Application of Deep Autoencoder on Damage Detection for Bridge Bearings

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1. INTRODUCTION

The encoder-decoder architecture-based deep learning (DL) approaches have been widely applied in various civil engineering tasks like crack segmentation [1] and anomaly detection [2]. Nowadays there are studies showing that appearance-based judgement like corrosion during the inspection is not sufficient, instead field measurement like displacement monitoring could demonstrate the degree of damage more accurately. For example, there are bridge bearings that heavily corrode but keep the mechanical function well. Currently, the evaluation of the damage of a bridge bearing is case-by-case analysis; DL approaches are expected to provide a generally applicable solution for the evaluation work. Due to the available displacement data of bridge bearings being limited and imbalanced, the unsupervised deep autoencoder (DAE) model was proposed for the damage detection task; the DAE model was trained for extracting complex features commonly existing in non-damage bridge bearings. There was displacement data collected for 38 bridge bearings under service status, where the accuracy of the trained model reached 85% on the test set, and the feedback from the results was discussed in this paper.

2. DATASET PREPARATION

The measurement data is the horizontal displacement of the movable part of bridge bearings along the longitudinal direction of decks. The duration of the measurement is from several hours to 24 hours. As the short-term representation of the response of bridge bearings under live load, the displacement data sampled under 100Hz was evenly sliced per 5.12s and then arranged by descending order of the short-term waveform amplitude, at last the first 200 short-term waveforms were selected per measurement case. The selected waveforms were normalized by min-max normalization before feeding into DAE models. As for the labels of bridge bearings, 18 cases were labelled directly as non-damage since the measurement was conducted right after the replacement of bridge bearings; the rest 20 cases were human-labelled, in which 10 cases were damage and the other 10 cases were non-damage. The dataset was split into 2 groups named training and test as shown in Fig. 1; the training group selected from after-replacement cases contains 12 cases as training set and 6 cases as validation set, the test group from human-labelled cases contains 10 damage cases as test-1 and 10 non-damage cases as test-2. In more detail, the type of 38-measured bridge bearings contains sliding bearings, roller bearings, and elastomeric bearings; the traffic type and road class contain railway, expressway, national road, and city road. The common features of non-damage bridge bearings were explored by DAE models in this study.

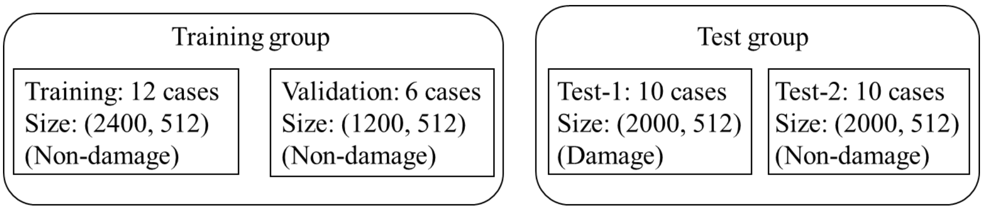

Fig. 1 Dataset splitting

3. DAE MODELS FOR DAMAGE DETECTION

The DAE model is expected to learn how to efficiently compress and encode non-damage measurement data, then to learn how to reconstruct the data back from the reduced encoded representation to a representation that is as close to the original input as possible. There are two DAE models proposed in this study; Model-1 shown in Fig. 2 is composed of fully connected layers; Model-2 shown in Fig. 3 is composed of convolutional layers, pooling layers and dropout layers. The activation function and dropout layers are not illustrated in the two figures.

4. RESULTS OF DAMAGE DETECTION

EarlyStopping callback was set to ensure the training epochs were enough, then the final models were tested for all sets in the prepared dataset. Considering the real usage for each measurement case, the final classification result of each case was voted by the results of selected 200 examples with the threshold of 50%. The loss distributions for Model-1 and Model-2 are demonstrated in Fig. 4 and Fig. 5 respectively; which show that both models can distinguish the damage from the non-

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damage by different trend directions. As for the threshold, it was adjusted by maximizing the accuracy of each set generally. The case-level classification results in Table 1 show the overall accuracy in the test group reached 85% for Model-2 which contains convolutional layers. Although losses in Model-2 are generally greater than those in Model-1, Model-2 is more capable to distinguish the damge from the non-damage. For unsuccessfully classified cases; in Test-1, it turns out to be the bearing of a railway bridge, whose response to live load is supposed to be reflected in a complete waveform which is much longer than 5.12s; in the rest datasets, the ones belong to the same bridge, there were on-site projects ongoing during measurement, therefore high-frequency noises were introduced.

