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Application of Artificial Neural Networks to Identify Earthquake-Induced Structural Damage in Residential Buildings

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Abstract

Structural damage in residential buildings can significantly compromise the safety of occupants, reduce the structural integrity of the building, and shorten its overall lifespan, potentially leading to costly repairs, decreased property value, and increased risk during natural disasters such as earthquakes or storms. Traditional methods for assessing structural damage primarily depend on manual inspections, which are not only time-consuming and labor-intensive but also susceptible to human error, subjectivity, and inconsistency. These limitations can lead to delayed detection of critical issues, inaccurate assessments, and increased risk of overlooking hidden or early-stage damage, ultimately compromising the effectiveness of maintenance and safety measures. By employing a comprehensive dataset that includes a range of structural characteristics and damage indicators, this study trains a neural network model to identify and learn patterns linked to structural damage. This study investigates earthquake-induced damage in different structural components of residential buildings, employing hundreds of feature sets including building height, number of floors, earthquake intensity, damping ratio, crack location, and material properties to train and validate a network for damage prediction. The performance of the ANN is evaluated, demonstrating superior accuracy and efficiency. The results highlight the potential of ANNs to revolutionize structural health monitoring by providing rapid, cost-effective, and reliable damage assessments, thereby enhancing preventative maintenance and mitigating risks associated with structural failures.

1. Introduction

Structural damage to buildings poses significant challenges and risks to both the safety of occupants and the integrity of the structure itself. Whether caused by natural disasters such as earthquakes, floods, or storms, or by human made factors like poor construction or aging infrastructure, structural damage can result in significant impacts on communities, economies, and individuals [1-3]. The common visible occurrence structural damage that is experienced by the communities are cracks in the building. Cracks are caused by an externally applied load such as dead, live, wind, or seismic loads. To prevent and minimize further damage within a structure, it is essential to first identify the existing damage in the affected building.

Traditional practices for identifying damage in structural buildings often rely on visual inspections, experience-based assessments, and basic measurement techniques. These practices may have limitations in detecting underlying issues or assessing structural performance under dynamic loads or environmental conditions. Pattern recognition is one of the most popular approaches to structural damage detection. Artificial neural networks (ANNs) are commonly adopted in pattern recognition to match pattern features, mainly because of their outstanding pattern generalization capabilities [4-5]. While there are several ways that have been studied and are currently being developed to diagnose building damage, those that do not need in-depth understanding of the structure's failure mechanisms or vulnerable portions have an advantage in handling unexpected failure patterns [6-7].

Additionally, techniques that take less time and have fewer obstacles during design and execution are also becoming more popular. Artificial Neural Networks (ANNs) are the most widely used machine learning approach in structural engineering. ANNs are widely used in structural engineering for damage detection, capacity prediction, and reliability analysis of steel and concrete structural components [8-10]. For instance, Aloisio et al. [11] developed an ANN model to predict the code-based seismic vulnerability index using a dataset of approximately 300 buildings. The ANN surpassed other models, achieving over 85% precision with a well-balanced dataset. The study confirmed the ability of ANNs to identify patterns and precisely classify damage levels. However, its focus on masonry structures restricts the model's applicability to other structural types, such as tall buildings or bridges.

Moving on, Xu et al. [12] developed an ANN framework to predict the nonlinear seismic responses of diverse buildings within a cluster exposed to multiple earthquake inputs. Drawing inspiration from collaborative filtering techniques, the method converts regional response prediction into a matrix completion problem, utilizing historical data and structural features to improve accuracy. Applied in an urban area with 2,788 buildings and 3,798 ground motions, the framework demonstrated considerably faster performance than time history analysis, reaching high computational efficiency with errors under 3% across different response metrics.

