A Novel Deep Convolution Neural Network Model for CT Image Classification Based on COVID-19

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Abstract*-Since the outbreak of novel coronavirus pneumonia (COVID-19) in 2019, normal learning and living have been severely affected, and human life and health have been seriously threatened. Therefore, it is crucial to diagnose the novel coronavirus pneumonia rapidly and efficiently. In this study, based on the classical image classification neural network model, a novel deep convolutional neural network model based on the attention mechanism is proposed and named the LACNN_CBAM model. The accuracy Acc, precision Pre, recall Rec and F-1 scores of the model in the public dataset collated from published papers are 0.989, 0.992, 0.992, and 0.992, which are respectively higher than existing learning models. The model determines whether a patient has COVID-19 and community-acquired pneumonia by patient's CT images. The effectiveness of the model was demonstrated by experimental results on a clinical dataset. We believe that the model proposed in this paper can help physicians to diagnose COVID-19 and community-acquired pneumonia efficiently and accurately in reality.

Keywords: COVID-19; CT; Medical image classification; Convolutional neural network; deep learning;

I. Introduction

Novel coronavirus pneumonia (COVID-19), or 'new coronavirus pneumonia', emerged in Wuhan, China, in late 2019 and was subsequently named the '2019 coronavirus disease' by the World Health Organization in a global epidemic [1,2]. Novel coronavirus pneumonia is an RNA virus that is transmitted mainly through respiratory droplets and close contact. It is highly contagious, making it possible to be infected when the distance between people is within one meter [3]. Therefore, close contact with patients with NCCP is an important way of transmission of COVID-19. Most Patients with severe new crown pneumonia develop respiratory distress or hypoxemia a week after the onset of the disease, rapidly progressing to acute respiratory distress, very severe dyspnea, and shock in severe cases. Patients may also develop very severe disorders of acid-base metabolism, leading to complete loss of lung function, resulting in multiple organ failures in the body, which can be life-threatening and death from complications caused by pneumonia [3,4]. Our goal is to train an excellent model in clinical lung CT datasets to efficiently diagnose COVID-19, which is a daunting and urgent task in the fight against the new coronavirus.

Nucleic acid detection errors in clinical diagnosis are relatively large. For patients who have a serious case of computed tomography (CT) examination but negative nucleic acid test, CT is a fast, cheap and efficient diagnostic modality currently used in hospitals. A CT image of a healthy person's lungs is essentially black because air attenuates X-rays so weak that the CT values are small. The human lung is almost composed of alveoli. After the new coronavirus invades the lung through the respiratory tract, it uses the alveolar pores to proliferate and attach to the alveolar epithelium, at this time, the human immune system makes an immune response at this time. The immune system produces immune cells and the new coronavirus to fight a war leading to alveolar swelling, exudation of alveolar septal fluid, and thickening of the alveolar septum, which causes some damage to the alveoli. [5,6]. CT can help doctors observe changes in the lungs and quickly determine if the patient has pneumonia, its extent, degree and period, etc. New crown pneumonia needs to be differentiated from other viral pneumonia and non-viral infections. Doctors can determine whether a patient is infected with neo-coronavirus based on different features of CT images. Neo-coronavirus pneumonia is viral pneumonia, and there is some overlap in the chest images of viral pneumonia [7,8]. Therefore, in this study, the lung CT dataset is selected for training to provide doctors with a more accurate diagnostic model.

Tracing back to the middle of the 20th century, image classification techniques have made great progress in the field of computer vision, and convolutional neural network-based image classification techniques have achieved good results in intelligent data acquisition and efficient processing [9]. Medical image classification plays a crucial role in clinical treatment and teaching tasks. This paper is dedicated to learning pneumonia features using convolutional neural networks to efficiently and accurately identify community-acquired pneumonia [10,12]

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(CAP), neo-coronavirus pneumonia, and normal. The LeNet convolutional neural network model [13] shows excellent performance on the Minst dataset. Subsequently, related networks such as AlexNet[14] emerged, which have a wide range of applications in medical image classification. In this paper, by improving the LeNet network and AlexNet network and adding an attention mechanism, we construct a COVID-19 image classification model based on the classical CNN model for medical image processing and diagnosis of COVID-19.

This paper is organized as follows: Section 2 introduces the dataset used in this paper and the improved COVID-19 image classification model improved and constructed based on the classical CNN model; Section 3 compares the results of the proposed model with the classical convolutional neural network model LeNet, AlexNet network model and the proposed existing models in recent years in the classification of COVID-19 dataset; Section 4 summarizes the work of this paper and identifies the next research plan.

