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Method for Predicting and Evaluating Post Earthquake Damage of Urban Buildings Based on Artificial Intelligence Algorithms

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Abstract. This article mainly focuses on the damage assessment of buildings after earthquakes. Firstly, a structural damage model was established based on most reinforced concrete buildings and described using a function. Then, a BP neural network was used to solve the function. Traditional neural networks are prone to falling into local optima. Therefore, in order to improve the performance of neural networks, cross fusion with genetic algorithms is used to avoid falling into local optima, Improve the efficiency of the algorithm. Finally, through experimental verification, the proposed method can quickly evaluate the damage of building structures, with an accuracy rate of 97%.

Keywords: damage assessment, BP neural network, genetic algorithm, structural damage

1 Introduction

Earthquakes are the largest natural disasters that humans are generally exposed to, and their occurrence often brings a large number of casualties and property losses. After an earthquake, a large number of buildings have been damaged. Due to the differences in the location, structure, and seismic resistance of each building, different degrees of damage have occurred to each building after the earthquake. Therefore, how to accurately evaluate the degree of damage to each building is an important research topic at present.

The development of artificial intelligence technology has provided a foundation for intelligent decision-making and judgment based on the accumulation of a large amount of data. Therefore, this article establishes an evaluation model for the post earthquake state of buildings, matches the relationship between structural response and damage modes that can characterize the structural damage state, and establishes criteria for evaluating the post earthquake safety of structures. It develops intelligent prediction methods based on nonlinear time history analysis, on-site detection, and machine learning. Therefore, the work done in this article is as follows:

1) Taking reinforced concrete as the main research object, a damage model for post earthquake building structures is established, described using mean and variance of damage, and evaluation indicators are elaborated.

2) In order to solve the damage model, a BP neural network is used as the prediction model, with input of building damage structural data and output of prediction results.

3) Training the model using existing seismic data has improved prediction accuracy.

This article consists of the following chapters. Chapter 2 mainly introduces the relevant research results. Chapter 3 mainly constructs a post earthquake damage model for reinforced concrete structures. Chapter 4 is the algorithm improvement chapter, which introduces the process of algorithm improvement. Chapter 5 is simulation, which evaluates and simulates real building structures. Chapter 6 is the conclusion, summarizes the work done, and makes arrangements for further research.

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2 Related Work

Most modern seismic structures of buildings are designed as plastic hinges, which can absorb vibration. Marder took the residual bearing capacity of plastic hinges after the earthquake as the standard to evaluate the degree of earthquake damage of buildings, established a mathematical model, and proposed a Reinforcement learning method [1]. Rasulo Alessandro proposed a seismic resilience model for road networks, which takes transportation capacity, congestion level, bridge damage, and intervention measures as parameters to describe the characteristics of the situation evolution stage. Finally, a 14 node and 31 road network was used as an example to validate the model [2]. Yi Pan, from Southwest Jiaotong University, studied the ancient buildings with masonry as the main material. Based on the theory of fuzzy mathematics, the membership function method and analogy method were used to construct the evaluation matrix, and a three-level and two-stage fuzzy comprehensive evaluation model was established. The establishment of the model has reference value [3]. Ruifang Xia used neural network algorithms to evaluate post earthquake building losses. In order to avoid the problems of local convergence and low efficiency of ordinary algorithms, the LM-BP algorithm was proposed. Simulation results showed that the evaluation model error was 0.1% [4]. Zhiqiang Li took highway subgrade as the research object, explored the typical seismic damage manifestations and characteristics of highway subgrade structures, as well as the seismic damage influencing factors of subgrade and its supporting structures. He provided post earthquake safety diagnosis items and evaluation methods for subgrade structures [5].

3 Establishment of Post Earthquake Evaluation Model for Buildings

Reinforced concrete frame structure is currently the largest building structure in China. Firstly, a concrete building model is established and further research is conducted using the model as the analysis object. This article selects a 5-story shopping mall in a certain area as the building model, and the structural plan is shown in Fig. 1.

