Classification of cracking sources of different engineering media via machine learning

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Abstract

Complex civil structures require the cooperation of many building materials. However, it is difficult to accurately monitor and evaluate the inner damage states of various material systems. Based on a convolutional neural network (CNN) and the acoustic emission (AE) time-frequency diagram, we used the transfer learning method for classifying the AE signals of different materials under external loads. The results show the CNN model can accurately classify cracks that come from different materials based on AE signals. The recognition accuracy can reach 90% just by re-training the full connection layer of the pre-trained model, and its accuracy can reach 97% after re-training the top 2 convolutional layers of this model. A realization of cracking source identification mainly depends on the differences in mineral particles in materials. This work highlights the great potential for real-time and quantitative monitoring of the health status of composite civil structures.

Keywords: Transfer learning; Acoustic emission; Convolutional neural network; Structure damage recognition

1 Introduction

Composite structures made of concrete-concrete, concrete-rock or rock-rock are widely found in civil engineering, such as in underground constructions,[1,2] tunnels,[3] lined rock caverns (LRC).[4-6] During their serving periods, these civil structures are inevitably subjected to the comprehensive effects of environmental erosions (such as high temperatures, freezing and thawing), impact geo-pressure, engineering disturbances (blasting, digging, etc.) and sudden disasters (e.g., earthquakes). Cracks are initiated, extended and accumulated in structures, reducing service performance or even triggering fatal failure.[7,8] Understanding the damage status of structures is critical.

The micro-compositions of different civil materials are various, which makes a material's crack mechanism and related acoustic emission signals different. The acoustic emission (AE) technique is a widely used tool for structural health monitoring (SHM). The principle of AE technique is that infer the cracking behavior of structures via the released AE signals.[9-12] AE signals carry information on the energy, frequency, and coordinates of cracks, which can be used to quantitatively evaluate the damage processes of structures in real-time[13-16]. For example, distinguishing failure mechanisms,[17,18] monitoring damage locations,[19,20] and determining crack types.[21,22] Although various studies have proved that there are significant differences in the AE characteristics of different civil materials,[23,24] it is difficult to identify and cluster AE signals that come from different material systems in real-time. When a material starts cracking, a large number of AE signals is formed. AE signals that come from different material systems are intertwined and collected in the form of a wave-stream. Therefore, it is hard to accurately monitor and evaluate the damage state of composite engineering structures via existing AE techniques from the perspective of on-site application (see Figure 1).

With rapid advances in computer capabilities and sensing techniques over the past decade, machine learning algorithms have been widely applied in civil engineering for numerous tasks, for example, for the prediction of mechanical properties of materials,[25,26] design and analysis of eco-friendly materials,[27,28] and the assessment and warning of accidents in construction.[29,30] As a typical algorithm in machine learning, convolutional neural networks (CNN) have advantages in image recognition.[31] In previous studies, CNN (or improved-CNN) algorithms were used for identifying structural cracks in buildings in combination with advanced image acquisition techniques. For example, to overcome the interference of strong light spots and shadow changes in actual measurements, Cha et al.[32] designed a new method for detecting concrete cracks using the deep architecture of CNN, which does not need to calculate defect characteristics. Kim et al.[33] introduced a CNN-related method for determining the existence and location of surface cracks on concrete structures and built a classification model based on accelerated robust features and CNN. Li et al.[34] proposed a new method for auto-classifying image blocks from 3-D road images using CNN and trained four supervised CNN models with different receiving field sizes (with a classification accuracy higher than 94%). To realize crack detection under complex road conditions, Fan et al.[35] used CNN for learning crack structures from original images without any pre-processing and proposed a strategy to adjust the ratio of positive and negative samples to solve the problem of serious data imbalance. Gopalakrishnan et al.[36] trained deep CNN using the open-source database ImageNet and tried to train the classifier with a combination of HMA-surfaced and PCC-surfaced images with different surface features. To reduce the residual noise generated by the crack edge detection method in binary images, Dorafshan et al.[37] proposed a hybrid method that combines deep CNN and edge detector reducing the noise by 24 times. Park et al.[38] put forward a method that used CNN based on laser sensors, which provides the possibility for real-time monitoring of structural surface cracks. The abovementioned studies significantly contributed to engineering applications of SHM. However, they used data collected by vision techniques, so that only surface cracks could be studied, ignoring inner cracks. In fact, compared with surface cracks, inner cracks have a more substantial effect on the performance, reliability, and service life of structures.

