Assessment of Post-Disaster Building Damage Levels Using Back-Propagation Neural Network Prediction Techniques

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Abstract— **Indonesia is susceptible to natural disasters, with its geographical location being one of the contributing factors. To mitigate the harmful effects of natural catastrophes, it is required to undertake a disaster emergency response, which consists of a set of steps taken immediately following the event. These operations include rescue and evacuation of victims and property, addressing basic needs, providing protection, and restoring buildings and infrastructure. Accurate data is required for effective recovery after a disaster. The Badan Penanggulangan Bencana Daerah (BPBD) oversaw disaster relief efforts, but faulty damage assessments slowed restoration. Surveyor subjectivity and differing criteria result in discrepancies between reported damage and reality, generating issues during the post-disaster reconstruction phase. This study's objective is to develop a prediction system to measure the extent of damage caused by natural disasters to buildings. Based on the five criteria that determine the level of building damage after a disaster, namely, building condition, building structure condition, physical condition of severely damaged buildings, building function, and other supporting conditions. The data used are from the BPBD of Malang city from 2019 to 2023. This system would allow surveyors to make speedy and objective evaluations. Five different models were tested using the Neural Network Backpropagation approach. Model A2 produces the highest accuracy of 93.81%. A2 uses a 40-38-36-34 hidden layer pattern, 1000 epochs, and a learning rate of 0.1. These findings can lay the groundwork for advanced prediction models in post-disaster building damage evaluation research.**

Keywords— **Predictions; Post-Disaster; Building Damage; Neural Network;**

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I. INTRODUCTION

Area Indonesia is potentially vulnerable to disasters [1], [2]. One reason is that it is located next to three plates: the Eurasian Plate, Pacific Plate, and Australian Plate, and next to the Mediterranean Rim and Pacific Rim. [3], [4]. Furthermore, the volcanoes of the Indonesian archipelago, which make up about 13% of the world's surface, can cause disasters of a variety of severity and scale [5]. As a result, it is impossible to deny that earthquakes, volcanic eruptions, and other natural calamities strike Indonesia frequently. This is corroborated by a statement on the Badan Nasional Penanggulangan Bencana (BNPB) website, which states that there were 4,649 natural catastrophes in 2020 and 3,092 in 2021.

The BNPB is a legally recognized entity with authority over disaster management tasks [6]. The BNPB is a state-owned institution in Indonesia that manages information regarding natural catastrophes. Badan Penanggulangan Bencana Daearah (BPBD) is a BNPB branch that was established at the province and district/city levels in Indonesia [7]. Equitable guidance and direction for disaster management initiatives, including emergency response, rehabilitation, and reconstruction, is the responsibility of the BPBD [8]. Natural disasters hurt people's life, such as causing damage to agricultural land and cattle, as well as residences and public structures [9]. To mitigate the harmful effects of natural catastrophes, a disaster emergency response, which consists of a set of steps conducted promptly following a disaster, must be implemented. These efforts include rescuing and evacuating victims and property, addressing basic needs, providing protection, dealing with refugees, and reconstructing buildings and infrastructure [8].

A successful post-disaster recovery strategy must be based on reliable data and information [10], [11], [12]. According to the declaration in the Final Draft Changes to the Provincial BPBD Strategic Plan. Incorrectly determining the extent of post-disaster damage and loss is one of the challenges that must be overcome in the rehabilitation and reconstruction of disaster-affected districts in East Kalimantan 2019-2023. This occurs because each surveyor's perspective of the criteria for planning post-disaster rehabilitation and rebuilding measures varies, resulting in difficulties and disaster data that differ from the situation in the field [11].

Inspectors must not only have the skills to assess a natural disaster, but they must also have the skills to evaluate that area. According to *Almais et al.* building condition, status, physical condition, function, and other factors can be used to calculate the level of damage caused by natural disasters [13]. There is no scientific debate about how badly natural disasters affect the sector, although some natural disasters are recorded according to official standards but not quantitatively.

Bachriwindi et al. Using the Decision Support System (DSS) method, this study determines the severity of damage to the sector caused by natural disasters [11]. This study used the approach on three separate test datasets to examine pattern data. The WP approach demonstrated a great confusion matrix as the data used rose. In addition, *Wibowo Almais et al.* used the ME-MCDM approach to estimate the amount of sector damage following natural catastrophes [14]. Existing research reveals a flaw: surveyors continue to use the DSS stages to assess the level of damage to sectors after disasters. In this work, Machine Learning (ML) is utilized to evaluate the level of damage to sectors following catastrophes, reducing the need for surveyors to perform DSS stages.

