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E-Mail :
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INTEGRATING BENCHMARK NUMERICAL MODEL AND PCNN NETWORK FOR CIVIL ENGINEERING STRUCTURAL DAMAGE IDENTIFICATION

[1]Mohd Khadeer, [2]Dendukuri Vijaya

Abstract: Ensuring the safety and service life of civil engineering projects greatly depends on improving the real-time and precise identification of civil structures. Consequently, the project intends to use deep learning techniques to enhance the availability, safety, and integrity of building structures while decreasing the occurrence of civil structural accidents in buildings. This research combines the Benchmark numerical model with a parallel Convolutional neural network that can detect structural deterioration based on both one- and two-dimensional features. In order to guarantee some coverage of damage feature recognition content, this network topology can efficiently use two parallel branches to extract response characteristics at various scales and temporal domains. Furthermore, the Benchmark numerical model is able to enhance the visualization of identification in civil structure simulations. Results from the fusion algorithm model testing demonstrate that the network structure can successfully extract features from damage signals, with a minimum classification loss value approaching 0.01. As compared to other comparative algorithms, the maximum damage indicators on connecting beams, frame beams, and shear walls reached 0.472, 0.117, and 0.055, respectively. When it comes to structural joint deterioration, the fusion algorithm performs admirably with an identification accuracy of more than 85%. In civil engineering projects, this fusion algorithm can give new ideas and opportunities for relevant researchers to explore, as well as reference value and relevance for developing structural inspection and related risk avoidance plans.

Keywords: Benchmark model, PCNN, civil engineering, structural damage, vibration response signal, CWT.

INTRODUCTION

Machine learning's ability to learn and understand data without human logic makes it a potent tool for evaluating statistical and mathematical models. As processing power has increased and more sensors have been widely used, the amount of data and information gathered by humans has been growing exponentially. Data content analysis and associated feature extraction have so entered popular consciousness and the academic sphere. Two types of structural damage identification exist, based on the differences in their detection goals: broad detection and local detection. The related modal parameters in the structural domain will change when a mechanical system is damaged [1]. In civil engineering constructions, dam-age identification is obviously significant and important. In civil engineering, the safety and dependability of structures are of utmost importance. If there is any kind of damage or defect to a structure, it could collapse. Correctly identifying and evaluating the damage condition is crucial for ensuring the safe operation and longer service life of structures. Damage to civil engineering structures can cause loss of property and human lives. Identifying structures allows for early damage detection and repair activities, which in turn decreases maintenance and replacement costs and ensures the safety of the structure. In

[1,2] Assistant Professor, ACE Engineering College, Hyderabad
[1]khadeer0103@gmail.com, [2]dendukurivijaya9@gmail.com

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addition, damage detection can aid in the evaluation and detection of civil engineering structures, which can aid in the optimization of current structural resources, the enhancement of fund utilization efficiency, and the attainment of maximum economic benefits. In civil engineering, detecting structural deterioration is critical for ensuring the reliability and sustainability of engineering structures. This will provide the field with the scientific groundwork and technical support it needs to thrive. The relationship between structural conditions and civil engineering works is infamously difficult to explain due to the inherent complexity of environmental components and common detection data.

I. RELATED WORKS

The structural parameters of damaged buildings provide proof of damage, and identifying the strengthening system is an essential part of detecting structural health. In order to assess structural variables, Zhang [4] looked at shear-type structures. In addition, he analyzed the structures using frequency domain response construction. In addition to more accurately reflecting the structure's dynamic responsiveness, the suggested non-iterative approach reduces the number of mistake results and the amount of time consumed. By combining the K-means clustering method with the Simulated annealing approach, Ding et al. [5] created a structural damage identification tool. In order to detect structural damage using modal data, this function was employed. Because the initial finite element modeling attempts to detect structural deterioration introduced error and noise, this method was selected as a replacement. This method has less of an impact on structural damage detection, and it is also generalizable and long-lasting. Better still, it has a lower sensitivity to background noise in data. Combining a transfer function with a sequential Extreme learning machine is the technique suggested by Sun et al. [6] to detect impact damage to composite materials. It is possible to identify impact damage using this technique. The structure is input into the neural network after principal component analysis to lessen feature noise. The next step is to pinpoint exactly where the harm is. If you want to know if the building is deteriorating, this method can be very accurate. Guo et al. [7] used an upgraded particle swarm optimization method and wavelet transform to detect and assess the level of structural damage, and they did performance tests in several damage situations.

This approach not only effectively accomplishes structural damage, but it also shows robustness, convergence, and generally stable performance. The anti-directness of evidence theory in structural health detection leads to evidence conflicts. Ding et al. [8] suggested integrating the Dempster combination rule with knowledge priors as a possible solution to this problem. When it comes to space frame structures, this approach has a history of reliability and provides very accurate diagnostics and identifications. Fathnejat [9] cholar offered a more precise method for investigating damage locations and identifying possible structural damage by combining a confusion matrix with a sensitive evaluation index of modal features. Moreover, the GMDH network contributed to the evolution of the modal feature modifications that enhanced damage assessment. Both in terms of the Mean squared error value and its ability to detect and evaluate structural behavior, this method outperforms previous methods. Chen [9] evaluates the probability of different structural problems and performs health monitoring identification to guarantee accurate structural damage detection. The Whale Optimization Algorithm's (WOA) predator mechanism is responsible for this. The weighted modal data and the needs for

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flexibility assurance are also considered. Not only does this approach provide a more efficient tool for structural monitoring, but the results of the numerical simulation also show how accurate this method is in locating damages.The amount of damage to civil and building structures can be determined with the use of an Improved Genetic Algorithm (IGA) suggested by Ramezani et al. [10].

