Expert System for Building Damage Assessment Due to Earthquake Using Backpropagation Artificial Neural Network Algorithm

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Abstract **Earthquake is one of the most destructive natural disasters. After the earthquake, the Government mobilizes experts to assess the building damage based on the condition, especially its structural aspects. The experts conduct a building damage assessment with three categories, namely mild, moderate, and severe damage. This study proposes an expert system that facilitates the building damage assessment due to an earthquake based on the crack information of its structure using the Backpropagation Artificial Neural Network. In this case, the expert system is designed and developed for Android-based mobile devices. The developed expert system was tested by using black-box, accuracy, and Mean Opinion Score (MOS) testing techniques to determine its performance. In general, the proposed system has worked properly indicated by its functionality and MOS about 4.54 of 5 scales. Additionally, this expert system also provides an average accuracy of 82.22% from 30 cases tested by three building damage experts.**

Key words: **Earthquake, building damage, expert system, Artificial Neural Network, Backpropagation.**

I. Introduction

Earthquake is vibrations originating from within the earth, which then propagates to the surface of the earth due to the shifting of the earth's faults. The causes of earthquakes can be in the form of earth dynamics (tectonics), volcanic activity, due to falling meteors, landslides (under seawater levels), and nuclear bomb explosions [1]. Earthquake is one of the most destructive natural disasters.

After the earthquake, the building structural experts are mobilized to survey/assess the damage that occurred. One of the main objectives of the assessment task carried out by experts is to evaluate and classify buildings into several categories commonly as minor, moderate, and severe damage. Many damaged buildings are vulnerable and dangerous, especially when aftershock occurs. Insecure buildings must be marked and prohibited from being occupied [2].

Evaluation of building damage by experts is very important to prevent casualties from collapsing buildings. The assessment process can be facilitated by a system that can carry out the assessment automatically. The system referred to in this paper is an expert system that can assess building damage due to an earthquake, without the help of a building structure expert. The building structure experts themselves and the general public who have little knowledge of building structures can use this expert system.

The expert system can be designed using the Backpropagation Artificial Neural Network (BP-ANN) algorithm which is a common method for pattern recognition and classification. The use of BP-ANN in the expert system can provide several benefits, namely, being able to gain knowledge even though there is no certainty, have adequate fault tolerance, and the ability to forward steps so that the process of concluding becomes faster. The expert system applications will be developed for Android mobile devices to be flexible and easy to carry and use.

Based on these explanations, this research aims to build an expert system to diagnose building damage due to earthquakes. The expert system will be developed using the BP-ANN algorithm for Android-based mobile devices.

II. Literature Review and Basic Theory

A. *Literature Review*

The BP-ANN approach has been used to detect lung disorders and shows good performance by about 99.75% of accuracy [3]. Additionally, it has also been successfully applied to diagnose children's skin diseases and provide by about 87.22% of accuracy[4].

Integration between BP-ANN and expert systems has been successfully implemented to identify digestive diseases with treatment using herbal medicines. This application provides fast and accurate diagnostic results with an average accuracy about 91.56% [5].

The application of the Kohonen Self Organizing Map (K-SOM) network has been successfully implemented as an expert system to recognize human facial expressions. The application provides accuracy by about 80.00% obtained from testing of 30 facial expressions with 90x60 resolution [6]. In addition to using the backpropagation method and K-SOM for intelligent systems, the perceptron has also been successfully developed for the expert system for diagnosing goat diseases. The application can help goat

E-ISSN:2541-0806
P-ISSN:2540-8895

farmers to know the symptoms of diseases that attack their goats[7].

Other studies that have applied perceptron for intelligent systems of internal disease diagnosis and produced an accuracy of 78.9% with 48 training data [8]. Whereas the application of Perceptron for the identification of dental diseases has provided accuracy of up to 75%[9].

Based on the description, that the use of various variations of the neural network method for the expert system produces pretty good accuracy (above 70%). Therefore, this research will implement the BP-ANN as an inference engine of the expert system and develop it as the android-based expert system application for building damage assessment due to earthquakes.

B. *Basic Theory*

B.1 Expert System

The expert system is a computer-based system that copies the expertise of one or more specialists in a particular field that can be used to solve problems like the expert itself. The expert system consists of two important parts, namely the development environment and the consulting environment. Expert system makers use the development environment to build system components and incorporate knowledge from humans (experts) into the knowledge base. While the consultation environment is used by users to consult so that users get knowledge and advice from expert systems, just like consulting with an expert. The expert system consists of several components, such as:

1. Data acquisition, which is the accumulation, transfer, and transformation of expertise to solve problems, from knowledge sources (humans) into computer programs.
2. Knowledgebase, which is a process of knowledge collection for understanding, formulation, and problem-solving.
3. Inference engine, which is a program that serves to guide reasoning to a condition based on the existing knowledge base, manipulate and direct the rules, models, and facts stored in the knowledge base to produce solutions.
4. Workplace, which is an area of a set of working memory.

