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An improved post-hurricane building damaged detection method based on transfer learning

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ABSTRACT

After a natural disaster, it is very important for the government to conduct a damaged assessment as soon as possible. Fast and accurate disaster assessment helps the government disaster relief departments allocate resources and respond quickly and effectively to minimize the losses caused by the disaster. Usually, the method of measuring disaster losses is to rely on manual field exploration and measurement, and then calculate and label the damaged buildings or land, or rely on unmanned collections to remotely collect pictures of the disaster-stricken area, and compare the original pictures to carry out the disaster annotation and calculation. These methods are time-consuming, labor-intensive, and inefficient. This paper proposes a post-hurricane building damage detection method based on transfer learning, which uses deep learning image classification algorithms to achieve post-disaster satellite image damage detection and classification, thereby improving disaster assessment efficiency and preparing for disaster relief and post-disaster reconstruction. The proposed method adopts the theory of transfer learning, establishes a disaster image detection model based on the convolutional neural network model, and uses the 2017 Hurricane Harvey data as the experimental data set. Experiments have proved that our proposed model accuracy of disaster detection reaches 97%, which is 1% higher than other models.

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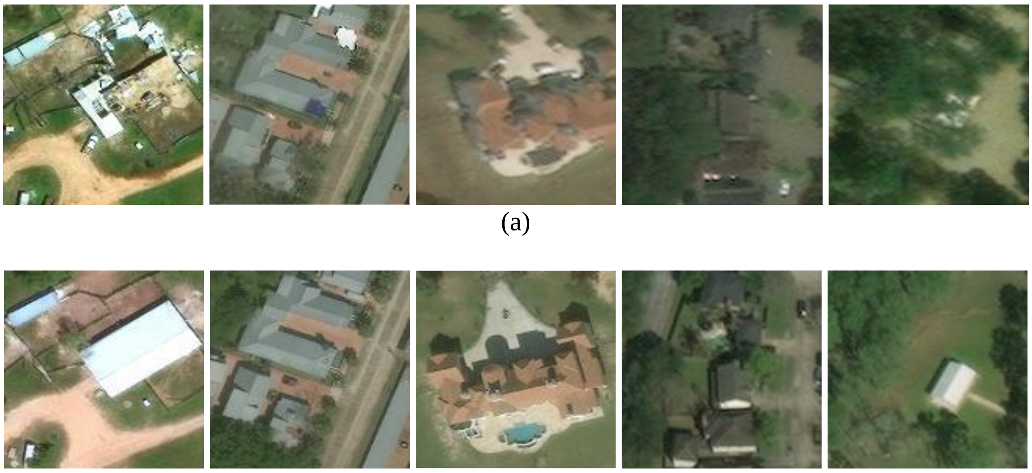
1. INTRODUCTION

When natural disasters (such as hurricanes and floods) occur, quickly and accurately assessing the damage caused by the disaster is the primary task of the emergency rescue department. It can provide a basis for the reasonable allocation of disaster relief resources and minimize the personnel caused by the disaster casualties and economic losses [1]. Traditional disaster loss assessment is usually based on satellite remote sensing images or images of the disaster area collected by unmanned aircraft for manual judgment and labeling [2]. Using traditional methods is not only time-consuming, but will also result in frustrating accuracy. In recent years, the application of machine learning has achieved great success in satellite remote sensing, medical imaging, and other image processing with the in-depth development of machine learning (ML) technology [3], [4]. Machine learning technology is used to establish a neural network model, and the neural network model is trained through the correctly labeled data set in advance, and then trained model is used to judge and predict unlabeled samples. Using machine learning to solve image recognition and classification problems can significantly improve work efficiency and improve classification accuracy. Figure 1 shows the satellite remote sensing image of buildings damaged after the hurricane, Figure 1(a) shows the damaged building image after the hurricane, and Figure 1(b) shows the normal building image.