According to Almais et al., the Backpropagation Neural Network approach was used to improve the Self-evaluation Questionnaire (SAQ) evaluation on the East Java Provincial Government website by applying scraping techniques (data retrieval from the internet) [15]. The scrape results will be processed by the Backpropagation Neural Network utilizing four different kinds of data models, each with several iterations and hidden layers. The data model with 2000 iterations and 9 hidden layers has an MSE value of 0.0036, a MAPE of 18.71%, and a maximum accuracy of 81.28%, according to the test results.

According to *Sudarsono*, the advantage of Backpropagation Neural Networks is that they can be trained repeatedly, allowing them to create systems that are consistently dependable and damage-resistant [16]. Aside from that, no research has been done using Backpropagation Neural Networks to predict the level of building damage after natural disasters. Given these assertions, this study will use the Backpropagation approach to anticipate the level of damage to sectors after disasters. So it is hoped that the level of accuracy using the Backpropagation technique may be calculated and that the resulting model can accurately estimate the extent of building damage depending on field conditions.

II. Materials and Methods

This material and method chapter explains the flow of methods and how to process the data used in this study:

A. Materials

Our research analyzes building damage data collected by the Malang City BPBD after natural disasters in 2019-2023. The information analyzed includes the location, physical condition, and level of damage to the building. This data is then categorized into five main criteria: Building Condition, Building Structure, Physical Damage, Building Function, and Additional Condition. A total of 365 data with various features are used in this analysis. Table 1 is the alias name and code of the 5 criteria mentioned above, plus 1 output data or data label.

TABLE I
DATA FEATURES

No	Criterion Name	Alias Name	Code
1	Building Condition	Criteria 1	X1
2	Building Structure	Criteria 2	X2
3	Physical Damage	Criteria 3	X3
4	Building Function	Criteria 4	X4
5	Additional Condition	Criteria 5	X5
6	Light/Medium/Heavy Damage	Output/Label	Y1

The target to be predicted is the level of damage to buildings, which are expressed in three categories as in Table II below:

TABLE II
DATA TARGET [12]

No	Level of Damage	Value
1	Light	0
2	Moderate	1
3	Heavy	2

The rating scale and values for each criterion in determining the level of building damage are presented in Table III.

TABLE III
DAMAGE AND VALUE LEVEL SCALE [17]

No.	Criteria	Criteria Assessment Scale	Scale of Interest	Value
1	Building's state	Stand	Light	1
		Crooked	Moderate	2
		Destroyed	Heavy	3
2	Building structure's state	A small part is damaged	Light	1
		Some Damaged	Moderate	2
		Mostly Damaged	Heavy	3
3	Physical Condition of Damaged Building	<30%	Light	1
		30-50%	Moderate	2
		>50%	Heavy	3
4	Building's Functions	Not Harmful	Light	1
		Relatively Dangerous	Moderate	2
		Dangerous	Heavy	3
5	Other Building Conditions	Small Part Damaged	Light	1
		Mostly Damaged	Moderate	2
		Damaged	Heavy	3

B. Methods

Prediction of building damage levels is done using a neural network-based approach with a backpropagation algorithm. The following are the steps we took:

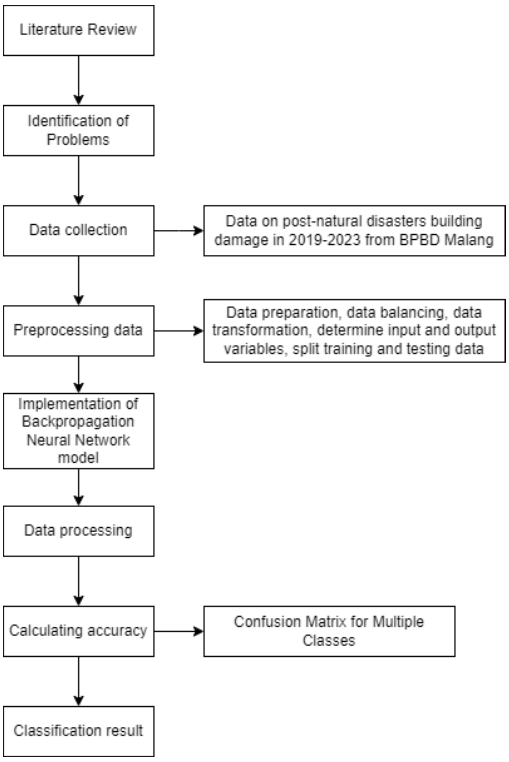

Fig. 1. Research Methodology

The research is divided into the following stages, as shown in Figure 1:

1. A literature review seeks out research-related sources.
2. Identify issues with assessing the degree of structural damage to structures following natural catastrophes.
3. Collecting data on building damage after natural disasters from BPBD Malang City.
4. Data preprocessing includes removing missing values, balancing data, transforming data from categorical to numeric attributes, and splitting training and test data with a ratio of 80:20 and 70:30.
5. Implementation of the backpropagation neural network model.
6. Training neural network models with training data and testing with test data.
7. Accuracy calculation using confusion matrix.