Fig. 1 shows the components of an expert system and its relation [10].

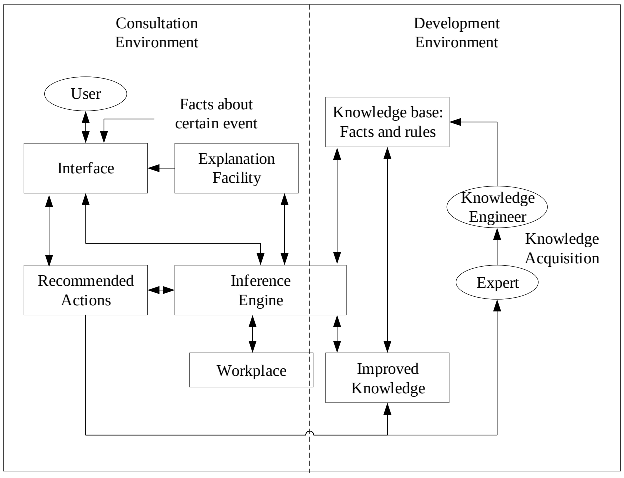

Fig. 1. Expert system architecture [10]

B.2 Artificial Neural Network

Artificial Neural Network (ANN) is artificial brains that often appear in science fiction stories. The ANN can think and infer something like the human brain based on the information received. Many researchers are trying to realize this artificial brain using computer programs that can think like humans. This is done by imitating the activity of the human biological nerve system [11].

Biological neural networks consist of processing elements that are connected and operate in parallel. An ANN imitates biological neural networks consisting of nerve cells (neurons). The neural network processing element works in the same way as biological neurons, which encode information received by the brain.

The ANN is programmed to produce conclusions or outputs based on experience gained during the training process. This ANN architecture is divided into frameworks and interconnection schemes. ANN framework consists of several layers and each layer consist of several neurons. ANN consists of 3 layers, as follows [11]:

1. Input layer
   In this layer, the neurons are called input units, where these units receive input from the outside world. Input entered into this input layer is a description of a problem.
2. Hidden layer
   The neurons in the hidden layer are called hidden units. The output signal from this layer cannot be seen directly.
3. Output layer
   In this output layers the neurons are called output units. The output of this layer is the result or conclusion of a problem.

The architecture in Fig. 2 is an example of a multilayer neural network architecture consisting of an input layer (x), a hidden layer (z), and an output layer (y)[4].

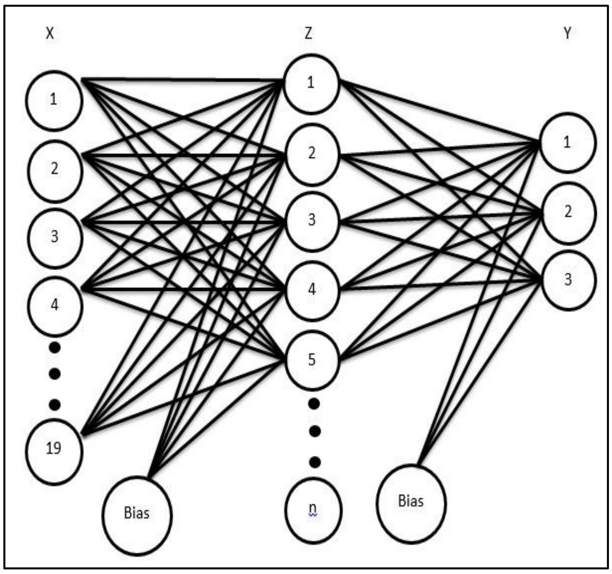

Fig. 2. An example of artificial neural network architecture [4]

B.3. Backpropagation Artificial Neural Network(BP-ANN)

ANN that is only composed of a single layer has limitations in the process of recognition. This weakness can be resolved by adding one or more hidden layers between the input layer and the output layer. BP-ANN can be trained to recognize patterns. Training means to tune the weight of neurons to obtain conclusions/responses that are fit with input patterns[12].