The research on building damage assessment after natural disasters has a long history, but there are not many efficient and straightforward methods. Yamazaki [5] discussed using the color index and edge elements in damage classification. Adams *et al.* [6] and Matsuoka *et al.* [7] involve using edge-based metrics to analyze texture differences. Sampath [8] proposed a disaster detection method based on image grayscale statistics. Chen *et al.* [2] proposed a framework for damage pattern mining in hurricane image databases (DPMHIDB). This method uses image segmentation and annotation methods to label and index the damaged building images in the hurricane image database, search, query, and finally return the query results. This method is a semi-automatic disaster detection method. Barnes *et al.* [9] proposed a system-level method to classify buildings' damaged images after a disaster. This method is an image-driven data mining technology with a Sigma number structure. The modified method has proven to be very useful, but the premise is that it needs to be labeled and classified based on high-resolution satellite remote-sensing images. In the past decade, methods based on texture and statistics have been used for damage detection. Chen and Hutchinson *et al.* [10] used wavelet feature extraction to enhance the physical signs proposed by Womble *et al.* [11]. Vijayaraj *et al.* [12] use correlation analysis, principal component analysis and extract the roof boundary tightness index. Sirmacek and Unsalan [13] use local binary pattern (LBP), local edge pattern (LEP) and Gabor texture features calculated on pixels and pixel blocks. Thomas *et al.* [14] used the difference in shadow length as an indicator of damage, and used the ratio of roof area to shaded area as an indicator of damage. These works are all based on image pixels, and only provide information about image patches that may have been changed, without detailed analysis of the nature of building roof damage, and no deep-level features of the image. Therefore, these methods have certain limitations, and the reliability of damage detection is very low.



(a)

(b)

Figure 1. Example of Examples of satellite remote sensing images (a) images of buildings damaged post-hurricane and (b) images of normal buildings

With the leap-forward development of artificial intelligence (AI) technology, deep learning (DL) models for disaster detection have achieved particular success, especially the use of neural network models to achieve image feature extraction and classification problems have achieved significant results. Inspired by the damage detection method proposed by Cao and Choe [1] and Thomas *et al.* [15], this paper proposes an improved post-hurricane building damage detection method based on transfer learning, which can quickly realize post-disaster building. The classification and labeling of damaged images of objects provide a scientific basis for rescue and disaster relief. The method is mainly divided into three steps. First, data preprocessing. For the purpose of the validity of the model and improving its performance, satellite remote sensing images of the disaster-stricken area will be obtained for screening processing, that is, invalid images such as incomplete images and images of buildings blocked by clouds will be removed. Second, feature extraction. In this stage, the model is mainly used to extract the building's damaged features in the image, such as the main features with the roof incomplete and the building being surrounded by floods. Finally, damage evaluation. The satellite remote sensing image is judged and annotated through the building damage detection model. The post-hurricane building damage detection method proposed in this paper is based on the convolutional neural network (CNN) model in machine learning. Since image feature extraction procedures are very critical, the method of transfer learning (TL) is introduced and used in the large image dataset ImageNet [16]. The pre-trained neural network model such as VGG16 [17] can realize feature extraction. In the actual modeling process, we have improved and fine-tuned the VGG16 network to adapt to the image processing task of building damage detection after the hurricane. The improvement method and fine-tuning will be introduced in the third part. The main contributions of this paper are as follows.

Firstly, an improved detection method for post-hurricane building damaged is proposed. This method can quickly and efficiently label and classify satellite remote sensing images of damaged buildings, and provide a scientific basis for decision-making and reasonable allocation of disaster relief resources. Second, through the establishment of a neural network model, a time-consuming and laborious disaster assessment problem is resolved into an image classification problem, which realizes the application of machine learning technology to the real topic of natural disaster assessment.

The rest of the paper is organized as follows. Section 2 will introduce related work, including CNNs introduction, image classification techniques, and transfer learning. Section 3 is building damage detection method description. Section 4 is the experiment. The last is the conclusion.

2. RELATED WORK

2.1. CNN

LeCun *et al.* [18] proposed the CNN network in 1998. The CNN network was created to simulate the information transmission method of biological neural networks using local links and shared weights. The CNN network is a multi-layer perception. The advantage of the CNN network is that, on the one hand, it reduces the number of weights and makes the network easier to use and optimize. On the other hand, it reduces the complexity of the model while suppressing model overfitting. In processing image classification tasks, CNN has more obvious advantages than traditional image processing methods. CNN simplifies the complexity of feature extraction and data reconstruction in image processing algorithms, such as image displacement recognition, scaling, distortion, texture and other features, and has high computational efficiency and good robustness.