II. Data and Methods

A. Experimental data

The dataset for this paper is from www.Kaggle.com. The site's dataset is public and is available to all. This paper uses the large COVID-19 CT scan slice dataset [15]. This dataset was constructed by collating data from 7 public datasets to create a large CT scan dataset of the lungs for COVID-19. These datasets have been publicly used in the COVID-19 diagnostic literature and have demonstrated their efficiency in deep learning applications. Therefore, the merged dataset is expected to improve the generalization ability of deep learning methods by learning from all these resources.

All images in this dataset are 8-bit and have a consistent depth. Closed normal slices of the lung that do not carry information on intrapulmonary presentation were removed from this dataset to ensure data quality. In addition, images that lack clear category labels or patient information were not included. In total, the dataset collected 7593 COVID-19 images from 466 patients, 6893 normal images from 604 patients, and 2618 CAP images from 60 patients. All CAP images are from the Afshar et al. dataset, in which 25 cases have been annotated. The dataset was annotated by radiologists for the remaining 35 CT scan volumes. According to the dataset authors, this is the largest COVID-19 lung CT dataset to date.

Figure 1 shows lung CT images from 7 open-source datasets in the dataset. In this paper, the single-channel data images are read in the experiments and all the images are processed to the size of 512*512. Finally, the images of this dataset are divided into training and test sets according to 7:3 as shown in Table 1.

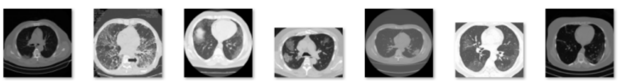

Figure 1 CT images of new coronary pneumonia in the dataset

Table 1 Data set division

Type	Training set	Test set	Total
NonCOVID	4825 sheets	2068 sheets	6893 sheets
COVID	5315 sheets	2278 sheets	7593 sheets
CAP	1833 sheets	785 sheets	2618 sheets

B. Classical deep convolutional neural network model

The earliest proposed convolutional neural network model is the LeNet[16] model proposed by LeCun et al. in 1998, which achieves 99% accuracy on the MNIST handwritten digit set. The structure of the LeNet5 network model is shown in Figure 2, which contains 2 convolutional, 2 pooling, and 2 fully connected, and consists of a convolutional layer→ pooling layer→convolutional layer→pooling layer→fully connected layer. The convolutional layer extracts spatial features, the pooling layer performs downsampling, and the fully connected layer transforms the output of the previous convolutional layer into a global convolution of the convolutional kernel. The final output uses the softmax function, which outputs a vector whose number of elements is the number of categories for the classification, the element values are the probability values of the predicted images in each category, and the category with the largest element value is the category to which the model is predicted to belong.

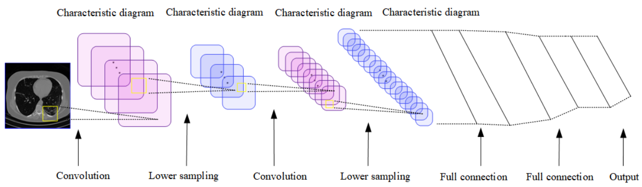

Figure 2 LeNet network model structure

AlexNet[14] is the winning model in the ImageNet competition in 2012. Compared with LeNet, AlexNet network layers are deeper with 3 additional layers. AlexNet is an 8-layer convolutional neural network containing 5 convolutional layers, and 3 fully connected layers, and the final output is classified by softmax. The Dropout method is proposed in this model to alleviate the overfitting problem. The structure of the AlexNet model is shown in Figure 3.

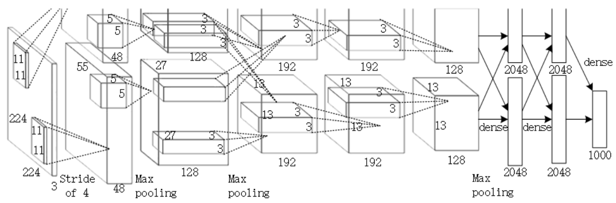

Figure 3 AlexNet network model structure

C. Attentional mechanisms

In the process of human learning, the brain will pay attention to more important or valuable information first, and ignore the unimportant or low-value information, so that the learning effect will be better. In the process of simulating human learning, computers also need to be trained to focus on more useful features, pay more attention to what deserves to, and learn the features that should be learned, so that the model can classify the images more accurately and improve the model performance [17]. Therefore, the attention mechanism also plays an important role in image classification and has powerful advantages. Generally, attention mechanisms are classified into channel attention mechanisms and spatial attention mechanisms or a combination of both.