In BP-ANN, the activation function of the output signal of each hidden neuron must meet several conditions: continuous, easily differentiated, and is a function that does not go down. Binary Sigmoid is an activation function that fulfills all three requirements and is often used in BP-ANN. This function has a range from 0 to 1 [13]. The equation of the binary sigmoid activation function and its derivative are given in Eq. (1) and (2)

$$f(\mathrm{x}) = \frac{1}{1+e^{-x}} \quad (1)$$

$$f'(\mathrm{x}) = f(\mathrm{x})(1 - f(\mathrm{x})) \quad (2)$$

The architecture of BP-ANN can be a structure consisting of several hidden layers that have several neurons. For example, Fig. 3 is a multilayer architecture BP-ANN with one hidden layer. The input unit accepts the input vector denoted by *X*, *Z* is the hidden unit, and *Y* is the output unit. *V* is the weight between the input unit and the hidden unit (*Z*), while *W* is the weight between the hidden unit (*Z*) and the output unit (*Y*).

III. Research Method

A. *BP-ANN Based Expert System*

The proposed expert system for building-damage diagnosis has several stages, as shown in Fig. 4. The expert system is designed to deploy as an application for android based mobile devices.

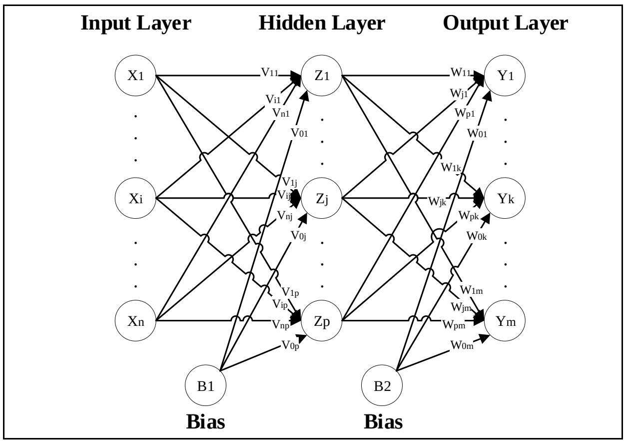

Fig. 3. BP-ANN architecture

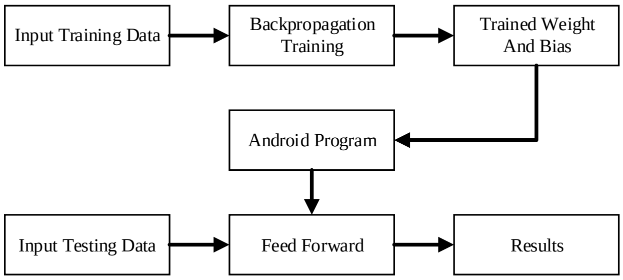

Fig. 4. Block diagram of the system process

A.1. Input of Training Data

The training data is based on the knowledge provided by a building-damage expert (Mr. Pathurahman, ST., MT.) from the Structural Engineering Laboratory of the Civil Engineering Department, Faculty of Engineering, University of Mataram.

A.2. Training Process

The backpropagation training algorithm is implemented to train building-damage data, and obtain the trained biases and weights. The training algorithm is divided into 2 main phases, i.e. the feedforward and backpropagation phases. This process is carried out several times until obtaining the most optimal bias and weight of the BP-ANN.

A.3. Android Program

The most optimal bias and weight of BP-ANN are embedded in the android program. This program functions as a building-damage diagnosis after the earthquake. The output of the application is one of three categories of building-damage namely light, moderate, and severe.

A.4. Input Testing Data

The testing data were obtained from the building-damage expert which consisted of damage symptoms and diagnosis conclusions. The testing data are used to evaluate the proposed expert system. To know the performance the output of the expert system will be compared with the conclusion of a building-damage expert as given in the testing data.

A.5. Feedforward

There are two phases namely feedforward and backward in the backpropagation algorithm. The feedforward phase is employed to obtain the output of the network and the backward phase is employed for updating the bias and weight of the BP-ANN. Additionally, the feedforward is also employed to determine the output of the diagnosis based on the most optimal bias and weight of the training process.

B. *Knowledge Acquisition*

Knowledge acquisition is an important stage in creating an expert system because the expert system is built based on knowledge. A knowledgebase is obtained from one or several experts. In this study, two experts were used, namely structural engineering experts, and building damage assessment expert from the Section for the Building Management of the Public Works and Public Housing (PWPH). Obtaining knowledge data, symptoms, and types of damage from the annotation of building-damage structures are used to develop expert systems.