Convolutional neural networks are a subset of machine learning and are one of the artificial neural networks used in different applications and data types. CNN is also a network architecture of DL algorithms. Because CNN models are easy to build and deploy, they are widely used in image recognition and pixel-level data processing tasks. The CNN network mainly has three key operations: local receptive field, weight sharing and pooling. By configuring these three operations, pixel-level image processing tasks can be achieved. Compared with traditional algorithms, CNN can greatly improve the accuracy of image processing. Although there are many parameters in the neural network, there are shortcomings in overfitting and extended training time. However, compared with methods based on statistical learning theory such as boosting, logistic regression (LR), and support vector machine (SVM) [19]–[21], the CNN model has more great superiority.

In the past decade, with the in-depth development of ML, CNN has performed well in natural language processing, image classification, and satellite remote sensing image processing tasks, achieving better precision and accuracy, and significantly improving work efficiency [22]–[24]. Various CNN-based variants (such as AlexNet, VGGNet, and ResNet) have shown excellent performance in specific tasks. Since CNN is used to implement natural language processing and computer vision, it is essential to process and extract feature values. Especially in processing image classification tasks, the more deep-level features of an image are extracted, the higher the precision and accuracy of image classification. Therefore, in order to reduce model training time, improve model precision and accuracy, and further improve model performance, researchers often use pre-trained models on large data sets, such as VGG16 and VGG19 models.

2.2. Transfer learning

Before model training, data annotation is a task that drives researchers crazy. Data annotation is boring and costly. The quality of data samples determines the results of model training to a certain extent. The study of TL brings hope to researchers. There are many TL types, such as instance-based transfer, feature-based transfer, shared parameter-based transfer, and a combination of DL and TL. The mathematical definition of TL is shown in formula (1).

$$\begin{cases} D = \{x, P(X)\} \\ T = \{y, f(\cdot)\} \end{cases} \tag{1}$$

Where D represents a domain, x is marked feature space, $P(X)$ is marked transfer probability distribution, where $X=\{x_1, x_2, \ldots, x_n\} \in \chi$. T is marked the task, y is marked the label space, and $f(\cdot)$ is marked the target prediction function.

Wang *et al.* [25] developed a deep neural network in the form of ResNet for simulating the heat transfer model of composite materials, which is a typical example of transfer learning. In general, there are two methods for TL based on DL context in actual image classification tasks.

a. TL based on feature extraction

In the TL based on feature extraction. Firstly, we can treat the CNN as a feature processor for extracting image features. Secondly, the CNN is processed and processed, such as cutting off pre-designated layers, and only extracting specific feature values. Then, the transformed convolutional neural network's output value is flattened and used as the original input feature vector in another classification algorithm. Finally, the classifier is used to output the feature vectors in the model to achieve image classification. Commonly used TL models based on feature extraction are logistic regression and SVMs. However, in solving image classification problems, the CNN model is a nonlinear model capable of learning nonlinear features. The nonlinear feature vector is often extensive and has a high latitude. Therefore, compared with traditional linear models, CNNs are more suitable for solving image classification problems. This section will introduce the related research of CNNs and TL to prepare for the method proposed in this paper.

b. TL based on fine-tuning

The fully connected layer of the network is usually deleted in fine-tuning-based TL methods and replaced by a new fully connected layer. The weights are then fine-tuned to suit the new task. In addition, when the number of samples in the image processing task is large and very similar to the original data set of the pre-trained model, fine-tuning the model parameters is usually adopted.

3. PROPOSED METHOD

3.1. Data processing

Since the satellite remote sensing image is an aerial view, there is a phenomenon that clouds block buildings or the image have dark patches. Therefore, in order to ensure the validity of the input image, the output training set image needs to be preprocessed firstly, that is, to remove the blurry image occluded by clouds and the image with dark patches. Secondly, when using a small data set to train a model, in order to eliminate the phenomenon of model overfitting and non-convergence, data expansion methods are usually used to increase the number of training samples. The commonly used data expansion methods are based on the original image through rotation, cropping, and scaling. Besides, the shuffle method is used to sort the training dataset sent to the model randomly. The advantage of this operation is that it can effectively suppress the model overfitting and accelerate the convergence.

