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RESEARCH ARTICLE

Civil Engineering Structural Damage Identification by Integrating Benchmark Numerical Model and PCNN Network

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ABSTRACT Strengthening the real-time and accurate identification of civil structures is of great significance for ensuring the safety and service life of civil engineering projects. Therefore, in order to reduce the incidence of civil structural accidents in buildings and improve the safety, availability, and integrity of building structures, the study plans to adopt deep learning methods. In this study, the parallel Convolutional neural network covering one-dimensional and two-dimensional features is combined with the Benchmark numerical model to identify structural damage. This network structure can effectively utilize two parallel branches to extract response features at different scales and time domains, ensuring the coverage of damage feature recognition content to a certain extent. And the Benchmark numerical model can effectively improve the visualization of identification in the simulation of civil structures. By testing the fusion algorithm model, the results show that the network structure can effectively extract damage signal features, and its minimum classification loss value can approach 0.01; The maximum damage indicators on connecting beams, frame beams, and shear walls reached 0.472, 0.117, and 0.055, far higher than other comparative algorithms. The fusion algorithm has a recognition accuracy of over 85% for structural joint damage, showing good damage recognition performance. This fusion algorithm can effectively provide reference value and significance for the development of structural inspection and related risk prevention plans in civil engineering projects, and also provide new ideas and possibilities for relevant researchers to study the field of civil engineering.

INDEX TERMS Benchmark model, PCNN, civil engineering, structural damage, vibration response signal, CWT.

I. INTRODUCTION

Machine learning, as an important tool for evaluating mathematical statistical models, can complete learning and data processing without relying on human reasoning. The development of computer technology and the emergence of various sensors have led to an exponential growth trend in the amount of data and information obtained by people. Therefore, the analysis of data content and the extraction of related features have gradually entered people's perspectives and research fields. Structural damage identification can be divided into local detection and overall detection based on the differences in its detection targets. As a mechanical system, the structural domain's corresponding modal parameters will also change when damage occurs [1]. The importance and value of damage identification in civil engineering structures are self-evident. In the field of civil engineering, the safety and reliability of structures are crucial. Any damage or defect may lead to structural failure. Accurately identifying and evaluating the damage status of structures is crucial for ensuring their safe operation and extending their service life. Damage or defects in civil engineering structures can lead to casualties and property losses. Identifying the structure can detect structural damage early and take corresponding repair measures to ensure the safety of the structure and reduce maintenance and replacement costs. And damage identification can achieve the evaluation and detection of civil engineering structures, maximize the utilization of existing structural resources, improve fund utilization efficiency, and achieve maximum economic benefits. Identification of structural damage in civil

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engineering can provide scientific basis and technical support for the field of civil engineering, ensuring the reliability and sustainable development of engineering structures. Due to the complexity of load conditions and the variability of the environment, there is a complex relationship between common detection data and structural conditions in civil engineering structures. Therefore, using machine algorithms for damage detection and identification can effectively grasp the nonlinear features between the two. The proposed Benchmark numerical model is combined with neural networks to perform damage. The Benchmark numerical model is a public platform that relies on international standardization of damage diagnosis research. It can evaluate the performance of different structural damage identification algorithms, and its standardized evaluation methods can effectively reduce data errors. Currently, most damage identification based on structural vibration response only considers single features and cannot achieve multi information fusion of damage sensitive features. Although there are currently many recognition methods based on deep learning, there is less attention paid to improving algorithm efficiency. Based on this, the study utilizes the vibration response characteristics of civil structures to introduce intelligent algorithms for structural damage detection, in order to better extract and identify their damage features.Convolutional neural network (CNN) and other deep learning methods are mostly used in image classification, speech recognition, structural damage recognition and other fields [2] by virtue of their nonlinear mapping ability for sample processing. When applying CNN to damage identification, the differences in its data format will limit its usage, and to some extent, it will overload the system pressure or lead to over dependence and overfitting between data [3]. Therefore, the Parallel CNN (PCNN) considering 1D and 2D features is used for damage identification, and the Benchmark numerical model is used for visual analysis. The purpose is to distinguish the degree and type of damage, and to provide better suggestions for structural safety monitoring. The Benchmark numerical model is a common method used to simulate and evaluate the performance and damage of structures. By combining the Benchmark numerical model with the PCNN network, the learning and feature extraction capabilities of the PCNN network can be utilized to extract more meaningful information from the numerical model. Compared to traditional methods such as threshold and rule-based damage identification, the fusion of Benchmark numerical models and PCNN networks can improve the accuracy of structural damage identification and reduce the rate of misidentification. And the fusion approach of this method can provide a new approach and framework for researchers in the field of civil engineering, which can be explored and validated in more practical applications. This study mainly identifies and analyzes structural damage in civil engineering from four aspects. The first part is a literature review and discussion on current damage identification algorithms and related detection algorithms; The second part proposes improved PCNN algorithm and Benchmark model respectively to achieve damage structure identification and detection; The third part is to test and analyze the damage recognition effect under this fusion method; The final part is an overview summary of the entire content.

II. RELATED WORK

Structural parameters in buildings can directly reflect their damage, and strengthening System identification is an important content of structural health detection. Zhang [4] proposed the theory of identifying structural parameters based on frequency domain response construction and analyzed shear type buildings. The proposed non iterative algorithm can better reflect the dynamic response of the structure, and has lower time consumption and lower error results. In view of the error and noise caused by the original finite element Metamodeling in structural damage identification, Ding et al. [5] proposed to combine the K-means clustering algorithm with the Simulated annealing algorithm to build a structural damage identification function under modal data. This method has good robustness and generalization in structural damage identification, and is less affected by noise data interference. Sun et al. [6] proposed a combination of transfer function and sequential Extreme learning machine to detect impact damage of composite materials, and input the structure with principal component analysis for feature noise reduction into the neural network to determine the damage location. This method has good accuracy in structural damage identification. Guo et al. [7] used wavelet transform and improved Particle swarm optimization algorithm to identify the location and severity of structural damage, and conducted performance tests in different damage scenarios. This algorithm can effectively achieve structural damage and exhibits good robustness and convergence, with relatively stable algorithm performance.Based on the anti directness of evidence theory in structural health detection, Ding et al. [8] proposed combining the Dempster combination rule with knowledge priors to solve the problem of evidence conflicts. This method shows high reliability, and has high identification and diagnosis accuracy in Space frame structures. Fathnejat [9] cholar proposed to introduce Confusion matrix and sensitive evaluation index of modal characteristics to conduct damage location research for structural damage detection. And with the help of the Data Processing Grouping Method (GMDH) network, the changes in modal characteristics were achieved to better estimate the degree of damage. Compared with other algorithms, this method shows a lower Mean squared error value, and can better realize the identification and evaluation of structural behavior. To ensure the accuracy of structural damage identification, Chen [10] utilizes the predator mechanism of the Whale Optimization Algorithm (WOA) to compare the probability of different structural damages, thereby achieving health monitoring identification. It takes into account weighted modal data and flexibility assurance criteria. This algorithm has high damage localization accuracy in numerical simulation results and provides a more effective tool for structural monitoring.Ramezani et al. [11] proposed an Improved Genetic Algorithm (IGA) based on a finite number of modes to identify the degree of damage to civil and building structures. The healthy elements in the algorithm structure were removed, and two numerical variables, 2D truss structure and 3D structure, were introduced to evaluate the algorithm's recognition ability. A cantilever beam model was also introduced for performance testing. This algorithm can effectively reduce noise errors and has high effectiveness in detecting damage. To reduce the influence of outdoor temperature on the prediction of vibration frequency of civil structures, Huang et al. [12] took temperature as a variable of material properties and introduced the Cuckoo search (CS) to identify the damage of civil structures. The results indicate that the algorithm has high accuracy in damage identification and temperature change identification. Li et al. [13] proposed a new inverse finite element method damage identification algorithm based on strain damage indicators. It obtains building structure simulation data through strain sensors and conducts experimental verification with single damage and multiple damage as variables. This algorithm has been improved in both speed and accuracy, and the direct damage index can meet the damage structure detection standards, which has high practicality.

