AN APPROACH TO RAPID POST-EARTHQUAKE DAMAGE PREDICTION USING MACHINE LEARNING AND IOT DEVICES

Saitama University Student Member 〇Sanjeev Bhatta
Saitama University Regular Member Ji Dang

1. INTRODUCTION

Following a major earthquake, the quick evaluation of the buildings that are impacted by the event is essential for emergency response management and recovery planning. Machine learning (ML) methods have advanced quickly in recent years, allowing for rapid and reliable prediction of buildings seismic damage. Building damage is associated to the features of structural system and ground motion characteristics, which consists of many parameters. Considering only the structural or seismic characteristics, the proposed ML models may not fully reveal the underlying complexity of the interactions between input parameters and building performance (Tang et al. 2022). To capture the seismic properties, a low-cost internet of things (IoT) devices is used, which can be beneficial to underdeveloped or developing countries that is prone to earthquakes and where the installation of seismometers is limited (Takai et al. 2016). Figure 1 represents an overview of the proposed approach. In this study, a random forest (RF) ML model is developed considering both the seismic parameters and structural parameters as inputs and the degree of damage as outputs. The model accuracy is evaluated based on the prediction of damage state of buildings in testing dataset which were not used during training and validated with the time history analysis results obtained from ETABS software. The trained model is further used to predict the seismic damage of buildings at Saitama university.

2. PREPARATION OF DATASET AND DEVELOP ML MODEL

The total of 5856 dataset, as shown in Figure 1, is prepared conducting a nonlinear time history analysis of 2-10 stories reinforced concrete buildings with 732 earthquake waves downloaded from K-Net and Kik-Net networks. The bilinear MDOF shear model is considered where the mass is taken as unity and the inter story stiffness is calculated based on the eigen-value analysis (Lu et al. 2014). In this study, random forest ML model is developed considering six structural parameters: number of stories, story height (3 meter), height of building, fundamental period, construction year (1-120 years) and plan configuration (rectangular and square) and three seismic properties: peak ground acceleration (PGA), peak ground velocity (PGV) and the ratio of PGV/PGA are considered as input and the degree of damage: null, slight, moderate, heavy and collapse as output.

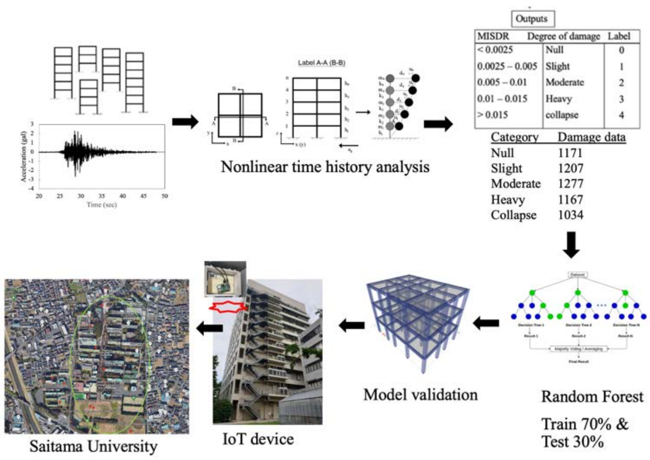

Fig. 1. Overview of proposed method

3. PERFORMANCE OF MODEL ON TEST DATASET

A random forest ML model is developed using the training dataset (70%) and its performance is

Predicted Label

True Label	Null	Slight	Moderate	Heavy	Collapse	Recall
Null	319	16	8	2	6	90.9%
Slight	101	192	41	11	17	53.0%
Moderate	38	112	199	26	8	52.0%
Heavy	19	29	119	105	78	30.0%
Collapse	5	13	26	18	248	80.0%
Precision	66.2%	53.0%	50.6%	64.8%	69.5%	Acc 73.7%

Fig. 2. Confusion matrix on test dataset

Keywords: seismic damage assessment, IoT device, machine learning, nonlinear time history analysis
Contact address: 255 Shimo-Okubo, Sakura-Ku, Saitama University, 338-8570, Japan, Tel: +81-070-8518-7147

evaluated on the testing dataset (30%). Figure 2 shows the confusion matrix on testing dataset where an overall accuracy of 73.7% is obtained. It is observed that the recall for other damage category is above 50% with 90% for null and comparatively lower for heavy category around 30%.