3.2. Feature extraction

In the task of detecting damage to buildings after a hurricane, the primary function of the model is to extract and label the damaged features of buildings in satellite remote sensing images. Building damage character is mainly composed of the shape of the roof of the building in the image and the abnormal environment around the building. Therefore, it is essential for the accuracy of damage detection to accurately extract buildings' damaged features in satellite remote sensing images. We know that the basic CNN can only lift shallow image features, and the deeper CNN can extract more in-depth image features, but the training is very time-consuming and inefficient. This disadvantage will affect the performance of the entire model. The method of TL can solve this problem well. It was inspired by Thomas *et al.* [26], further extraction and detection of abnormal color features.

First of all, because the VGGNet model is an image classification model trained on the large-scale image dataset ImageNet, the model does not need to be trained and used directly, which can quickly achieve image feature extraction. Therefore, we first use the VGG16 model to extract building damage features from satellite remote sensing images. Second, we extract the features of each satellite remote sensing image on the R, G, and B channels, and finally merge the features on the three channels into the color image features, as shown in Figure 2. Finally, analyze the feature value on each channel, extract the most significant building damage feature, and use the extracted feature vector as the next layer's input vector. The advantage of this is that it can extract more subtle images of damaged buildings and improve classification accuracy. Figure 3 shows the histogram of the characteristic colors of the R, G, and B channels of the sample image. This diagram intuitively shows the nuances of the image features, which facilitates the model to distinguish better and identify and improve classification accuracy.

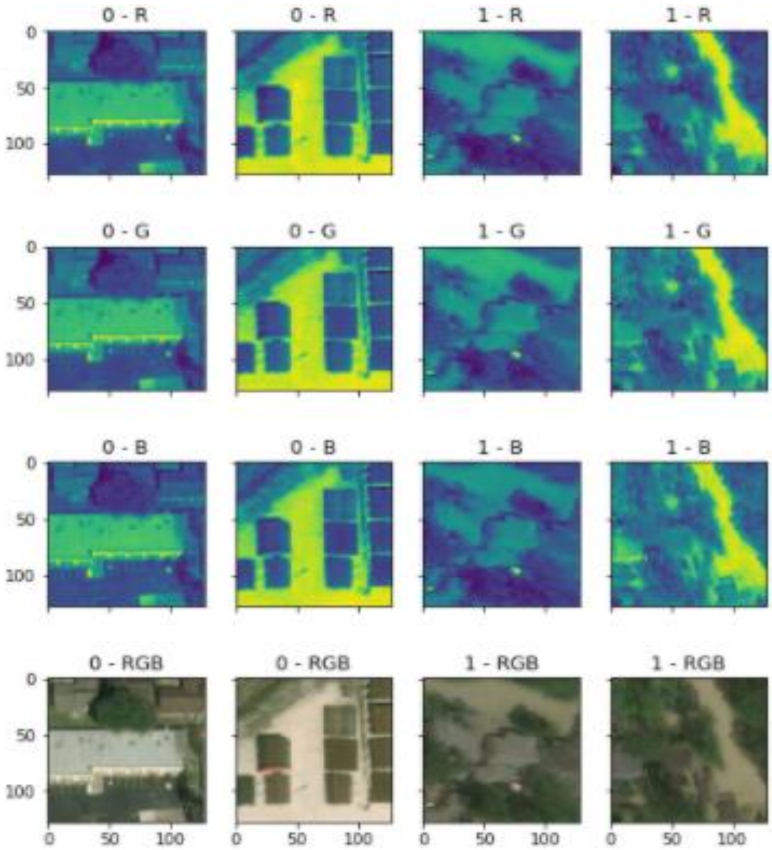


Figure 2. Example of RGB three-channel feature map

3.3. Post-hurricane building damage detection method

Using satellite remote sensing images to achieve building damage detection is to check whether the top view of the building edge, and shape, has changed through satellite remote sensing images. Since the satellite remote sensing image is an aerial view, the usual method is to judge whether the roof of the building has changed and whether the building's surrounding environment has changed through the image. For example, the shape of the roof is deformed, the roof is missing corners, and the roof is missing are all characteristics of damage to the building. Similarly, the building's surrounding area has changed from the original green to a piece of earthy yellow (the color of the flood is usually earthy yellow), indicating that the building is experiencing flooding. Therefore, these buildings' damaged features become the color feature extraction of critical parts of the building. In other words, building damage detection is actually the problem of image classification, and it is a problem of image classification. From the satellite remote sensing image of the building, it can be judged whether the image is the normal state of the building or the damaged state.