A more detailed explanation of the research methodology in Figure 1 is found in the sub-section below:

- *Data Preparation*: The data preparation stage is an important stage that can affect the accuracy of machine learning predictions [18]. Data preparation includes processes that transform raw data into quality data, such as data collection, balancing data, transformation, cleansing, and split dataset [19]. Below is an explanation of each of these stages for the preparation of post-natural disaster building damage data obtained from the Malang City BPBD.
- *Data Balancing:* To reduce bias in model predictions and, as a result, improve classifier performance, one of the most important steps is data balancing [20]. This is because the classifier has a bias towards the majority of class examples, meaning that the prediction of majority examples is better than the prediction of minority examples. Figure 2 depicts an imbalance in the distribution of data labels in the dataset to be used.

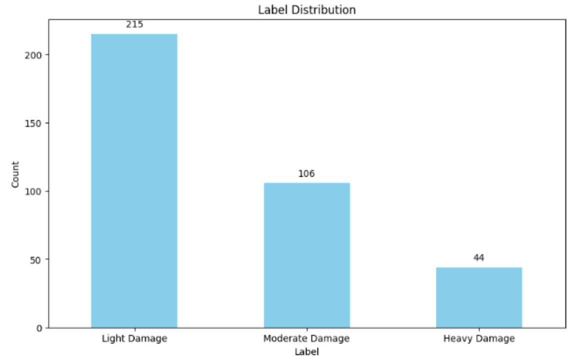

Fig. 2. Label Distribution

This study uses random oversampling to solve the problem of data imbalance. Random oversampling is a data-balancing strategy that includes replicating instances from the minority class to obtain a more balanced dataset [21]. Oversampling is a common and well-studied approach to data imbalance problems [22]. The distribution of labels after random oversampling is seen in Figure 3.

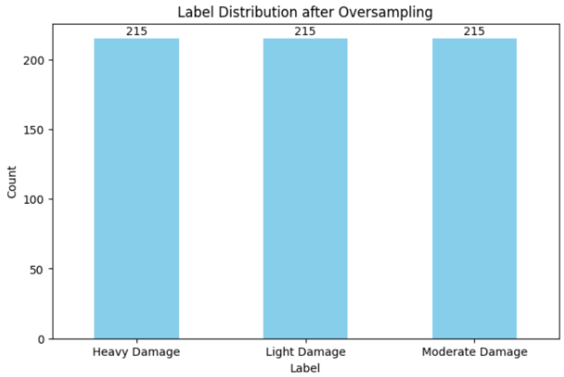

Fig. 3. Label Distribution After Data Balancing

- *Data Transformation:* Labeling categorical variables into numerical values has two techniques: label encoding and one-hot encoding [23], [24]. This study uses the label coding technique because it changes the parameters in Table I into numerical values to replicate them in the Neural Network Backpropagation (NNBP) process. Label coding provides numerical representations of categorical variables, allowing the model to process and understand the data. Because many machine learning algorithms including NNBP perform better on numerical data, label encoding is often used when working with those algorithms [24]. The label encoding process in our research can be implemented in a complete computational procedure using the following algorithms:

Algorithm: Label Encoding Process

```
Input      :  Parameter (X1, X2, X3, X4, X5)
              Output/ Label (Y1)
Process    :  Declare (X1, X2, X3, X4, X5)
              Set X1(Stand)=1
              Set X1(Crooked)=2
              Set X1(Destroyed)=3
              Set X2(A small part is
              damaged)=1
              Set X2(Some Damaged)=2
              Set X2(Mostly Damaged)=3
              Set X3(<30%)=1
```

```
                Set X3(30-50%)=2
                Set X3(>50%)=3
                Set X4(Not Harmful)=1
                Set X4(Relatively Dangerous)=2
                Set X4(Dangerous)=3
                Set X3(Small Part Damaged)=1
                Set X3(Mostly Damaged)=2
                Set X3(Damaged)=3
                Set Y1(Light Damage)=1
                Set Y1(Medium Damage)=2
                Set Y1(Heavy Damage)=3
Output      :   Numeric value parameters (X1,
                X2, X3, X4, X5) and
                Output/Label (Y1)
```

The encoding process results can be seen in Table IV, which presents the data results that have gone through the encoding process.