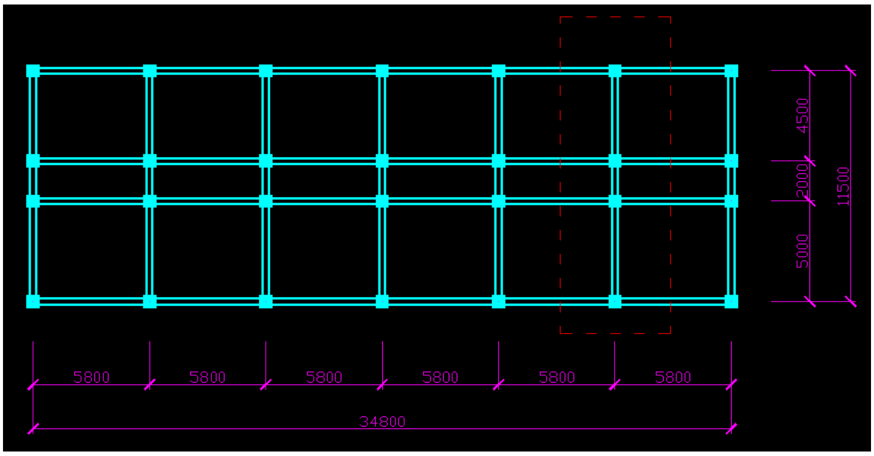


Fig. 1. Structure plan

In order to simplify the calculation and facilitate the description of the loss model during the earthquake process, a frame model in the dashed box was selected for dynamic analysis. The selected frame parameters are shown in Table 1.

Table 1. Floor structure frame parameters

Parameter	Numerical value	Notes
Side span length	5600mm	
Mid span length	2100mm	
Floor height	3720mm	
Height	148800mm	
Floor thickness	100mm	Cast concrete structure
Cross section size of load-bearing beam	$500\times500mm^2$	
Cross section size of edge beam	$300\times500mm^2$	
Cross section size of mid span beam	$350\times500mm^2$	
Insulation thickness	22mm	
Concrete strength grade	C30	
Rebar model	HRB400	
Seismic fortification intensity	8	

3.1 Damage Level Model

The post earthquake damage assessment model for buildings consists of two main parts. As modern buildings mainly consist of reinforced concrete structures, the first is to determine the seismic damage level of reinforced concrete columns in the building, and the second is to locate the damage location of the building. Firstly, the mean and variance of the damage ratio for the damage level of the building structure are described.

$$\rho = \frac{1}{m}\sum_{i=1}^{m} y_i . \tag{1}$$

$$\lambda^2 = \frac{1}{m}\sum_{i=1}^{m}\left(y_i - \rho\right)^2 . \tag{2}$$

In the formula, ρ is the mean, λ is the standard deviation, m is the number of earthquakes under different degrees, and y_i is the failure ratio of the earthquake damage level. In order to more intuitively display the distribution of building damage grades after different earthquakes and aftershocks, the mean value of the statistical damage ratio is fitted using the normal distribution and Log-normal distribution, so the probability density function of the Normal distribution is expressed as:

$$f\left(y\right) = \frac{1}{2\lambda\pi}\exp\left[-\frac{\left(y-\rho\right)^2}{2\lambda^2}\right]. \tag{3}$$

Improve the above density function, introduce new parameters, and organize the formula. The formula becomes:

$$f(y) = \frac{1}{2y\sqrt{\ln\frac{\rho^2}{\sqrt{\rho^2+\lambda^2}}}}\exp\left[-\frac{(\ln y - \ln\frac{\rho^2}{\sqrt{\rho^2+\lambda^2}})^2}{2\lambda^2}\right]. \tag{4}$$

3.2 Establishment of Post Earthquake Evaluation Indicators

This article uses the weighted method to represent the damage indicators of buildings after earthquakes, and the indicator formula is as follows:

$$T=\sum_{i=1}^{m}\delta_i T_i. \tag{5}$$

$$\delta_i=\frac{E_i}{\sum_{i}^{m}E_i}. \tag{6}$$

In the formula, T is the layer damage index, T_i is the damage index of the i -th component, δ_i is the weighting coefficient of the i -th component, m is the total number of components, and E_i is the energy consumption of the i -th component [6]. Weighting the layer damage index of each layer to obtain the structural damage index layer damage index, the expression is improved to:

$$T=\sum_{i=1}^{M}\frac{M+1-i}{\sum_{i=1}^{M}(M+1-i)}T_i. \tag{7}$$

4 Improved Neural Network Prediction of Building Damage Degree

This article judges the degree of earthquake damage based on existing data and conditions such as earthquake intensity. The prediction model uses a neural network model. Therefore, based on the BP neural network model, an improved model structure incorporating genetic algorithm is proposed. This model uses the failure ratio and variance of building structures during earthquakes, extracts time-domain and frequency-domain features of acceleration records using residual neural networks, and inputs structural information as damage information, Extract structural features using fully connected layers, and finally output the predicted degree of structural damage.

BP network is mainly composed of three parts: input layer, output layer and one or more layers of hidden layer [7]. Genetic algorithm GA is a random optimization algorithm based on Natural selection and genetic theory [8]. It comes from Natural selection and evolution mechanism in the biological world. It mainly completes prediction through coding, population initialization, selection, crossover and mutation.

The fused crossover operator is mainly used to generate new individuals, while the mutation operator is mainly used to increase the diversity of the population to expand its size. The combination of the two operators can improve the algorithm's global optimization ability. Considering the poor adaptability of the initial population, a high crossover probability should be set to update the individual's genes as much as possible to obtain more individuals carrying excellent genes. The performance of individuals in the later stage is good (with high adaptability), and most excellent genes have been identified, expressed as:

$$P(t)_c=\begin{cases}P_{c\max}+\dfrac{\left(P_{c\max}-P_{c\min}\right)\cdot t^3}{T_{\max}^3}\cdot\dfrac{f(t)_a-f(t)\min}{f(t)_{avg}-f(t)_{\min}} & f(t)_a<f(t)_{avg}\\ P_{c\min}-\dfrac{\left(P_{c\max}-P_{c\min}\right)\cdot t^3}{T_{\max}^3}\cdot\dfrac{f(t)_a-f(t)_{avg}}{f(t)_{\max}-f(t)_{\min}} & f(t)_a\ge f(t)_{avg}\end{cases}. \tag{8}$$

t is the current iteration of the algorithm, $P(t)_c$ is the crossover probability of the t -th iteration, $P_{c\max}$ and $P_{c\min}$ are the maximum crossover probability and minimum crossover probability, with values of 0.7 and 0.3, respectively $T_{\max}$ is the total iteration number of the algorithm, $f(t)_a$, $f(t)_{\max}$, $f(t)_{\min}$, and $f(t)_{avg}$ are the individual fitness, maximum population fitness, minimum population fitness, and average population fitness at the t -th iteration, respectively.

The specific steps to determine the self structure of the BP network and optimize the initial weight threshold using an improved adaptive crossover probability and mutation probability genetic algorithm are as follows:

Step 1: Data processing, normalizing the training sample data.

Step 2: Encode the number of hidden layer neurons and weight threshold of the BP network to form a 2-layer chromosome structure. Set the number of hidden layer neuron nodes of the neural network to M, and the first layer parameter gene is in the lower layer. Control and optimize the weight and threshold of the BP neural network. The encoding length of the weight threshold value is:

$$Length = 4 \cdot M + M \cdot 1 + M + 1 = 6M + 1. \tag{9}$$

The number of neurons in the hidden layer of the second layer network should be increased based on the weight threshold, and the encoding length should be:

$$Length = 4 \cdot M + M \cdot 1 + M + 1 + M = 7M + 1. \tag{10}$$

Step 3: Set the population size N and the total number of iterations $T_{\max}$.

Step 4: Decode step 2 and determine the number of hidden layer neurons in the BP network based on the activation genes counted from the upper structure. The lower layer can determine the weight threshold of the BP network, and finally form multiple different structures of the BP neural network as the candidate structure.

Step 5: Use the training sample data processed in Step 1 as input, test the selected BP neural network, and calculate the network error. If the error cannot meet the requirements, proceed to Step 6, otherwise proceed to Step 9.

Step 6: Determine the fitness function of individuals in the population, and use the sum of squares of the difference between the actual output value and the expected output value as the fitness function H.

$$H = \sum_{i=1}^{K} (Y_i - \overline{Y_i})^2. \tag{11}$$

K represents the number of output points of the BP neural network model, while Y_i and $\overline{Y_i}$ represent the actual output value and expected value of the i -th output node, respectively.