Yosinski *et al.* [27], we combine DL and migration learning, and use pre-training models to extract deep features of images. In the proposed model, in order to increase the training speed of the model, accelerate the model convergence, and achieve a higher accuracy rate, we use the top layer of the VGG16 to extract the image deep features, and then add it after the VGG16 model by sharing parameters global average pooling layer. Finally, a fully connected layer is added for output. The detailed settings of the proposed model structure are shown in Table 1. Firstly, the top layer of the VGG model is used to convert each input 128*128*3 image into a 4*4*512 feature block. Secondly, add a global average pooling layer, and use the output vector of VGG16 as the input vector of the new pooling layer. Thirdly, the fully connected layer accepts the new pooling layer's output and performs the fully connected vector operation of the image. Finally, the Sigmoid classification function is used in the output layer to classify the image. After the above operations, input a satellite remote sensing image to determine that the building is damaged or in a normal state. After the model is established, optimization measures such as data expansion are taken to expand the training data further to prevent the model from overfitting. The shuffle method is used to randomly sort the training data and set a litter learning rate. The adoption of these optimization measures can accelerate the model's convergence, thereby improving the accuracy of the model.

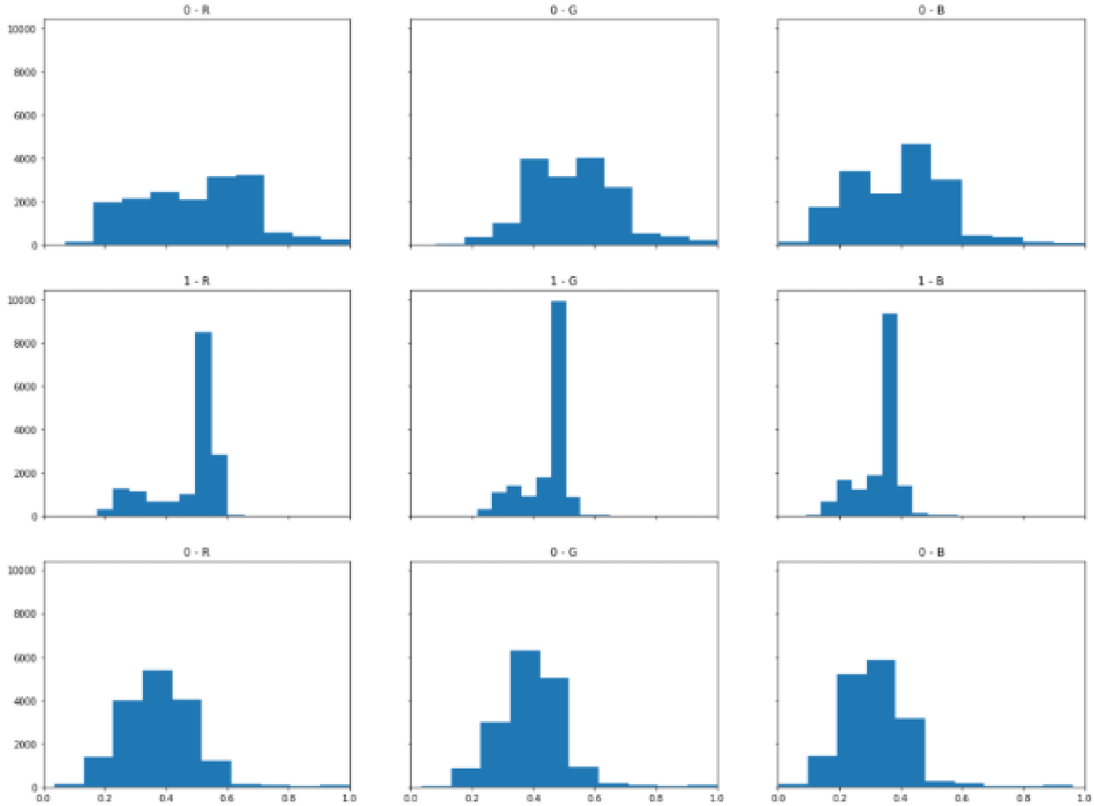


Figure 3. RGB color component histogram

Table 1. Structure of the proposed model

Layer	Out shape	Parameters
Input	3*128*128	0
Conv2D	64*128*128	1792
Conv2D	64*128*128	36928
MaxPooling2D(2*2)	64*64*64	0
Conv2D	128*64*64	73856
Conv2D	128*64*64	147584
MaxPooling2D(2*2)	128*32*32	0
Conv2D	256*32*32	295168
Conv2D	256*32*32	590080
Conv2D	256*32*32	590080
MaxPooling2D(2*2)	256*16*16	0
Conv2D	512*16*16	1180160
Conv2D	512*16*16	2359808
Conv2D	512*16*16	2359808
MaxPooling2D(2*2)	512*8*8	0
Conv2D	512*8*8	2359808
Conv2D	512*8*8	2359808
Conv2D	512*8*8	2359808
MaxPooling2D(2*2)	512*4*4	0
Flattening	1*8192	0
Dropout	1*8192	0
Fully connected layer	1*512	4194816
Fully connected layer	1*1	513

Parameters indicate the number of trainable parameters

4. EXPERIMENT
4.1. Data processing
4.1.1. Experiment data

In this experiment, we used a satellite image of the Greater Houston area captured by an optical sensor with sub-meter resolution in 2017, and it has been preprocessed. In the process of preprocessing, we discarded images with low pixels, occluded by clouds, and black patches, and adjusted the image size to the 128*128 color image. The satellite remote sensing images used in this experiment are 21,000, of which 1,000 are training images, 2,000 are verification images, and 9,000 are test images. The dataset images are distinguished according to the labels of "damaged" and "non-damaged". We only considered the case of unbalanced data sets to test the robustness of the model. The detailed image distribution of the data set is shown in Table 2.

