A Damage Recognition Method for Civil Engineering Structures Based on MTL-1DCNN

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Within the discipline of civil engineering, real-time and accurate identification of building structure damage is an important means to ensure the service life and safety of civil engineering. To reduce the occurrence of civil engineering accidents and enhance the health, usability and integrity of building structures, this research uses deep learning to build detection models. The model mainly combines a one-dimensional hollow CNN with a multi-task learning method to construct a multi-task learning one-dimensional convolution network (MTL-1DCNN) model and use it for automatic feature extraction of structural damage signals. The model has a good performance in the position information judgment and damage degree diagnosis of structural damage. In the experiment of the two-story building model, the research proposed that the MTL-1DCNN model correctly identified 2031 locations out of 2048 samples, with a recognition accuracy of up to 99%, and the MSE of the calculation result was 3.47×10−5, demonstrating that the suggested strategy could mine effective and reliable damage information from the structural vibration response signal, which was of significant importance and engineering value to the good development of damage identification technology and real-time intelligent monitoring of the health status of engineering structures.

Povzetek: Predstavljena je nova metoda prepoznavanja poškodb inženirskih konstrukcij z uporabo MTL-1DCNN, ki združuje eno-dimenzionalne konvolucijske mreže in učenje več nalog za natančno zaznavanje poškodb in oceno njihove resnosti.

1 Introduction

The Chinese civil engineering industry is transforming from large-scale construction to new construction, renovation and maintenance, and the importance of engineering diagnosis is becoming increasingly prominent. The key to intelligent detection and diagnosis of structural damage using vibration response lies in the extraction of damage-sensitive features and pattern classification in the signal [1]. This paper presents a technique for recognizing structural damage based on a One-Dimensional Dilated Convolutional Neural Network (1-DCNN), which uses dilated convolutions to replace the traditional combined layers of convolution and pooling. The suggested model expands the receptive field while maintaining the same number of parameters, so as to solve the problems of large model parameters, loss of signal detail information, and generalization performance in the traditional deep Two-Dimensional Convolutional Neural Network (2-DCNN) model when processing one-dimensional structural vibration signals [2]. Meanwhile, this paper uses global pooling instead of the traditional fully connected layer to decrease model parameters to prevent over fitting. In addition, aiming at the phenomenon of unbalanced data set categories in the process of actually collecting vibration signals, this paper trains a cost-sensitive classifier by setting penalty weights for different categories of signals. This method can effectively extract damage-sensitive features from unbalanced vibration signal samples, thereby improving the accuracy of structural damage detection in the case of unbalanced samples [3]. This paper also establishes two branch tasks to realize structural damage location identification and damage degree quantification. This paper achieves more comprehensive and deeper extraction of damage information through information complementation between different tasks, and further improves the accuracy of damage recognition and damage degree recognition. The purpose of this paper is to help the increasing number of engineering and construction projects to improve the precision of structural damage identification under vibration signals, and to realize the construction of multi-task detection models in relation to building damage location and damage degree.

2 Related work

Lei et al. suggested an improved Support Vector Machine (SVM) damage detection method for steel frame engineering structures. After analyzing the damage data, the damage index was obtained and optimized. Structural damage indicators were then fused to identify more damage states. In experiments, the model showed good robustness and damage state recognition accuracy [4]. Demi et al. proposed a method of integrating electromechanical admittance and 2D-CNN, and applied it to the damage detection of concrete cubic structures. Experiments showed that this method was very sensitive to stress changes such as crack expansion, and was superior in quantitative evaluation of structural damage [5]. Yang et al. suggested an improved deep CNN model for the defect of signal feature extraction in the current stage of intelligent structural damage recognition, which converted low-level characteristics in the original signal into high-level characteristics automatically, and then fused the features through a multi-layer fusion optimization method, indicating that the feature fusion CNN method was more accurate than other algorithms in structural damage identification [6]. Cordeiro et al. applied Bayesian networks to structural damage identification. The experiment mainly optimized the collection of state parameters through the HMC method, thus solving the problem of response to parameter changes and continuity of the structural model. In the results, this method produced a Markov chain with a high convergence rate in damage scene recognition [7]. Masoud et al. also used structural damage localization and structural damage quantification as various ideas for model construction. The feature extraction of this method relied on a residual classifier constructed by temporal analysis and supervised learning, aiming to calculate the error between damaged and undamaged structures. The findings indicated that the method was better than the traditional technology in feature extraction, damage location, and damage degree judgment in the experiment [8]. Yan et al. proposed a bridge damage assessment method based on deep learning. By modeling the spatial model and physical parameters of the bridge, combined with vehicle load data, wavelet packet decomposition was used to analyze the data structure and eliminate the influence of temperature. The sensor data input into the deep learning model had an overall and local installation rate of over 92%, with an average fitting rate of 89.72%. It effectively predicted bridge damage caused by vehicle loads and had practical application value for health monitoring of small and medium-sized concrete bridges [9]. Zhou et al. explored the mechanical state of rock creep damage in the empirical model of rock constitutive model, linear unit combination model, nonlinear combination model and other theories [10]. Ahmadi-Nedushan et al. combined modal flexibility, strain energy index, and Multiple Teaching-Learning-Based Optimization (MTLBO) algorithm and applied it to detect structural damage of buildings. The experimental results showed that in the noisy environment, the iterative convergence speed and diagnostic accuracy of the algorithm in structural damage detection were higher than other algorithms [11]. Yang et al. developed a novel transform wavelet packet, which was mainly used to extract the damage characteristics of acoustic emission signals of metal plate buildings. Experiments showed that the method was appropriate for metal building structures with complex geometrical states [12].

In summary, although deep learning methods have been commonly used in civil and architectural structural damage, most of the techniques are based on supervised learning algorithms. These techniques usually face the problem of data imbalance. In addition, in the above research results, the number of single-task models accounts for the vast majority, and few models can take into account both the position information and the degree information of structural damage.

3 Structural damage diagnosis model of mlti-task one-dimensional atrous convolutional neural

3.1 Convolutional neural model construction of one-dimensional hole fusion global pooling

When the deep learning methods such as Convolution Neural Network (CNN) are used for the damage assessment of civil engineering structures in the experiment, the first step is to realize the automatic extraction of data features at multiple levels through the recognition training of a large number of data. The data of engineering damage identification and diagnosis comes

Table 1: Analysis of related work.