Step 7: Perform population selection operations, improved crossover and mutation operations, to generate new excellent individuals and form new offspring populations.

Step 8: Decode the 2-layer chromosome structure of the offspring population, obtain the number of hidden layer neurons and weight threshold of the BP network, calculate the network error, and calculate individual fitness. If the individual fitness cannot meet the requirements but is still within the iteration range of genetic algebra, go to step 4, otherwise go to step 9.

Step 9: Obtain the optimal initial weight threshold and the number of hidden layer nodes, and assign them to the BP neural network. As deeper networks have better recognition efficiency than shallow networks, a hierarchical strategy is applied to the obtained number of hidden layers, and then the layered neural network is trained to calculate network errors.

Step 10: When the network exceeds the number of iterations or the error meets the set requirements, compare the error of the network and retain the BP neural network with the smallest error. The schematic diagram of the recognition network structure is shown in Fig. 2.

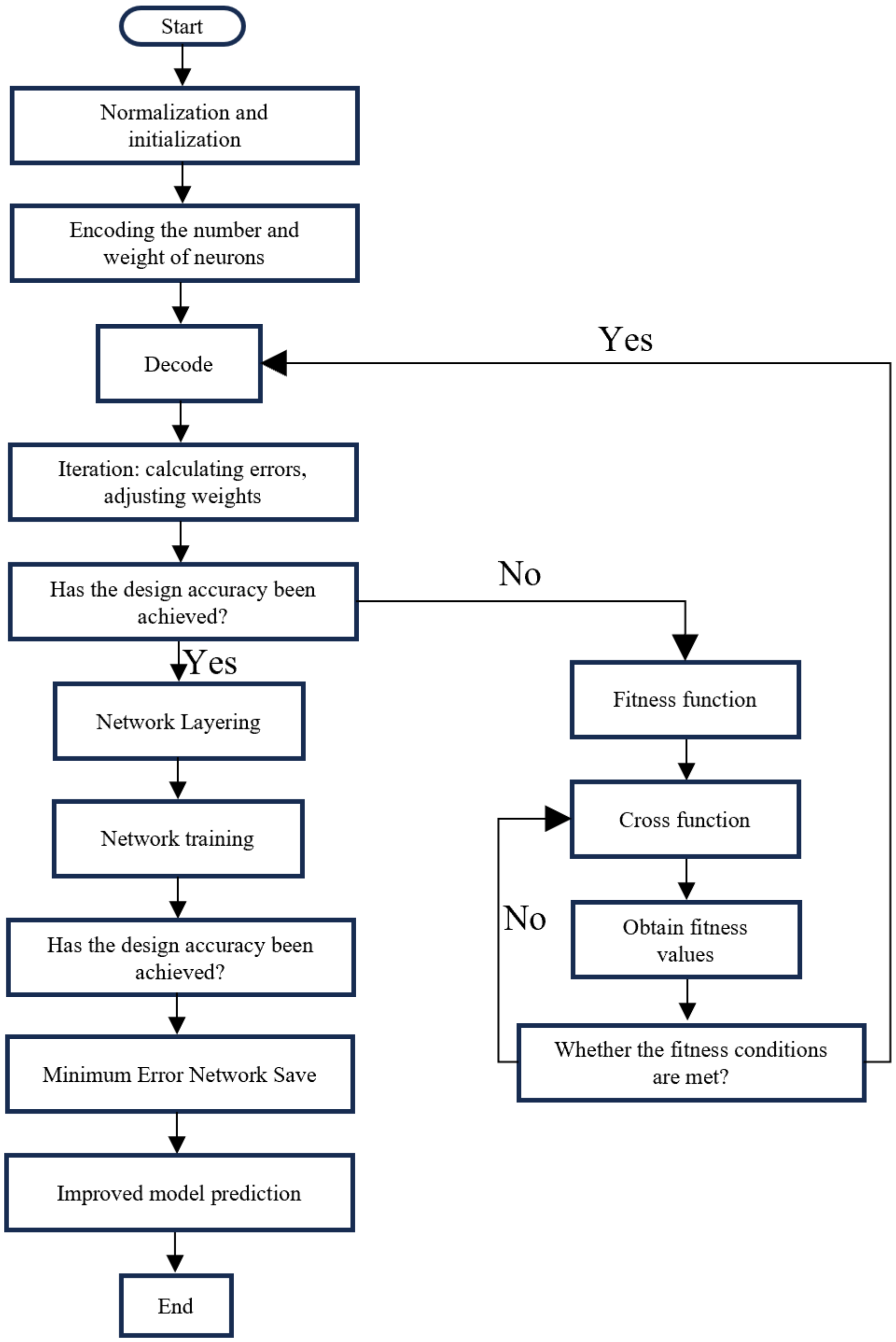


Fig. 2. Algorithm flowchart

5 Simulation Experiment Results and Analysis

To verify the feasibility of the proposed method, the method proposed in this paper is applied to predict and evaluate the post earthquake state of a certain urban complex in the northern region, and to determine the level of building damage.

5.1 Overview of Working Conditions

The urban complex adopts a large chassis double tower building layout, with a total of 28 floors, 3 underground floors, including a parking lot, 25 above ground floors, and a total structural height of 82m. The area where the building is located is in an 8 degree seismic fortification zone, with a design basic seismic acceleration value of 0.1g. The design earthquake group is the first group, and the site category is a Class II site. The distribution of various functions inside the building is as follows: the second and third floors underground are parking lots, the first floor underground is a supermarket, the fifth floor above is for commercial use, and the remaining floors are office floors. The internal power and water sources of the building are both located underground, and the water supply