TABLE IV
AFTER ENCODING

1st Index	X1	X2	X3	X4	X5	Y1
0	3	3	3	2	3	2
1	3	3	3	3	3	2
2	1	1	1	1	1	0
3	3	3	2	3	3	2
4	1	1	3	1	1	0
…	…	…	…	…	…	…
640	1	2	2	1	2	1
641	3	2	2	2	2	1
642	3	2	2	1	2	1
643	2	2	2	2	2	1
644	2	2	2	2	2	1

- *Data Splitting for Training and Testing:* Splitting data is the process of dividing a dataset into two or more mutually exclusive parts (which cannot occur simultaneously) to train and test a model [25]. From this understanding, it can be seen that data splitting is carried out to produce a dataset that can be used to train models and test model performance. This research will use split data with a ratio of 70:30 and 80:20. The data distribution refers to research conducted by Santoso, et al on the topic of Predicting Waste Volume at Banyuurip TPSA Using a Backpropagation Neural Network. In the research of *Santoso et al*., the distribution of training and testing data with a ratio of 80:20. The data used is time series data in the form of waste volume at the Banyuurip TPSA from 2019 to 2022. From the results of the study, the Backpropagation Neural Network method with input layer 30, hidden layer of 1, hidden neuron 7, epoch 1000 produced the best UMK value of 0.018870 [26].
- *Neural Network Backpropagation (NNBP):* Backpropagation is a basic process in training neural networks, which allows them to learn from data [27]. It involves adjusting the weights of the network to minimize the difference between its output and the desired output [28], [29], [30]. The word network propaganda only has one input and one output in a neural network. In the therapeutic propagation neural network, the most powerful neurons participated in the acquisition of the password. *Şekeroğlu* found that there is a different time window for each situation since the number of hidden neurons influences the number of training models [30]. *Karsoliya* highlights the importance of hidden layers for network performance, especially for complex cases. Furthermore, he proposed a method to calculate the number of neurons present in each hidden layer [31]. Research on NNBP has been carried out in research conducted by *Almais et. al* [15] implementing the NNBP method to assess the East Java Provincial Government website, 4 types of data models are used which differ in terms of several iterations and hidden layers to obtain the best accuracy. According to the findings of these trials, the D data model, which includes nine hidden layers and 2000 iterations, achieves the highest level of accuracy, making it eligible for use as a benchmark for evaluating the outcomes of the East Java Provincial Government website in 2021. In our research experiments, a number of parameter values have been determined, including the number of hidden layers, the number of neurons on the hidden layer, training, testing data ratio, maximum epoch, and learning rate,

Five variations in the number of hidden layers were tested to find the optimal hidden layer design for classifying data. The number of neurons in the hidden layer varies in one way: the number of neurons decreases as the number of hidden layers increases. The value of the parameters and their variations can be seen in Table V.

TABLE V
PARAMETER VALUES AND VARIATIONS

Model	Hidden Layer	Neurons in the Hidden Layer	Split data ratio	Epoch
A	4	40→38→36→34	70:30 80:20	500 1000 2000
B	6	40→40→38→38→36→36	70:30 80:20	500 1000 2000
C	8	40→40→38→38→36→36→34→34	70:30 80:20	500 1000 2000
D	10	40→40→38→38→36→36→34→34→32→32	70:30 80:20	500 1000 2000
E	12	40→40→40→38→38→38→36→36→36→34→34→34	70:30 80:20	500 1000 2000

The above parameter values and variations are used based on research conducted by [32]. In this study, 2 tests were carried out with learning rates, namely 0.1 and 0.9. To find out which learning rate is best to predict the level of building damage after a natural disaster.

- *Accuracy:* Calculation of artificial neural network accuracy using Multiclass Confusion Matrix. Confusion Matrix is a technique used to measure the accuracy of classifiers [33]. The multi-class confusion matrix displays a comparison of the classification results carried out with the actual data as in the following Table VI [34].