B.1. Determine the Input Variables

Based on the judgment of the building damage assessment expert, symptoms can be grouped based on the building's structural elements. These symptoms (Table I) are derived from walls, columns, and beams. Each symptom has 3 variables (light, moderate, and severe) that define based on the percentage of damage that occurs on walls, columns, and beams.

TABLE I. BUILDING DAMAGE SYMPTOM

Code	Building Damage Symptom	Variable	Encode
G01	Beam	Light	1
		Moderate	2
		Severe	3
G02	Column	Light	1
		Moderate	2
		Severe	3
G03	Wall	Light	1
		Moderate	2
		Severe	3

B.2. Determine the Output Variables

There are three outputs produced by the expert system of building-damage as presented in Table II.

TABLE II. BUILDING DAMAGE CATEGORIES

Code	Damage Level	Value
K01	Light	1
K02	Moderate	2
K03	Severe	3

B.3. Determine the Neuron Layer

Not every building has the same number of structural elements. Therefore, each building was initialized by 10 neurons for symptoms of beam damage, 10 neurons for column damage symptoms, and 15 neurons for wall damage symptoms. So that there are a total of 35 neurons in the input layer which by default is set to zero. Each element of the damage building structure is coded by a value of 1 ~ 3 according to the level of damage and zero for undamaged structure. The number of hidden layers is determined by the trial and error process until the best training results are obtained by the accuracy criteria over 90%. The output layer contains only one neuron because it only produces one of the 3 levels of damage as given by Table II.

C. *Backpropagation Algorithm*

As mentioned early, the backpropagation training algorithm consists of the feedforward and backward processes. The algorithm is as follows [14]:

Step 0: Initialize weights (commonly give weights with fairly small random values)

Step 1: If the termination criteria does not satisfy yet, do steps 2 to 9

Step 2: For each training data in the training process, complete steps 3 through 8

Phase I: *Feedforward*

Step 3: Each input unit (x_i, i = 1,2, ..., n) receives the signal and passes it on to the next unit in the hidden layer

Step 4: Calculate all outputs in the hidden layer (Z_j, j = 1, 2,…, p)

$$Z\_net_j = v_{0j} + \sum_{i=1}^{n} x_i v_{ij} \tag{3}$$

applying the activation function (Eq. (4)) to determine the output signal:

$$Z_j = f(Z\_net_j) \tag{4}$$

sending the Z_j to next layer units (output units).

Step 5: Calculate all network outputs using the Eq. (5) (Y_k, k = 1, 2,…, m)

$$Y\_net_k = w_{0k} + \sum_{j=1}^{p} z_j w_{jk} \tag{5}$$

applying the activation function (Eq. (6)) to calculate the output signal of network outputs

$$Y_k = f(y\_net_k) \tag{6}$$

Phase II: Backpropagation

Step 6: Calculate the δ unit of output factor based on the error in each unit of output (y_k, k = 1, 2,…, m)

$$\delta_k = (t_k - y_k)\, f\,'\,(y\_net_k) \tag{7}$$

E-ISSN:2541-0806
P-ISSN:2540-8895

δ is the unit of error that will be used in changing the weight of the previous layer (step 7). $f'(y\_net_k)$ is a derivative function of the binary sigmoid activation function. Calculating the weight correction (which will be used to correct w_{jk}) with the learning rate α using Eq. (8).

$$\Delta w_{jk} = \alpha.\delta_k .z_j \quad (8)$$

Then calculate the correction bias (which will be used later to correct the value of w_{0k}) using Eq. (9).

$$\Delta w_{0k} = \alpha.\delta_k \quad (9)$$

Step 7: Calculate the δ hidden unit factor based on the error in each hidden unit (z_j, j = 1, 2,…, p)

$$\delta\_net_j = \sum_{k=1}^{m} \delta_k.w_{jk} \quad (10)$$

δ hidden unit factor:

$$\delta_j = \delta\_net_j\, f\,'(z\_net_j) \quad (11)$$

Calculate the weight correction (which will be used later to correct the value of v_{ij})

$$\Delta v_{ij} = \alpha.\delta_j.x_i \quad (12)$$

Then calculate the correction bias (which will be used later to correct the value of v_{0j})

$$\Delta v_{0j} = \alpha.\ \delta_j \quad (13)$$

Phase III: Weight Correction

Step 8: Correct the weight (j = 0, 1, 2,..., p) for each output unit (Y_k, k = 1, 2,…, m)

$$w_{jk}\ (\text{new}) = w_{jk}\ (\text{old}) + \Delta w_{jk} \quad (14)$$

Correct the weight (j = 0, 1, 2, 3,..., n) for each hidden unit (Z_j, j = 1, 2, 3,..., p)

$$v_{ij}\ (\text{new}) = v_{ij}\ (\text{old}) + \Delta v_{ij} \quad (15)$$

Step 9: Training stopped

These three phases are repeated continuously until reaching the termination criteria. Generally, the BP-ANN utilizes the number of iteration and error limit[12] as the termination criteria[12].

