Application of 3D-CNN Model in the Diagnosis of COVID-19

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Abstract. In recent years, COVID-19 has become the largest epidemic in the world and has had a great impact on the world. The diagnosis of COVID-19 also heavily relies on lung CT. This study presents a COVID-19 CT scan categorization computer-aided diagnostic (CAD) system. The performances of two 3D-CNNmodels with the similar structures are compared. The data used from MosMedData is the Chest CT Scans with COVID-19 Related Findings Dataset. The best segmentation technique for separating the chest tissue from the rest of the CT picture is threshold segmentation. If a volume has several slice groups, the characteristics from each group are extracted and added together to create the eigenvector for the whole CT scanning volume. The combined eigenvectors are then further categorized using a straightforward multi-layer perceptron (MLP) network. One model generated a test set with an accuracy of 78.8%, while the other model generated a test set with an accuracy of 79.8%. This study demonstrates the particular potential of 3D-CNN for COVID-19 diagnosis.

Keywords: COVID-19, pooling layer, convolution layer, 3D-CNN, computer tomography, medical image classification.

1. Introduction

Numerous pneumonia cases have been connected to the 2019-nCoV novel coronavirus since December 2019 in Wuhan, Hubei Province, China. Coronavirus Disease 2019 (COVID-19) has been reported to have spread widely in several cases. The first wave of the worldwide pandemic started in late 2019 [1]. As of June 19, 2022, there were more than 6.3 million fatalities and more than 536 million confirmed cases worldwide. The recently discovered Severe-Acute-RespiratorySyndromeCoronavirus2 (SARS-CoV-2) is the cause of COVID-19 infection. From moderate upper respiratory tract infections to sepsis, which can be lethal, SARS-COV-2 infection symptoms can range widely [2]. 2019-nCoV is highly infectious. It mainly spreads through respiratory droplet and contact. People are generally susceptible. The severity of the Middle East Respiratory Syndrome (MERS) and Severe Acute Respiratory Syndrome (SARS) is well documented. How the novel coronavirus found this time is different from SARS and MERS coronavirus is still in the process of understanding. The genetic characteristics of SARSr-CoV and MERSr-CoV are significantly different based on the current gene sequencing. In current research, it has been shown to share more than 85% homology with bate SARS-like coronavirus (bat-SL-CoVZC45).

At present, clinical medicine uses the patient's epidemiological contact history, clinical manifestations (fever, lymphocyte count decreased, and early white blood cell count normal or decreased) and typical pneumonia imaging features as the criteria for the suspected or clinically diagnosed cases of 2019-nCoV infection. Real-time fluorescence RT-PCR was also employed to identify 2019-nCoV nucleic acid positives in lung or blood samples as etiological evidence. 2019-nCoV has a high degree of homology with gene sequencing. The diagnosis can be confirmed. The COVID-19 virus often causes lung damage as well as pneumonia and interstitial fibrosis, which is histologically confirmed. According to estimates, pneumonia, the main cause of mortality and morbidity, is a major problem for COVID-19. Determining the severity of lung injury has important implications for the efficient use of health care resources. It is in that context that healthcare workers require a diagnostic tool for COVID-19. In other words, they need a tool that is capable of catching

almost all cases. CT scans of the chest are largely used to determine radiological findings. Less than 1 out of 20 instances will be missed, according to the biggest research of more than 1000 patients to date on chest CT, which has an initial sensitivity of above 95%. Significantly fewer COVID-19 patients would be returned to their homes, where they may continue to deteriorate and spread the disease, which would have extremely negative effects. Depending on the stage and severity of COVID-19, there are differences in the lung involvement and radiological findings. A CT scan may show ground glass opacities (GGO) in the early phases, but in the later phases and in patients who are near death, it may show inflammatory exudates infiltrating the epithelium and the alveoli. As a final point, the "crazy paving" pattern, which is a finding, is thought to be the result of an enlargement of the interstitial space along the lung lobule walls. This causes the walls to appear thicker, as if they were made of white lines against a ground glass background. It resembles the appearance of the unevenly shaped stones used to pave streets.

