Figure 1 – Simulation of LW passing though the adhesive joint and mesh used.

Discussion

A data set was created with a total of 1000 simulated cases, where only the strongest 5% were considered as “no damaged”. The raw time signals were then processed in order to obtain relevant features for the machine learning methods. The chosen features were the magnitudes and the time of the peaks present in the signals (Fig. 2). The data were then applied to a conventional feedforward neural network (ANN) and a convolutional neural network (CNN). As the number of “no damaged” cases was small compared with the possible “damaged“ ones, “no damaged” cases were artificially created, by applying Gaussian noise to the actual cases, until the dataset included the same number of cases of each type.

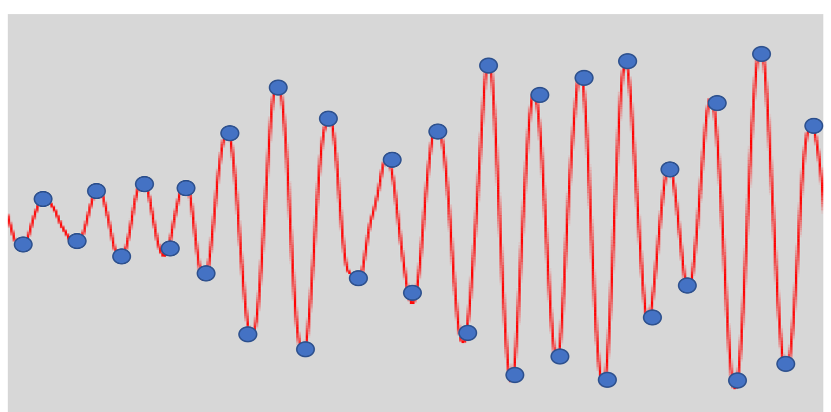

Figure 2 –Features extracted from the raw signal marked in blue.

Results

Both the ANN and CNN used 2 classes, namely “damaged” and “no damaged”, and presented an accuracy of over 97% and a loss under 0.1 for both testing and training samples. It is also possible to see results with a low number of epochs (Figs. 3-4). The confusion matrices show that that the algorithm does not classify a “damaged” case as “no damaged” (Fig. 5), which, in the aeronautical field, could be critical.