TABLE VI
MULTICLASS CONFUSION MATRIX

Actual Label	Prediction Class A	Class B	Class C
Class A	TP_A	E_{BA}	E_{CA}
Class B	E_{AB}	TP_B	E_{CB}
Class C	E_{AC}	E_{BC}	TP_C

Accuracy can be calculated based on the values in the confusion matrix. Calculating the accuracy of the confusion matrix is by using the following Equation (1):

$$Accuracy = \frac{TP}{Total\ data} \times 100\% \quad (1)$$

The TP value in Equation (1) is the sum of $TP_A+TP_B+TP_C$. The accuracy value is the value obtained from the quotient of all the correct test data with the total test data [35].

III. Result And Discussion

In this research, the NNBP implementation uses the Python programming language. 5 models will be used in this research, models A, B, C, D, and E. Each model uses a learning rate of 0.1 and 0.9 and uses epochs 500, 1000, and 2000. Thus each model consists of 6 different types with iteration and data split ratio.

A. Model A

Model A comprises various types, namely models A1 to A6. The parameters utilized for each model are presented in Table VII.

TABLE VII
Model A Parameters

Parameter	A1	A2	A3	A4	A5	A6
Learning rate	0.1 and 0.9					
Epoch	500	1000	2000	500	1000	2000
Hidden layer	40→38→36→34					
Training Data	70%	70%	70%	80%	80%	80%
Testing Data	30%	30%	30%	20%	20%	20%

Model A consists of four hidden layers, each with a decreasing number of neurons: 40, 38, 36, and 34, sequentially. The training and testing data-sharing ratio for models A1 to B3 is 70:30, while models A4 to A6 adopt a ratio of 80:20. The outcomes of model A are depicted in Table VIII.

TABLE VIII
Model A Results

Model	Accuracy Learning rate 0.1	Accuracy Learning rate 0.9
A1	89.18%	90.20%
A2	93.81%	93.29%
A3	93.30%	93.29%
A4	89.15%	91.40%
A5	93.02%	92.20%
A6	92.25%	93.02%

Table VIII presents the experimental results of various machine learning models tested with different learning levels in model A. Model A2 is one of the models tested, showing excellent performance. With a learning rate of 0.1, the A2 model managed to achieve an accuracy of 93.81%. This indicates that the A2 model is very effective in studying and making predictions from the data provided. A learning rate of 0.1 indicates how quickly the model adjusts its weights during the learning process to minimize prediction errors. Figure 4 is a graphical representation showing the performance of the A2 model. Graphs typically display curves that illustrate the accuracy or loss of the model during the training process. With a learning rate of 0.1, it is possible to observe that the A2 model is stable and converges to optimal results quickly, which is reflected in the high accuracy achieved. It can also indicate that the model is not overfitting or underfitting, which is an important indicator of a good model.

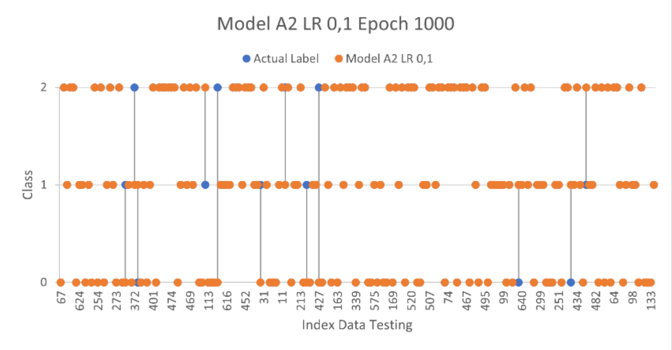

Fig. 4. Comparison Graph of Actual Data VS Prediction Model A2 Learning Rate 0.1

B. Model B

Model B encompasses various types, namely models B1 to B6, with the parameters utilized for each model listed in Table IX.

TABLE IX
Model B Parameters

Parameter	B1	B2	B3	B4	B5	B6
Learning rate	0.1 and 0.9					
Epoch	500	1000	2000	500	1000	2000
Hidden layer	40→40→38→38→36→36					
Training Data	70%	70%	70%	80%	80%	80%
Testing Data	30%	30%	30%	20%	20%	20%

Model B consists of six hidden layers with the following neuron configurations in order: 40, 40, 38, 38, 36, and 36. Models B1 to B3 utilize a training and testing data-sharing ratio of 70:30, while models B4 to B6 adopt a ratio of 80:20. The results of model B are presented in Table X.