COVID-19 is typically characterized by diffuser ground-glass opacities on chest computed tomographic images. Smooth or atypical interlobular or septal thickening, air bronchograms, poorly defined borders, and thickening of the surrounding pleura are all characteristics of ground-glass opacities. About 15% of people with early-stage disease will have normal chest computed tomography imaging findings, and 40% of people will have normal chest radiograph findings. Within the initial two weeks of symptom onset, anomalies may evolve quickly before progressively fading away [3]. A number of ground-breaking achievements have been made using deep learning as a cutting-edge machine learning approach in the field of computer vision [4]. In several studies, the problem of medical picture segmentation has been successfully addressed by the convolutional neural network (CNN) technique. The use of the general CNN structure for CT image segmentation has the following drawbacks: on the one hand, the computational efficiency is low; on the other hand, the size of the image block limits the size of the receptive field RF (Receptive Field). The features extracted from image patches only contain local features for pixel classification, so the performance of directly utilizing the general CNN structure for image segmentation is limited.

This research suggests a method based on 3D CNN to differentiate CT scans of new coronal pneumonia and builds a depth convolution network with 18 layers and a depth convolution neural network with 22 layers in order to automatically and accurately diagnose COVID-19.Both the first and second models feature 4 and 8 3D convolution layers as well as 4 and 8 3D pooling layers, respectively.

2. Related works

Convolutional neural networks (CNN), which are a type of deep artificial neural network, have grown in popularity in recent years for pattern recognition and machine learning. In 2012, another CNN method was applied to image classification, called embedded CNN, and its results were better than the best results popular in computer vision. In the field of medical imaging, there are also some hot research and the latest research results of applying deep learning.

For difficult brain damage segmentation tasks, Kamnitsas et al. [5] suggested a two-way, 11-layer depth three-dimensional convolutional neural network.Performance can be considerably improved by using this innovative training technique. Utilizing a 3D fully linked CRF for post-processing is novel. In their study [6], Alakwaa et al. Showed that in unlabeled nodules on CT scans, a computer-aided diagnosis (CAD) system could be used to classify lung cancer. Zou et al. [7] developed an ADHD classification method based on deep learning through 3D CNN applied to MRI scanning.Hussein et al. [8] proposed a nodule representation strategy based on 3D CNN. Tan et al. [9] proposed an automatic 2019 coronavirus disease diagnosis framework based on lung CT scanning slice images.

In the current research on benchmark computer vision data sets, convolutional neural network has achieved better results than depth belief network. Over the past few years, CNN has demonstrated great representational capabilities when learning meaningful characteristics from incoming data, so it has aroused great interest in machine learning.

3. Methodology

3.1. Data

Although COVID-19 has become the most serious epidemic in the world, it is difficult to find a public and useful CT data set of COVID-19. After some digging, we discovered some information made available by medical facilities in Moscow, Russia.

The patient chest CT scan dataset from MosMedData: Chest CT Scans with COVID-19 Related Findings Dataset serves as our main dataset [10]. These statistics were provided by the municipal hospital in Moscow, Russia, and were collected between March 1st, 2020, and April 25th, 2020. This data collection includes both anonymous COVID-19-related and COVID-19-unrelated human chest computed tomography (CT) findings. There are 1110 data in this data set, including 42% of men and 56% of women. Ages range from 18 to 97. Each data includes multiple CT scans of a patient, as shown as Figure 1. All data were classified into 5 categories according to classification, CT-0 – CT-5. The data in CT-0 are all normal lung CT scans, while other categories are abnormal lung CT scans. Additionally, each piece of data was stored in nifti format and archived in gzip. Only one out of every ten photos are kept in the final data file.

