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Machine learning-based method for prediction of impact load damage

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ABSTRACT

Local damage of reinforced concrete (RC) panel subjected to impacting load is predicted using a machine learning (ML) approach. The investigated damage levels are no damage; penetration; scabbing; and perforation. Gradient Boosting Machine Learning (GBML), one of the most powerful techniques in machine learning is used for the prediction. Besides that, an artificial neural network (ANN) model is developed to compare with GBML model and evaluate the effectiveness of machine learning approach on the damage prediction problem. Several implementing results are obtained showing the accuracy rate and potential of this approach for further researches.

1. INTRODUCTION

In general, an impacting load may lead to local damage or global collapse of a RC walls, e.g. storage vessels, nuclear power plant containment, etc. Thus, the impact load damage is one of the important factors which need to be considered in practical structural design. In order to study the effects of the impact load on the structure, the RC panel has been analyzed and tested by many researchers (Hashimoto et al. 2005; Rajput and Iqbal 2017; Wu et al. 2015). Recognizing the damage level of structure in the designing stage may significantly contribute to an appropriate design (Kosteski et al. 2015; M. and J. 2003).

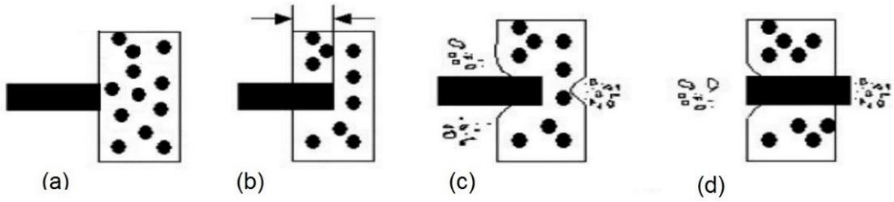

Fig. 1 Damage levels on the panel: (a) no damage; (b) penetration; (c) scabbing; and (d) perforation

The damage of RC panel was classified into seven levels: penetration, cone cracking & plugging, spalling, radial cracking, scabbing, perforation and overall

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structure collapse (Li et al. 2005). However in this study, four typical damage levels are selected: (a) no damage, (b) penetration, (c) scabbing, (d) perforation, which are often considered in practical analysis and design. The illustration of the four damage levels is presented in Fig. 1.

Many empirical formulas have been developed to predict the damage levels of RC panel by conducting the experiments (Kosteski et al. 2015; Thai, Kim, and Bui 2018). However, they are limited to accurately evaluate the performance of existing structures and new structures design due to the small scope of the experiment data. Therefore, this study introduces a new approach to predict the damage level of RC panel subjected to impact load which is based on the machine learning method. Two different machine learning models used in this study are the GBML, one of the most powerful techniques in ML (Chen and Guestrin 2016) and the ANN, which is a branch of ML (Lee et al. 2018). A dataset consisting of extensive 254 experimental tests which are collected from literature is employed in this study. The performance of two models in identifying the damage levels is estimated and compared. The efficiency of this approach is evaluated through the prediction performance.

2. EXPERIMENTAL DATABASE

Experimental data of the impact load on the RC panel were collected from various published studies. The database consists of comprehensive and extensive 254 test specimens with 17 input variables corresponding to the dimension of the panel, boundary condition, reinforcement, concrete properties, and missile characteristics. The output of dataset includes 4 classes representing for 4 damage levels: no damage, penetration, scabbing, and perforation. The dataset is divided into 5 equal parts in which one part is used as a test set, the rest four parts are used as a training set. The models are trained and tested 5 times using k-fold cross-validation technique (He and Fan 2019; Ling et al. 2019). Then, the accuracy of the model is obtained by averaging the metrics of each part.

Level of damage	Class	Number of tests
No damage	0.0	14
Penetration	1.0	45
Scabbing	2.0	69
Perforation	3.0	126

Table 1. Classification of dataset

3. MACHINE LEARNING APPROACHES

3.1 Gradient Boosting Machine Learning (GBML) model

GBML is a method of converting weak learners into strong learners. In GBML, each new tree is a fit on a modified version of the original data set. It trains many models in a gradual, additive and sequential manner (Chen and Guestrin 2016). The loss function of GBML is a measure evaluating the model’s coefficients under the input data. XGBoost which is a library developed based on the gradient boosting algorithm is efficiently used to predict the variable y_i using the training data with multiple features x_i . The objective function of training which is based on an additive manner is presented as follows:

$$L^{(t)} = \sum_{i=1}^{n} l\left(y_i, \hat{y}_i^{(t-1)} + f_t(x_i)\right) + \Omega\left(f_t\right) \quad (1)$$

where $l(y_i, \hat{y}_i^{(t-1)} + f_t(x_i))$ is the training loss function; $\Omega\left(f_t\right)$ stands for the complexity of the tree; and $f_t(x_i)$ is added to minimize the objective.