In this paper, we propose a method for identifying in which material systems inner cracks occur via CNN models and AE signals. This method combines the advantages of CNN and AE techniques, while avoiding the respective shortcomings, as discussed above. We proved that this method is reliable through a series of lab experiments. In our experiments, firstly, the AE waveforms of 3 types of concrete and

3 types of rocks were collected during Brazilian split. Then, all AE waveforms were transformed into time-frequency diagrams by wavelet transform. Next, we randomly selected 90% of the AE time-frequency diagrams of the entire database as training data. Afterward, the remaining 10% of the AE time-frequency diagrams were used as testing data to determine the recognition accuracy of the trained CNN model. Finally, the recognition accuracy of the CNN model was analyzed. The proposed method is one of the necessary steps for reaching automation in health monitoring and evaluation of complex civil structures.

2 Experimental apparatus

2.1 Specimen preparation

In this paper, three types of rocks and three types of concretes were used as specimens. The rock blocks (sandstone, dolomite and granite) were collected in Chongqing, Southwest China. The concretes were made from cement, sand and water (different proportions). All concretes were stirred and vibrated to ensure that the specimens are homogeneous and bubble-free, and then maintained in a standard curing room for 28 days. By curing, cutting, and end grinding, disc-shaped specimens with a height-to-diameter ratio of 1:2 were made. According to the recommendations of the International Society of Rock Mechanics (ISRM), the perpendicularity and parallelism of all specimens were controlled to within the range of ±0.02 mm. The physical properties of the testing specimen are as shown in Table 1, where ρ is the density, σ_c denotes the uniaxial compressive strength, σ_t is the uniaxial tensile strength, E is the elastic modulus and v is Poisson's ratio.

2.2 Apparatus

The Shimadzu AGI-250 high-precision material testing machine was used to perform mechanical experiments. With a maximum load of 250 kN and a stiffness of 15 GN/m, this machine can perform uniaxial compression, Brazilian split, three-point bending and other mechanical experiments by force/displacement control loading methods and record stress-strain data in real-time. The accuracies of the measurements for force and deformation are ±0.5% and ±0.1%, respectively.

The *DISP* series of digital AE workstations produced by the American Physical Acoustics Corporation (PAC) was used to identify and collect AE signals during the entire the process of the mechanical experiments. The Nano-30 ceramic-surface AE sensors (produced by PAC) with a resonant response of about 300 kHz and a good frequency response in the range of 125-750 kHz were uniformly fixed on the specimen. The 2/4/6 AE pre-amplifier was used to amplify weak AE signals and improve the signal-to-noise ratio related to cable noise during signal transmission. It was supplied with a gain of 20/40/60 dB (switched to 40 dB in this study). The threshold and pre-amplification were set to 45 dB and 40 dB, respectively, to obtain effective AE signals. The peak defined time, hit defined time and hit lock time were set to 50 μs, 100 μs and 300 μs, respectively.

2.3 Testing procedures

Failure experiments were carried out using the Brazilian split method.[39,40] A schematic diagram of the loading unit, the stress distribution, and a disc-shaped specimen with AE sensor locations were as shown in Figure2a-c, respectively.

The testing procedures are as follows. First, 8 AE sensors were uniformly attached onto the surfaces of the specimen (see Figure2c). Vaseline was applied evenly between the contact surfaces of the specimen and the AE sensors acting as couplant. Then, the specimen was placed into the loading unit, and a slight contact between the piston push rod of the Shimadzu testing machine and the upper loading plate was established. The connectivity of all AE sensors was detected by the lead-breaking method before loading. Finally, we loaded the specimen by displacement mode until failure. The loading rate was fixed to 0.1 mm/min. AE signals were collected during the entire process.

3 Neural network calculation

3.1 Data preparation

Due to different materials containing different particle compositions and composition structures, the AE signals that are generated during the cracking processes of different materials have a specific frequency and amplitude. These frequency and amplitude features are reflected by AE time-frequency diagrams. This is meaningful for identifying which material system the related-cracks occurred in. This process is similar cases in our daily lives: we can easily distinguish whether a sound comes from a fracturing wooden rod or a fracturing plastic rod just by listening. To better cater to the powerful image recognition capabilities of the CNN technique,[31,41] the AE waveforms were transformed into time-frequency diagrams via the wavelet transform method, as shown in Figure 3.