4.1.2. Experiment environment and steps

In the experiment, we used the Python language to compile the post-hurricane damage detection program, and configured the Tensorflow deep learning framework, used the Tensorflow data processing API, and used the Matplotlib dynamic link library to achieve data visualization. We deployed the established model on a graphics workstation, configured with the Inter-core i7-4790 chip, 16G memory and 2T hard disk, and a GTX960 graphics display card. The practical steps are as follows:

Firstly, data processing. Since the satellite images we collect are named after the latitude and longitude names, we must first establish the mapping relationship between the image and the corresponding label, establishing a data set of the image and the corresponding label mapping. Secondly, data expansion. Due to the relatively small size of the data set, in order to prevent the model from failing to converge and consistent model overfitting, we use data expansion, shuffle, and other methods to increase the number of training data. Thirdly, model training and tuning. The VGG16 pre-training network is used to extract the deep features of the image, and the R, G, and B channels of the feature image are analyzed, and the deep features of the damaged building are found, such as roof damage and incompleteness, and the color around the building is ocher. Set up a new global average pooling layer, add a fully connected layer to further train and verify the model, and compare the two training results.

Finally, model testing. Use the tuned model to test the test set, and output indicators such as the accuracy of the test results and F1 Score. And compared with the experimental results of traditional LR and SVM classification models.

Table 2. Distribution of the number of data samples

Data set	Lable	
	damage	no_damage
Training	5000	5000
Validaton	1000	1000
Test	1000	1000
Test_another	8000	1000

4.2. Experiment results and analysis

Model training can be divided into two stages, namely the initial training stage and the tuning stage. In the initial stage of training, we only used the top structure of the VGG16 network to extract image features, and output each input training image 128*128*3 as 4*4*512 feature blocks. After harvesting, add a global average pooling layer, set the basic learning rate to 1e-4, the number of initial training epoch to 15, the verification step Val step to 20, and the batch size to 32. Then the model is initially trained. The accuracy is 50%, and the loss rate is 7.13. After initial training, use the training set to train the model formally, and the resulting classification accuracy and loss rate curves are shown in Figure 4. The trained model is then evaluated in the validation set and test data set to obtain the accuracy and loss rate of classification.