The foundation of this algorithm is a small set of modes. After we took out the algorithm's healthy parts, we added two numerical variables—a two-dimensional truss structure and a three-dimensional structure—to test its recognition capabilities. During the whole performance testing procedure, a cantilever beam model was also used. It is possible that these techniques can significantly reduce noise mistakes, and they can also detect damage quite well. In order to detect damage to civil constructions, Huang et al. [4] used cuckoo search (CS). To mitigate the impact of ambient temperature on vibration frequency prediction, temperature was used as a material quality variable. According to the study's findings, the algorithm is a powerful instrument for detecting temperature changes and damage. A new approach to damage identification using the inverse finite element method was presented by Li et al. [5]. This approach relies on markers of strain age. Strain sensors are used to collect data from building structural calculations, which are then experimentally verified with both single and multiple damage variables. Thanks to the enhancements made to the direct damage index, which now meets the criteria for damage structure identification, this method is now highly practical due to its increased speed and accuracy.

II. PROPOSED METHODLOGY

In most cases, the optimizer responsible for the loss function in a deep learning algorithm will be the one to guide the network parameters toward a more optimal size selection. To improve the model's training performance, the traditional optimizer mainly changes the orientation and step size. Methods like gradient descent, adaptive learning rate, and momentum mutual love are common. This research led to the development of the Adam algorithm, which has the potential to adaptively change parameters by taking into account the square and mean of past gradients.

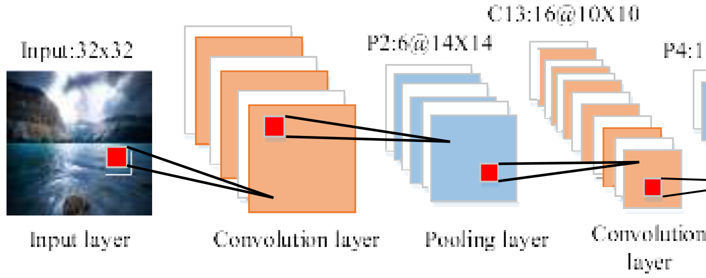

Figure 1: Framework of PCNN.

Valuation of the historical gradient squared in Once you've done that, you may update the parameters to acquire the updated network parameters from all the iterations. Using the information provided above, one may create a PCNN schematic framework diagram; Figure 4 shows the results. In order to extract features, PCNN makes use of two sub-branches: 1D and 2D. It supplies the network with time series data and time-frequency feature maps that depict the response of the structure to vibration. Both 120 160 and 1 1024 are assumed to be input sizes. The network advances to the next completely linked activity after the initial cycle of feature map stretching and fused feature vector concatenation; with this structure, maximal pooling can reduce network parameters. With PCNN's dual channel feature extraction advantage, classification results can be great. As the network iterates, the Adam algorithm's learning rate must be configured. Using a single set learning rate won't get your algorithm model to converge to the best accuracy; instead, you need to process the learning

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rate attenuation using the initial learning rate from the beginning of training again. To evaluate the model and investigate the regularization processing method in two cases, the Cross-entropy Loss function is employed. Doing so ensures that the model's predictions are somewhat near to the true value.

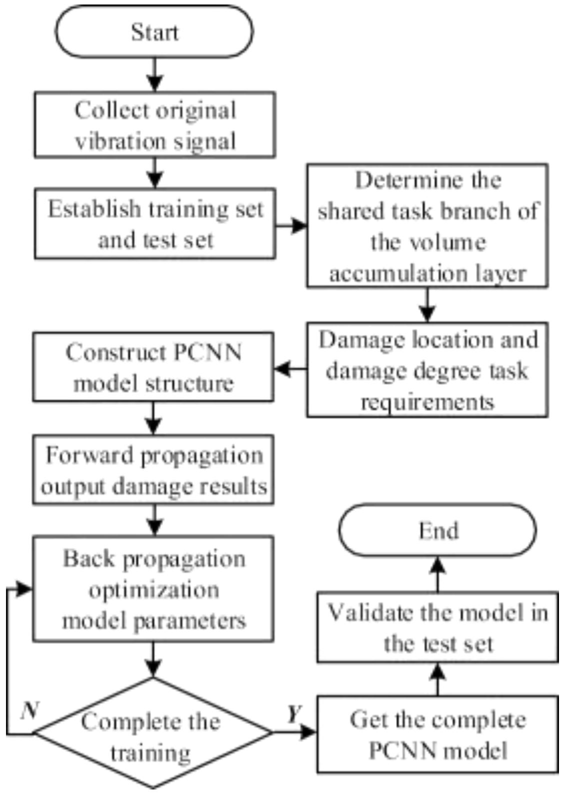

FIGURE 2. Schematic diagram of PCNN network structure loss process.