IV. Results and Discussions

A. *Determining Best BP-ANN Architecture*

In order to obtain the optimal BP-ANN architecture for the building-damage expert system after the earthquake, some training and testing were carried out by using the following parameters. The dataset in the training process consisted of 5081 data, and the data for the testing process consisted of 30 sample cases which had been annotated by the experts.

- *Input layer* : 35 *neurons*
- *Hidden layer* : 1, 2, 3, 4, 5 and 6 *layers*
  The number of neurons for layers 1 to 6 = 18, 12, 10, 6, 3 and 2 *neurons*
- *Output layer* : 1 *neuron*
- Activation function: *Sigmoid biner* and *sigmoid bipolar*
- Epoch limit : 1000
- Error limit : 0.0001
- *Learning rate* : 0.01, 0.1, 0.3, 0.5, 0.8

Additionally, the detail hidden layers of each network architecture for the experiments are given in Table III.

TABLE III. Hidden Layer of Testing Architectures

Architecture	Number of hidden layers	Number of neurons
1	1	18
2	2	18, 12
3	3	18, 12, 10
4	4	18, 12, 10, 6
5	5	18, 12, 10, 6, 3
6	6	18, 12, 10, 6, 3, 2

Based on the experimental results of network architectures as presented in Table IV, it can be concluded that the accuracy of training and testing did not significantly change between network architectures. Training accuracy of all architectures ranges from 96.99% to 99.17%, which proves that the expert system of building damage assessment using BP-ANN works properly. Additionally, the BP-ANN with the second architecture of Table III, binary sigmoid activation function, and a learning rate of 0.3 provides the best training and testing accuracy (99.17% and 90% respectively). Thus, this architecture is potentially developed for the application of the expert system for building damage diagnosis.

B. *Implementation of the Expert System*

As mentioned early, the BP-ANN with the architecture 2 hidden layer (number of hidden neurons 18 and 12), binary sigmoid activation function, and a learning rate of 0.3 is implemented as the engine to determine the conclusion of the expert system. The implementation of the expert system also discusses the interface of the diagnosis page including the input and output page and how it works.

The diagnosis page as shown in Fig. 5 presents how the expert system performs the diagnosis process. This page displays three-building structural elements, namely beams, columns, and walls, which are equipped with buttons to input the number of structures and the degree of damage. The degree of structural damage is determined by the width and depth of the crack.

 E-ISSN:2541-0806
P-ISSN:2540-8895

TABLE IV. NETWORK ARCHITECTURE EXPERIMETAL RESULTS

Activation function	***Learning rate***	**Accuracy (%)**											
		Architecture 1		**Architecture 2**		**Architecture 3**		**Architecture 4**		**Architecture 5**		**Architecture 6**	
		Train	**Test**	**Train**	**Test**	**Train**	**Test**	**Train**	**Test**	**Train**	**Test**	**Train**	**Test**
Sigmoid biner	0.01	98.84	73.33	99.13	86.67	98.88	73.33	99.03	83.33	98.70	83.33	98.79	73.33
	0.1	98.82	73.33	99.05	83.33	99.09	76.67	98.35	80.00	98.42	80.00	98.96	80.00
	0.3	98.52	73.33	**99.17**	**90.00**	99.09	76.67	98.86	80.00	98.96	76.67	98.74	86.67
	0.5	98.37	73.33	99.13	86.67	99.01	86.67	98.44	76.67	98.72	80.00	98.86	83.33
	0.8	98.45	73.33	99.05	70.00	98.99	83.33	98.60	83.33	99.02	73.33	98.84	76.67
Sigmoid bipolar	0.01	98.48	73.33	98.31	70.00	98.98	73.33	98.84	76.67	98.89	76.67	96.99	76.67
	0.1	98.70	73.33	98.66	80.00	98.72	73.33	98.52	80.00	97.84	80.00	98.27	76.67
	0.3	98.56	80.00	99.08	66.67	98.73	70.00	98.70	80.00	99.01	70.00	97.66	70.00
	0.5	98.19	76.67	98.74	83.33	98.72	83.33	98.64	80.00	98.92	70.00	98.72	86.67
	0.8	98.54	70.00	98.78	76.67	99.05	76.67	99.01	80.00	98.98	80.00	98.46	83.33