Tuning stage; We start to optimize the model from the 15th round, set the optimizer to Adam, calculate the learning rate is 1e-5, use two-class cross-validation to calculate the loss rate, and set the optimized number of training epoch to 25. Therefore, the total number of training epoch is 40. Use the training data set to continue training the model, and finally, the accuracy and loss rate curves of the optimized model are shown in Figure 5. Then, evaluate the optimized model in the verification set and test data set to obtain the accuracy and loss rate of classification. Finally, the accuracy and loss rate of classification results are compared with the traditional LR and SVM to verify the model performance further. The experimental results are shown in Table 3.

4.2.1. Analysis of experimental results

First, evaluate the optimization effect of the model. Figure 4 is the accuracy and loss rate curve before model optimization. It can be concluded that the model training process is over-fitting and does not converge. The loss rate obtained by classification is greater, and the accuracy rate is lower, less than 90%. The set initial learning rate mainly causes this result is too large. On the other hand, because the initial model directly uses the VGG16 pre-training model to achieve feature extraction without training each layer, there are problems such as inconspicuous extracted features or deviations from actual image features, which leads to the model does not converge. Figure 5 is the optimized model accuracy and loss rate curve. It can be seen from Figure 5 that after 15 epochs, the accuracy of model training and verification has increased rapidly, and as the training progresses, the accuracy tends to be consistent and close to 100%. The model's loss rate drops rapidly after 15 epochs, the training loss rate tends to 0, and the verification loss rate tends to 0.20. These indicate that the model converges well and is stable. Compared with Figure 4, the optimized model obtain a higher accuracy rate and a lower loss rate, and the optimization strategy of the model plays an important role.