Reference number	Method	Detection object	Accuracy	Limitation
[4]	SVM	Structural damage in steel frame engineering	85.71%	This method is sensitive to the number and location of test points, as well as the position of force loading.
[5]	2D-CNN	Damage to concrete cubic structure	92%	Only local features can be captured through local perception mechanisms
[6]	Deep-CNN	General structural damage	96.92%	Recognition accuracy is affected by data sources
[7]	Bayesian network	General structural damage	/	Different assumptions can lead to higher prediction accuracy
[8]	ResNet-50	General structural damage	95.52%	The risk of fitting is higher when the structure is complex
[9]	Wavelet packet decomposition	Bridge engineering damage	89.72%	It involves the spatial model of bridges and vehicle stress, with a large computational workload
[10]	Empirical Model	Rock creep damage	/	The reliability of the model and the accuracy of predictions may be affected by duplicate data
[11]	Teaching-Learning-Based Optimization	General structural damage	95.49%	This model needs to consider the impact of noise.
[12]	Wavelet packet decomposition	Metal plate building damage	/	This model needs to consider the impact of noise.

from the vibration response information collected by the accelerometer in the monitoring structure [13]. The acceleration signal is converted into an index reflecting the structural damage, and the damage is located and quantified. CNN is popular in image and signal recognition, which can automatically learn the data features of structural damage through direct training [14]. Then, the extracted features are mapped to the category of the data through the model to complete the classification of the degree of engineering damage. The 2-DCNN mainly deals with the scene of two-dimensional image recognition. In the engineering damage in this study, the data object is the signal feature, so the 1-DCNN is used. The advantage of 1-DCNN is translation invariance. Only one-dimensional array operation is needed in forward propagation and back propagation, which can reduce the computational complexity. The convolution kernel structure of a 1-DCNN employs the same dimension as the network's input, which is one-dimensional data. One-dimensional convolution operation can be expressed as equation (1).

$$x_k^l = \sum_{i=1}^{N_{l-1}} conv1D(\omega_{ik}^{l-1}, s_i^{l-1}) + b_k^l \tag{1}$$

In equation (1), x_k^l represents the input of the k th neuron in the layer l; b_k^l denotes the bias parameter of the neuron. ω_{ik}^{l-1} is the convolution kernel between the i th neuron and k th neuron in layer $l-1$. s_i^{l-1} represents the output of the i th neuron in layer $l-1$. N_{l-1} is the number of neurons in layer $l-1$. $conv1D$ represents the one-dimensional convolution operation. In the activation layer of 1-DCNN, to enhance the model's ability to express the nonlinear relationship between input and output data, nonlinear functions are usually used for activation. Equation (1) displays the ReLU activation function employed in this equation (2).

$$g(x) = \max(0, x) \tag{2}$$

The ReLU activation function has the benefit that, when the input is positive, the gradient remains constant at 1, according to equation (2). Therefore, there will be no problem of gradient saturation and gradient disappearance. But when the input is negative, the ReLU activation function is completely invalid, and the parameters cannot be updated at all. Therefore, the Leaky ReLU function is used for optimization, and its equation is equation (3).

$$g(x) = \max(\alpha x, x) \tag{3}$$

In equation (3), α is in the interval of [0, 1]. The images of the two activation functions are detailed in Figure 1.

The biggest difference of the Leaky ReLU activation function is that the function's output value won't be 0 if the input value is less than 0, but a value much smaller than the input. Thus, the elimination of gradients issue can be alleviated to a certain extent. The remaining structure of the CNN is the pooling layer and the fully connected layer. The job of pooling layers is to compress the data and number of parameters to prevent over fitting [15]. The pooling layer scales and maps the output characteristics of the previous layer, and uses the overall statistical features of the adjacent area at a certain position as the output of the network at that position. Through the convolutional layer, pooling layer, and activation function layer, the fully connected layer translates the learnt "distributed feature representation" to the sample label space.

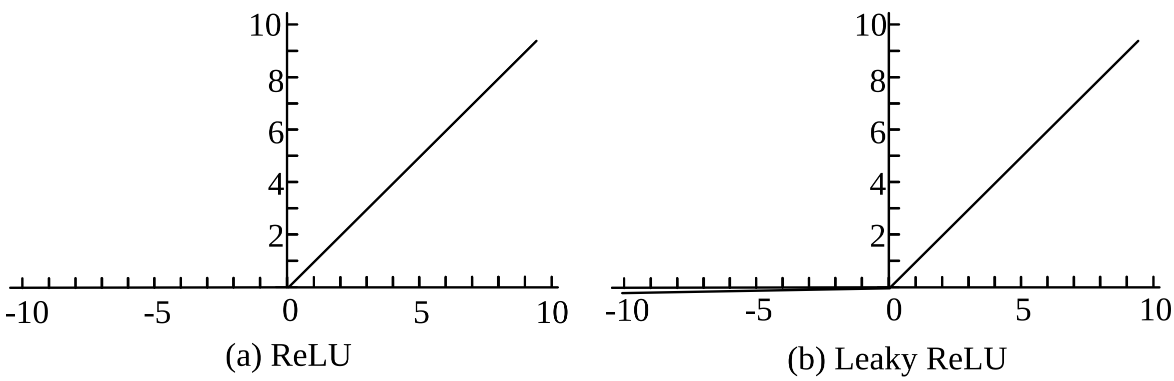
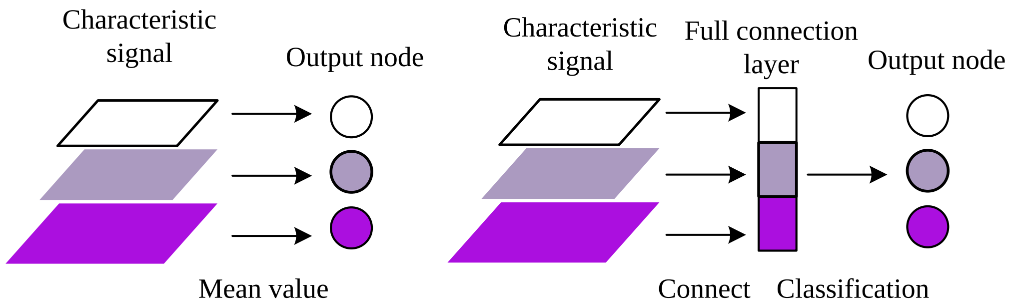


Figure 1: Image of ReLU activation function and leaky ReLU function.



(a) Global average pooling layer (b) Full connection layer

Figure 2: Global average pooling layer and full connection layer S structure.