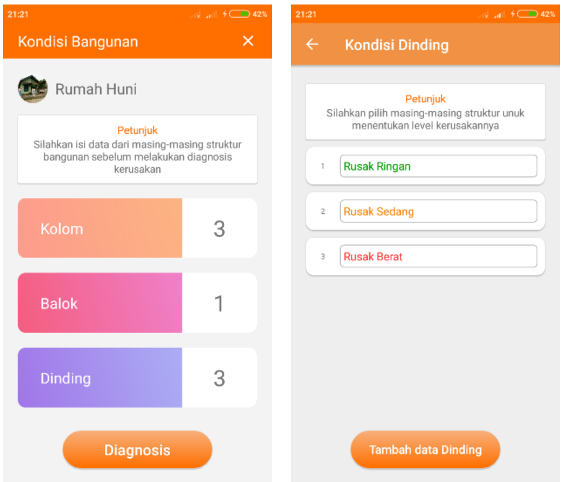

Fig. 5. Diagnosis page interface

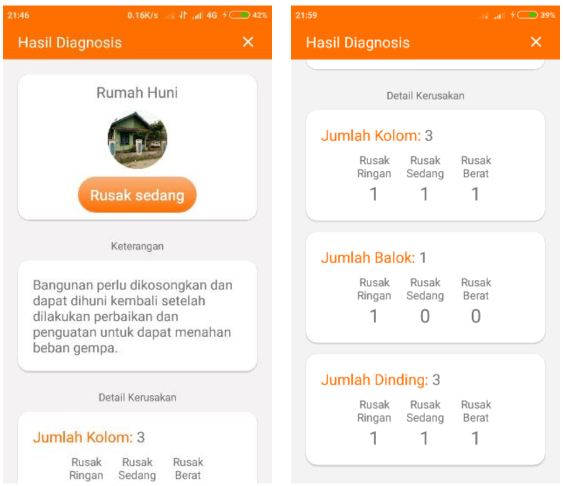

Fig. 6. Diagnosis result page interface

The diagnosis page is also completed with a diagnostic button that functions to activate the BP-ANN system to perform calculations to get damage conclusions from buildings. The conclusions of the BP-ANN results as a diagnosis result are shown in Figs. 6. Fig. 6 presents detailed information on the damage to each element of its structure.

C. *System Testing*

Expert system testing is carried out to find out whether the developed expert system has worked well and provides a satisfactory output. There are three tests carried out namely black box testing, accuracy testing, and MOS testing. Blackbox Testing aims to test the expert system functionality including the functionality of info, form, history or start page, diagnosis, update, and about. Black box testing was conducted by five respondents of Informatics Engineering students at the Informatics Engineering Laboratory of Mataram University. The experimental result shows that all of the tested functionality has operated properly, which is indicated by the same opinion of all respondents.

B.2. System Accuracy Testing

This test aims to determine the validity of the building damage expert system in generating conclusions compared to the assessment of damage by experts. This test involved three experts namely two from the Management Section of the Public Works Building and Public Housing (PWPH) of Mataram City (I Ketut Deresta Wirata, ST. And Dani Yunandar, ST.) And one from the Structural Engineering Department of the University of Mataram (Mr. Pathurahman, ST., MT). Testing uses 30 cases of building-damage obtained from 5 buildings with 6 different case variations from each building. All case data has been verified by I Ketut Deresta Wirata, ST.

In the test, the 30 cases of building-damage were inputted into the developed expert system and the diagnosis results of the developed expert system were compared with the conclusions of the experts as shown in Table 5 for the first expert, Table 6 for the second expert, and Table 7 for the third expert. The level of concordance between expert conclusions and expert systems is expressed with accuracy calculated by Eq. (16).