Activation functions play an important role in the determination and performance of nonlinear factors in neural networks, among which nonlinear and asymmetric activation functions can play a significant role in deep neural networks [14]. The probability mapping problem in deep feedforward networks can be represented as an iterative transformation of distributions, which is crucial for the recognition and representation of data information. Strengthening the correlation between information processing can provide an interpretable perspective for classification [15]. Deep convolutional neural networks have been widely used in many fields such as natural language processing and computer vision. Adjusting the number and architecture of hyperparameters in the network is a new approach for feature extraction [16]. Deep learning systems have good application value in information demand analysis and accurate health status diagnosis in today's rapidly changing world of human-robot interaction and communication [17]. To estimate the correlation between damage status and vibration characteristics in structures, researchers such as Wang [18] proposed a vibration structural damage identification algorithm based on Densely Connected Convolutional Networks (DCCN). It achieves acceleration response requirements by implementing dense links, and solves the Vanishing gradient problem. A lot of experimental training shows that this algorithm has higher accuracy and good robustness in locating structural damage. With the rapid development of machine learning algorithms, the Benchmark model and PCNN algorithm have been applied to multiple fields such as meteorology, biology, and medicine. Among them, scholars such as Li [19] used Benchmark in solving air quality regulation problems and further proposed a numerical model for fine particulate matter.It uses the objective assessment project management model to statistics the air quality results, and analyzes the air quality within the statistical range through the Random forest method. The proposed algorithm model has higher reliability and robustness. Manchester et al. [20] used Benchmark to build the benchmark nozzle model for food and drug supervision, and filled the gap of Laminar–turbulent transition through Large eddy simulation. The experimental data confirms that this method can accurately simulate laminar flow rate and simultaneously consider the contribution values of laminar flow and turbulence to shear stress. PCNN has been used in multiple fields, and Han's et al. [21] has proposed an EEG signal preprocessing algorithm, which further combines PCNN to classify various signals, and optimizes model performance by combining spatial filtering and frequency band extraction. The accuracy of the algorithm model trained on the dataset has reached about 83%, and the accuracy evaluation index is also close to 0.7, which has obvious advantages compared to other algorithms.In response to the shortcomings of current vibration based structural loss detection, Yang [22] proposed an end-to-end structural loss detection method that combines parallel convolutional neural networks with bidirectional gated recursive units. The results indicate that this method has better detection performance than other existing methods. When designing a handwriting classification model, Hamida [23] scholardesigned a cascaded feature combination using convolutional neural networks and utilized parallel deep feature extraction methods for design. The results show that the average recognition accuracy of this method exceeds 95%, and the overall loss value is less than 5%. Han [24] scholars use parallel convolutional neural networks for classification of motion signals recognition, combining spatial filtering and frequency band extraction, and optimizing classification performance by stacking sub models. The results show that the average accuracy of this method is 83%, and compared to the comparative algorithm, its improvement level is also over 20%.In summary, the above algorithms based on civil engineering structural damage identification (CESDI), such as DCCN, finite number modal IGA, and CS, all have certain shortcomings. To improve the accuracy of damage identification results and enhance the applicability of the algorithm for identifying objects, the study utilizes machine algorithms to fuse Benchmark and PCNN. Moreover, Continuous Wavelet Transform (CWT) is introduced to obtain an improved algorithm based on ASCE Benchmark CESDI.

III. DESIGN OF DAMAGE IDENTIFICATION BY INTEGRATING BENCHMARK NUMERICAL MODEL AND PCNN NETWORK

This chapter is based on the algorithm advantages of CNN structure, proposes a PCNN network that considers 1D and 2D features based on their input feature differences, and uses it to design a damage identification framework. At the same time, research is being conducted in conjunction with ASCE Benchmark for condition damage identification, to better achieve CESDI detection and provide new means and tools for safety inspection of engineering projects.

A. DESIGN OF CIVIL ENGINEERING STRUCTURAL DAMAGE FRAMEWORK BASED ON PCNN NETWORK

On the basis of CNN, this study proposes PCNN to extract signal multi domain features and network information, transforming the vibration response information collected by the accelerometer in the monitoring structure into an indicator for evaluating structural damage. By locating and identifying it, one can grasp the damage situation and degree. CNN can be divided into one-dimensional CNN (1D-CNN) and two-dimensional convolutional structures (2D-CNN) based on the dimensional differences of input signals. The input data forms of 1D-CNN and 2D-CNN are sequence data and image spectrum data [25]. When CNN performs feature extraction on input data, the "moving window" corresponding to each convolution kernel can be convolved, biased, and feature traversed at a fixed step size to obtain the output feature map. The convolution operation formula can be seen in Eq.(1).

$$x_k^l = f(\sum\nolimits_{j \in Mk} x_j^{l-1} * w_{jk}^{l-1} + b_k^l) \tag{1}$$

In equation (1), x represents the input sample point, x_k^l represents the input of the k-th neuron in layer l, and b_k^l represents the bias parameter of the neuron. ω_{jk}^{l-1} is the convolutional kernel between the j-th and k-th neurons in the $l-1$-layer. $f(\cdot)$ is the Activation function of the convolution layer, and x_k^l is the characteristic diagram of the l layer after convolution output. Convolutional layers, due to their local connectivity, translation invariance, and weight parameter sharing characteristics, can effectively reduce parameter computation and avoid overfitting risks in feature extraction. Common Activation function of CNN include Sigmoid, Tanh, Relu, Leaky Relu and other functions. Fig.1 is a schematic diagram of its function.