Meanwhile, the fully connected layer also integrate the discriminative information characteristics extracted by the above convolutional layer and pooling layer. Due to its fully connected characteristics, generally fully connected layers also have the most parameters. Therefore, to prevent the network over fitting problem caused by redundant parameters, this paper introduces a pooling layer with a global average to compress each feature signal into a real number along the channel direction. The structure of the global average pooling layer and the fully connected layer is shown in Figure 2.

In Figure 2, in the fully connected layer and the global average pooling layer, the output of the neural network can be controlled by measuring the gap between the output and the expected value. Therefore, setting an objective function can effectively help train the neural network [16]. In the classification of vibration signal features for structural damage detection, this paper uses the most commonly used cross-entropy loss function as the objective function, and its equation is shown in equation (4).

$$L(y,\hat{y}) = -\sum_{i=1}^{n} y^{(i)} \log\hat{y}^{(i)} + (1-y^{(i)})\log(1-\hat{y}^{(i)}) \quad (4)$$

In equation (4), y is the output result of the model; $\hat{y}$ is the predicted output value. To minimize the loss function, the CNN needs to fine-tune the weight values. The core of weight optimization is error back propagation. First , it is necessary to calculate the derivative of the loss function with respect to the neurons in the last layer of the network, and then, using the network topology, determine the derivative value of the loss function with respect to the ownership value of each layer in turn [17]. During the back propagation derivation process of the fully connected layer, equation (5) displays the loss function's derivative with regard to the unnormalized probability value logits value produced by the network's last layer.

$$\frac{\partial L}{\partial z^{l+1(j)}} = \sum_{k=1}^{m} p_k^j q_k^j - p_k^j \quad (5)$$

In equation (5), $z^{l+1(j)}$ represents the value of the last layer of logits. After solving equation (5), compute the loss function's derivative with regard to the fully linked layer's weight and bias, and the equation is equation (6).

$$\begin{cases} \frac{\partial L}{\partial W_{ij}^{l}} = \frac{\partial L}{\partial z^{l+1(j)}} \cdot \frac{\partial z^{l+1(j)}}{\partial W_{ij}^{l}} = \frac{\partial L}{\partial z^{l+1(j)}} \cdot a^{l(i)} \\ \frac{\partial L}{\partial b_{j}^{l}} = \frac{\partial L}{\partial z^{l+1(j)}} \cdot \frac{\partial z^{l+1(j)}}{\partial b_{j}^{l}} = \frac{\partial L}{\partial z^{l+1(j)}} \end{cases} \quad (6)$$

In equation (6), $a^{l(i)}$ is the completely linked layer's output value, and the derivative of its derivative and the value of logits $z^{l(i)}$ is expressed as equation (7).

$$\begin{cases} \frac{\partial L}{\partial a^{l(i)}} = \sum_{j} \frac{\partial L}{\partial z^{l+1(i)}} \cdot \frac{\partial z^{l+1(i)}}{\partial a^{l(i)}} = \sum_{j} \frac{\partial L}{\partial z^{l+1(i)}} \cdot W_{ij}^{l} \\ \frac{\partial L}{\partial z^{l(i)}} = \sum_{j} \frac{\partial L}{\partial a^{l+1(i)}} \cdot \frac{\partial a^{l(i)}}{\partial z^{l(i)}} = \begin{cases} 0, z^{l(i)} \le 0 \\ \frac{\partial L}{\partial a^{l(i)}} z^{l(i)}, z^{l(i)} > 0 \end{cases} \end{cases} \quad (7)$$

During the back propagation of the pooling layer, the sum of the gradients does not change. During the forward propagation process, the maximum value and position of the pool region are tracked. When $t = t_m$, then $\max_{(j-1)w+1 \le t \le jw}\{a^{l(i,t)}\} = a^{l(i,t_m)}$. In the process of error back propagation, the derivative value is directly passed to the t_m -th neuron, and the derivatives corresponding to the remaining neurons are 0, as shown in equation (8).

$$\frac{\partial L}{\partial a^{l(i,t)}} = \frac{\partial L}{\partial p^{l(i,j)}} \cdot \frac{\partial p^{l(i,j)}}{\partial a^{l(i,t)}} = \begin{cases} 0, t \ne t_m \\ \frac{\partial L}{\partial p^{l(i,j)}}, t = t_m \end{cases} \quad (8)$$

Finally, the convolutional layer's reverse derivation procedure is split into two parts. The loss function's derivative is first calculated in relation to each convolutional layer's output logits value, as shown in equation (9).

$$\frac{\partial L}{\partial y^{l(i,j)}} = \frac{\partial L}{\partial a^{l(i,j)}} \cdot \frac{\partial a^{l(i,j)}}{\partial y^{l(i,t)}} = \begin{cases} 0, y^{l(i,j)} \le 0 \\ \frac{\partial L}{\partial a^{l(i,j)}}, y^{l(i,j)} > 0 \end{cases} \quad (9)$$

The second step is to calculate the loss function derivative with respect to the convolutional layer input $x^{l(j)}$, as shown in equation (10).

$$\begin{aligned}\frac{\partial L}{\partial x^{l(j)}} &= \sum_j \frac{\partial L}{\partial y^{l(i,j)}} \cdot \frac{\partial y^{l(i,j)}}{\partial x^{l(j)}} \\ &= \sum_j \frac{\partial L}{\partial y^{l(i,j)}} \cdot \sum_{j'=0}^{w} K_i^l(j')\end{aligned} \tag{10}$$

In equation (10), $K_i^l(j')$ represents the convolution kernel, and its calculation equation for the derivative of the loss function is expressed as equation (11).

$$\begin{aligned}\frac{\partial L}{\partial K_i^l(j')} &= \sum_j \frac{\partial L}{\partial y^{l(i,j)}} \cdot \frac{\partial y^{l(i,j)}}{\partial K_i^l(j')} \\ &= \frac{\partial L}{\partial y^{l(i,j)}} \cdot \sum_j x^{l(j)}\end{aligned} \tag{11}$$

The above is the optimization process of the 1-DCNN model. In this process, this paper mainly optimizes the signal detection and recognition of the CNN suitable for deep learning. Meanwhile, the traditional 2-DCNN is changed to 1-DCNN to adapt to the vibration signal data analysis of engineering damage. The activation function of the network is improved based on 1-DCNN, and the typical pooling layer is replaced with a global average pooling layer.