The real distribution of the target is stated to be pi(x), but the predicted distribution of the model is stated to be qi(x). The variables y and y′, respectively, are used to indicate the actual values of the target and the expected values of the target. It is possible to calculate the loss equation by taking the square root of the total amount of losses in the 1 and 2 indexes.The weights of the Loss function for various occupations are represented by the symbols ς and ϑ. Fig. 2 provides a schematic representation of the PCNN training technique, which may be seen here.

The first thing to do is to choose out features. Large-scale kernel clusters are utilized in the first two convolutional layers in order to obtain a greater quantity of time-domain input. On the other hand, small-scale clusters are utilized in the subsequent two layers. There are two functional branches that are able to handle multi-target detection. These branches are damage location identification and damage degree identification.

III. RESULTS AND DISCUSSION

Figure 3 (a) demonstrates that after 20 iterations, the PCNN network fusion algorithm's training, testing, and validation accuracy all show an increasing trend; the first upward trend is the fastest, and there is a tiny overall fluctuation range. And after forty repetitions, the three curves' accuracy stabilises, staying above 90% the whole time. An average number of 87.12% indicates that the testing accuracy is roughly 80%.

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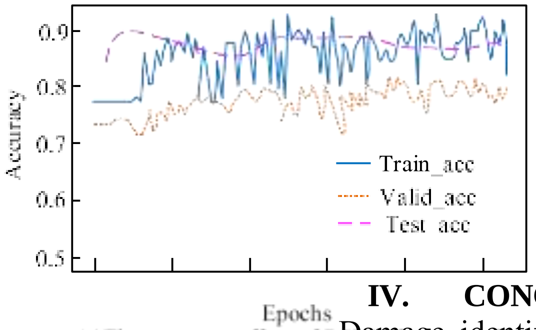
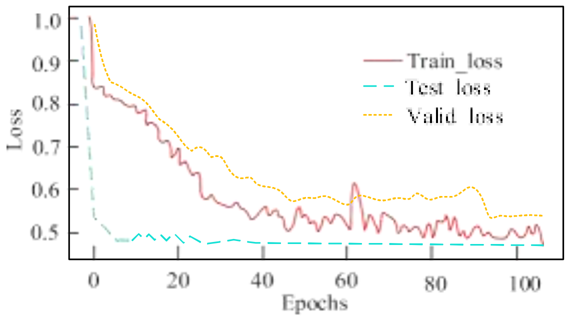


(a)The accuracy effect of PCNN fusion model under different training batches



(b) The Loss of PCNN Fusion Model under Different Training Batches

FIGURE 3. Loss results of PCNN network fusion algorithm.

The study's suggested model shows little inaccuracy in its results since the variation curves of training loss values and test loss values are smaller than the effective loss values. The fusion model appears to have good effective accuracy based on the results shown above. In terms of its loss results, a bigger loss number indicates a more significant discrepancy between the model's projected and actual outcomes. A greater standard deviation indicates that the model's predictions are closer to the true values. Losses during training and testing of algorithms drop precipitously as the iteration count rises, as seen in the figure. In addition, the model value approaches 0.5 after the minimal number of iterations surpasses 80, suggesting high fitting performance. Next, the PCNN's true positive rate for detecting various loss nodes was compared using the ROC (Receiver Operating Characteristic) characteristic curve.

IV. CONCLSUION

Damage identification algorithms that combine Benchmark and PCNN networks are proposed to improve CESDI detection. The program will have a higher chance of deciphering vibration response signals that carry damage information. When compared to other algorithms, PCNN performs better in terms of loss and error in damage classification results. The fusion algorithm's performance test and application analysis show that PCNN can extract signal features under two conditions: removing all slant support; and loosening the side beam bolts. Specifically, compared to 1DCNN's 0.14 reduction to 0.046 and 2DCNN's 0.11 drop to 0.023, the PCNN algorithm's regression loss is minor and its classification loss value dropped from approximately 0.10 to 0.01. After 100 iterations, the mean absolute error (MAE) for 2DCNN is 0.55 and for 1DCNN it reduces to 0.46, while for PCNN it approaches 0.40.At peak accelerations greater than 0.25, the PCNN Benchmark model assigns maximum damage indications of 0.472, 0.117, and 0.055 to connecting beams, frame beams, and shear walls, respectively. Both the

1DCNN Benchmark (0.468, 0.075, 0.026) and the 2DCNN Benchmark (0.456, 0.088, 0.042) have much lower results. With an accuracy of over 85% for identified joint damage and superior performance in damage-related feature extraction, the PCNN fusion technique surpasses 1DCNN and 2DCNN. The fusion method has shown some promise in identifying civil structural damages, but it does have some limitations. For example, all of the selected model data originate from training data simulation, and there is just one scenario for investigating operating settings. Improving it should be the primary goal of future studies.

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