Next, Jia and Wu [13] developed a structural damage dataset through incremental dynamic analysis (IDA) and trained an integrated ANN using ten-fold cross-validation for damage prediction. By incorporating uncertainties in structural models and seismic excitation, they produced vulnerability curves depicting failure probability limits. The results show that the proposed ANN model provides excellent stability and robustness, with a narrow range of structural failure probability. In recent years, the interest of applying ANNs to structural health monitoring has increased and several attempts have been made to assess damage in civil structures using ANNs [14-17]. Regardless of the presently available research efforts, there are remaining needs to diagnose defects in structural systems and to assess both its location and severity using artificial neural networks. As such, the major concentration of this present study was to investigate the potential of ANNs to detect damage in residential buildings. The feasibility of this approach was proved through its implementation to different damage detection scenarios.

2. Methodology

ANNs are a form of data processing method that imitates the functioning of biological nervous structures, such as the human brain. ANNs consist of many interconnected processing units, or neurons which employ a form of human-like learning by example to solve problems [18-20]. Like biological systems, the learning process in neural networks entails modifying the connections between neurons. Various types of ANN exist with differences in how their neurons are connected, the computations they perform, how patterns of activity are transmitted, and how they learn. ANNs have become increasingly popular for solving real-world problems as they can address complex problems that traditional technologies cannot handle, especially those that do not have a defined algorithmic solution or have a solution that is too complicated to define. Among various types of neural networks, the multilayer perceptron stands as the most employed [21]. It typically comprises an input layer with a neuron count equivalent to the number of parameters relevant to the given problem, while an output layer is presented with a neuron count matching the desired number of quantities obtained from the inputs. The intermediate layers are referred to as hidden layers [22]. Figure 1 shows an example of the architecture of an ANN, including an input layer with 5 neurons, a hidden layer with 3 neurons, and an output layer with four neurons. Signals, or information enters through the input layer, traverses the hidden layer, and eventually proceeds to the output layer. The Backpropagation (BP) algorithm is widely utilized in ANNs due to its ability to mathematically model complex nonlinear relationships [23-25]. This algorithm is evaluated based on its performance index, which seeks to minimize the Mean Square Error (MSE). It involves minimizing the error between the predicted outputs of the network and the actual outputs, until a level is reached where an acceptable agreement is achieved with the training datasets.

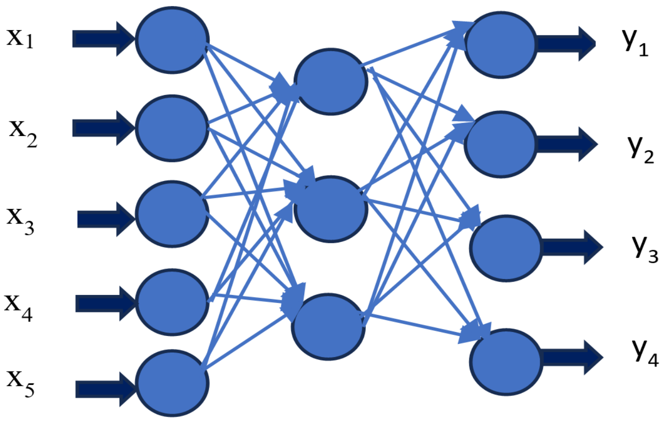

Fig. 1 *An example of an artificial neural network architecture*

The MSE algorithm calculates the error by comparing the target output with the output produced by the network. This algorithm belongs to the category of supervised training, where a learning rule is given a collection of examples that demonstrate the desired behavior of the network. This algorithm adjusts the weights and biases of the ANN to decrease the magnitude of the average error between predicted and real values. The fine-tuning that the weights and biases persist until the error is diminished to a satisfactory level. The equation representing the MSE operation is denoted as Equation (1) [26-27].

$$MSE = \frac{\sum_{i=1}^{n}(t_i - o_i)^2}{n} \tag{1}$$

In Equation (1), the symbol "n" indicates the total number of training patterns considered, t_i indicates the output of target and o_i is output predicted by network. After the networks are deemed as trained, they are presented with testing data, and the results are contrasted with the actual outcomes for validation. Within this study, the backpropagation learning algorithm is employed. The primary focus of the learning process revolves around determining the connection weights of the neural network.