3.2 MTL-1DCNN-based damage classification and identification model for engineering structures

In order to enhance the recognition performance of the 1DCNN model for engineering structural damage categories, a multi task learning mechanism will be introduced to optimize the 1DCNN model and construct a damage classification and recognition model based on a multi task learning one-dimensional convolutional network (MTL-1DCNN). The advantage of the improved 1-DCNN model is that the feature is compressed by the pooling layer, which increases the receptive field and reduces the quantity of variables and computational complexity. But its disadvantage is that the model improvement process causes the loss of detailed signal features. In some recognition tasks that are sensitive to detailed information, it may have a greater impact on the final prediction [18]. Therefore, the experiment introduces the advantage of dilated convolution on the basis of 1-DCNN to expand the receptive field. In the experiment, the ordinary one-dimensional convolution and pooling layers in the model are replaced with one-dimensional dilated convolutional layers, and the conventional fully linked layer is replaced with the global pooling layer. Meanwhile, according to the characteristics of unbalanced sample data in actual detection, the experiment uses cost-sensitive learning to further improve the recognition effect of damage. Atrous convolution introduces an expansion coefficient in the traditional convolution calculation, that is, the number of intervals of the convolution kernel [19]. The experiment sets the expansion coefficient to r, which expands the convolution kernel to the scale constrained by the expansion coefficient, and fills $r-1$ zeros in the original convolution kernel. This procedure expands the receptive field while maintaining the same number of parameters, so that each convolution output carries a broader range of information. The effect of the expansion coefficient is shown in Figure 3.

Figure 3 demonstrates that the dilated convolution computation has no effect on the number of convolution kernels, while increasing the receptive field, and the calculation parameters are still the same. To measure the detection accuracy on each joint of the building, the damage state index of the structural joint is defined as equation (12).

$$Pod_i = \frac{D_i}{T_i} \tag{12}$$

In equation (12), T_i represents the complete number of signals processed by the detection network at joints; D_i represents the number of signals classified as damaged. Therefore, when the value of Pod_i is 1, it means that the building joint is damaged; when the value of Pod_i is 0, it means no damage. In the challenge of detecting structural deterioration, the number of vibration signal samples with damage information and without damage information is usually quite different, that is, there is a problem of unbalanced distribution of data categories. Therefore, this paper introduces cost-sensitive learning to increase the constraints and weights of the damage function. Among them, the penalty weight is set according to the measured ratio of positive and negative samples. Small-sample categories are penalized with higher weights, while large-sample categories are penalized with smaller weights. As a result, the trained model can pay more attention to a small number of sample categories. The specific basis for determining the penalty weight is usually related to the different levels of acceptance of FP and FN losses in the scene. The loss function is adjusted to reflect these different loss costs. In practical operation, the penalty weight can be determined by constructing a cost matrix, where the elements of the matrix represent the actual loss of misclassified categories. By optimizing this cost matrix, the model can focus more on misclassifications with higher loss costs during prediction, thereby achieving the goal of improving the performance of the model on

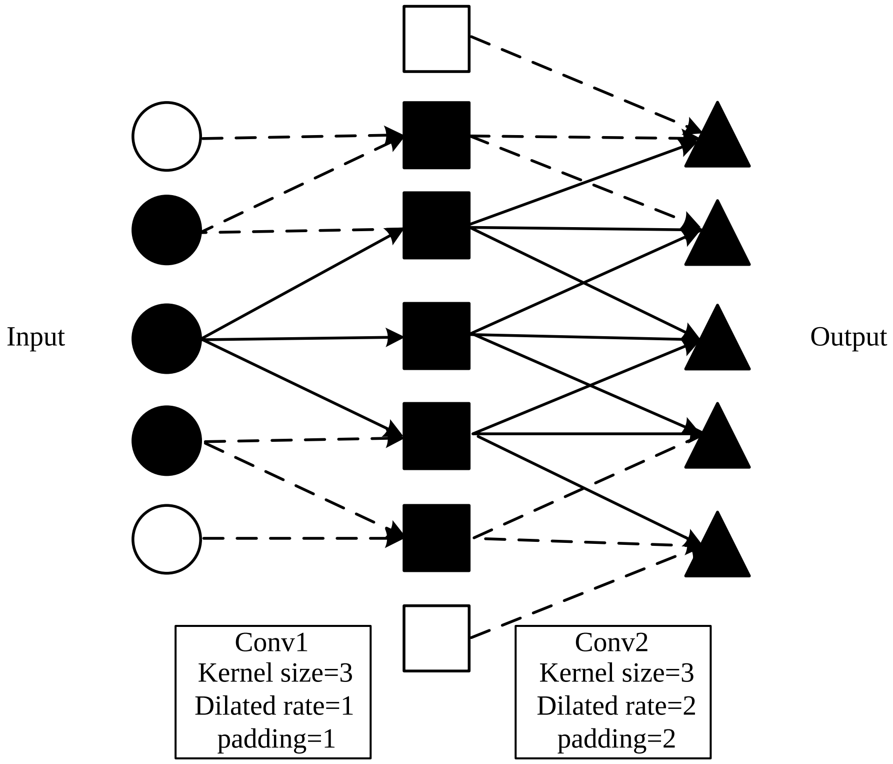


Figure 3: Schematic diagram of one- dimensional dilated convolution receptive field under different expansion coefficients.

specific categories. The equation of the loss function is optimized as equation (13).

$$CE(x) = -\sum_{i=1}^{c} \alpha_i y_i \log f_i(x) \qquad (13)$$

In equation (13), x denotes the input sample ; α_i denotes the weight applied to the i -th category ; c is the total number of categories to be classified ; y_i is the true label corresponding to the i -th category ; $f_i(x)$ represents the output value of the model. Finally, to maximize utilisation of the damage information in the vibration response signal of the lossy structure to avoid the one-sidedness of single target task learning, this study introduces the idea of multi-task learning on the basis of the above 1-DCNN model. This study builds a model that can simultaneously complete the two tasks of damage location identification and damage degree judgment. The multi-task learning model's training adopts the method of joint training, that is, one optimizer is used to train the entire network. This study uses the mean square error function to provide the job one loss function; uses the cross entropy loss function to define the loss function of task two. The two jobs' individual loss functions are added to create the overall model's loss function. Equation (14) represents the multi-task model's loss function.

$$\begin{cases} Loss_1 = \dfrac{\sum_{i=1}^{n} (y_i - y_i')^2}{n} \\ Loss_2 = \sum_i p_i(x) \log q_i(x) \end{cases} \qquad (14)$$

In equation (14), y represents the real value; y' represents the predicted value of the model; $p_i(x)$ represents the actual distribution of the target; $q_i(x)$ represents the predicted distribution of the model. Finally, the overall loss function of the model is expressed as equation (15).

$$Loss = \phi Loss_1 + \varphi Loss_2 \qquad (15)$$

In equation (15), ϕ and φ represent the weights of the loss functions for different tasks. Figure 4 shows the operation process of the Multi Task Learning Model Based on 1-DCNN (MLT-1DDCNN).