Different materials produce different amounts of AE signals under external stress. To avoid the impact of different numbers of training samples during training on the recognition accuracy, 1300 pictures were randomly selected from composite (7800 pics in total) to form the database. We randomly selected 90% of the database to be the training dataset, and the remaining 10% as the testing dataset (see Table 2). In addition, these images were uniformly processed to 256×256 pixels before being used as input for the CNN model.

3.2 Construction of CNN

3.2.1 VGG16 model and training method

The CNN model VGG16 was used in this work. VGG16 contains 13 convolutional layers and 3 full connected layers (see Figure 4). The convolutional layer obtains the detailed characteristics of the time-frequency diagrams, and the fully connected layer adjusts the weights of the features to obtain a high recognition accuracy. The convolutional layer in CNN is good at extracting complex nonlinear features from the AE time-frequency diagrams and optimizing the parameters (weights and bias) of the convolution kernel during training. The CNN model can effectively extract and learn the detailed features of the diagrams after training.

Although VGG16 has a high potential in image recognition, it requires a high amount of data for model training. In relative terms, the amount of data obtained in our experiment was small, and not enough to fully train the entire CNN model. Therefore, we used the transfer learning method for training a pre-trained VGG16. The learned features in the pre-trained model were transplanted to different tasks, which is called transfer learning.[42-45] Specifically, VGG16 was pre-trained by massive images to obtain many general image recognition abilities, such as recognition of edges, areas, stripes, and colors. Therefore, we only needed to train the last 2 convolutional layers and 3 fully connected layers using the AE time-frequency diagrams obtained in our experiments. The advantages of the transfer learning method make it very effective to use VGG16 for solving small data tasks.

3.2.2 Parameter optimization

The back-propagation algorithm was used in the VGG16 model for parameter optimization. The specific optimization process included the following 4 steps[46,47]:

1) Forward propagation: Input training data into the model. Connect adjacent layers of the network to each other according to Equation 1 and send them to the output layer after the calculation. Then, output the results.

$$a_j^l = \sigma\left(\sum_k w_{jk}^l a_k^{l-1} + b_j^l\right) \tag{1}$$

where a_j^l is the output result of the j^{th} neuron in layer l; $\sigma(x)$ is the activation function; w_{jk}^l is the weight of the j^{th} neuron connected to the network in layer l by the k^{th} neuron in layer (l-1); b_j^l is the bias of the j^{th} neuron in layer l.

2) Calculate loss value: The loss value is obtained by comparing the network output results with the real results. In this work, "sparse_categorical_crossentropy"

was used for calculation, which is shown in Equation 2.

$$loss = -\sum_{i=1}^{n} \hat{y}_{i1}\log y_{i1} + \hat{y}_{i2}\log y_{i2} + \cdots + \hat{y}_{im}\log y_{im} \quad (2)$$

where n is the number of samples , m is the number of categories. y_i is the real result, and $\hat{y}_i$ is the predicted result.

3) Loss value back propagation: According to the calculated loss value, the loss value generated by each layer of a network is calculated from back to front based on Equation 3.

$$\delta^{l} = ((w^{l+1})^{T}\delta^{l+1}) \odot \sigma'(z^{l}) \quad (3)$$

where δ^{l} is the loss value generated in the l^{th} layer; w^{l+1} is the weight matrix in the $(l+1)^{th}$ layer; $\sigma'(z^{l})$ is the result output in the l^{th} layer; $\odot$ is the Hadamard product, which is used for point-to-point multiplication between matrices.