In structural damage identification, time-domain signals are the main data type, but the response distribution of the structure is within a wide frequency range. Its damage characteristics are easily concealed in abundant redundant information. Manual extraction methods such as wavelet transform need to be combined with deep learning algorithms to achieve better fault diagnosis. Here, this study proposes to transform this type of time series data into a dimensional matrix and achieve visual expression of time-domain signals. Structural vibrations that are too light or too heavy can have an impact on the stability of the structure. Therefore, based on multi branch feature extraction, combined with the characteristics of vibration acceleration data in Structural health monitoring, and combined with artificial experience feature extraction, an improved network structure P-CNN is proposed. The P-CNN network consists of two parallel network branches, which are used to extract features from 1D time-domain signals and 2D time-frequency maps. P-CNN can effectively extract response features from different scales and time domains, and achieve feature fusion to ensure the

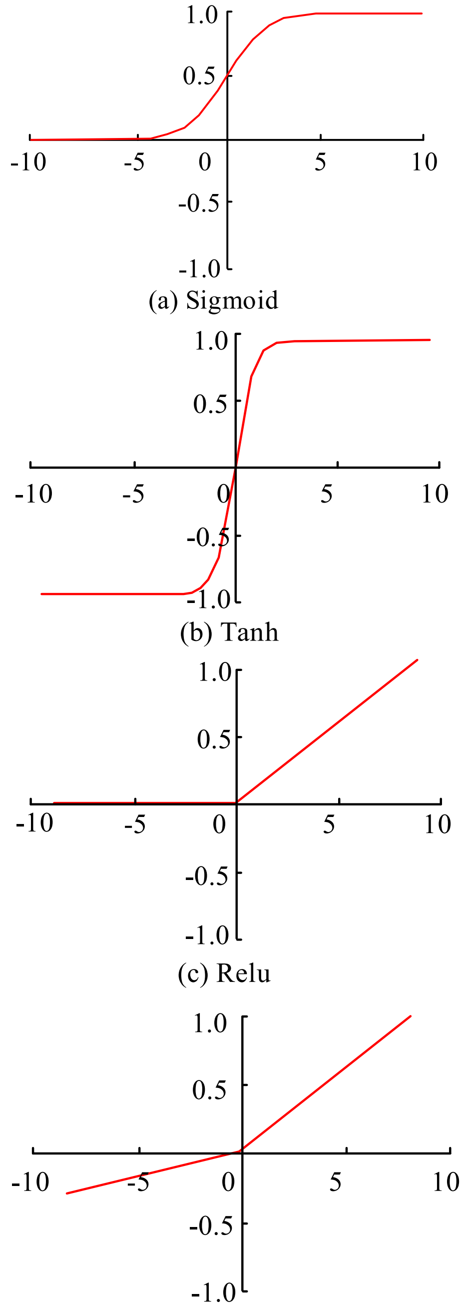


FIGURE 1. Common activation function of CNN.

effectiveness and comprehensiveness of damage information coverage [26]. When designing P-CNN convolutional kernels and network depths, refer to the classic convolutional network LeNet-5. Fig.2 shows the structural diagram of the LeNet-5 network.

To avoid overfitting in the network, research is conducted to improve the model's generalization ability and stability through regularization processing, and different regularizations are designed considering different network situations. L1/L2 regularization is to conditionally limit some

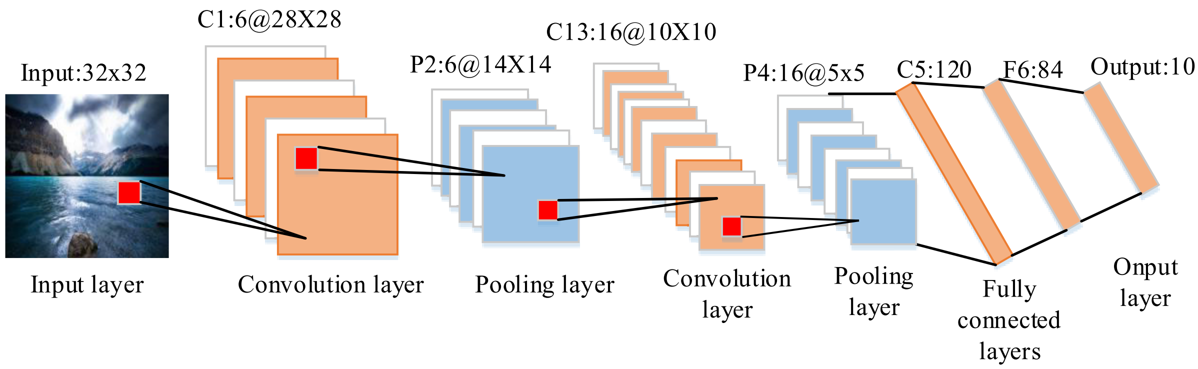


FIGURE 2. LeNet-5 network.

parameters in the Loss function. The regularization calculation formula for L1 is Eq.(2).

$$\begin{cases} LossL1 = LOSS + \lambda \sum_{\omega} |\omega| \\ LossL2 = LOSS + \lambda \sum_{\omega} \left|\omega^2\right| c \end{cases} \tag{2}$$

In formula (2), $LOSS$ represents the original Loss function value, λ represents the regularization coefficient, and ω represents the weight value. The weight update formula for L2 is Eq.(3) [26].

$$\omega' = \omega - (1 - 2\eta\lambda) - \eta \frac{\partial LOSS}{\partial \omega} \tag{3}$$

In equation (3), η represents the learning rate. L1 and L2 regularization are better applicable to Feature selection and multi-dimensional features, and can avoid model precision reduction due to excessive dispersion of model weights. Considering the impact of overly complex deep networks on network computation, Dropout regularization can be achieved by modifying the neural network architecture. Fig.3 is a schematic diagram of Dropout.

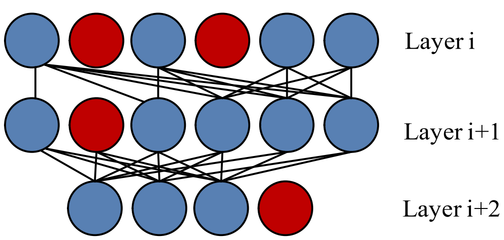


FIGURE 3. Dropout framework.

In the deep learning algorithm, the optimizer that can guide the Loss function will often guide the network parameters to a more appropriate size for selection. The traditional optimizer mainly improves the training performance of the model by optimizing the direction and step size. The common methods are the Gradient descent, momentum mutual love and Adaptive learning rate method. The research introduced the Adam algorithm, which can take into account the mean and square of historical gradients and achieve adaptive parameter adjustment. The square value of the historical gradient (HGSV) in this algorithm can be expressed as Eq.(4).

$$\begin{cases} mt = \beta 1mt - 1 + (1 - \beta 1)gt \\ vt = \beta 2vt - 1 + (1 - \beta 2)gt^2 \end{cases} \tag{4}$$

In equation (4), mt and vt represent the average HGSV attenuation values of RMSprop and Momentum. t represents the number of iterations; gt represents gradient. $\beta 1$ and $\beta 2$ represent the Exponential decay rate estimated by the first and second moments [27]. After HGSV is initialized, it is necessary to perform deviation correction to ensure that it is biased towards 0, resulting in Eq.(5).

$$\begin{cases} \hat{m}t = \dfrac{mt}{1 - \beta 1^t} \\ \hat{v}t = \dfrac{vt}{1 - \beta 2^t} \end{cases} \tag{5}$$

Subsequently, update the parameters and obtain network parameters updated with different iterations. Based on the above description, a schematic framework diagram of PCNN can be constructed, and the results are shown in Fig.4.