As shown in Figure 4, the multi-task learning model's training adopts the method of joint training, that is, the whole network is trained using a single optimizer. Based on the idea of multi-task learning, the experiment constructs two branch tasks that can simultaneously complete the location of the damage being identified and the diagnosis of the damage degree [20]. The two branch tasks can extract shallow signal features from the original vibration response through the model sharing layer, and then extract deeper damage-sensitive features according to specific task requirements. Through joint training, different tasks can complement each other with the relevant information of the specific field learned by each other through the shared layer, which improves the generalization performance of the model and realizes more efficient and comprehensive structural damage recognition.

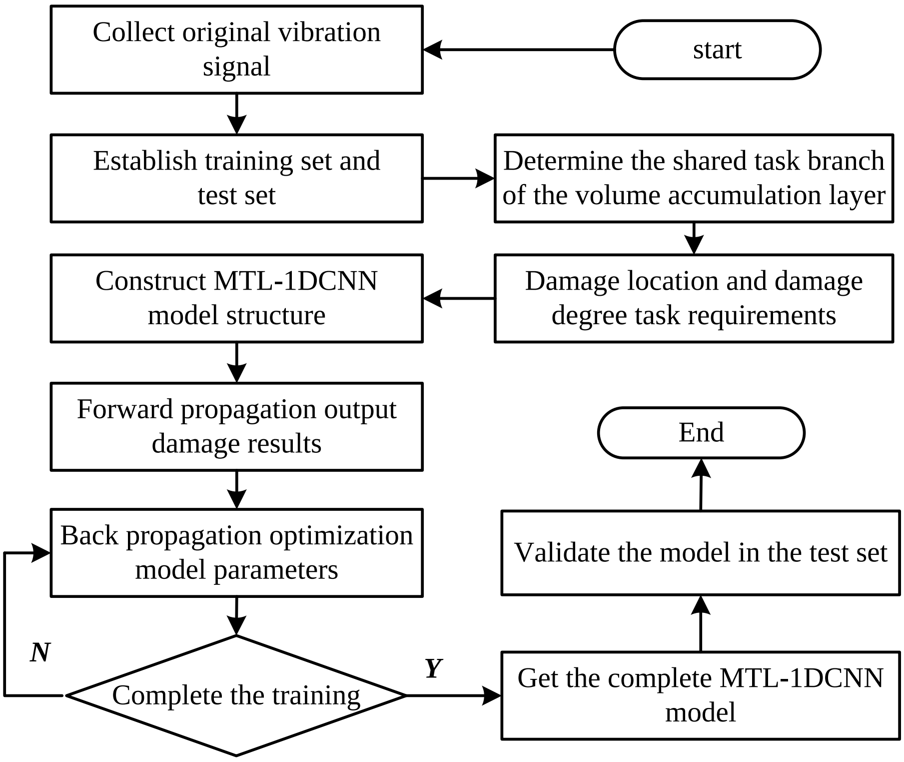


Figure 4: Construction process of MLT-1 DDCNN.

Figure 5: Engineering framework model of experiment.

Table 2: Structural damage of engineering frame model.

Category	Joint1	Joint2	Joint3	Joint4	Joint5
Mode 1	normal	normal	normal	normal	normal
Mode 2	damage	normal	normal	normal	normal
Mode 3	normal	damage	normal	normal	normal
Mode 4	normal	normal	damage	normal	normal
Mode 5	normal	normal	normal	damage	normal
Mode 6	normal	normal	normal	normal	damage

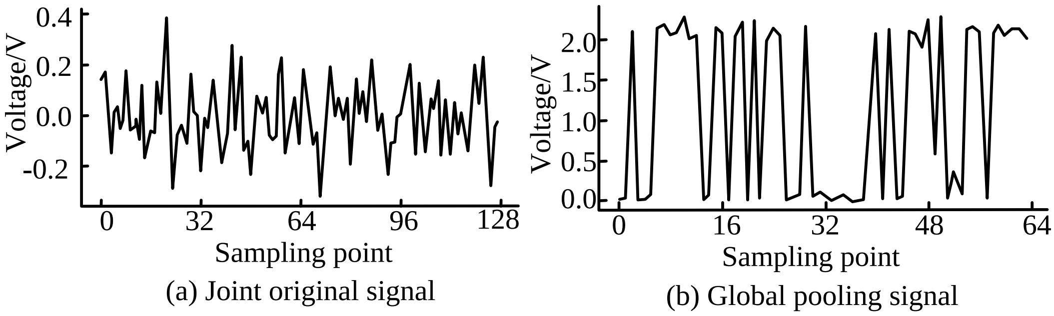


Figure 6: Damage characteristics of S signals collected under the global pool.

4 Application case study of civil engineering structure damage identification model

4.1 Analysis of optimization performance of 1-DCNN

In this study, two experimental validation analyzes were performed on the model. Firstly, the data set experiment analysis was carried out on the global pooling layer, cost-sensitive learning and other optimization measures of the 1-DCNN model to test whether its optimization performance played the expected role in the application. The experimental object of this verification model was the scale model experiment of the grandstand structure built by Qatar University. It's structure is shown in Figure 5.

In Figure 5, the engineering structure applied in this research consisted of 4 frame beams, 4 transverse main beams and 25 longitudinal filling beams. The experiment installed 30 accelerometers on the main beam at 30 joints inside the steel frame. In the experiment, the vibration acceleration signal was recorded at a sampling frequency of 1024 Hz for 256 seconds. The typical sensitivity value of the accelerometer at 25°C was 1V/g. The accelerometer was set to cover 30 internal joints of the steel frame, ensuring comprehensive coverage of key areas of the structure to capture the dynamic response of the structure under different working conditions. Meanwhile, the experiment set damages on five joints of a single beam of the frame. By releasing the fasteners holding the connecting beams together, structural damage was mimicked. A total of six engineering structure damage models were set up in the experiment, as shown in Table 2.

In Table 6, two sets of random vibration experiments were carried out using the vibrator in this study. Both the training and testing of the models employed the same set of gathered signals. In the experiment collection, the vibration acceleration signal of 256s was recorded at the frequency of 1024Hz. The collected original signal was compared with the signal extracted by the global pooling layer. The precise outcomes are shown in Figure 6.