4) Parameter optimization via gradient descent method: The parameter optimization includes weight optimization and bias optimization. Putting Equation 3 into Equations 4 and 5, we can calculate the gradient descent of the weight and bias.

$$\frac{\partial C}{\partial w_{jk}^{l}} = \frac{\partial C}{\partial z_{j}^{l}} \cdot \frac{\partial z_{j}^{l}}{\partial w_{jk}^{l}} = \delta_{j}^{l} \cdot \frac{\partial (w_{jk}^{l} a_{k}^{l-1} + b_{j}^{l})}{\partial w_{jk}^{l}} = a_{k}^{l-1}\delta_{j}^{l} \quad (4)$$

$$\frac{\partial C}{\partial b_j^l} = \frac{\partial C}{\partial z_j^l} \cdot \frac{\partial z_j^l}{\partial w_j^l} = \delta_j^l \cdot \frac{\partial (w_{jk}^l a_k^{l-1} + b_j^l)}{\partial b_j^l} = \delta_j^l \tag{5}$$

Therefore, we obtained the weight gradient $a_k^{l-1}\delta_j^l$ of the k^{th} neuron in the $(l\text{-}1)^{th}$ layer that is connected to the j^{th} neuron in the l^{th} layer. δ_j^l is the bias gradient of the j^{th} neuron in the l^{th} layer. Also, we can calculate the updated parameter matrix by adding the original parameter matrix and the gradient matrix. Using the above-mentioned calculations, the optimal parameters can be obtained after several iterations of the network.

3.2.3 Feature extraction

CNN can extract the time series characteristics of AE parameters such as amplitude and frequency. The implementation process of the data feature extraction is as follows (see Figure 5): three convolution kernels are applied to sequentially obtain the brightness features, range features, and strip features, which correspond to the information on the energy magnitude, energy range and frequency range, respectively. When performing convolution calculations, data information similar to the features of the convolution kernel will be amplified. After a series of convolution operations on the data set, it will output feature data with the same number of convolution kernels. Each datapoint can show the information of that feature is enlarged. Then the it will be input into the next convolution operation. After continuous convolution processing, the feature information of the data is continuously enlarged, the size is continuously reduced and the field of view of the convolution kernel is continuously expanded. Finally, stable classification features are obtained and input into the fully connected layer for classification. The image convolution process can be expressed by Equation 6:

$$(f \otimes g)_{ij} = \sum_{m=1}^{m} \sum_{n=1}^{n} \sum_{c=1}^{c} f_{m,n,c} g_{m,n,c} \tag{6}$$

where f is the area of an image that is as large as the convolution kernel. g is the convolution kernel. m, n and c represent the pixels in the m^{th} row and n^{th} column in the c^{th} image channel, respectively.

It should be pointed out that after a series of convolution operations, feature data information similar to the convolution kernel is amplified, and non-similar feature information is suppressed. However, the suppressed information has not disappeared, and still consumes computing resources. Therefore, a pooling layer is used to remove the suppressed information and only retain the main feature information. As shown in Figure 5, the main information of the image is not lost after the pooling layer processing. This method is very helpful in reducing computational cost, while also preventing overfitting. Therefore, based on the feature extraction capabilities of CNN, it will be able to effectively extract AE signal features from time-frequency diagrams after supervised training.

In the VGG16 network, 13 convolutional layers are divided into 5 groups. These convolutional layers can sequentially extract image details and macro-features, and the fully connected layer integrates all features for classifying the AE type. Therefore, in transfer learning the part of the convolutional layer is generally retained, and the fully connected layer is trained for specific problems to achieve image classification weight training, and then, a stable fully connected layer (classification function) is obtained. If the ideal classification effect cannot be obtained based on the classification function, the top 2 convolutional layers of the pre-trained network are trained to obtain the characteristics of the broad features of the AE time-frequency map. At the same time, the pre-training network for image detail feature extraction is retained, which in turn helps with providing the image recognition effect of the network. We added a softmax layer as a classifier to the new network for solving a multi-classification problem.

Loss functions are critical for model training. They are used to quantify differences between the model predictions and the real objects. Loss functions are the basis for adjusting the training weight and bias of the CNN model. In this work, the “sparse_categorical_crossentropy” was applied. Compared with the calculation methods of other loss functions (e.g., the “squared_difference”), this method can amplify the value of the loss function when the prediction results deviate greatly and improve the convergence speed of the network.

To improve memory utilization and operating efficiency, we set the batch size to 32 during the training process. Model validation was carried out at each epoch after model training. In contrast to during training, in the testing process, only the test set (after normalization) was fed to the classifier to compute the categorical_crossentropy and prediction accuracy without model optimization. The result of the value of the validation loss was used as criterion for ending the training process. If the value of the validation loss no longer dropped and remained stable, the training was ended. The model with the minimum value of validation loss was taken to be the optimal model and selected.