room is located on the second underground floor. Water pressure direct water supply is used from the second underground floor to the fifth above ground floor. Tower A and Tower B both use a combined water pump and water tank for water supply, which is pumped through a well to the top water tank of the tower, and then transported downwards from the water tank; The power transformation and distribution room is located on the first underground floor, and the interlayer is transmitted through an electrical shaft.

5.2 Overview of Working Conditions

In order to better predict the degree of damage to commercial complexes after earthquakes, existing dynamic experimental datasets were used to collect residual displacement as samples, and a total of 690 sets of seismic response samples were obtained as the sample database for the seismic response prediction model. Each group of samples includes structural information such as column size, column reinforcement ratio, total height, height to span ratio of edge beams, and height to span ratio of middle beams, which have a significant impact on the seismic performance of the structure. The dataset is shown in Table 2.

Table 2. Floor structure frame parameters

Column size	Reinforcement ratio	Height	Height to span ratio of edge beams	Mid beam height to span ratio	Residual displacement of the top layer	Maximum inter-layer displacement angle (°)
0.6m	1.7%	22.4m	0.112	0.207	52.7cm	0.0125
0.65m	1.65%	23.3m	0.113	0.207	67.4cm	0.0138
0.7m	1.6%	29.1m	0.112	0.211	89.2cm	0.0078
0.7	1.0%	28.7m	0.113	0.213	14.1cm	0.0123
0.6m	1.1%	29.3m	0.113	0.211	21.6cm	0.0065
0.65m	1.25%	30.2m	0.111	0.214	6.2cm	0.0147
0.7m	1.3%	30.3m	0.111	0.207	5.7cm	0.0063
0.65m	1.2%	29.7m	0.113	0.199	79.3cm	0.0142
0.7m	1.5%	29.1m	0.111	0.213	67.4cm	0.0096
0.7	1.6%	28.7m	0.112	0.207	11.3cm	0.0087
0.6m	1.0%	29.3m	0.113	0.211	23.7cm	0.0103
0.65m	1.1%	30.3m	0.112	0.202	14.3cm	0.0132

5.3 Improved Algorithm Iteration Results

To demonstrate the performance of the algorithm, the algorithm is iterated in a computer with the following configuration: single core CPU: 3 30GHz, 16GB memory, NVIDIA GTX960 GPU, and 64 bit Win710 operating system. The model iteration results are shown in Fig. 3. It can be seen from the figure that when the algorithm iterates 73 times, the Loss function tends to be stable, so the iteration speed meets the requirements.