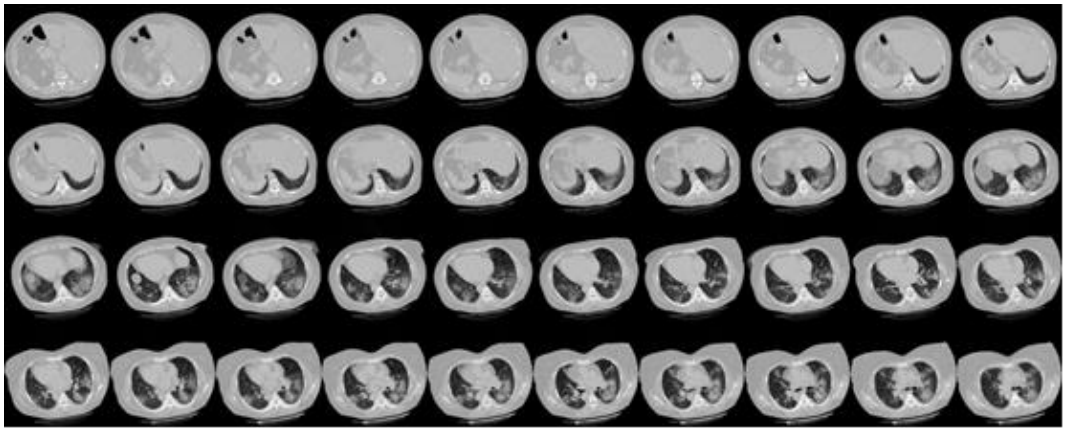


Figure 1. Scans from different locations for one patient

In this paper, we select CT-0, CT-2 and CT-3 based on classification, and divide 70% of them into training set and 30% of them into test set.

3.2. Methods

Traditional computer aided diagnosis (CAD) schemes usually include image preprocessing, segmentation, feature extraction and classification tasks. Its performance largely depends on intermediate steps. The closest deep learning technology can carry out classification jobs and automatically look for characteristics in training images. It can be regarded as an integrated tool for identifying 2019 coronavirus diseases without pattern recognition and complex image processing steps in traditional methods.Convolutional neural networks (CNN) are among the most often used techniques for deep learning classification; nevertheless, most CNN models and those from the Visual Geometry Group (VCG) are two-dimensional.Accordingly, if we wish to use these models to analyze three-dimensional pictures, such CT scans, we should think of the channels as CNN channels and compute the convolution total of all the channels using two-dimensional filters.Since each channel corresponds to a 2D slice of the three-dimensional images, the three-dimensional qualities will be diminished.In light of this, 3D-CNN is innately more suited for 3D pictures, and 3D features may be retrieved using 3D filters.In recent years, the existing research work has made a good attempt on the application of 3 D-CNN to lung CT image recognition, but its network structure and learning technology are still at a preliminary and rough stage. In this article, we present two 3D-CNN models and use a purposeful learning strategy to distinguish between images of healthy people and those who have the 2019 coronavirus infection.

3.3. Preprocessing

Due to the data set, all files are provided in Nifti format. CT scan stores the original voxel intensity in Hounsfield units (HU), which is a method for measuring the radiation density. In this data set, the radiation density ranges from -1024 to more than 2000. To preprocess the data, we first rotate the volume 90 degrees to fix the direction. Then scale the Hu value between 0 and 1 to make the data easy to classify. We adjusted the size of width, height and depth, and reduced the scanned sample to a shape of 128x128x64, as shown as Figure 2. The 3D image is normalized by compressing all pixels of the original non segmented image to a value between 0 and 1. Following preprocessing, the data are separated by 70% and 30%, respectively, into a training set and a test set.

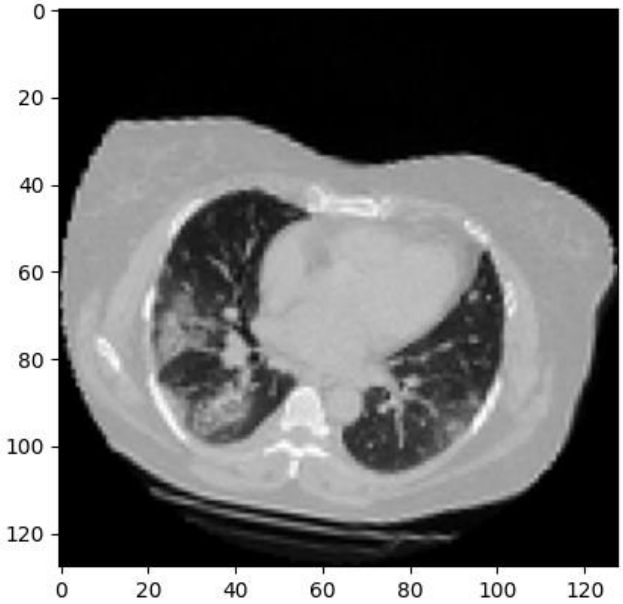


Figure 2. CT image of 128x128

3.4. 3D-CNN Model

In this paper, after referring to the 3D-CNN structure in several papers.We constructed two different 3D-CNN architectures to assess performance of 3D-CNN in the diagnosis of COVID-19.