The performance of an ANN model is a crucial aspect of its overall effectiveness, as it directly influences the reliability, accuracy, and applicability of the model in solving real-world problems. Evaluating the ANN model's performance ensures that the trained network can generalize well to unseen data and provide meaningful predictions. One of the most widely used performance evaluation metrics in ANN modeling is the Coefficient of Determination (R^2), which measures the proportion of variance in the dependent variable that is predictable from the independent variables. The R^2 value ranges from 0 to 1, where a higher value indicates a stronger correlation between the predicted and actual outputs, signifying better model accuracy.

The use of R^2 as an evaluation metric in this study provides an understanding of how well the ANN model captures patterns in the data and minimizes errors in predictions. An R^2 value close to 1 indicates that the model's predictions align closely with the actual values, while a lower R^2 value suggests a weaker predictive capability.

To compute R^2, the mathematical expression is as Equation 2.

$$R^2 = 1 - \frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \bar{y})^2} \tag{2}$$

y_i = Actual values

$\hat{y}_i$ = Predicted values

$\bar{y}$ = Mean of actual values

The ANN model's performance testing using R^2 ensures that the trained model is not only fitting the training data well but also capable of making accurate predictions when exposed to new input data. Additionally, the evaluation helps identify issues such as underfitting when the model is too simple to capture patterns or overfitting when the model memorizes training data but fails to generalize to unseen data.

In this study, Orange Data Mining software was utilized for ANN model processing, offering an intuitive, user-friendly interface for implementing and evaluating neural networks. The software enables efficient testing of models through visual programming, simplifying the process of training, testing, and analyzing model performance. By employing R^2 as a key performance indicator, the study effectively quantifies the model's ability to predict the damage index based on various input parameters such as building height, material type, number of floors, earthquake intensity, damping ratio, and crack location. Ultimately, the evaluation of ANN models through R^2 in this study provides valuable insights into the effectiveness of different network architectures. The comparison of these architectures allows for a better understanding of their strengths and limitations, helping to determine the most suitable model for accurate and reliable damage index prediction in structural analysis. The model creation of ANN using Orang Software is shown in Figure 2.

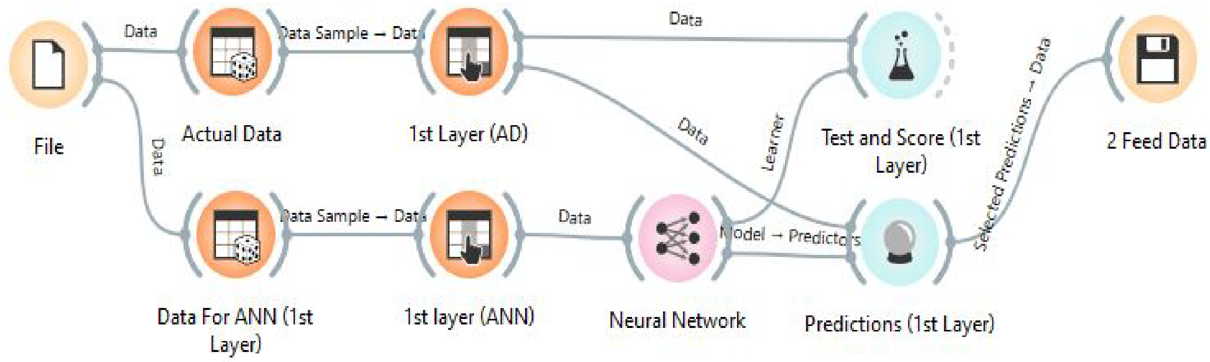

Fig. 2 *Model creation of ANN in this study*

In this study, through Orange Software a dataset consisting of 650 records was prepared to analyse the relationship between structural parameters and the damage index of buildings subjected to seismic activity. The dataset was segmented into three parts: 350 samples were allocated for training, 150 samples for testing, and an additional 150 samples were reserved for validation purposes. The selected parameters include building height (m), material type, number of floors, earthquake intensity (g), damping ratio (%), and crack location. The damage index was chosen as the key feature, serving as the primary output variable for model prediction and comparison. The purpose of this dataset division is to ensure that the models are trained effectively while retaining an independent set of data to evaluate their predictive accuracy.