4 Results and Analysis

4.1 Recognition accuracy

The recognition accuracy of different training stages was separately evaluated in this paper. In the first stage, all convolution layers are locked (pale blue layers in Figure 4) and only the fully connected layer is trained. The recognition accuracy of the CNN model after the first training stage is shown in Figure 6. The recognition accuracy of the model reached 90% after 12 epochs, which was approximately maintained after subsequent training. However, a higher recognition accuracy could not be achieved because the selected parameters of the broad vision layers were not perfectly suitable for the AE time-frequency diagram classification task. This indicates that the parameters need to be further optimized.

The second stage consisted of training the top 2 convolutional layers of the VGG16 and making the CNN model more suitable for the time-frequency diagram classification task. Finally, the pre-trained fully connected layers of the VGG16 model were trained for a further 50 epochs. All training data was obtained from the AE time-frequency diagram database gathered in our experiments. The recognition accuracy of the CNN model after the second training stage is shown in Figure 7. After opening the top convolutional layer, the trainable parameters of the CNN increased largely. Consequently, it can be seen that the recognition accuracy increased rapidly. Lastly, the recognition accuracy stabilized at 97%. Only a small part of the AE time-frequency diagrams could not be identified, which is because the related cracks were too similar.

4.2 Pairwise comparison

To find the factors that restrict the recognition accuracy of the CNN model, 15 types of pairwise comparisons were carried out. Firstly, the fully connected layers were trained for 30 epochs. After the recognition accuracy had stabilized, the top 2 convolutional layers of the pre-training network were trained for 50 epochs. The loss function used for the binary classification problem was the "binary_crossentropy" and its expression can be expressed as in Equation 7.

$$C = -\frac{1}{\text{output size}} \sum_{i=1}^{\text{output size}} y_i \cdot \log \hat{y}_i + (1 - y_i) \cdot \log(1 - \hat{y}_i) \tag{7}$$

where C is the loss value, y_i is the real result, and $\hat{y}_i$ is the predicted result.

The recognition accuracy and loss values of the CNN models for all pairwise comparisons are shown in Figure 8. It can be seen that the recognition accuracy of the CNN model rapidly increased with an increase in the number of training epochs. From the 30th epoch, the convolutional layer started to be trained, so that the loss value suddenly increased. After 1-2 epochs of training, the loss value decreased to the normal trend due to the weight automatically being adjusted after the back-propagation.

The recognition accuracy by the trained fully connected layers (the first 30 epochs) for dolomite-granite (DL-GN) and sandstone-dolomite (SS-DL) reached over 95%. The recognition accuracy reached more than 99% after training the convolutional layers (the next 50 epochs). However, the recognition accuracy of CNN models for concrete was relatively lower. For instance, the recognition accuracy of CS1:1 and CS2:1 just reached about 88% after the first 20 epochs and 94% after the next 50 epochs. In the training processes, all CNN model eventually produced over-fitting. The recognition accuracy of the network reached an upper limit. Figure 9 shows the final recognition accuracy of the CNN model for all pairwise comparisons.

4.3 Reliability evaluation

Although the CNN model indicates the recognition results of the testing dataset, the reliability of the results still needs to be evaluated. In the process of CNN model recognition, the model firstly gives a prediction probability. Then, the classifier outputs the recognition result according to the training dataset and the prediction probability. Different classifiers will lead to different numbers of TP (True Positive) samples and FP (False Positive) samples. Based on this, TPR (True Positive Rate) = TP / (TP + FN) and FPR (False Positive Rate) = NP / (NP + TN) can be applied.[48]

A Receiver Operating Characteristic (ROC) curve is drawn according to the TPR value and the FPR value (see Figure 10). In the ROC graph, the location of point “O” represents the point at which the true positive rate is equal to the true negative rate. The distance between point “O” and point (0, 100) is called EER (equal error rate).

The lower the EER value, the higher the reliability. The closer the OB segment is to the top axis, the higher is the sensitivity of the model as well as the stronger is the classifier’s ability to recognize positive cases. The closer the OA segment is to the left axis, the higher the specificity of the model as well as the better the classifier’s ability to recognize negative cases.