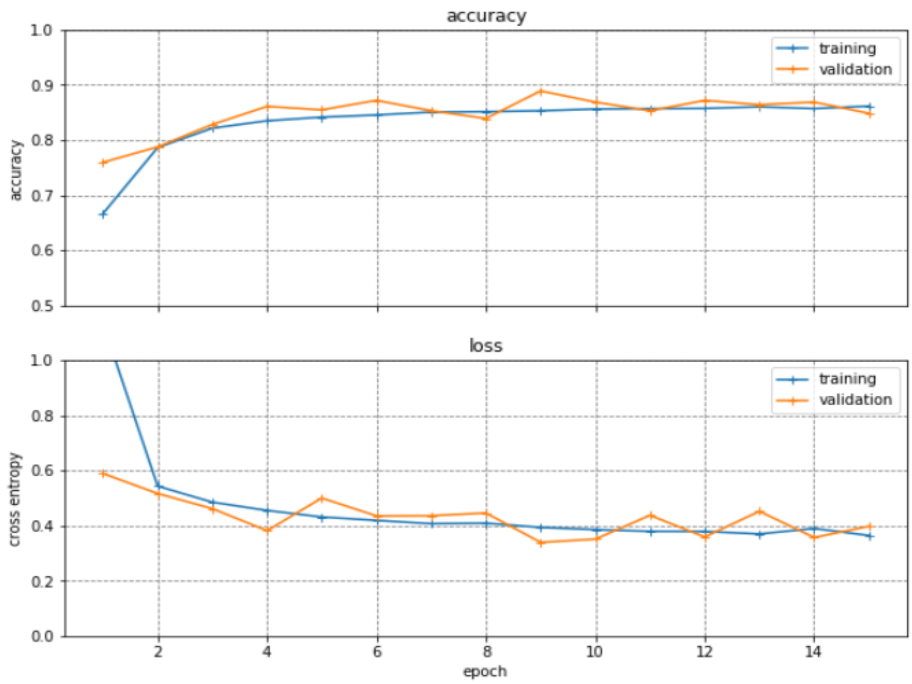


Figure 4. Model accuracy and loss rate curve

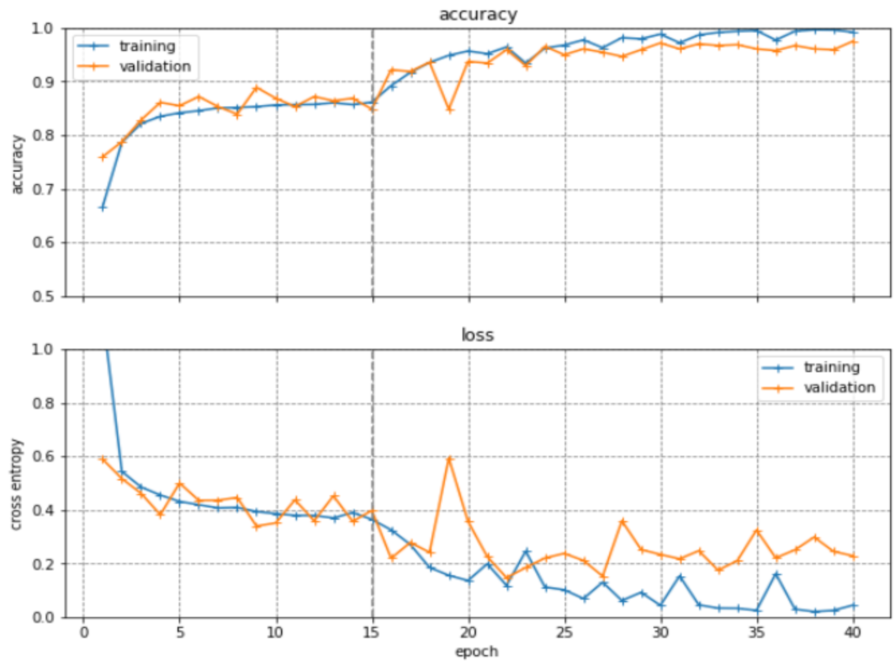


Figure 5. Optimized model accuracy and loss rate curve

4.2.2. Comparison with traditional classification algorithms

In the post-hurricane building damage detection experiment, and the classification experiment of the CNN model, the classification experiment of the traditional classification algorithm of LR and SVM was also carried out. All experiments used the same data set. The experimental results are shown in Table 3. Table 3 shows the classification accuracy and F1 Score obtained by four classification algorithms, such as LR in the verification dataset and the test dataset.

It can be concluded from Table 3 that the accuracy and F1 Score obtained by the classification algorithm based on the CNN are generally higher than that of the traditional classification algorithm. Our proposed optimization model accuracy and F1 Score are the highest, reaching 96.75%, 96.42%, and 0.9635. Compared with the CNN model, the improved model's verification accuracy and test accuracy are increased by 0.9916% and 0.9951%, respectively, indicating that the improved model has excellent classification performance.

Table 3. Accuracy of different methods

Method	Validation accuracy (%)	Test accuracy (%)	F1 score
LR	93.55	91.45	0.7713
SVM	92.02	90.95	0.7002
CNN	95.80	95.47	0.9575
Ours	96.75	96.42	0.9635

5. CONCLUSION

Natural disasters such as hurricanes and floods bring substantial economic and property losses to human society every year, and even cause casualties. How to quickly and accurately assess the damage condition of buildings and other buildings in the disaster-stricken area, timely rescue, and post-disaster reconstruction, and minimize the damage caused by the disaster, this is the primary problem that the national emergency rescue department solves. This paper introduces an improved rapid detection method for house damage after a hurricane based on transfer learning. Compared with the traditional manual labeling method, this method has the advantages of high labeling efficiency and high classification accuracy. It can provide the national disaster emergency response department with timely housing damage and provide a reasonable allocation of disaster relief resources and post-disaster reconstruction. The strategy provides timely scientific support. This method collects satellite remote sensing images of the disaster-stricken area, builds a post-hurricane damage detection model based on CNNs, and compares the satellite remote sensing images of the area before and after the disaster to achieve rapid detection and labeling of the damaged building.

In establishing the building damaged detection model, we use the pre-training model VGG16 to extract features such as building damage from satellite remote sensing images, and optimize the model by adding global pooling and fully connected layers. Besides, we use data expansion, shuffle, and other technical means to increase training data to prevent model overfitting. Use a small learning rate to prevent the model from not converging. The optimized model was used for building damaged detection experiments on the 2017 Hurricane Harvey Imagery satellite remote sensing image data set in the Greater Houston area. The verification accuracy and test accuracy of the damage detection reached 96.75 and 96.42%, respectively. Compared with the traditional LR and SVM algorithms, the proposed CNN algorithm obtains the highest accuracy rate. Compared with the detection model before the improvement, our proposed model's verification accuracy and test accuracy are increased by 0.9916% and 0.9951%, respectively, and it has excellent classification performance. Of course, the proposed method accuracy has space for further improvement. It can be extended to detecting damage to buildings after natural disasters such as earthquakes, tsunamis, and mudslides. This is the content that we will study in the future.

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