3. Results and Discussions

To model the relationship between input parameters and the damage index, several ANNs architectures were developed. The final architecture has a four-layer with a structure of 6-10-20-1, incorporating two hidden layers with 10 and 20 neurons, respectively. It should be noted that incorporating a larger number of neurons in the network increases computational complexity and time requirements. In summary, the 6-10-20-1 architecture of the ANN was chosen to achieve an optimal trade-off between compatibility cost and accuracy, providing a balance between efficiency and performance. The architecture was trained using the training dataset to learn complex nonlinear relationships between input features and the damage index. During training, the models adjusted their weights through backpropagation to minimize the prediction error. Once trained, its performance was evaluated using the testing dataset to assess the generalization ability. The predicted damage index values were compared with actual values from the dataset to determine accuracy and reliability. Figure 3 presents a comparison between the predicted damage index values generated by the ANN and the actual values for the training datasets.

The performance evaluation of the ANN architecture was analyzed based on Mean Squared Error (MSE), and the coefficient of determination (R^2) for training datasets. The four-layer feed-forward network demonstrated superior performance comparing to other networks, achieving lower MSE while maintaining higher R^2 scores. In the training phase, the model yielded an MSE of 0.0031 with an R^2 value of 0.987. The close match between the ANN predicted results and the actual damage index values during training indicates that the model has successfully learned the underlying patterns and relationships within the training data. This suggests that the ANN was effectively trained using a well-structured dataset with relevant input features, appropriate architecture, and optimized parameters. Such high accuracy in training implies that the model can capture the nonlinear complexities of the damage prediction problem.

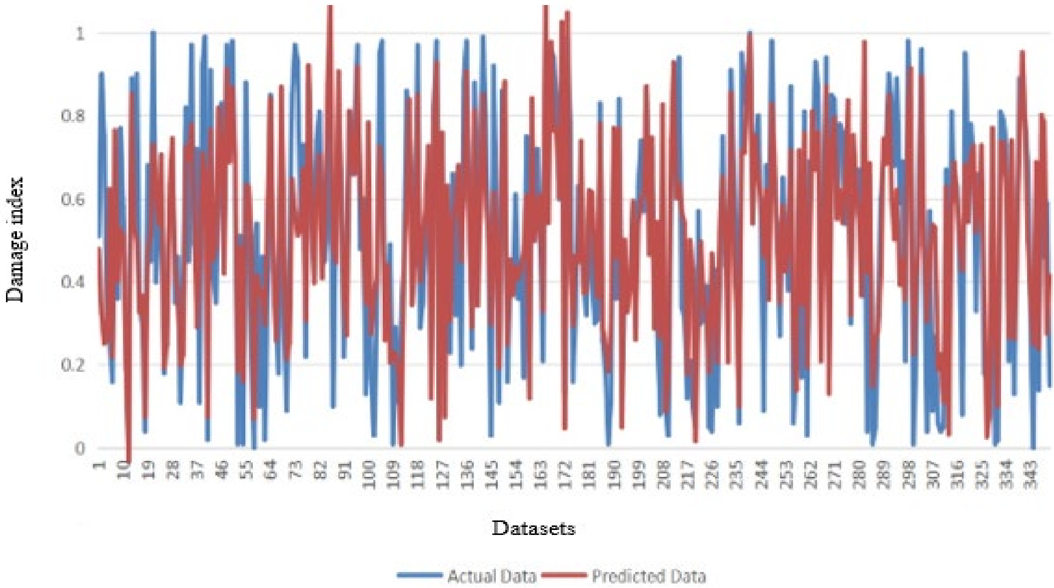

Fig. 3 *Comparison of damage index predicted by ANN and actual datasets (training sets)*

However, while this performance is promising, it must be justified by evaluating the model's performance on unseen data to ensure that it has not overfitted and can generalize well to real-world scenarios. The testing phase of an ANN model is essential for assessing its ability to make accurate predictions on new data. During this phase, the model, which has been trained using a specific dataset, is subjected to a separate testing dataset to measure its performance under conditions that simulate real-world applications. Figure 4 presents a comparison between the predicted damaged index values generated by the ANN and the actual values for the testing datasets.