TABLE X
Model B Results

Model	Accuracy Learning rate 0.1	Accuracy Learning rate 0.9
B1	89.18%	73.70%
B2	90.21%	92.20%
B3	93.30%	91%
B4	88.37%	37.90%
B5	91.47%	57.36%
B6	92.25%	92.20%

Table X displays the results of a series of B models on machine learning that have been tested with different learning levels. In TABLE X, the B3 model is the best-performing model, achieving a high accuracy of 93.30% with a learning rate of 0.1. This learning rate shows how many changes are made to the model's weights in each iteration during the training process to reduce errors. An accuracy of 93.30% shows that the B3 model with this learning level can predict the test data very well, showing a low error rate and strong generalization ability. Figure 5 provides a visualization of the performance of the B3 model during the training process. Typically, this graph will show a curve that illustrates the accuracy or loss of the model over time. With a learning rate of 0.1, we can expect that the curve shows a steady trend of increasing accuracy without large fluctuations, indicating that the B3 model is not overfitting or underfitting.

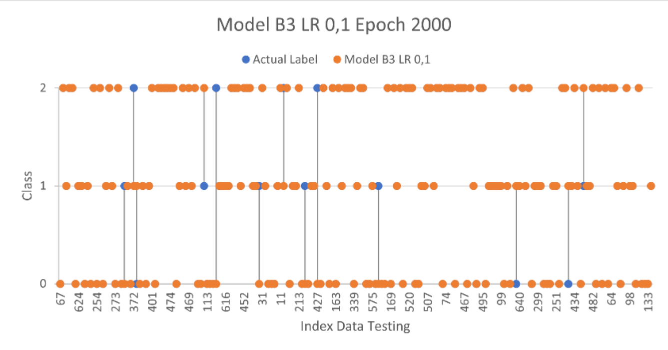

Fig. 5. Comparison Graph of Actual Data VS Prediction Model B3 Learning Rate 0.1

C. *Model C*

Model C encompasses various types, specifically models C1 to C6, and the parameters employed for each model are detailed in Table XI.

TABLE XI
MODEL C PARAMETERS

Parameter	C					
	C1	C2	C3	C4	C5	C6
Learning rate	0.1 and 0.9					
Epoch	500	1000	2000	500	1000	2000
Hidden layer	40→40→38→38→36→36→34→34					
Training Data	70%	70%	70%	80%	80%	80%
Testing Data	30%	30%	30%	20%	20%	20%

Model C is structured with eight hidden layers, arranged with the following neuron counts: 40, 40, 38, 38, 36, 36, 34, and 34. For models C1 to C3, a 70:30 training and test data sharing ratio is employed, while models C4 to C6 utilize an 80:20 data sharing ratio. The outcomes of model C are displayed in Table XII.

TABLE XII
MODEL C RESULTS

Model	Accuracy	
	Learning rate 0.1	Learning rate 0.9
C1	90.72%	36.60%
C2	92.78%	72.68%
C3	93.30%	59.79%
C4	88.37%	59.69%
C5	91.47%	55.81%
C6	92.25%	29.46%

In Table XII, the experimental results of model C show that model C3 achieves the most optimal performance compared to other models. The C3 model managed to record the highest accuracy of 93.30%, which indicates a very accurate prediction rate of the test data provided. This success was achieved using a learning rate of 0.1, an important parameter in the model training process. Further, the graph in Figure 6 visually illustrates the performance of the C3 model. The graph shows how the C3 model with a learning rate of 0.1 has experienced a consistent increase in accuracy as the training iteration progresses. This indicates that the model can learn effectively from the training data and generalize the learning to the test data well.

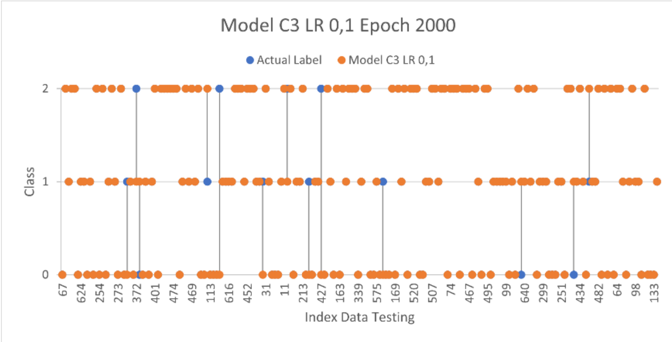

Fig. 6. Comparison Graph of Actual Data VS Prediction Model C3 Learning Rate 0.1

D. *Model D*

Model D includes various types, denoted as models D1 to D6, and the parameters utilized for each model can be found in Table XIII.