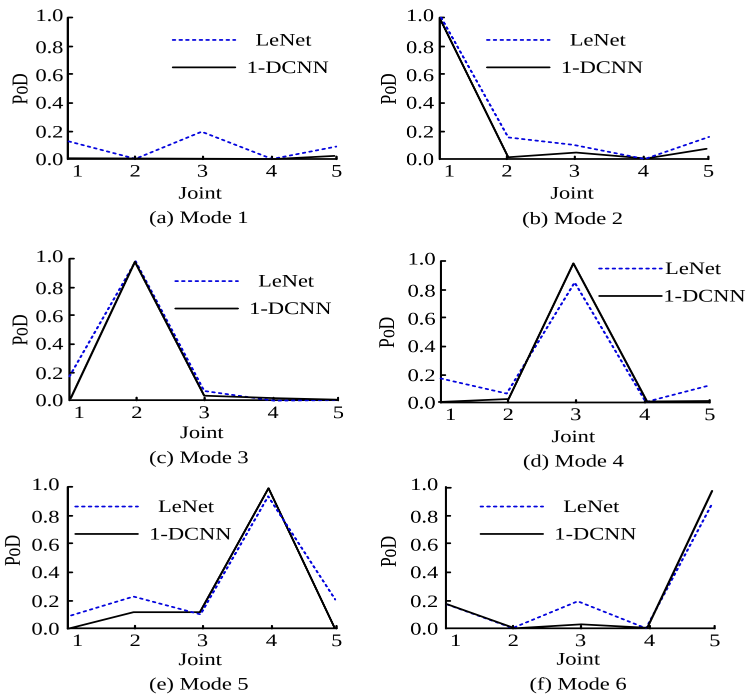


Figure 7: Distribution of PoD values for different models under different damage modes.

Figure 6(a) demonstrates that the original signal fluctuates in the voltage range from -0.2 to 0.4. Signals were denser in both waveform and frequency spectrum, making it difficult to effectively distinguish structural damage. After the extraction of the global pooling layer, the signal had an increased level of discrimination as a whole. Therefore, the optimized 1-DCNN model could extract effective features from the original signal and had good classification performance. After joint training, the 1-DCNN dilated convolution model proposed in this study was compared with the traditional one-dimensional LeNet model. The specific results are shown in Figure 7.

In Figure 7, at the damaged joint, the PoD value of the LeNet model in mode 3 was only about 0.8, while the PoD value obtained in each damage mode of the model in this paper was larger and closer to 1. In lossless joints, the one-dimensional LeNet model had the phenomenon of misclassifying lossless signals into damaged signals, while the PoD value obtained by the model in this paper was smaller and closer to 0. Experiments showed that the correct recognition rate of the model for damage signals and lossless signals was higher than that of the one-dimensional LeNet model. When constructing the neural network training sample set and verification sample set, the experiment uniformly set the sample length to 128. For each joint, 262144/128=2048 damage signal samples and 5×262144/128=10240 lossless signal samples could be obtained after the measurement signal was truncated in the experiment . In data preprocessing, the experiment used random shuffling to take 1/2 of the damaged signals and 1/10 of the lossless signals to form balanced data samples, and took the other 1/2 of the damaged signals and 9/10 of the lossless signals to form unbalanced samples. Therefore, when constructing the sample set, the number of samples of the lossless signal reached 5 times of that of the damaged signal. To verify the difference in the detection capability of the models trained with balanced samples and unbalanced samples, this study compared the confusion matrix of the detection results in the test set, as shown in Figure 8.

In Figure 8, Y-true denotes the true label, while Y-pred denotes the predicted label. By comparing the confusion matrix, in the balanced sample set, the recall rate of the model was 83.3%, the accuracy rate was 99.80%, and the F1 score was 90.41%. In the imbalanced sample set, the recall rate of the model was 83.4%, the accuracy rate was 99.84%, and the F1 score was 90.62%. By comparing the confusion matrix, it was evident that increasing the number of lossless signals was indeed conducive to improving the network model's ability to identify lossless signals. However, learning directly using unbalanced samples would cause deviations in the learning ability of the model. Compared with the previous model detection results obtained by training with balanced samples, the model's ability to recognize objects for damage signals was reduced. Therefore, the test set setting of balanced samples was more reasonable.

4.2 Application performance research of MTL-1DCNN engineering structure damage recognition model

The feature information of damage location and degree was extracted from the vibration signal simultaneously. This study introduced a multi task learning method based on 1-DCNN and further constructs the MTL-1DCNN model. Table 3 displays the particular parameters and model's structure.

Table 3 demonstrates that the shared layer part of the structure uses 4 convolutional layers to extract the shallow shared features of the two branch tasks from the original vibration signal of the structure. Among them, the first two convolutional layers used large-size kernels to obtain more time-domain information with a larger receptive field. The last two convolution layers all used 3×1 small convolution kernels. Then the experiment established two task branches of damage location recognition and damage degree recognition. Different task branches used two convolutional layers to further extract deeper features from shallow shared features, and finally used their respective task-specific layers (regression layer or classification layer) to realize damage location identification and damage degree diagnosis. In this experiment, initial learning was done at a pace of 1e -4; the amount of repetitions is 200. 1e-4 is a relatively small learning rate, which means that the update step of the model weights is small, which helps the model to converge more stably during training, avoiding crossing the minimum value or oscillation due to a large step size. In this experiment, the Adam optimizer were used to adjust the learning rate of each parameter based on the square of past gradients. In addition, this study set a two-story frame structure model as the research object, and simulated damage by reducing the stiffness at specific positions. The training curves of the comprehensive diagnosis of injuries of the single-task model and the comprehensive diagnosis of the multi-task model are shown in Figure 9.

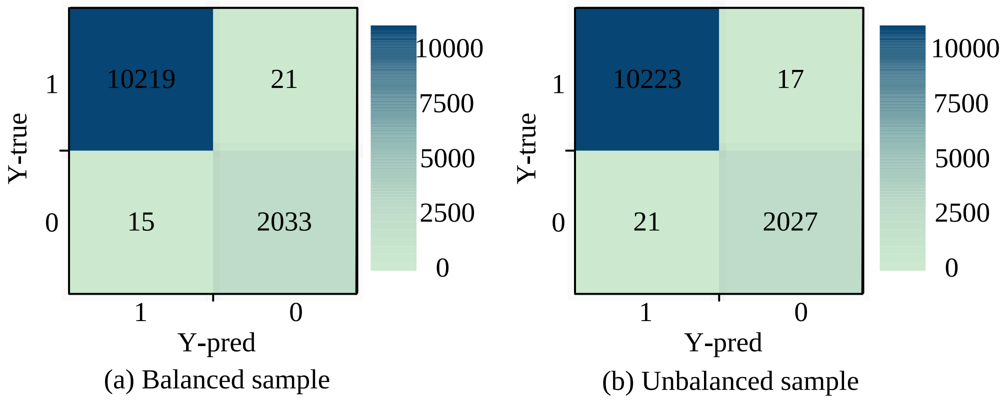


Figure 8: Confusion matrix of joint 1 in D different t raining sets.