The actual 3D convolution layer is created by stacking many successive frames to create a cuboid, with filter size, stride length, filling choices, and number of filters being the primary factors to be taken into account. Here is the formula that is employed.

$$O_n^j(x,y,z) = \sigma\left(b_{jn} + \sum_n \sum_{p=0}^{p_j-1} \sum_{q=0}^{q_j-1} \sum_{r=0}^{r_j-1} w_{mn}^j(p,q,r) \cdot I_{im}(x+p, y+q, z+r)\right) \quad (1)$$

Where w_{mn}^j is the weight between the m-th feature map of the i-th layer and the n-th of the j-th layer, O is the output of the j-th layer, I is the input of the i-th layer to the j-th layer, σ is the activation function, and b_{jn} is the shared bias of the cube.

The function of the 3D Max pooling layer is to reduce the complexity of the calculations and extract the key characteristics. The following equation is the one utilized in this phase.

$$O(x,y,z) = max_{(0\le i\le s_1, 0\le j\le s_2, 0\le k\le s_3)}\left(I_{x\times p+i, y\times q+j, z\times r+k}\right) \quad (2)$$

3.4.1 Model I

Four 3D convolution layers, four 3D max pooling layers, one input layer, and one dropout layer make up the model we created. In Table 1, the structure's specifics are displayed.

Table 1. Structure of model I

Layer	Type	Output Shape
Input I	Input Layer	(128, 128, 64, 1)
Conv 3D I	Conv3D	(126, 126, 62, 64)
Max Pooling3d I	Max-Pooling3D	(63, 63, 31, 64)
Batch Normalization I	Batch Normalization	(63, 63, 31, 64)
Conv 3D II	Conv3D	(61, 61, 29, 64)
Max pooling3D II	Max-Pooling3D	(30, 30, 14, 64)
Batch Normalization II	Batch Normalization	(30, 30, 14, 64)
Conv 3D III	Conv3D	(28, 28, 12, 128)
Max Pooling 3D III	Max-Pooling3D	(14, 14, 6, 128)
Batch Normalization III	Batch Normalization	(14, 14, 6, 128)
Conv 3D IV	Conv3D	(12, 12, 4, 256)
Max Pooling 3D IV	Max-Pooling3D	(6, 6, 2, 256)
Batch normalization IV	Batch Normalization	(6, 6, 2, 256)
Global Average Pooling3D I	Global-Average-Pooling3D	256
Dense I	Dense	512
Dropout I	Dropout	512
Dense II	Dense	1

3.4.2 Model II

We constructed a second model structure that resembles the previous one. Eight 3D convolution layers, four 3D pooling layers, one input layer, and one dropout layer are all present. Table 2 provides a breakdown of its structural features.

Table 2. Structure of model II

Layer	Type	Output Shape
Input I	Input Layer	(128, 128, 64, 1)
Conv 3D IA	Conv3D	(126, 126, 62, 64)
Conv 3D IB	Conv3D	(126, 126, 62, 64)
Max Pooling3D I	Max-Pooling3D	(63, 63, 31, 64)
Batch Normalization I	Batch Normalization	(63, 63, 31, 64)
Conv 3D IIA	Conv3D	(61, 61, 29, 64)
Conv 3D IIB	Conv3D	(61, 61, 29, 64)
Max Pooling 3D II	Max-Pooling3D	(30, 30, 14, 64)
Batch Normalization II	Batch Normalization	(30, 30, 14, 64)
Conv 3D IIIA	Conv3D	(28, 28, 12, 128)
Conv 3D IIIB	Conv3D	(28, 28, 12, 128)
Max Pooling 3D III	Max-Pooling3D	(14, 14, 6, 128)
Batch Normalization III	Batch Normalization	(14, 14, 6, 128)
Conv 3D IVA	Conv3D	(12, 12, 4, 256)
Conv 3D IVB	Conv3D	(12, 12, 4, 256)
Max Pooling 3D IV	Max-Pooling3D	(6, 6, 2, 256)
Batch Normalization IV	Batch Normalization	(6, 6, 2, 256)
Global Average Pooling 3D I	Global-Average-Pooling3D	256
Dense I	Dense	512
Dropout I	Dropout	512
Dense II	Dense	1

4. Results

After 28 epochs, we obtained the accuracy and loss line chart of the two models. Figure3 is the accuracy line chart of model I. As can be observed, the model's accuracy rises with each passing epoch, reaching a maximum accuracy of roughly 0.75. At the same time, Figure 4 is the loss curve of model I. Similarly, the loss also decreases with epoch, and the final loss is about 0.5.