PCNN inputs the time series data and time-frequency feature maps reflecting the structural vibration response into the network, and then uses two feature extraction branches, 1D and 2D, to achieve feature extraction. Determine the input sizes for both as 1×1024 and 120×160. The maximum pooling in this network structure can reduce network parameters, and in the second round of pooling, the feature maps are stretched and concatenated into a fused feature vector, which then advances to the next fully connected operation. The dual channel feature extraction advantage of PCNN can achieve excellent classification results. In the process of network iteration, the Learning rate of Adam algorithm needs to be set [28]. A single fixed Learning rate is difficult to lead the model to converge to the best, so the Learning rate attenuation needs to be iteratively processed with the help of the initial Learning rate at the beginning of the training, and ensure that the algorithm model can converge to the best accuracy. The regularization processing method in two scenarios is studied by introducing the Cross entropy Loss function to realize the measurement of the model, so as to ensure that the model output results have a good fit with the real value. Therefore,

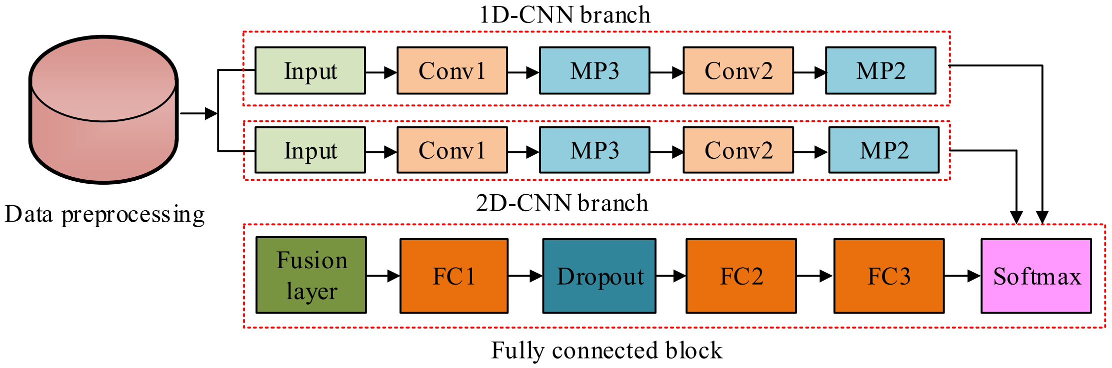


FIGURE 4. Framework of PCNN.

a flowchart of structural loss can be obtained using PCNN (Fig.5).

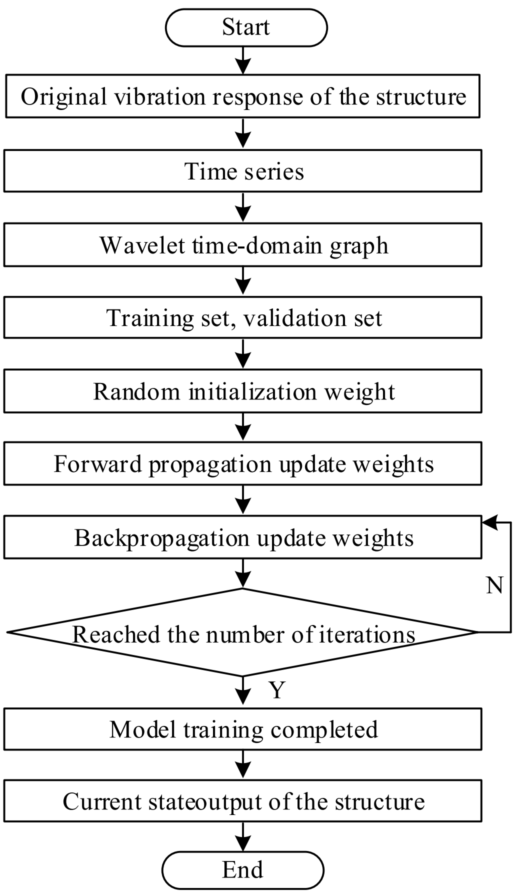


FIGURE 5. Schematic diagram of PCNN network structure loss process.

After the original data samples are standardized, the time series is obtained, and together with the wavelet time domain diagram, the data set is formed. The network processing and model training of the data set can obtain the state of the output structure.

B. ANALYSIS OF STRUCTURAL DAMAGE CONDITIONS BASED ON ASCE BENCHMARK

In depth learning framework, structural loss identification is mostly data driven, but civil engineering structures are subject to more external incentives and it is difficult to collect negative samples, so its data is not Completeness. To ensure the performance of data collection for structural detection, a study is conducted using sliding windows to achieve data augmentation, that is, to achieve non overlapping division of data samples by truncating the length of the sliding window. The rationality of selecting the length of the sliding window will have an impact on the processing of the dataset and the extraction of data information. The study uses Shannon's theorem to determine the window length, and the calculation formula is Eq.(6).

$$I \geq z\frac{fs}{f1} \tag{6}$$

In formula (6), I represents the length of the sliding window, z represents the number of window data points, f represents the sampling frequency, and $f1$ represents the Fundamental frequency of the original vibration response. Standardize feature values of different magnitudes, that is, handle outliers with a zero mean, and the expression is Eq. (7).

$$\begin{cases} xi = \dfrac{xi - \mu i}{\delta i} \\ \mu i = \dfrac{\sum_{j=1}^{N} xi^{(j)}}{N} \\ \delta i = \dfrac{\sum_{j=1}^{N} (xi^{(j)} - ui)^2}{N-1} \end{cases} \tag{7}$$

In equation (7), i represents the dimension, N represents the number of samples in the training set, $xi^{(j)}$ represents the j-th dimension of the jth sample, μi is the estimated mean of the training set, and δi represents the training set and variance. CWT can provide another type of data with typical vibration characteristics based on the temporal variation of signal spectral content, and has good feature representation ability. CWT can select different basis functions as its shape based on the differences in signal characteristics, which can be defined as Eq.(8).

$$CWT(a, b) = \frac{1}{\sqrt{a}} \int f(t)\psi^{*}_{a,b}(t)dt \tag{8}$$

In equation (8), $f(t)$ represents Square-integrable function, a represents scaling function, b represents translation parameter, and $\psi^{*}_{a,b}$ represents complex conjugate of wavelet basis function. The fusion results of two types of signal features under PCNN can be used as the final input of the classifier, and its mathematical formula is Eq.(9).

$$F = [F1d; F2d] \tag{9}$$

In equation (9), $F1d$ represents the 1D time-domain signal feature, and $F2d$ is the feature of the 2D time-frequency map. ASCE Benchmark structure, as a standardized platform for international damage diagnosis, mainly conducts diagnosis and identification based on certain standard structures and damage conditions. This study is based on the MATLAB platform model to simulate the vibration response of structures under different experiments. The simulation model has four floors, two spans in transverse and longitudinal directions. The length, width and height of the plane dimensions of each floor are 2.5m, 2.5m and 0.9m respectively. The number of beam column elements is 48 and 36, and the number of slant support elements is 32. Subsequently, the acceleration sensors were designed in the reference structure layer, and two sensors were installed in both horizontal and vertical dimensions. In the Matlab software model, information is defined on the structural state, damage mode, sampling time, etc. There are five structural states in the Benchmark. The differences between structural states are mainly reflected in model degrees of freedom, mass distribution, and external incentive types.When conducting vibration control analysis on a Benchmark structure, it includes three stages of the building structure. In the first stage, the model mainly consists of two three-layer framework models; The Benchmark model in the second stage is a laboratory model structure; The third stage is the study of nonlinear structural vibration control problems. When researching damage extraction, it is necessary to extract the development interface. It is written in Python language, and when evaluating component damage, the average value of material damage in the area under failure mode is calculated based on the determination of the unit floor, the component described in the unit, and the cross-sectional distance. Subsequently, corresponding damage factors are extracted from the components, and their damage time history is calculated according to the calculation method of damage indicators. The overall damage situation of the components is obtained by weighting the damage indicators.