3.2 Artificial Neural Network (ANN) model

ANN is a computational-mathematical model which tries to describe the structure and functions of biological neural networks (Deng et al. 2018). An ANN model is composed of artificial neurons which are defined as the highly interconnected processing constituents working together to achieve better performances than the conventional models through calculating specific mathematical functions (Khademi and Jamal 2016). The artificial neuron consists of weights, bias and the activation function. The common structure of ANN includes an input layer, an output layer, and hidden layers. In this study, the ANN architecture is constituted by one input layer which is consisted of the 17 input variables, one output layer including 4 output classes and one hidden layer. The mathematical model of ANN is shown as below:

$$Y = f\left(\sum W_i X_i + b\right) \quad (2)$$

where Y is the output vector; f is the activation function; X_i is the input vector; W_i is the weight matrix; and b is the bias vector.

The prediction problem in this study is defined as a multi-class classification problem. Thus, the *softmax* loss function (Dunne and Campbell 1997) is used, expressed as:

$$P_i = \frac{e^{f_{y_i}}}{\sum_{j=1}^{n} e^{f_j}} \quad (3)$$

in which, y_i is output value; i is ith sample; f_j is output score: and n is the number of class.

4. PERFORMANCE AND COMPARISON OF THE MODELS

The performance of the models is evaluated by using confusion matrix and accuracy. In the confusion matrix, the column describes the predicted class while the row represents the true class. The diagonal values in the confusion matrix indicate the correct classification of each class, whereas all other values correspond to incorrect predictions. The prediction accuracy for the test set is calculated as:

$$p_a = \frac{D_p}{D_t} \times 100(\%) \tag{4}$$

where D_p is the total damage level successfully predicted in the test set, and D_t is the total number of damage level samples in the test set.

Fig. 2 shows the confusion matrices of GBML and ANN model. The prediction accuracy of both models according to 5 parts metrics are presented in Table 2. As can be seen, the average prediction accuracy of GBML model is 69.4%, which is slightly higher than the one of ANN model with 68.9%.

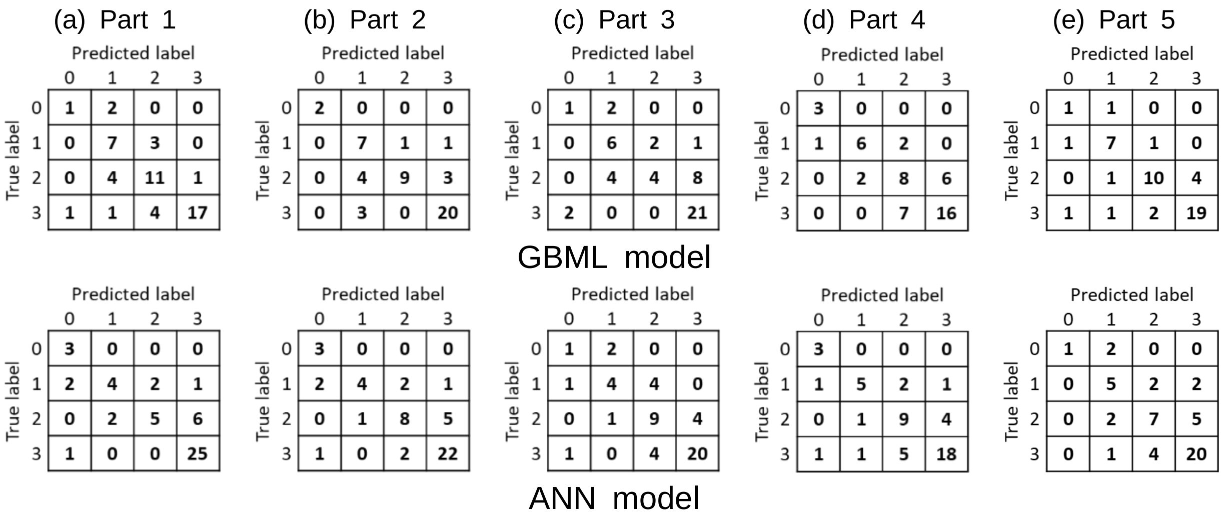

Fig. 2. Confusion matrix of GBML and ANN models

Table 2. Prediction accuracy of the GBML and ANN models on the test set.

Part / Model	1	2	3	4	5	Average accuracy	Standard deviation
GBML	69.2%	74.5%	62.7%	65.0%	75.5%	69.4%	5.65%
ANN	72.6%	72.0%	66.7%	68.6%	64.7%	68.9%	3.39%

However, the ANN model shows a more stable result than the GBML model described in their accuracy standard deviation. In addition, the confusion matrix shows that there are some parts in which the class 0, class 1 and class 3 are misdetected. In contrast, the class 4 which has 126 samples is well classified.

5. CONCLUSION

Two machine learning classification model, which are the GBML and ANN model, are described and conducted to classify the damange levels of the RC panel. The GBML model produces a slightly higher prediction accuracy than the ANN model. Some classes such as no damge, penetration, scabbing are sometimes misdetected due to the small amount of training data. However, the peforation class can be well classified with only 126 samples. This results reveal the efficiency of the machine learning approach for the prediction of damage level with an sufficient dataset.

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