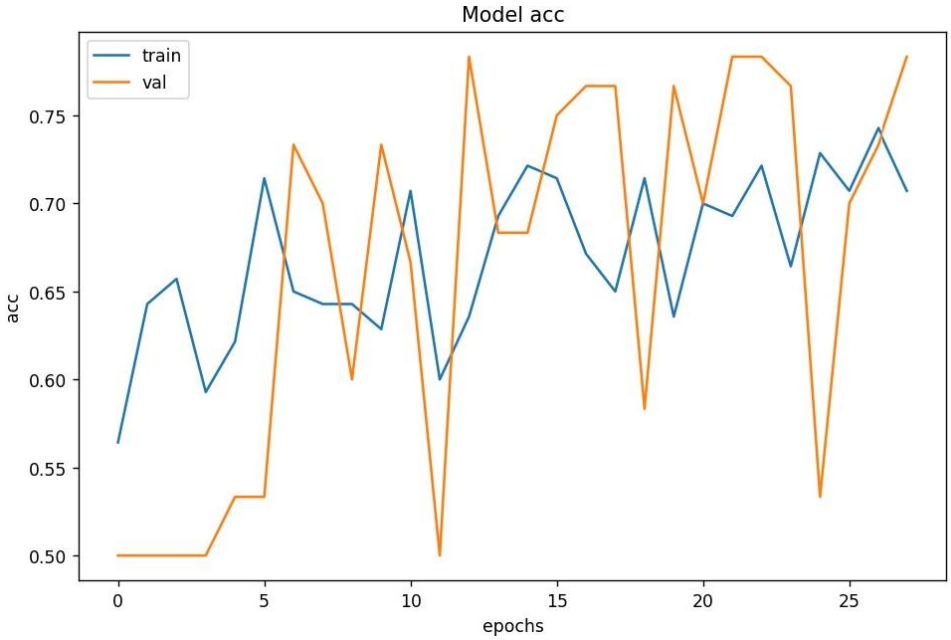


Figure 3. Accuracy line chart of model I after 28 epochs

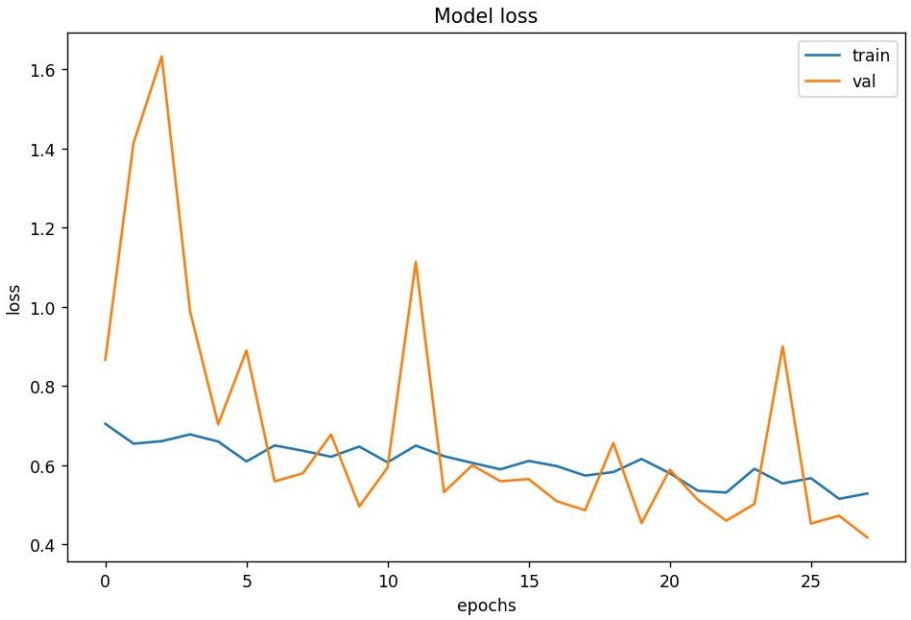


Figure 4. Loss line chart of model I after 28 epochs

Figure 5 and Figure 6 are the accuracy line chart and loss line chart of model II respectively. From these two figures, we can see that the performance of model II is similar to that of model I. Their final accuracy is about 0.75, and their final loss is about 0.5.