When evaluating the damage of civil structures, the differences in different constraint conditions and component damage characteristics make the method of simulating and analyzing individual components infeasible. Therefore, in response to this issue, research is conducted to extract methods for damage evaluation, and the damage state index of structural joints is defined as Eq.(10).

$$Pod_i = \frac{D_i}{T_i} \tag{10}$$

In equation (10), T_i represents the total number of signals processed by the joint detection network, and D_i represents the number of signals classified as damaged. Therefore, when the value of Pod_i is 1, it indicates damage to the building joint, and a value of 0 indicates non damage. And define the loss discrimination area formula for bending and bending shear components, as shown in Eq.(11).

$$\begin{cases} Dch = \dfrac{3}{2}Dcm \\ Dw = \dfrac{9}{8}Dcm \end{cases} \tag{11}$$

In equation (11), D represents component damage, Dcm represents the average compressive damage of the material, Dch represents the loss of the connecting beam, and Dw represents the shear wall damage structure. At the same time, in order to ensure that the vibration response damage signals of the structure can be collected, the research introduces the idea of multi task learning to complete the two task models of damage location identification and damage degree judgment. Multi task learning uses an optimizer to jointly train the multi task learning model, determines the Loss function based on the mean square error, and defines other Loss function with the Cross entropy Loss function. The sum of the two Loss function is used to represent the Loss function of the multitask model, and Eq.(12) is obtained.

$$\begin{cases} Loss_1 = \dfrac{\sum_{i=1}^{n} (y_i - y_i')^2}{n} \\ Loss_2 = \sum_{i} p_i(x) \log q_i(x) \end{cases} \tag{12}$$

In equation (12), y represents the true value, y' represents the predicted value of the model, $p_i(x)$ represents the actual distribution of the target, and $q_i(x)$ represents the predicted distribution of the model. Finally, the overall Loss function of the model is expressed as Eq.(13).

$$Loss = \varsigma Loss_1 + \vartheta Loss_2 \tag{13}$$

In equation (13), ς and ϑ represent the Loss function weight of different tasks. Fig.6 is a schematic diagram of the training of the PCNN.

From Fig.6, the joint training multi task learning model can achieve damage localization and damage level diagnosis of the structure at the same time. And the model sharing layer performs shallow feature extraction on the initial vibration response and deep damage sensitivity feature extraction based on specific task requirements. This model can effectively complement multiple tasks, improve the generalization ability of the model, and achieve rapid and comprehensive identification of structural damage. The shared layer part of this network structure uses four convolutional layers for

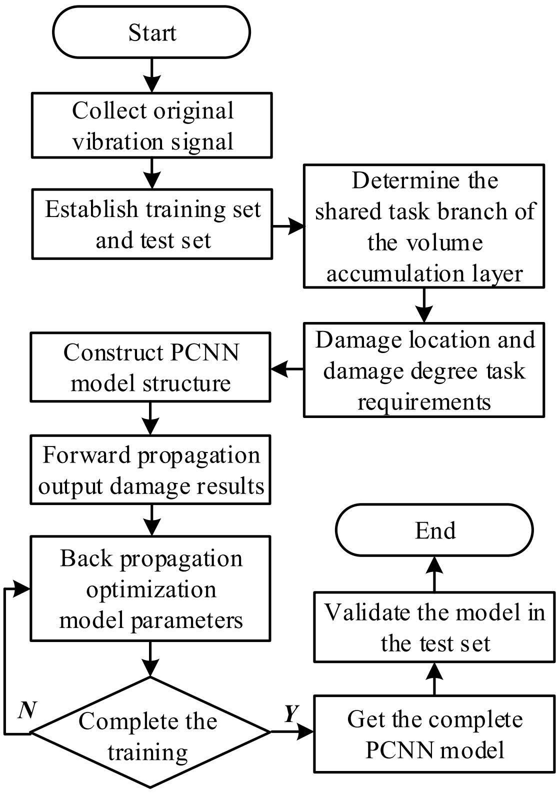


FIGURE 6. Structure training diagram of PCNN.

feature extraction. Among them, the first two levels of convolution use large-scale kernel clusters to obtain more time-domain information, while the latter two levels of convolution use small-scale kernel clusters. The two working branches of damage location identification and damage degree identification can meet the requirements of multi target detection results.

IV. ANALYSIS OF CESDI APPLICATION EFFECTIVENESS UNDER THE FUSION ALGORITHM MODEL

The processor and graphics card models of the computer are InterCorei5-10400F and NvidiaGeForceRTX2060, respectively. Programming in Python language, selecting random library, torch library, and scipy library for data processing and calculation, to achieve the construction of PCNN model. The initial Learning rate in the network model is set to 1e-4, the number of iterations is 200, and the weights and offsets are initialized. The study selected a four story frame structure as the research object for damage analysis, which consists of 4 frame beams, 4 transverse main beams, and 25 longitudinal filled beams. The accelerator is installed on the main beam at 30 joints in the frame, and the structural damage simulation is realized by removing the slant support or loosening the joint bolt for the design node damage on a single beam. Construct a dataset of node damage data under the engineering structure, and divide the dataset into training, validation, and testing sets in a 7:2:1 ratio. Evaluate the damage evaluation performance and generalization ability of the network damage model. The experimental results in the study are presented as the average of ten tests.Firstly, during the experimental process, the performance of the proposed PCNN network fusion algorithm was tested. Set the input feature vector of the neural network to 6 and the hidden layer size to 128, and divide the output classification results into three categories based on the recognition effect of structural damage nodes (good, medium, and poor). Analyze the loss results of the algorithm, as shown in Figure 7.

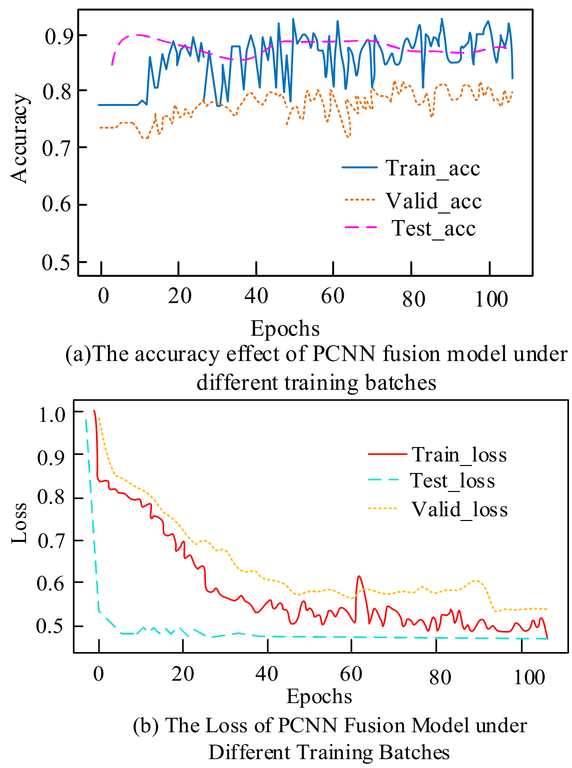


FIGURE 7. Loss results of PCNN network fusion algorithm.