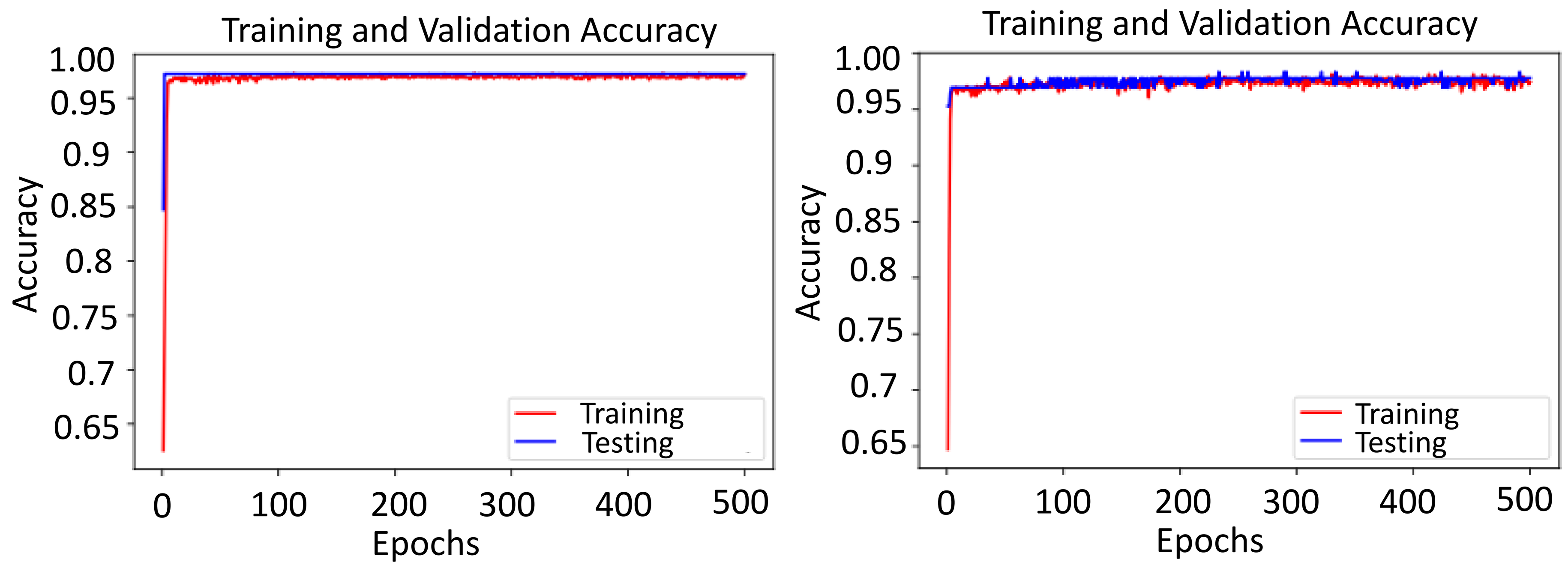

Figure 3 – Accuracy in each epoch: (Right) CNN, (Left) ANN.

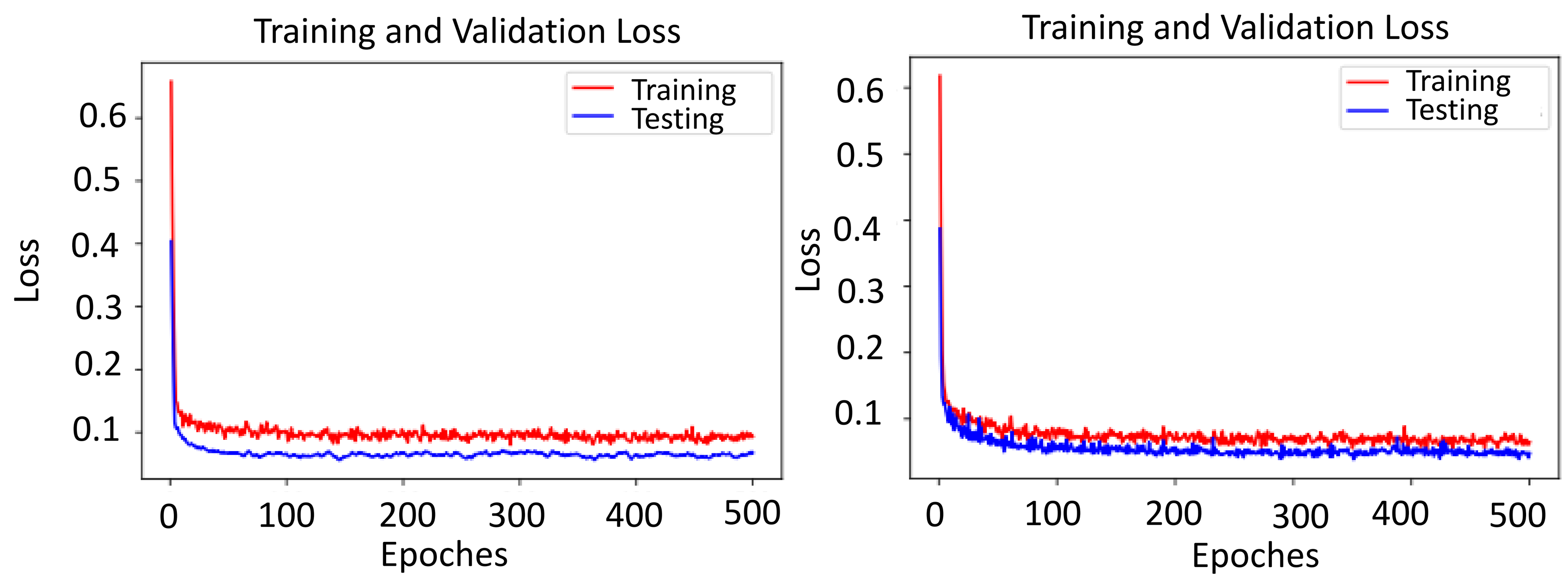

Figure 4 – Loss in each epoch: (Right) CNN, (Left) CNN.