4. MODEL VALIDATION

To validate this model for its use in predicting seismic damage of building, 15 finite elements (FE) models are developed in ETABS software and time history analysis is carried out using El-Centro earthquake record in both NS and EW directions. The FE dataset considering structural and seismic properties for these 15 buildings are tested by the trained model where an overall accuracy of 60% is obtained as shown in Figure 3.

Predicted Label (columns); True Label (rows)

	Null	Slight	Moderate	Heavy	Collapse	Recall
Null	2	0	0	1	0	66.7%
Slight	1	2	0	0	0	66.7%
Moderate	0	0	2	1	0	66.7%
Heavy	0	1	0	1	1	33.3%
Collapse	0	0	1	0	2	66.7%
Precision	66.7%	66.7%	66.7%	33.3%	66.7%	**Acc 60%**

Fig. 3. Confusion matrix on FE dataset

5. USE OF IOT DEVICE FOR SEISMIC DAMAGE PREDICTION

The 8th floor of research project building of Saitama University is equipped with IoT system which comprise of 3-axis ADXL355 accelerometer connected with raspberry pi 4 model B as shown in Figure 1. The measurement system is developed under Python open-source environment to handle data acquisition, data storage and data transfer in the real time. The structural properties of 55 buildings of Saitama university are extracted using google earth, however the construction year is taken tentatively, and the seismic properties is taken from the recorded acceleration time history wave using IoT system. The developed ML model predicted all the buildings as null category which is 100% prediction accuracy since no damage were observed in the 5.4 magnitude earthquake occurred on 8:16:14AM, 19 April 2022 as shown in Figure 4.

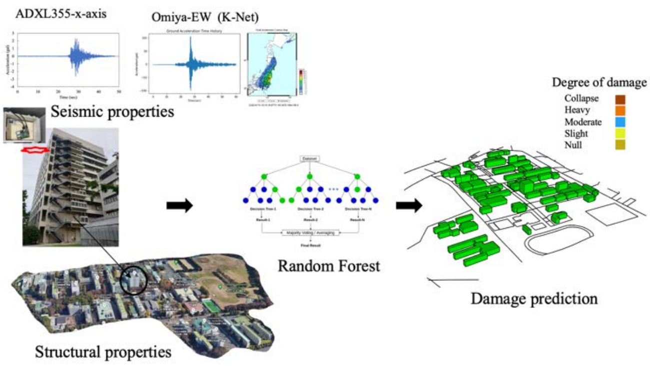

Fig. 4. Seismic damage prediction of Saitama university buildings

6. CONCLUSION AND LIMITATIONS

This study proposed an approach to rapid post-earthquake damage prediction using machine learning and IoT devices. For this, simulation dataset considering both structural and seismic properties is used to train RF model and its performance is evaluated on testing dataset and is further validated with FE results. The developed model is used to predict the seismic damage of buildings of Saitama university. This study benefits the earthquake-prone regions, where the installation of seismometer is limited, to carry out rapid seismic damage assessment of buildings. However, the training dataset can be increased further to increase the model prediction accuracy. In addition, this model should be validated on strong earthquake which can cause damage to building structure.

REFERENCES

Tang Q, Dang J, Cui Y, Wang X, Jia J. Machine learning-based fast seismic risk assessment of building structures. Journal of Earthquake Engineering, 26(15), 2022, pp. 8041-62.

Takai N, Shigefuji M, Rajaure S, Bijukchhen S, Ichiyanagi M, Dhital MR, Sasatani T. Strong ground motion in the Kathmandu Valley during the 2015 Gorkha, Nepal, earthquake. Earth, Planets and Space, 68(1), 2016, pp.1-8.

Lu X, Han B, Hori M, Xiong C, Xu Z. A coarse-grained parallel approach for seismic damage simulations of urban areas based on refined models and GPU/CPU cooperative computing. Advances in Engineering Software, 70, 2014, pp. 90-103.