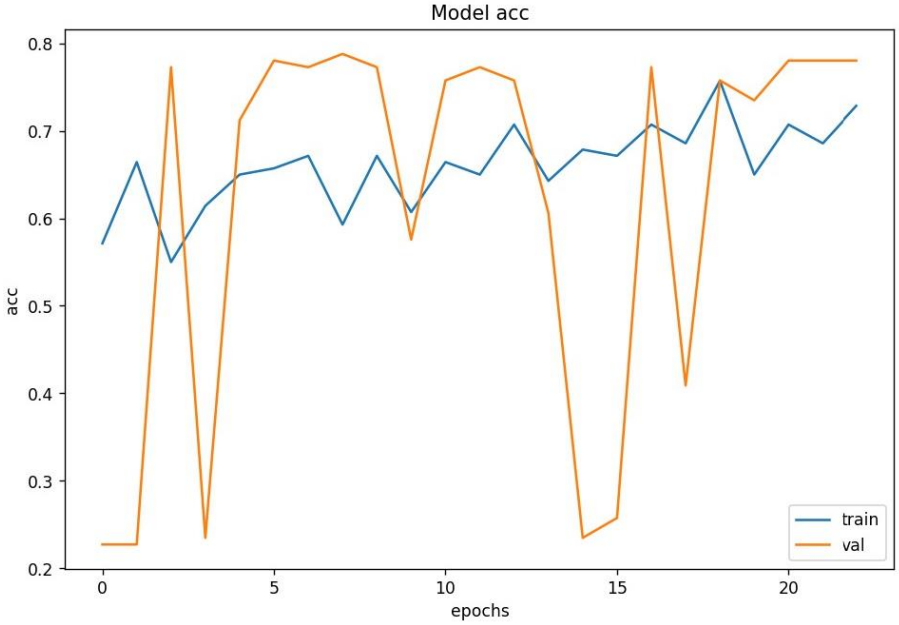


Figure 5. Accuracy line chart of model II after 28 epochs

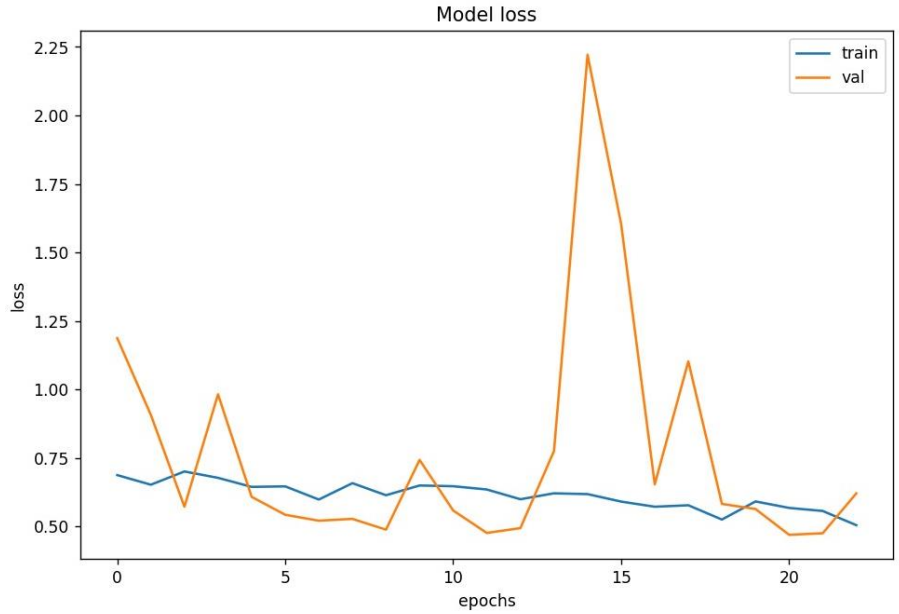


Figure 6. Loss line chart of model II after 28 epochs

5. Conclusion

Using the data set from the Moscow Municipal Hospital, we created two 3D-CNN models with a comparable structure to show how well 3D-CNN performed in the diagnosis of COVID-19. After the training of these data, it can be seen from the above results that the two models with different structures have similar performance in COVID-19 diagnosis based on lung CT scanning slice images. The final accuracy of the two models is about 78%, which shows the feasibility of 3D-CNN in the diagnosis of COVID-19. It also demonstrates that the model's performance is unaffected significantly by the addition of more 3D convolution layers.

However, there are still some limitations in this study. The more different 3D-CNN models were not performed in this study, so we may have missed a more efficient model for the diagnosis of COVID-19. Another limitation is that the dataset used in this study is not large, which may cause the accuracy of the model is less than 80%.

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