In 2017 Hu J et al. proposed SENet[18], a typical implementation of the channel attention mechanism, in the ImageNet competition and provided an extensive evaluation of the ImageNet 2012 dataset, which was proven to be generally applicable and advanced. SENet focuses on obtaining the input feature layer and the weights of each channel. The structure of the channel attention mechanism implementation is shown in Figure 4, which is implemented as follows: in the first step, the global average pooling of the input feature map is performed; in the second step, two full connections are made, the first with a smaller number of fully connected neurons and the second with the same number of fully connected neurons as the input feature layer; in the third step, after the completion of the two full connections, the values are then fixed between 0 and 1 by the Sigmoid function. The weights of each channel of the input feature layer are obtained; in the fourth step, after obtaining the weights, the weights are multiplied by the original input feature layer.

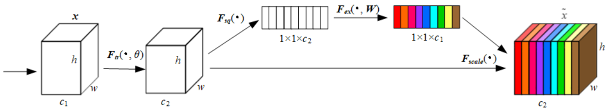

Figure 4 SENet structure diagram

In 2018 Woo S et al. first implemented CBAM [19], which combines channel attention mechanism and spatial attention mechanism as a lightweight general-purpose module. Extensive experimental validation on ImageNet-1K, MS COCO detection, and VOC 2007 detection datasets verified the effectiveness and generality of CBAM, which can be fused to any convolutional neural network architecture. The CBAM is better than the SENet attention mechanism. The CBAM module is shown in Figure 5. CBAM performs the input feature maps separately for the channel attention mechanism and spatial attention mechanism. Each attention sub-module of the CBAM module is shown in Figure 6. The top part is the channel attention mechanism, and the following part is the spatial attention mechanism [20,22].

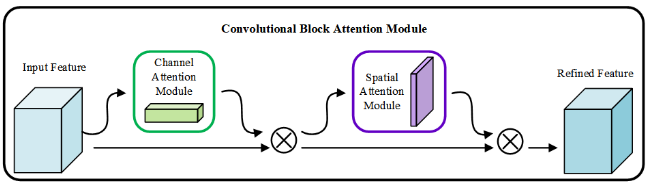

Figure 5 CBAM module

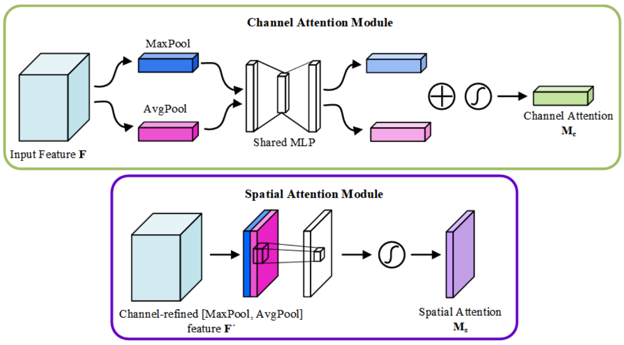

Figure 6 CBAM sub-modules of attention

D. Proposed LACNN_CBAM deep convolutional neural network model

Based on the two classical LeNet and AlexNet deep convolutional neural network models, a novel deep convolutional neural network model incorporating an attention mechanism is constructed in this paper, and the model structure is shown in Figure 7. Three convolutional layers are added to the LeNet model, the Dropout method in the AlexNet network is introduced to mitigate overfitting, and the CBAM module attention mechanism is added. The overall structure and parameters of the LACNN_CBAM network model are shown in Table 2.

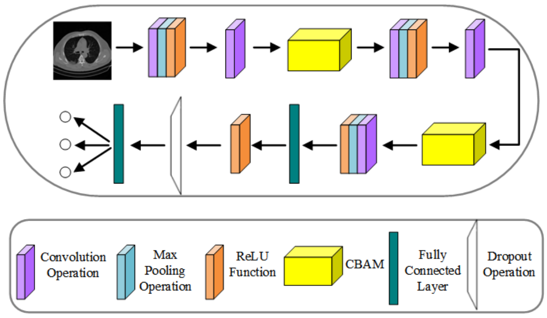

Figure 7 LACNN_CBAM network model junction structure diagram

Table 2 LACNN_CBAM network model junction structure parameters

Number	Type	Stride	Filter Size	Output Size
1	Input	-	-	512×512×1
2	Convolution1	3	5×5	170×170×16
3	Max pooling1	3	3×3	56×56×16
4	ReLU1	-	-	56×56×16
5	Convolution2	1	3×3	56×56×32
6	Block1 CMBA	-	-	56×56×32
7	Convolution3	1	3×3	56×56×32
8	Max pooling3	2	2×2	28×28×32
9	ReLU3	-	-	28×28×32
10	Convolution4	1	3×3	28×28×64
11	Block2 CMBA	-	-	28×28×64
12	Convolution5	1	3×3	28×28×64