In Figure 7 (a), as the number of iterations increases, the training, testing, and validation accuracy of the PCNN network fusion algorithm shows an increasing trend after more than 20 iterations, and its initial upward trend is the fastest, with a small overall fluctuation range. And the accuracy of the three curves gradually stabilizes after more than 40 iterations, maintaining an accuracy of over 90%. The testing accuracy is basically around 80%, with an average value of 87.12%. And the variation curves of training loss values and test loss values exhibited by the proposed model of the study are less than the effective loss values, indicating that the error results of the model are small. The above results indicate that the effective accuracy of the fusion model is good. From the perspective of its loss results, the larger the loss value, the deviation between the predicted results of the model and the actual results. The larger the deviation, the better the model results can reflect the actual values. The results in the figure indicate that the increase in the number of iterations leads to a rapid decrease in the loss value of algorithm training and testing. Moreover, after the low number of iterations exceeds 80, the model value tends to 0.5, indicating good fitting performance. Subsequently, the ROC(Receiver Operating Characteristic) characteristic curve was used to compare the true positive rate of PCNN in identifying different loss nodes. The results are shown in Figure 8.

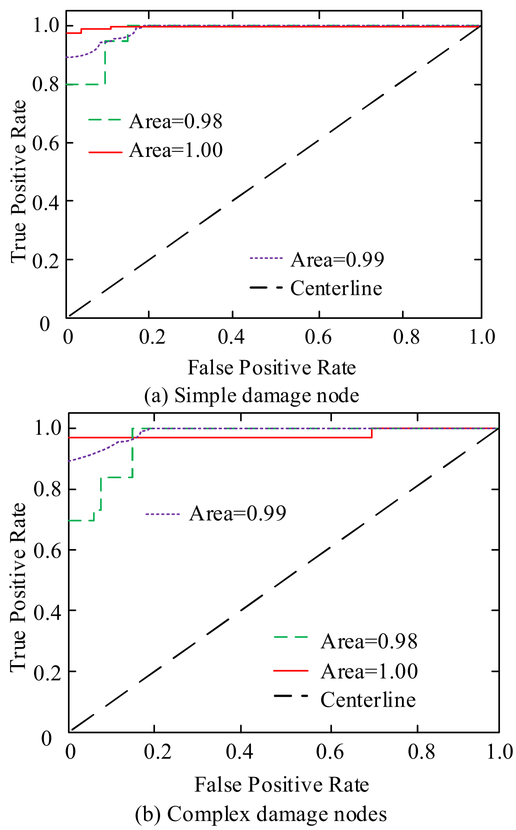


FIGURE 8. Classification results of simple and complex damage nodes in PCNN fusion networks.

AUC (Area Under Curve), as the area enclosed by the coordinate axis under the ROC curve, can better reflect the performance of the classifier. The closer its value approaches 1, the better the performance of the classifier. In Figure 8 (a), the effect curve of damage identification nodes in civil engineering structures shows good true positivity results, and in simple damaged structural nodes, the average classification AUC values exhibited by the PCNN fusion network are 0.98, 0.93, and 0.88, respectively. In Figure 8 (b), the average AUC of the PCNN network structure is also above 0.7. The above results indicate that the network structure exhibits good classification performance and threshold adaptability in civil structure damage identification.During the experimental data collection process, the Hertz frequency of the vibration acceleration signal was determined to be 1024Hz, and the collected signal was extracted using PCNN. The results are displayed in Fig.9.

Fig.9 shows the signal feature extraction results when all slant support are removed. When the slant support is removed, the voltage fluctuation range of the original signal feature is (−0.2,0.26), and its overall node distribution is relatively dense, which makes it difficult to better recognize the signal feature. The signal feature extraction results under PCNN are relatively clear, and the performance of each sample point data varies under different voltages.

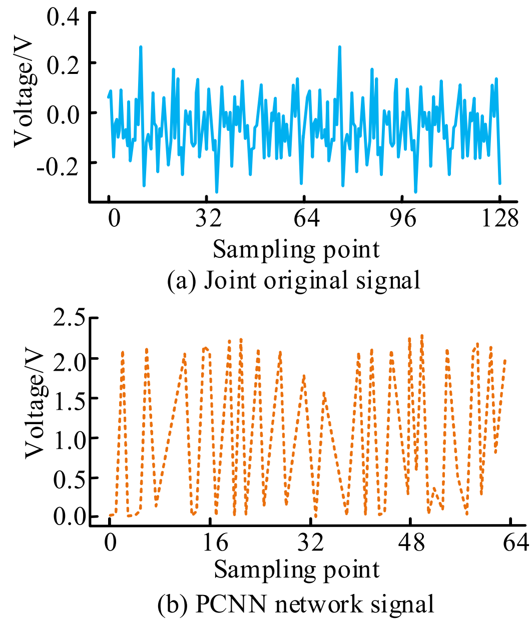


FIGURE 9. Signal feature extraction results after removing slant support.

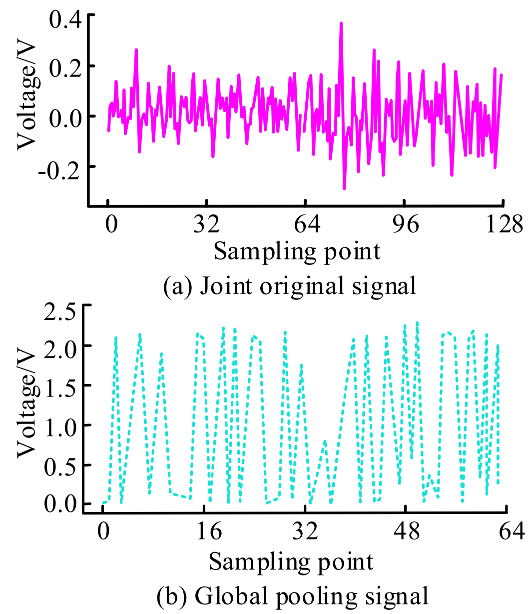


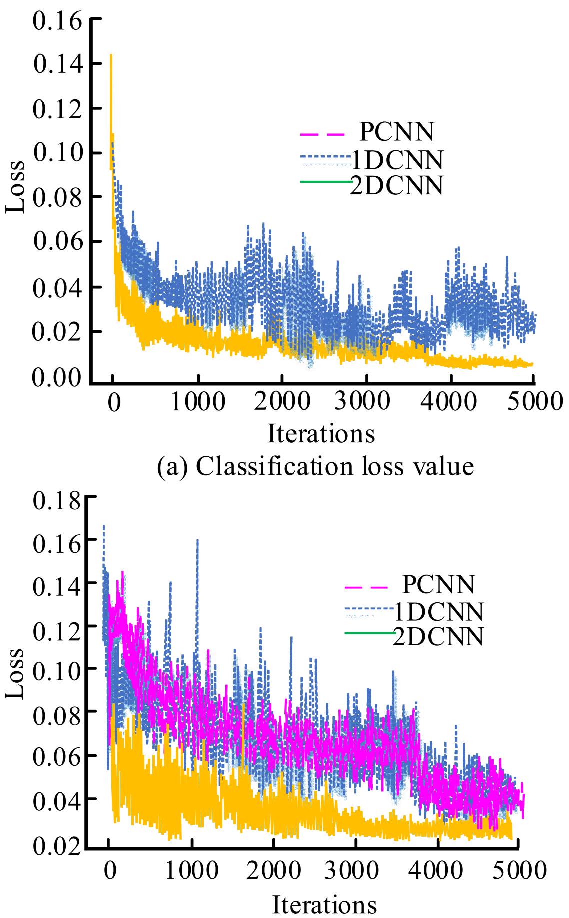
FIGURE 10. Signal feature extraction results after loosening the side beam bolts.