Table 3: MTL-1DCNN model structure.

No.	Layer Name	Layer	Kernel size/stride	Dilated rate	Kernels number	Output size
1	Shared layer	Conv1	64 × 1/1 × 1	1	16	1000×16
2		Conv2	64 × 1/1 × 1	1	16	1000×16
3		Conv3	3 × 1/1 × 1	3	64	1000×64
4		Conv4	3 × 1/1 × 1	3	64	1000×64
5	Task 1: Identification of damage degree	Conv5	3 × 1/1 × 1	5	128	1000×128
6		Conv6	3 × 1/1 × 1	5	128	1000×128
7		Global Pooling	/	/	/	128
8		Dense	5	1	1	5
9	Task 2: Damage location identification	Conv7	3 × 1/1 × 1	5	128	1000×128
10		Conv8	3 × 1/1 × 1	5	128	1000×128
11		Global Pooling	/	/	/	128
12		Dense	5	1	1	5

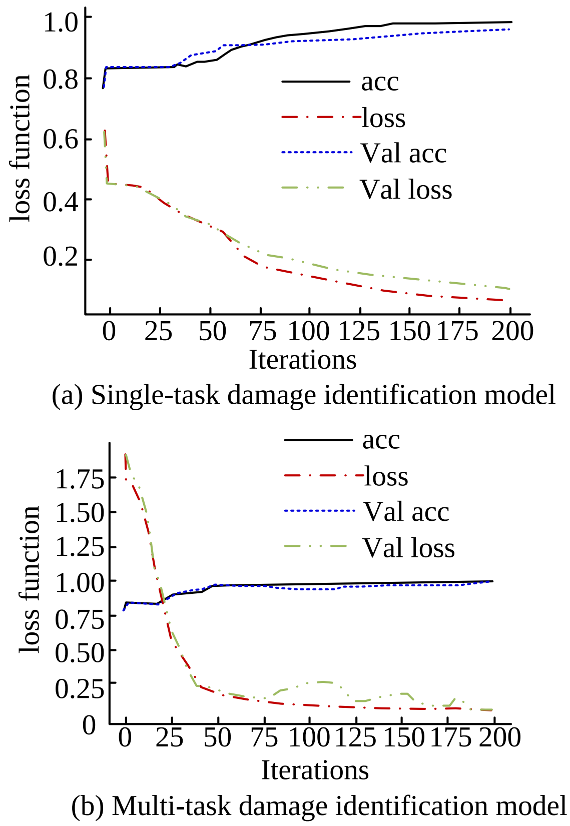
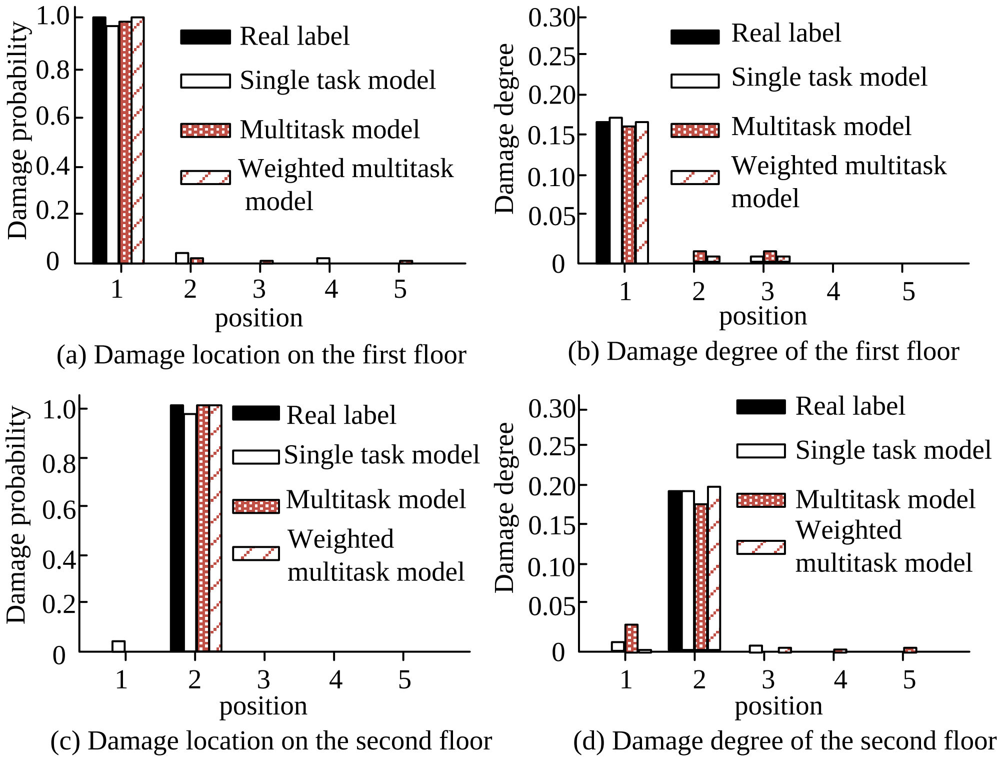