13	Max pooling5	2	2×2	14×14×64
14	ReLU5	-	-	14×14×64
15	Flat	-	-	1×1×12544
16	Fully connected	-	-	1×1×64
17	ReLU6	-	-	1×1×64
18	Drop6	-	-	1×1×64
19	Softmax	-	-	1×1×3

III. Experiments and evaluation

A. Experimental design

The parameter settings of the experiments in this paper are shown in Table 3, according to which the performance of the image classification model proposed in this paper is tested and compared. The experimental data in this paper are obtained from the public database named Kaggle, and the experimental data have authenticity and validity.

Experimental environment: Windows 10 64-bit OS, TensorFlow 2.0 framework, NVIDIA GeForce RTX 2060 GPU, 16G RAM.

Table 3 Experimental parameter settings

Parameters	Epoch	Batch size	Learning rate LR	Optimizer	activation function
	140	32	0.0001	Adam	Reply

B. Evaluation indicators

In this paper, four different evaluation metrics are used in testing the model's effectiveness, which are accuracy, precision, recall, and F-1 Score. The confusion matrix reflects the overall performance of the prediction model, and the following Table 4 shows the confusion matrix of evaluation metrics. The confusion matrix can also be used to calculate the values of these four evaluation metrics like the following equations (1), (2), (3), and (4). In this paper, set the parameters average='macro' to calculate the evaluation index precision, recall, and F-1 Score, so that the evaluation index values of each category label will be calculated and then averaged (without considering the difference in sample distribution of each category). When doing the averaging, the number of categories is not considered to be the number of categories in the target, nor the number of categories in the prediction, but the number of categories is taken as the total number of categories by combining the two. The values of evaluation indicators obtained in this way are more accurately predicted.

Table 4 Confusion matrix of evaluation indicators

Actual	Predicted		Total
	Positive	Negative	
Positive	TP	FN	TP+FN
Negative	FP	TN	FP+TN
Total	TP+FP	FN+TN	TP+TN+FP+FN

$$Acc = \frac{TP + FN}{TP + FP + TN + FN} \tag{1}$$

$$Pre = \frac{TP}{TP + FP} \tag{2}$$

$$Rec = \frac{TP}{TP + TN} \tag{3}$$

$$F\text{-}1 = \frac{2 \times Pre \times Rec}{Pre + Rec} \tag{4}$$

C. Experimental results

In this paper, experiments were conducted on the test set with multiple sets of comparison experiments in the process of determining the network model.

1) Model Improvement

After the improvement of the LeNet network and AlexNet network model, the base network model named as LACNN1 network model after adding the convolutional layer and pooling layer. The accuracy Acc, precision Pre, recall Rec and F-1 scores of the LACNN1 network model are 0.9801, 0.9838, 0.9840, and 0.9839 respectively. The accuracy Acc, precision Pre, recall Rec and F-1 scores of the LACNN2 network model are 0.9830, 0.9870, 0.9850, and 0.9860, respectively. The accuracy of the network model is improved by about 0.3% after adding the Dropout prevention overfitting function. The comparison of the evaluation indexes of the above two network models is shown in Figure 8.

Figure 8 Graph of evaluation index of each network model

The attention mechanism CBAM module is added to the LACNN2 network model, and to determine the optimal location for adding the attention mechanism and further determine the optimal network model, the CBAM module is added before the second convolutional layer and before the fourth convolutional layer, respectively, named LACNN2_CBAM network model. the accuracy Acc, precision Pre, recall Rec and F-1 score is 0.9641, 0.9695, 0.9696, 0.9695, respectively. The accuracy precision is decreased by about 2% relative to the LACNN2 network model. The attention mechanism CBAM module was then added to the middle of the second and third convolution and the middle of the fourth and fifth convolution, respectively, and named the LACNN_CBAM network model. the accuracy Acc, precision Pre, recall Rec, and F-1 scores of the LACNN_CBAM network model was 0.9893, 0.9915, 0.9916 and 0.9915, respectively. It is obvious that the LACNN_CBAM network model has the highest classification accuracy and is determined to be the optimal network model in this paper. The comparison graph of network model evaluation metrics is shown in Figure 8.