From Fig.10, when the side beam bolts become loose, the maximum voltage of the original damage signal features approaches 0.4, and the minimum voltage is less than 0.2. The overall node distribution is relatively dense. This is

TABLE 1. Model structure experimental parameters.

Data preprocessing	Data enhancement, standardization processing, wavelet transform					
Network Branch	1D feature (time series of 1 * 1024)			2D features (120 * 160 time domain map)		
	Network layer	Convolutional Kernel and Sampling Factor	Dimension	Network layer	Convolutional Kernel and Sampling Factor	Dimension
Feature extraction	CONV1	6@1*5	9*1020	CONV1	6@1*5	6*116*156
	MP1	1*2	6*510	MP1	1*2	6*58*78
	CONV2	16@1*5	16*506	CONV2	16@1*5	16*54*74
	MP2	1*2	13*253	MP2	1*2	16*27*37
Feature connection	Stretch/Tandem					
Feature classification	Fully connected layer 1 (120), fully connected layer 2 (84), fully connected layer 3 (9) regularization (50%)					

significantly different from the nodes with relatively balanced changes in the results of Fig.8(b). PCNN has good application performance. Subsequently, the loss and error situation of the proposed PCNN were analyzed and compared with the 1D and 2D structures of traditional CNN. The results are exhibited in Fig.11.

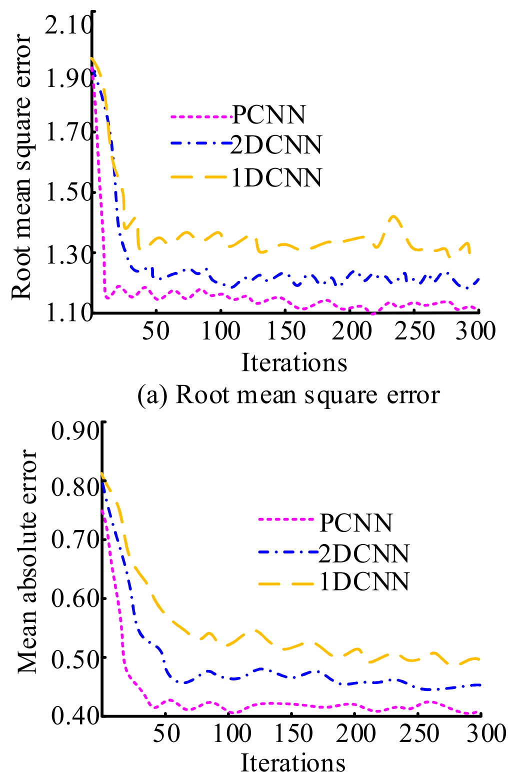


(a) Classification loss value

(b) Regression loss value

FIGURE 11. Classification loss and regression loss results of three network algorithms.

Fig.11 shows that the classification and regression loss curves of the three algorithms show a decreasing trend with increasing iteration times. Specifically, the classification loss value of PCNN decreased from approximately 0.10 to 0.01, 1D-CNN decreased from 0.14 to 0.046, and 2D-CNN decreased from 0.11 to 0.023. Moreover, the node changes in the classification loss curves of 1D-CNN and 2D-CNN are relatively obvious, and are to some extent susceptible to the influence of iteration times. From the regression loss results, the loss value of PCNN gradually stabilizes when the number of iterations exceeds 3000, reaching a loss value of 0.03. In the same situation, 1D-CNN and 2D-CNN showed a sudden drop in algorithm stability after 3800 iterations.



(a) Root mean square error

(b) Mean absolute error

FIGURE 12. Data feature extraction error results of three algorithms.

From Fig.12, the error results of the three algorithms differ significantly. From the trend of the graph, we can see that with the increase of the number of iterations, the Root-mean-square error (RMSE) and the Mean absolute error (MAE) of the algorithm gradually decrease and gradually become stable. Among them, the RMSE and MAE of the PCNN

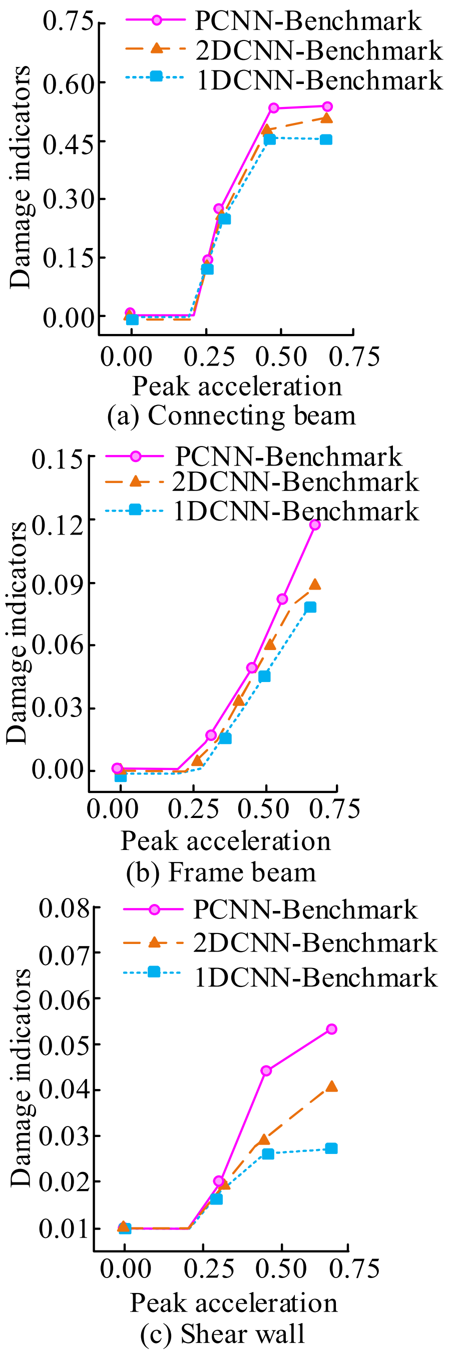


FIGURE 13. Loss Indicator results under different algorithm models.

algorithm are smaller than other algorithms at the same number of iterations, and they gradually tend to 1.10 and 0.40 in the later stages of iteration, with fewer fluctuations. For example, when the number of iterations is 100, the RMSE of the PCNN method tends to 0.40, and the MAE of 1D-CNN and 2D-CNN are 0.46 and 0.55. To analyze the damage feature recognition effect of the proposed PCNN fusion algorithm, the experimental parameter information of the designed model is listed in Table 1.

Subsequently, the mentioned CNN algorithms were imported into Benchmark for damage indicator identification, and the proposed fusion model was analyzed for the overall damage identification results of the components. Fig.13 shows the results.