TABLE XIII
MODEL D PARAMETERS

Parameter	D					
	D1	D2	D3	D4	D5	D6
Learning rate	0.1 and 0.9					
Epoch	500	1000	2000	500	1000	2000
Hidden layer	40→40→38→38→36→36→34→34→32→32					
Training Data	70%	70%	70%	80%	80%	80%
Testing Data	30%	30%	30%	20%	20%	20%

Model D is constructed with ten hidden layers, featuring the following neuron counts in order: 40, 40, 38, 38, 36, 36, 34, 34, 32, and 32. Models D1 to D3 are trained and tested using a data-sharing ratio of 70:30, while models D4 to D6 adopt a ratio of 80:20. The outcomes of model D are presented in Table XIV.

TABLE XIV
MODEL D RESULTS

Model	Accuracy	
	Learning rate 0.1	Learning rate 0.9
D1	91.24%	31.44%
D2	93.30%	31.96%
D3	93.30%	31.44%
D4	89.92%	29.46%
D5	92.25%	29.46%
D6	93.02%	29.46%

In the analysis presented in Table XIV, it can be seen that model D, namely models D2 and D3, both stand out in terms of accuracy, with each reaching 93.30%. The figure shows a very high degree of agreement between the model's prediction results and the actual value. Both models use a learning rate of 0.1 in their training process, which effectively optimizes the model's weight to achieve accurate results. In Figure 7, a graphical representation of the D3 modeling results with a learning rate of 0.1 can be seen. The graph shows a positive trend in improving accuracy during the training process, indicating that the D3 model can adjust its weights well and learn from each iteration. It also shows that the selected learning rate is suitable for the dataset used, allowing the model to learn efficiently without overfitting or underfitting.

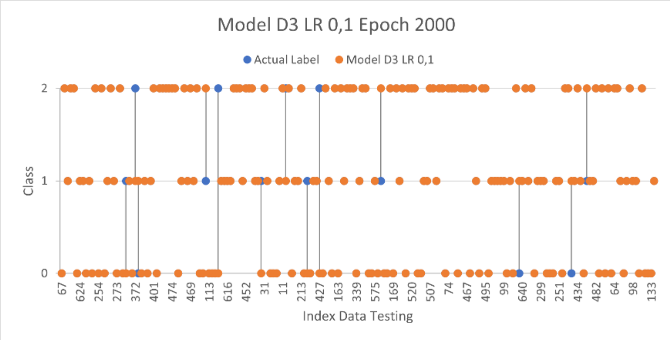

Fig. 7. Comparison Graph of Actual Data VS Prediction Model D3 Learning Rate 0.1

E. Model E

Model E encompasses several types, including models E1 to E6, and the parameters employed for each model are detailed in Table XV.

TABLE XV
MODEL E PARAMETERS

Parameter	E1	E2	E3	E4	E5	E6
Learning rate	0.1 and 0.9					
Epoch	500	500	500	500	500	500
Hidden layer	40→40→40→38→38→38→36→36→36→34→34→34					
Training Data	70%	70%	70%	80%	80%	80%
Testing Data	30%	30%	30%	20%	20%	20%

Model E is designed with twelve hidden layers, featuring the following neuron counts in sequence: 40, 40, 40, 38, 38, 38, 36, 36, 36, 34, 34, and 34. For models E1 to E3, a training and testing data-sharing ratio of 70:30 is applied, while models E4 to E6 utilize a data-sharing ratio of 80:20. The results of model E are displayed in Table XVI.

TABLE XVI
MODEL D RESULTS

Model	Accuracy Learning rate 0.1	Accuracy Learning rate 0.9
E1	56.70%	31.44%
E2	90.72%	36.60%
E3	91.24%	31.44%
E4	86.05%	29.46%
E5	89.15%	29.46%
E6	91.47%	29.46%

From the data listed in Table XVI, in model E the E6 model is showing impressive performance by achieving a peak accuracy of 91.47%. This number reflects the ability of the E6 model to make highly accurate predictions, which is the result of an effective training process and precise parameter setting. A learning rate of 0.1 has proven to be a key factor in the success of this model, allowing the machine learning algorithm to adjust the weights to the optimal steps, thus avoiding overfitting and underfitting problems. The graph shown in Figure 8 provides a clear visualization of how the E6 model progressed during the training phase on the E model. This indicates that the E6 model has successfully learned important patterns from the training data and applied them effectively to the test data.