2) Comparison with a classical convolutional neural network model

In this paper, we conduct validation experiments to compare the proposed LACNN_CBAM network model with the classical convolutional neural network LeNet and AlexNet network. Figure 9. shows the comparison diagram of LeNet, AlexNet, and the network model evaluation indexes proposed in this paper. The accuracy Acc of the LeNet network is 92.18%, the accuracy Acc of AlexNet network the accuracy Acc of the LeNet network is 97.54%, while the accuracy Acc of the network model LACNN_CBAM proposed in this paper is 98.92%. Obviously, the network model proposed in this paper has better performance.

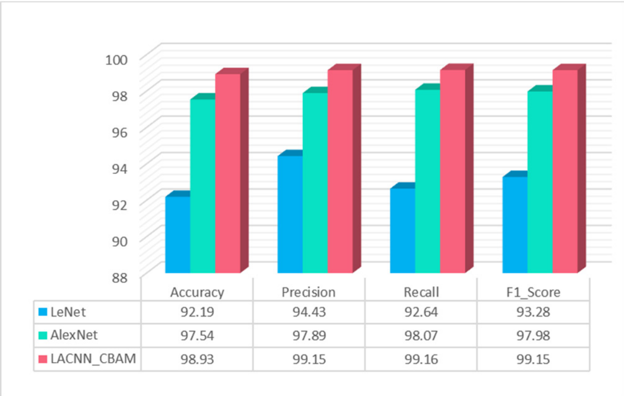

Figure 9 Graph of evaluation indexes of classical network and LACNN_CBAM network model

The confusion matrix of the proposed network model LACNN_CBAM in the test set prediction is shown in Figure 10. Combined with the above comparison experiments, it can be seen that the proposed network model has higher classification recognition accuracy.

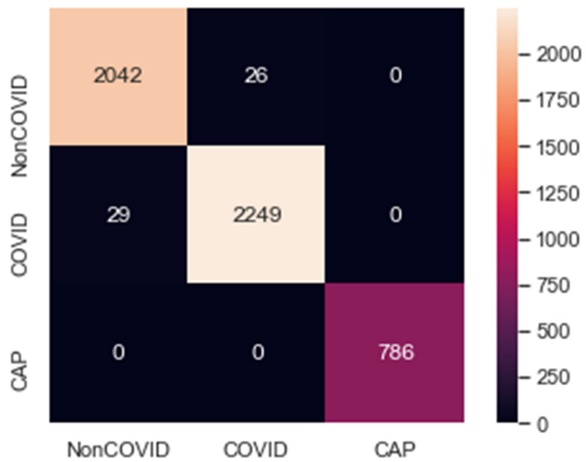

Figure 10 Confusion bureau matrix of LACNN_CBAM network model on the test set

3) Comparison with existing learner models

The network model proposed in this thesis is an improvement on the classical convolutional neural network model, and the dataset uses the public dataset collated by Maftouni et al. The accuracy of the two network models proposed by Maftouni et al. [15] is 95.07 and 95.31 respectively, while the accuracy of the network model proposed in this paper reaches 98.92, which is higher than the above results. For all evaluation index values, the higher the score, the better the performance, and the comparison of evaluation indexes are shown in Table 5 below. The experimental results clearly show that the network model proposed in this paper has a more accurate identification performance on the new coronavirus.

Table 5 Evaluation metrics of the existing learner model and the proposed model LACNN_CBAM in the test set

Model	Accuracy	Precision	Recall	F1_Score
FC	95.07	98.32	89.84	93.89
FC + SVM	95.31	97.93	90.80	94.23
LACNN_CBAM	98.93	99.15	99.16	99.15

IV. Summary and outlook

In the context of the current New Coronavirus pandemic, being able to efficiently and accurately diagnose whether a patient has New Coronavirus is a particularly important task in the medical field. Currently, artificial intelligence continues to develop, and the use of intelligent techniques for the diagnosis of New Coronary Pneumonia will help health care workers to better fight the virus. In this paper, a deep convolutional neural network model based on the attention mechanism, the LACNN_CBAM network model, is proposed. The model has an excellent performance in the classification and recognition of neo-crown pneumonia, community-acquired pneumonia, and no disease neo-crown virus pneumonia. The model has few convolutional layers and is simple and flexible. We believe that it can help physicians better diagnose COVID-19 disease effectively in practice. Most of the papers only identified two kinds of COVID-19 and non-COVID-19, but there are many types of pneumonia. In further work, we will study more CTs of lung diseases to detect New Coronavirus pneumonia and classify lung disease more accurately.

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