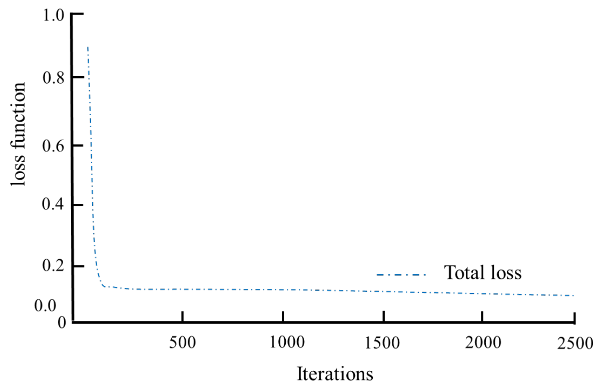
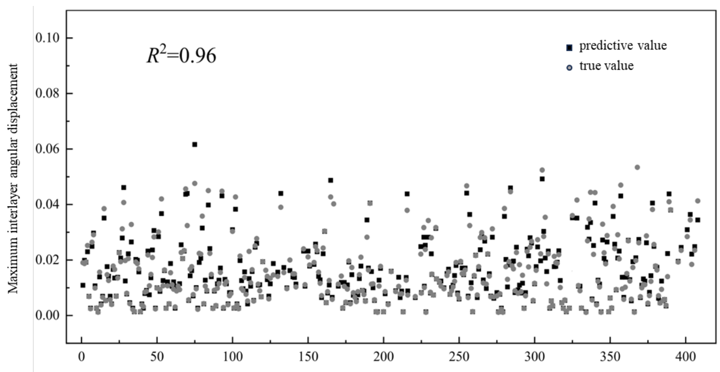
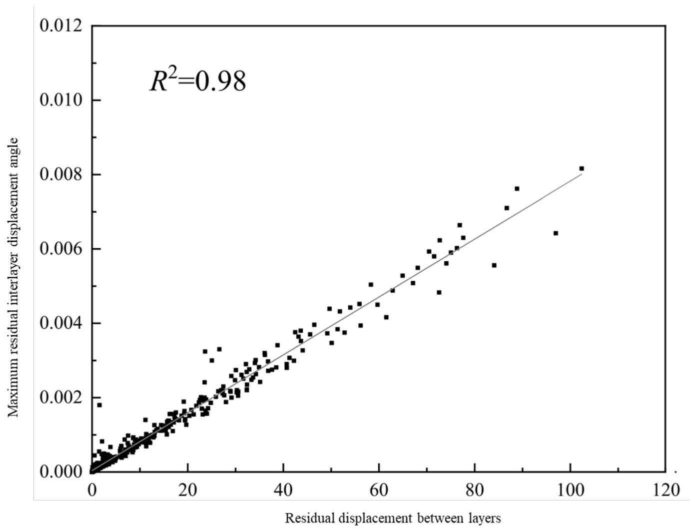


Fig. 3. Iteration results

Input the dataset into the model, train the model, and predict the maximum interlayer displacement angle and the residual displacement of the top layer using the 6th layer as an example. The prediction results are shown in Fig. 4.



(a)Prediction results of maximum interlayer angular displacement



(b) Prediction of residual displacement and angle between layers

Fig. 4. Model prediction results

From the figure, it can be seen that the algorithm predicts the maximum residual interlayer displacement angle response of a given structure after training with training set data, with errors of 0.98 and 0.96, respectively, and a prediction accuracy of 97%.

6 Conclusion

This paper mainly carries out damage assessment for the state of buildings after the earthquake, completes the establishment of the damage model and the improvement of the prediction Convolutional neural network model, and mainly completes the following work:

1) A damage model, namely the damage function, was established based on the displacement of the building and its measurement, and this function was used as the prediction target.

2) In order to better predict the results, the BP neural network is improved, which improves the ability of the model to avoid local optimization, and improves the Rate of convergence of the algorithm.

Further research will mainly focus on the following two aspects:

1) Establish a visual and 3D scanned image based image prediction model, which predicts the degree of damage to buildings and repair plans based on post earthquake damage images.

2) Further train the model to predict results based on more parameters, such as the degree of damage to floors and floors, and damage to steel structures.

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