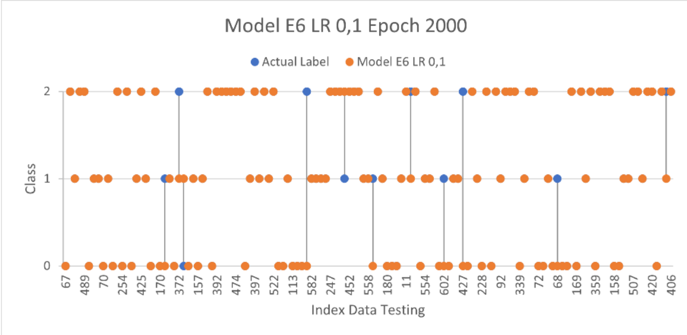

Fig. 8. Comparison Graph of Actual Data VS Prediction Model E6 Learning Rate 0.1

The following is a comparison of the accuracy of all models that have been tested.

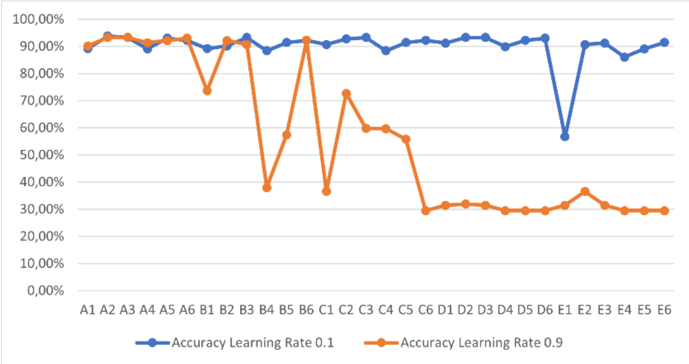

Fig. 9. Accuracy of All Models

The accuracy graph for all models is shown in Figure 9, which shows that using a learning rate of 0.1 resulted in stable and adequate accuracy on all models evaluated. When the learning rate increased to 0.9, models A and B maintained excellent accuracy, while model C's performance dropped significantly. Models with more hidden layers (such as C, D, and E) show the greatest drop in performance. This is related to the increasing complexity of the learning process, where weight adjustment becomes more difficult. Learning rates that are too high, such as 0.9, can cause instability and inhibit model convergence

IV. CONCLUSION

Test results indicate that among the models evaluated, model A2 produces the highest accuracy rate of 93.81% with a learning rate of 0.1. Model A2 has 4 hidden layers with a pattern of 40→38→36→34, uses 1000 epochs, a data split ratio of 70:30, and a learning rate of 0.1. With its ability to predict post-disaster building damage levels with high accuracy, the model can be used by stakeholders, such as governments, research institutions, and aid organizations, to inform effective decisions and response actions in emergencies. These findings can serve as a foundation for further research in the development of more sophisticated and accurate prediction models for evaluating post-disaster building damage.

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Materials and Methods:

A. Materials:
• The explanation of the criteria seems convoluted, making it difficult to understand.
• What is the purpose of the 'code' column?

B. Methods
• sub-Section 1) Data Preparation: It is stated, "Data preparation includes processes that transform raw data into quality data, such as data collection, integration, transformation, cleansing, and reduction." Does data collection fall under data preparation? This is inconsistent with the flowchart in Figure 1, where data collection and data preprocessing are shown as separate processes.
• In Figure 1: Data preprocessing includes data balancing, transformation, and splitting. However, the explanation below mentions data preparation (sub-Section 1)) separately from data balancing(sub-Section 2)), transformation (sub-Section 3)), and Data Splitting for Training and Testing (sub-Section 4)). Please confirm.
• Figure 3: The lines cut off the numbers at the top. Please adjust the layout.
• Data splitting: What do the parameters 30-7-1 mean?
Result And Discussion:• More detailed explanations are needed for Figures 4-8.
• Figure 9 needs to be mentioned in the paragraph for clarity and context.

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Introduction
Consider introducing the term "Badan Nasional Penanggulangan Bencana (BNPB)" also in English or providing a brief explanation of this agency in English.

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Provide comprehensive details about the data used, as depicted in Figure 1 (including the year of the data).

It is advisable to create Table 1 by first listing the original names of the features, followed by their aliases and codes. Include criteria directly to enhance the table's comprehensibility.

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Confirm if the data transformation mentioned here aligns with the subsequent explanation under "Data Transformation."

Data Transformation: Provide a detailed explanation of one-hot encoding applied to the dataset.

Neural Network Backpropagation (NNBP)

In the Results and Discussion section, it is stated that five models were developed and tested. It is advisable first to present the explanation of these five models, including differences in configuration and other relevant aspects in this sub-section (Neural Network Backpropagation (NNBP)' sub-section). This approach ensures a comprehensive discussion beyond the literature review of NNBP alone.

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