E-ISSN:2541-0806
P-ISSN:2540-8895

$$Accuracy = \frac{number\ of\ valid}{all\ tested\ cases} x100\% \quad (16)$$

TABLE V. DIAGNOSIS COMPARISON OF THE FIRST EXPERT WITH THE SYSTEM

Case	First expert's diagnosis	System's diagnosis	Information
Building 1 Case 1	Light	Light	Valid
Building 1 Case 2	Light	Light	Valid
Building 1 Case 3	Light	Moderate	Invalid
Building 1 Case 4	Moderate	Moderate	Valid
Building 1 Case 5	Severe	Severe	Valid
Building 1 Case 6	Severe	Moderate	Invalid
Building 2 Case 1	Light	Light	Valid
Building 2 Case 2	Light	Light	Valid
Building 2 Case 3	Moderate	Moderate	Valid
Building 2 Case 4	Moderate	Moderate	Valid
Building 2 Case 5	Severe	Severe	Valid
Building 2 Case 6	Severe	Severe	Valid
Building 3 Case 1	Moderate	Light	Invalid
Building 3 Case 2	Light	Light	Valid
Building 3 Case 3	Severe	Moderate	Invalid
Building 3 Case 4	Moderate	Moderate	Valid
Building 3 Case 5	Severe	Severe	Valid
Building 3 Case 6	Severe	Severe	Valid
Building 4 Case 1	Light	Moderate	Invalid
Building 4 Case 2	Light	Light	Valid
Building 4 Case 3	Light	Light	Valid
Building 4 Case 4	Light	Light	Valid
Building 4 Case 5	Severe	Severe	Valid
Building 4 Case 6	Moderate	Moderate	Valid
Building 5 Case 1	Light	Light	Valid
Building 5 Case 2	Light	Moderate	Invalid
Building 5 Case 3	Moderate	Moderate	Valid
Building 5 Case 4	Severe	Moderate	Invalid
Building 5 Case 5	Severe	Severe	Valid
Building 5 Case 6	Severe	Severe	Valid

Based on the comparison of diagnosis results from the first expert with the developed expert system for 30 cases of building-damage in Table V, there are 23 valid cases and 7 invalid cases. Thus, the accuracy obtained in the first expert test is 76.67%. From 30 cases of building-damage tested there are 27 valid cases and 3 invalid cases (see Table VI). Thus, the developed system provides accuracy by about 90%.

TABLE VI. DIAGNOSIS COMPARISON OF THE SECOND EXPERT WITH THE SYSTEM

Case	Second expert's diagnosis	System's diagnosis	Information
Building 1 Case 1	Light	Light	Valid
Building 1 Case 2	Light	Light	Valid
Building 1 Case 3	Moderate	Moderate	Valid
Building 1 Case 4	Moderate	Moderate	Valid
Building 1 Case 5	Severe	Severe	Valid
Building 1 Case 6	Severe	Moderate	Invalid
Building 2 Case 1	Light	Light	Valid
Building 2 Case 2	Light	Light	Valid
Building 2 Case 3	Moderate	Moderate	Valid
Building 2 Case 4	Moderate	Moderate	Valid
Building 2 Case 5	Severe	Severe	Valid
Building 2 Case 6	Severe	Severe	Valid
Building 3 Case 1	Moderate	Light	Invalid
Building 3 Case 2	Light	Light	Valid
Building 3 Case 3	Moderate	Moderate	Valid
Building 3 Case 4	Moderate	Moderate	Valid
Building 3 Case 5	Severe	Severe	Valid
Building 3 Case 6	Severe	Severe	Valid
Building 4 Case 1	Light	Moderate	Invalid
Building 4 Case 2	Light	Light	Valid
Building 4 Case 3	Light	Light	Valid
Building 4 Case 4	Light	Light	Valid
Building 4 Case 5	Severe	Severe	Valid
Building 4 Case 6	Moderate	Moderate	Valid
Building 5 Case 1	Light	Light	Valid
Building 5 Case 2	Moderate	Moderate	Valid
Building 5 Case 3	Moderate	Moderate	Valid
Building 5 Case 4	Moderate	Moderate	Valid
Building 5 Case 5	Severe	Severe	Valid
Building 5 Case 6	Severe	Severe	Valid

From Table VII, of 30 cases of building-damage tested there are 24 valid cases and 6 invalid cases. Thus, the developed system provides accuracy by about 80%. By taking their average, the developed expert system for building-damage provides quite good performance indicated by the average accuracy by about 82.22%. The different conclusions given by each expert in each case are influenced by differences of the knowledge and experiences possessed.