The advantage of the ROC curve is that the quantity distribution of positive and negative samples will not affect its shape. Therefore, this evaluation tool can reduce interference caused by using different testing datasets and measure the performance of the CNN model itself more objectively. The specific evaluation results via ROC curve are shown in Figure 11. For instance, it can be seen that the EER of the model of dolomite-granite (DL-GN) is small, which corresponds to the high recognition accuracy. All ROC curves of CNN models exhibit a good sensitivity and specificity, which indicates that the results determined with the transfer learning method have a high reliability. At the same time, the sensitivity and specificity of the recognition results of the models still vary. For example, in the ROC curves of CS2:1-GN, the curve did not fully fit the top axial, indicating that this model misrecognized the cracking AE signals of CS2:1 as the cracking AE signals of granite. In relative terms, the EER between concrete recognition results is slightly bigger. For example, the ROC curve of PC-CS2:1 is at a certain distance from the top and left axes, which indicates that the reliability of the model’s recognition result is slightly lower.

The AUC (area under curve) value represents the area between the ROC curve and the lower axis, which intuitively reflects the recognition reliability of the model.

The evaluation results of the model's recognition reliability are shown in Figure 12. From Figure 9 and Figure 12, it can be seen that although the CNN model has the lowest recognition accuracy for PC-CS2:1, it also achieves an accuracy of over 94% and a reliability of over 95%. This indicates that the proposed method for classifying the cracking sources of different engineering media via machine learning is reliable.

4.4 Mechanism analysis

In fact, there are many differences in mineral particle micro-structures between different kind of engineering materials, regardless of whether they are natural geo-mediums or man-made concretes (see Figure 13). We believe that these micro-structural differences cause significantly diverse cracking AE signals in different kinds of materials. For example, CNN has a very high recognition accuracy for GN-Others (over 99%), which indicates that the AE signals produced in granite are significantly different from those in other materials. It reflects that the mineral and structural composition of granite are quite different from those of other rocks or concretes used in this study, which is visualized in Figure 13.

However, the recognition accuracy of the CNN model for PC-CS2:1 and CS2:1-CS1:1 is relatively lower (94.1% and 94.9%, respectively), indicating that there are small parts of the cracking AE signals that are too similar for a CNN model to be able to distinguish between. The main reason is that PC, CS2:1 and CS1:1 have similar micro-components and manufacturing procedures. The first pairwise comparison with an accuracy recognition of higher than 95% is PC-SS (Figure 9). The SEM observation of PC-SS is shown in Figure 14. It can be seen that there are significant differences in the compositions, sizes and shapes of the mineral particles.

In contrast, the results discussed above also reveal that the recognition accuracy of the CNN model can also reflect similarities in cracking generation. Waveforms produced by materials with the same mineral composition are similar. Furthermore, the smaller the differences in composition, the more similar the waveforms are and the lower is the recognition accuracy of CNN.

5 Conclusion

Based on the VGG16 CNN model and the time-frequency diagram obtained using the AE technique, the transfer learning method is used to classify cracking sources from different engineering media (rocks and concretes). The high recognition accuracy of classification is achieved. The following conclusions can be reached:

(1) Transforming AE signals into time-frequency diagrams through wavelet transform can make full use of the image recognition capabilities of the CNN model. This method can assist the CNN model in monitoring the formation of cracks inside a structure in real time.

(2) Different types of engineering materials have different mineral particles and micro-compositions, so that their time-frequency diagrams of AE signals generated during the cracking process are also quite different. This physical mechanism makes it possible for CNN models to be trained and to recognize/classify the cracking sources of bi- or multi-material mixed engineering structures.

(3) The trained CNN model can recognize the AE signals of rocks and concretes well, with a classification accuracy higher than 97.3%. The recognition accuracy for a

concrete-concrete system is a little lower (the lowest is 95.3% for PC-CS:1). The recognition accuracy is directly related to the degree of difference in the micro-structures of the materials.

Declaration of Interest

The authors declare that there are no known conflicts of interest.

Credit authorship contribution statement

Jie Huang: Investigation, Data curation, Formal analysis, Writing-Original Draft. **Qianting Hu:** Resources. **Zhenlong Song:** Conceptualization, Investigation, Resources, Methodology, Data curation. **Gongheng Zhang:** Investigation. **Chaozhong Qin:** Resources, Writing-Review & Editing. **Mingyang Wu:** Investigation. **Xiaodong Wang:** Formal analysis.

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