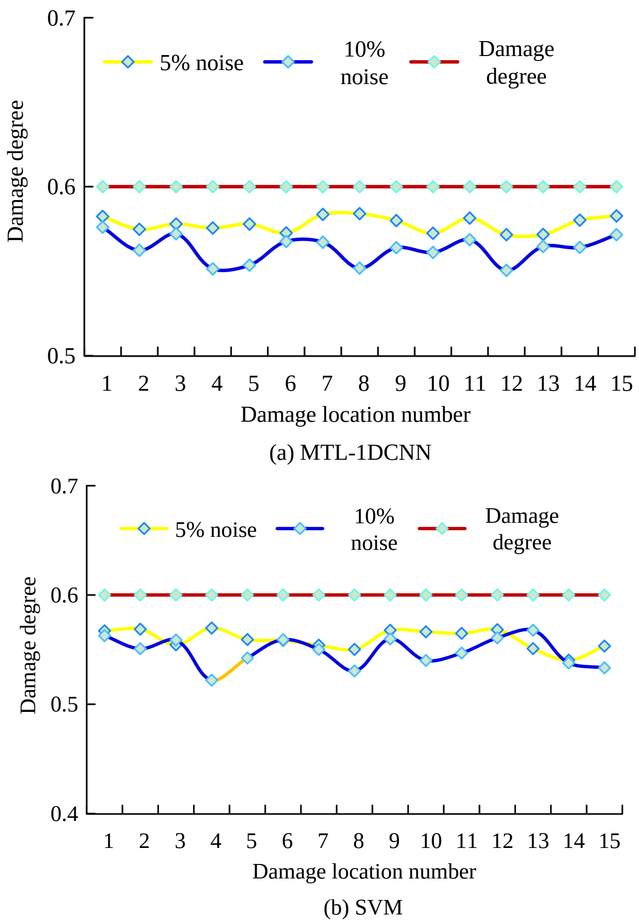
Figure 9: Iterative comparison between single-task model and multi -task learning model.



(a) Damage location on the first floor (b) Damage degree of the first floor

(c) Damage location on the second floor (d) Damage degree of the second floor

Figure 10: Application of MTL-1DCNN model for damage identification of double-storey buildings.



(a) MTL-1DCNN

(b) SVM

Figure 11: Detection and recognition performance of MTL-1DCNN and SVM models under multiple damage conditions.

The single-task damage degree diagnostic model achieved a condition of perfect convergence after 125 iterations, as shown by the training curve in Figure 9. At this time, the single-task damage location recognition model had not yet reached a state of complete convergence. The two models of multi-task damage comprehensive diagnosis and weighted multi-task damage comprehensive diagnosis both reached a stable convergence state after 75 iterations. Therefore, when the experiment used multi-task learning to optimize multiple tasks, the learning efficiency of the model was improved, and the model's convergence rate was significantly accelerated. To test the recognition ability of each model for building damage conditions, this study compared the weighted multi-task model with the single-task model. In the actual situation of the simulated building, the stiffness of the first layer was reduced by 17%; the stiffness of the second layer was reduced by 20%. Figure 10 displays the particular experimental outcomes.

In the test set, the accuracy of single-task learning to localize the site of damage was 96%, and the recognition accuracy of weighted multi-task learning could reach 99%. In the single lesion recognition problem, single-task learning also had high recognition accuracy, and the accuracy of lesion location recognition had been further improved by weighted multi-task learning. In addition, the prediction results of weighted multi-task learning were closer to the ground truth than those of single-task learning. In the problem of damage degree recognition, both multi-task learning and single-task learning had shown better regression recognition accuracy. By calculating the MSE value of the evaluation index, the MSE of the single-task learning calculation result was $7.04\times10{-5}$, and the MSE of the weighted multi-task learning calculation result was $3.47\times10{-5}$. Therefore, weighted multi-task learning could predict the damage degree more accurately than single- task learning in two-story building simulation.

Finally, the experiment conducted a practical exploration of the method performance using an aluminum structural model of a five layer plate frame, which consisted of 300 structural elements. The study compared the detection and recognition performance of MTL-1DCNN and SVM models under multiple damage conditions. The specific results are shown in Figure 11.

From Figure 11, MTL-1DCNN had an average damage degree of 0.578 at 15 locations when 5% noise was added, and an average damage degree of 0.5631 when 10% noise was added. When adding 5% noise to the SVM model, the average degree of damage at 15 locations was 0.559, and when adding 10% noise, the average degree of damage was judged to be 0.548. From the experimental results, the proposed method model performed better than traditional methods in identifying and judging the degree of damage when multiple damages were identified and noise interference was added, indicating that the proposed model had a certain degree of robustness.

5 Discussion

Currently, research on structural damage identification based on deep learning is mainly applied in single task learning frameworks. This means that to complete specific tasks, such as identifying the location of structural damage or assessing the severity of damage, a separate deep neural network model is trained. Deep learning techniques can extract key features from raw data based on different task objectives. For example, in reference [5], the EMA spectrum characteristics of resonance frequency and amplitude values were utilized to analyze stress development and crack damage progression. The highest accuracy of this method was 92%, with an average accuracy of 87%. When different degrees of damage were detected in specific parts of the structure, the single task learning model extracted features from the input signal that were more correlated with the location of the damage as the basis for classification and judgment, while ignoring the differences in the degree of damage. Similarly, when using a single task learning model to evaluate the degree of damage, signal information related to the location of the damage was ignored. In addition, most current deep learning based damage detection techniques relied on supervised learning algorithms, which required a large amount of labeled data to train the network. Therefore, how to improve the accuracy of vibration based structural damage identification in the presence of imbalanced data was an urgent key issue that needed to be addressed. In references [6] and [10], deep convolutional neural networks and empirical models were used for standard data extraction and analysis, respectively, with the highest recognition accuracy of 96.9%. However, its method was prone to the problem of data imbalance, and was therefore affected by data sources and data repetition. The method proposed in the study improved the accuracy of structural damage detection in the face of data imbalance by setting penalty weights for different categories of signals to train cost sensitive classifiers. In the results, the method constructed by the study identified only 17 incorrect samples among 2048 damaged sample data, which was higher than other models.

6 Conclusion

To make full use of the damage information in the vibration response signal of the damaged structure and avoid the one-sidedness of single target task learning, this paper constructs MTL-1DCNN to comprehensively improve the diagnostic ability of structural damage. This study compares the improved model with the traditional LeNet model. The experiment found that the PoD value of the LeNet model in mode 3 was only about 0.8; while the PoD value obtained in each damage mode of the model in this paper was larger and closer to 1. In the application experiment comparison of the two-story building model, the single-task damage degree diagnosis model reached a state of complete convergence after 125 iterations, and the single-task damage location recognition model had not yet reached a state of complete convergence. The two models of multi-task damage comprehensive diagnosis and weighted multi-task damage comprehensive diagnosis reached a stable convergence state after 75 iterations. Therefore, when using multi-task learning to optimize multiple tasks, the learning efficiency of the model was improved, and the model's convergence rate was significantly accelerated. In addition, this paper proposed that the recognition precision of the MTL-1DCNN model was as high as 99%; its MSE was 3.47×10^{-5}. The results showed that the MTL-1DCNN model predicted the damage degree and damage location more accurately than the single-task and traditional CNN methods. The study's flaw is that the model data studied are all derived from training data simulation, and there are still some differences with the real structure.

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