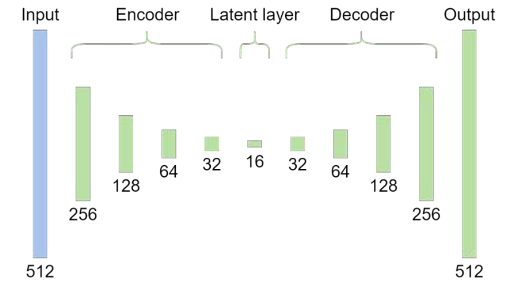

Fig. 2 The architecture of Model-1

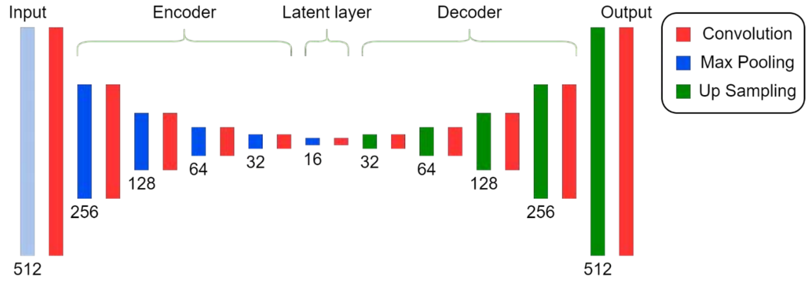

Fig. 3 The architecture of Model-2

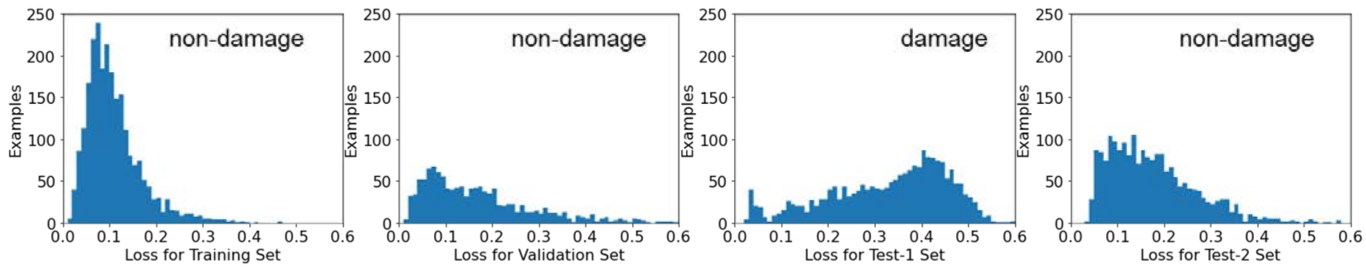

Fig. 4 Loss distribution for trained Model-1

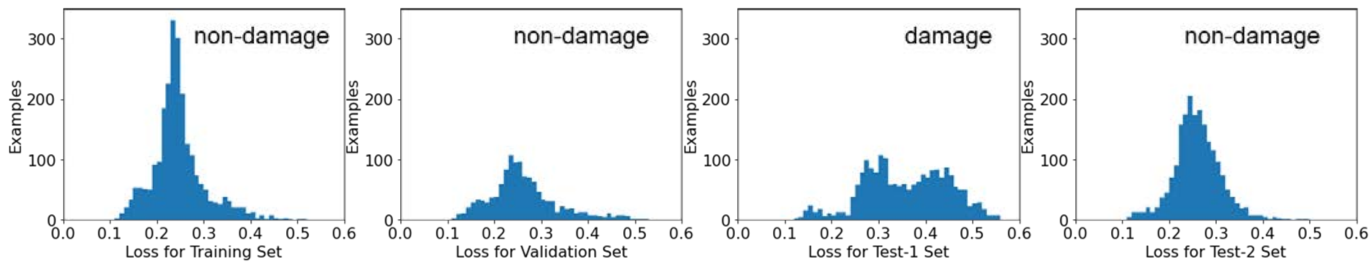

Fig. 5 Loss distribution for trained Model-2

Table 1: Training results of two models

Dataset	Model-1	Model-2
Training	100.0%	91.7%
Validation	83.3%	83.3%
Test-1	70.0%	90.0%
Test-2	80.0%	80.0%
Test group	75.0%	85.0%

5. CONCLUSIONS

In this study, two DAE models were proposed to classify the damage and the non-damage bridge bearings by the measurement data of displacement. The results demonstrate that the DAE model with convolutional layers achieved 85% accuracy on the test dataset. For improvements, data-preprocessing is promising for further studies.

REFERENCES

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