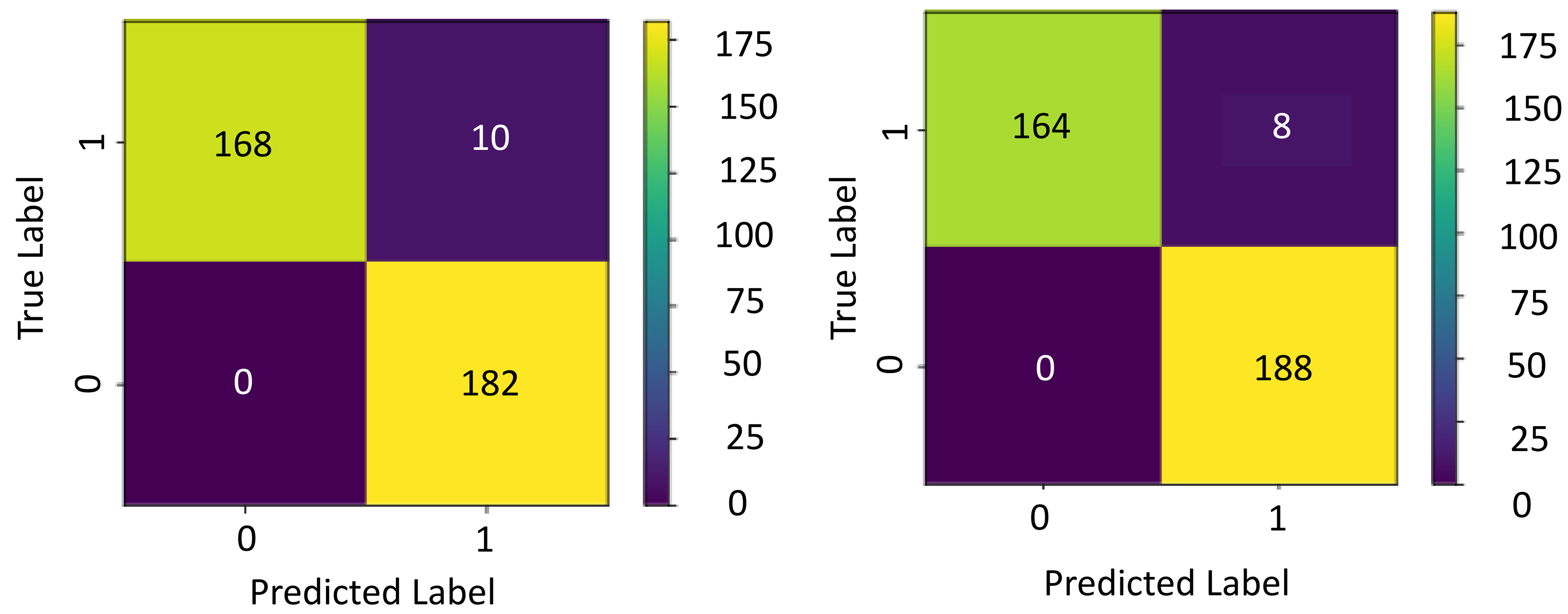

Figure 5 – Confusion matrix of best Epoch: (Right) ANN, (Left) CNN.

Conclusions

This work presented a novel approach using CNN and ANN to determine, with relevant accuracy of over 97% in the test batch, the presence or not of a weak adhesion in a single lap joint. The results will allow for further developments of adhesives in various high-end industries, such as the aeronautical field.

References

[1] Karachalios, E.F., Adams, R.D. and da Silva, L.F. (2013) . Strength of single lap joints with artificial defects. International Journal of Adhesion and Adhesives 45: 69–76. DOI:10.1016/j.ijadhadh.2013.04.009.

[2] da Silva, L.F.M., Öchsner, A. and Adams, R.D. (2011). Handbook of Adhesion Technology. 1st edition. Springer-Verlag, Berlin, Heidelberg. DOI:10.1007/978-3-642-01169-6-1.

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