E-ISSN:2541-0806
P-ISSN:2540-8895

TABLE VII. DIAGNOSIS COMPARISON OF THE THIRD EXPERT WITH THE SYSTEM

Case	Third expert's diagnosis	System's diagnosis	Information
Building 1 Case 1	Light	Light	Valid
Building 1 Case 2	Light	Light	Valid
Building 1 Case 3	Light	Moderate	Invalid
Building 1 Case 4	Moderate	Moderate	Valid
Building 1 Case 5	Severe	Severe	Valid
Building 1 Case 6	Severe	Moderate	Invalid
Building 2 Case 1	Light	Light	Valid
Building 2 Case 2	Light	Light	Valid
Building 2 Case 3	Moderate	Moderate	Valid
Building 2 Case 4	Moderate	Moderate	Valid
Building 2 Case 5	Severe	Severe	Valid
Building 2 Case 6	Severe	Severe	Valid
Building 3 Case 1	Moderate	Light	Invalid
Building 3 Case 2	Light	Light	Valid
Building 3 Case 3	Moderate	Moderate	Valid
Building 3 Case 4	Moderate	Moderate	Valid
Building 3 Case 5	Severe	Severe	Valid
Building 3 Case 6	Severe	Severe	Valid
Building 4 Case 1	Light	Moderate	Invalid
Building 4 Case 2	Light	Light	Valid
Building 4 Case 3	Moderate	Light	Invalid
Building 4 Case 4	Light	Light	Valid
Building 4 Case 5	Severe	Severe	Valid
Building 4 Case 6	Moderate	Moderate	Valid
Building 5 Case 1	Light	Light	Valid
Building 5 Case 2	Moderate	Moderate	Valid
Building 5 Case 3	Moderate	Moderate	Valid
Building 5 Case 4	Severe	Moderate	Invalid
Building 5 Case 5	Severe	Severe	Valid
Building 5 Case 6	Severe	Severe	Valid

B.3. MOS Testing

Mean Opinion Score (MOS) testing is done by giving some questions in the form of questionnaires to some respondents. The test is carried out to determine the feasibility of the system, the ease of use of the system, the appearance of the system, the informativeness of the system, and the ability of the system to facilitate the diagnosis of building damage. The number of respondents in the MOS test was 30 people, consisting of 15 Civil Engineering students and 10 Informatics Engineering students at the University of Mataram as Android users, as well as 5 employees of the Mataram City Public Works and Public Works Office (PWPH) as the target users of the expert system. Five questions asked of each respondent. The five questions are as follows:

Question 1 : Is the expert system application appearance for building damage diagnosis interesting and easy to use (user friendly)?

Question 2 : Are the colors and fonts used in the application appropriate?

Question 3 Is the structural damage building element information of the application clear and easy to understand?

Question 4 : Can the expert system application easily diagnose building damage and not overload your android device?

Question 5 : Can the expert system application for building damage diagnosis be used in the future?

Eq. (17) and (18) are employed to determine the average of each question and MOS on the respondent's answer [16].

$$mean\ pi = \frac{\sum Si\ .\ Bi}{n} \qquad (17)$$

where:

mean pi : average score of each question
S_i : the number of respondents who chose each answer attribute,
B_i : weight of each question attribute, and
n : the number of respondents.

$$MOS = \frac{\sum_{i=1}^{k} mean\ pi}{k} \qquad (18)$$

where:

MOS : average total score of all question attributes
k : number of questions

The results of the MOS testing of 30 respondents are presented in Table VIII. The application of an expert system gets the MOS about 4.54 of 5 scales. It shows that the application of an expert system for building damage diagnosis based on the BP-ANN has been well developed in terms of ease of use of the system, system appearance, system informativeness, and the ability of the system to facilitate the diagnosis of building damage.

TABLE VIII. MOS TESTING RESULTS

No	Question	Weight					To-tal	*Mean pi*
		(5)	(4)	(3)	(2)	(1)		
1	Question 1	21	9	-	-	-	30	4.70
2	Question 2	20	9	1	-	-	30	4.63
3	Question 3	17	13	-	-	-	30	4.57
4	Question 4	10	20	-	-	-	30	4.33
5	Question 5	15	14	1	-	-	30	4.47
Sub total		67	83	65	2	0	0	150
MOS (*Mean Opinion Score*)								**4.54**

E-ISSN:2541-0806
P-ISSN:2540-8895

V. Conclusion and Suggestion

Based on the achievement, the developed expert system for building damage diagnosis has run well as indicated by firstly, all system functionality has worked as expected; secondly, giving an average accuracy of around 82.22%; finally, obtaining a MOS of around 4.54 on a scale of 5. The best BP-ANN architecture that fits such performance is architecture with 2 hidden layers, a binary sigmoid activation function, and a learning rate of 0.3 that provides 99.17% of training accuracy and 90% of testing accuracy.

This paper will be developed by adding pattern recognition techniques to provide automatic structural damage input data. Furthermore, the expert system also needs more training and testing data to improve accuracy and requires more real building damage cases.

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