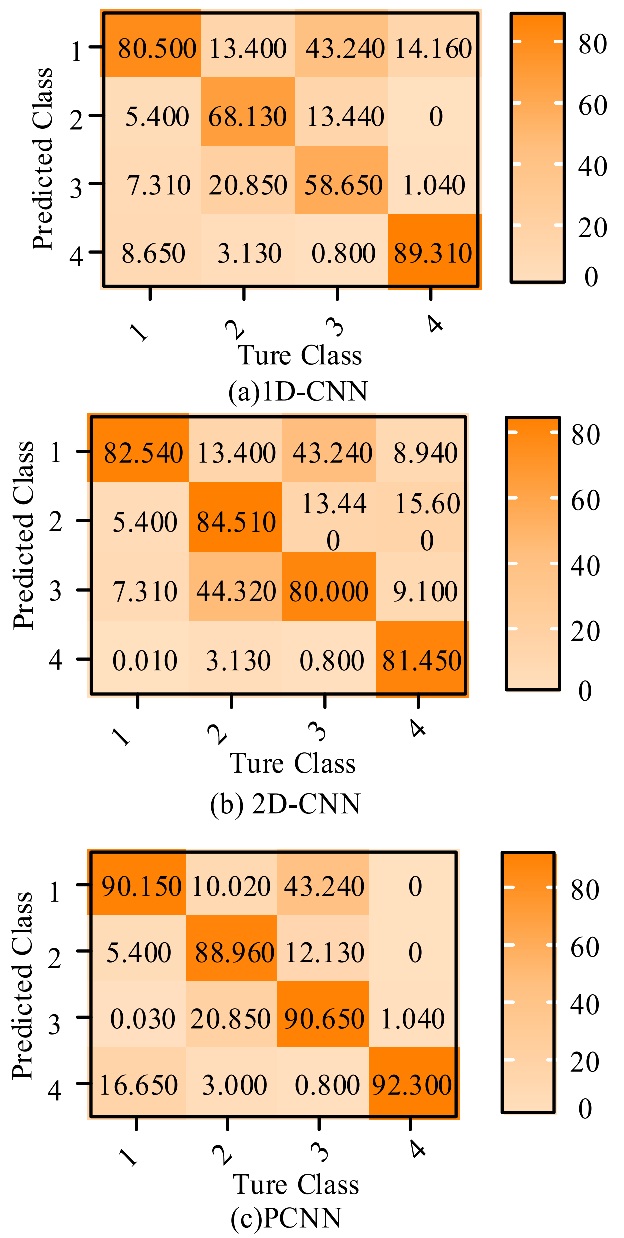


FIGURE 14. Overall damage identification results of different algorithms.

From Figure 13, it can be seen that the three models have different evaluation effects on structural damage indicators. The larger the damage index value, the more effective the model is in identifying damaged nodes. Among them, the PCNN combined Benchmark model has higher damage index values for connecting beams, frame beams, and shear walls than the other two algorithm models. Specifically, in Figure (a), the loss indicator values displayed by the three models of the connecting beam show a trend of first increasing and then slightly decreasing when the peak acceleration exceeds 0.25. The maximum loss value of the PCNN combined benchmark model exceeds 0.5, and its difference amplitude with the 1DCNN-Benchmark model and 2DCNN-Benchmark model reaches 0.03 and 0.05 at a peak acceleration of 0.5. In the frame beam shown in Figure (b), the loss values of the three models before 0.25 are relatively similar, with values around 0. As the peak acceleration increases, the increase in loss exhibited by the three models also varies. Among them, the maximum loss value of the PCNN Benchmark model reached 0.12, while the values of the 1DCNN Benchmark model and 2DCNN Benchmark model were 0.08 and 0.075, with differences of 0.04 and 0.045. This indicates that the PCNN-Benchmark model performs well in damage identification of frame beams. In Figure (c), the loss indication values of the shear wall in the PCNN Benchmark model and 2DCNN Benchmark model show an overall upward trend when the peak acceleration exceeds 0.30. The maximum loss value of the PCNN combined benchmark model exceeds 0.054, which is much greater than the 0.028 and 0.043 of the 1DCNN-Benchmark model and 2DCNN-Benchmark model.Strengthening the detection of CESDI can effectively grasp the damage relationship of different components and prevent it. Then analyze and compare the overall damage identification accuracy of Benchmark, select four joint injuries for loss identification, and use the Confusion matrix to detect the results. The results are Fig.14.

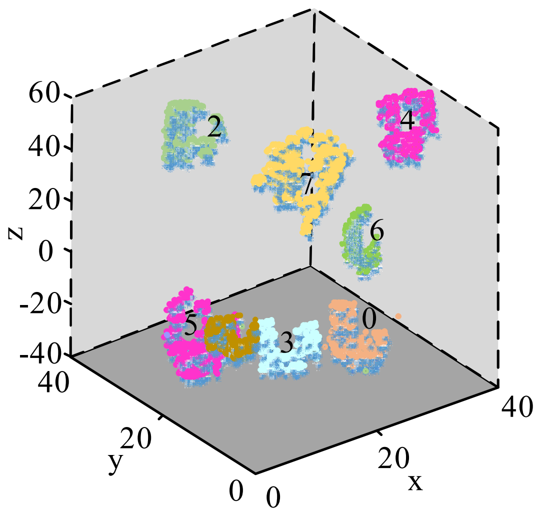


FIGURE 15. Feature recognition performance of PCNN benchmark model.

By comparing the Confusion matrix, it can be seen that the PCNN algorithm can effectively realize damage identification, and its recognition accuracy for selected joint damage exceeds 85%, far higher than 55% and 80% of 1DCNN and 2DCNN. To analyze the visualization results of feature recognition on the PCNN Benchmark model and obtain Fig.15.

The different damage features in Fig.15 have significant clustering recognition effects, due to the algorithm's dimensionality reduction and branch feature fusion being able to effectively classify and recognize experimental data. Therefore, its effectiveness in extracting damage related features from data is significant.

V. CONCLUSION

To better detect CESDI, a damage identification algorithm combining Benchmark and PCNN networks is proposed to better identify damage information in vibration response signals. The performance test and application analysis of the fusion algorithm show that PCNN can better achieve the extraction of signal features under the two conditions of removing all slant support and loosening the side beam bolts; And its loss and error performance in damage classification results is superior to other comparative algorithms. Specifically, the classification loss value of the PCNN algorithm decreased from approximately 0.10 to 0.01, which is much smaller than the 0.14 decrease of 1DCNN to 0.046 and the 0.11 decrease of 2DCNN to 0.023, respectively, and its regression loss is relatively small. When iterating 100 times, the MAE of PCNN tends to 0.40, while the MAE of 1DCNN and 2DCNN are 0.46 and 0.55.In the performance of structural damage feature recognition, when the peak acceleration exceeds 0.25, the PCNN Benchmark model achieves maximum damage indicators of 0.472, 0.117, and 0.055 for connecting beams, frame beams, and shear walls, which are much higher than the 0.468, 0.075, 0.026 of 1DCNN Benchmark and the 0.456, 0.088, and 0.042 of 2DCNN Benchmark. Moreover, the PCNN fusion algorithm can effectively achieve damage identification, with an accuracy of over 85% for selected joint damage identification, much higher than 55% and 80% for 1DCNN and 2DCNN, and has good damage related feature extraction performance. The fusion algorithm has shown good performance in identifying civil structural losses, but there are still some shortcomings. For example, the selected model data are all derived from training data simulation, and the scenario for analyzing operating conditions is relatively single. It needs to be improved in subsequent research.

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