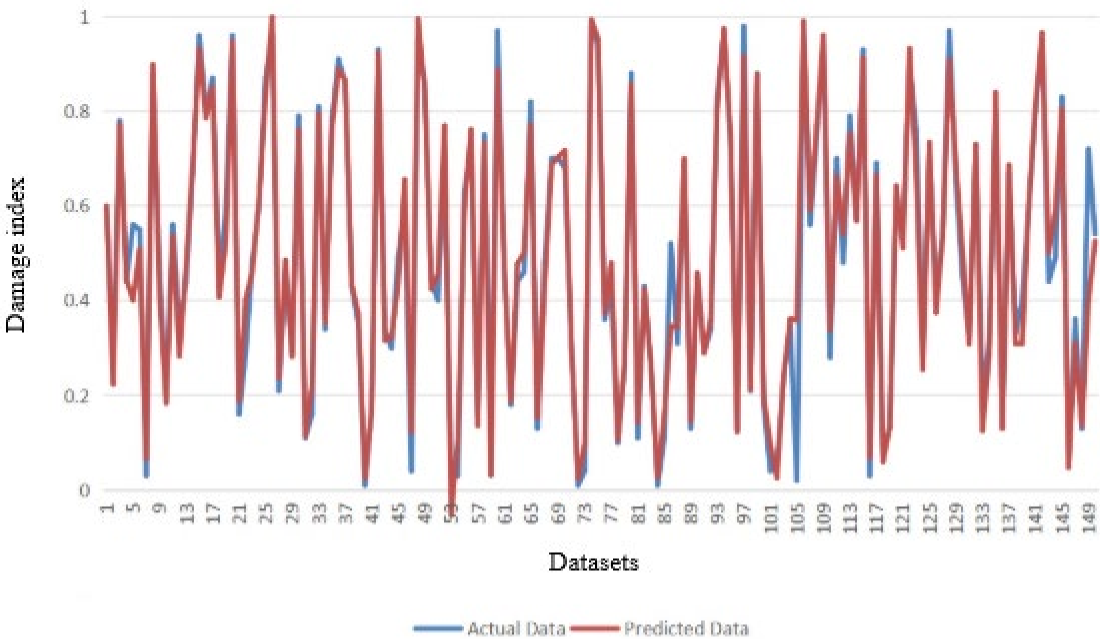

Fig. 4 *Comparison of damage index predicted by ANN and actual datasets (testing sets)*

In the testing phase, the model yielded an MSE of 0.0039 with an R^2 value of 0.981, indicating strong predictive accuracy on the test dataset. This consistency across both training and testing phases indicates that the model has not only learned the patterns in the training data but also generalizes well to new, unseen data. It reflects the robustness and reliability of the ANN in predicting structural damage, confirming that the selected input parameters and network configuration are appropriate for capturing the complex relationships involved in damage assessment. Such results validate the effectiveness of the ANN model for practical applications in structural health monitoring and damage prediction.

This validation dataset, which consisted of entirely new and previously unused data, was employed to double-check the robustness and generalization capability of the trained ANN. Figure 5 presents a comparison between the predicted damaged index values generated by the ANN and the actual values for the validation datasets.

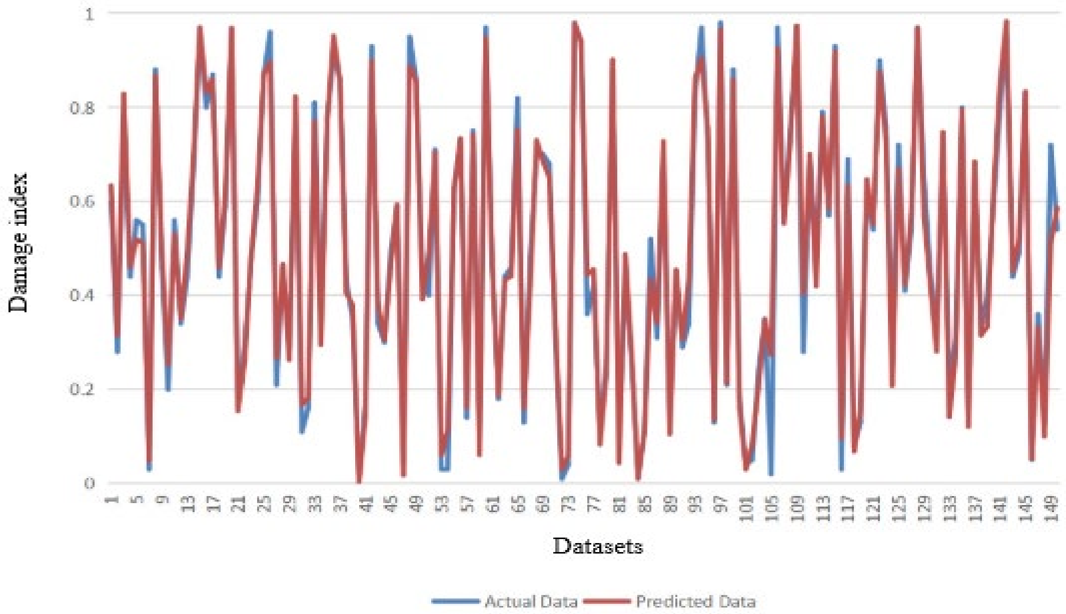

Fig. 5 *Comparison of damage index predicted by ANN and actual datasets (validation sets)*

The ANN model also performed well on the validation dataset, where the predicted damage index values closely matched the actual data. Similar trends were observed in validation phase with an MSE of 0.0043 and correlation of 0.979. These results suggest that an architecture with two hidden layers generalizes better and provides more accurate predictions for the damage index, likely due to its optimal complexity and reduced risk of overfitting compared to the deeper architecture. The strong agreement between predicted and actual values in the validation phase confirms that the model is not overfitted and can reliably predict damage indices even when presented with unfamiliar scenarios. This reinforces the credibility of the ANN as a dependable tool for structural damage prediction across diverse conditions.

4. Conclusions

This study demonstrates the significant potential of Artificial Neural Networks (ANNs) in identifying structural damage in residential buildings, particularly damage resulting from earthquake events. By training the ANN model on an extensive dataset comprising structural features such as building height, number of floors, earthquake intensity, damping ratio, crack location, and material properties, the model was able to accurately predict damage patterns. The ANN not only reduced the reliance on time-consuming and error-prone manual inspections but also provided consistent and rapid assessments across varying building conditions. The performance evaluation of the trained network revealed high levels of accuracy and reliability, confirming that ANNs can serve as a powerful tool in structural health monitoring systems. The successful application of this approach indicates a clear advantage in terms of cost-efficiency, speed, and objectivity when compared to traditional methods. The findings highlight the feasibility of integrating AI-based tools into existing maintenance and safety protocols, offering proactive solutions for damage detection and risk mitigation. Future research could focus on enhancing the model with real-time data, expanding it to different building types, or integrating it with other sensor-based systems for broader implementation. Ultimately, this work contributes to safer, smarter, and more resilient residential infrastructure.

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Conflict of Interest

Authors declare that there is no conflict of interest regarding the publication of the paper.

Author Contribution

The authors confirm the contribution to the paper as follows: I.I. Sigar: ***study conception, Data collection and analysis****; S.J.S. Hakim****: study conception and design, analysis and interpretation of results, supervision****; A. M. Mhaya:* ***analysis and interpretation of results****; S.N. Mokhatar:* ***Methodology, draft manuscript preparation****; N. Jamaluddin:* ***data collection, methodology****;* H. Tami: ***conceptualization and final version of the manuscript.****, N.A. Rahman:* ***data collection and analysis****. All authors reviewed the results and approved the final version of the manuscript.*

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