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A Simple Convolutional Neural Network for Precise and Automated Identification of COVID-19

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***Abstract*—Goal: To solve two key problems in the identification of people who are infected with COVID-19: the first problem is that the identification accuracy is not high enough. The second problem is that present identification method such as nucleic acid testing is expensive in many countries. Methods: So, I decided to design a fast identification method for COVID-19 patients which is based on deep learning. After the model (CoughNet) learns more than 6,000 cough spectrograms of both COVID-19 patients and normal people, the accuracy rate of identification of COVID-19 patients and normal people is higher than 99% in the test set. Structure: This paper is mainly divided into three parts: the first part introduces the main background and research status of the research; The second part introduces the research methods; The third part introduces the specific process of the experiment.**

***Index Terms*—computer vision, deep learning, CoughNet model.**

1 Introduction

1.1 Background

COVID-19 swept the world from 2019, bringing great disaster to people all over the world. However, at present, most of the identification methods of the COVID-19 patients remain in methods of clinical medicine: nucleic acid testing, chest CT, etc. These methods consume a lot of resources and are sometimes not accurate enough, especially for the identification of the asymptomatic COVID-19 patients and other specific COVID-19 patients. So, we want to develop a method to more quickly and accurately identify people infected with COVID-19. Through rapid identification of COVID-19 patients, the continued spread of COVID-19 can be controlled.

1.2 Research Status

Many scholars have carried out machine learning experiments on the features of COVID-19 patients. The features are extracted from people's cough, voice, lung films, and so on. Most experiments use the speech recognition method or image recognition method alone. For example, In April 2020, Brian Subirana et al. developed a voice-based COVID-19 AI detection tool Sigma, which uses transfer learning to training COVID-19 patients' voices to find who is a COVID-19 patient [1]. In September 2020, the Massachusetts Institute of Technology trained more than 200,000 infected persons and normal people's cough sound to identify infected persons. This model was evolved from a previous model which was constructed to identify Alzheimer patients. It can identify four unique cough characteristics related to COVID-19: muscle degeneration, vocal cord strength, mood changes, breathing, and lung function. The accuracy rate of this model in identifying the patients who are infected with COVID-19 is over 98 percent [2]. Subsequently, more and more scholars are engaged in using machine learning and other methods to identify COVID-19 patients [3].

2. Methodology

The main work is to establish a new convolutional neural network model to learn the cough spectrograms of COVID-19 patients and normal people and then to continuously improve the accuracy of model recognition. After converting people's cough into spectrograms, we can obtain picture samples.

2.1 CoughNet

CoughNet is a convolutional neural network model of deep learning. The schematic diagram of the convolutional neural network is shown below:

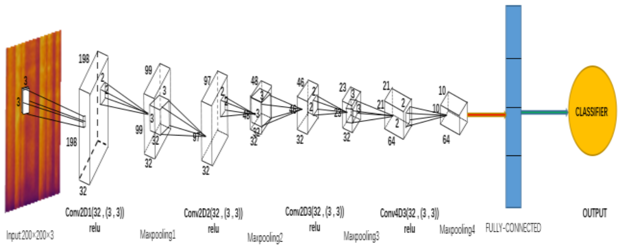

Fig. 1. Overview architecture of CoughNet model, including input layer, hidden layer, dense layer, and output layer.

We set the pixel size of the input color image to 200*200. In the CoughNet model, Conv2D is derived from the convolution layer of Keras. Here we use 32*198*198 for the first layer. The activation function used by the convolution layer is SoftMax. The subsequent convolution layers are similar to the first layer. A pooling layer is added after each convolution layer, where we use the MaxPooling. Then the layer is the FULLY CONNECTED layer, and the last layer is the CLASSIFIER layer, which is used to output the category (positive or negative) of the patient.

2.2 Optimization Method Used in Paper

The loss function used in this paper is the binary cross entropy loss function. We know that the general binary cross entropy loss function is expressed as follows:

$$H_p(q) = -\frac{1}{N}\sum_{i=1}^{N} y_i \cdot \log(p(y_i)) + (1-y_i)\cdot \log(1-p(y_i))$$

Where y_i is the mark of the sample, and the positive class is 1, and the negative class is 0. p represents the probability that the sample is predicted to be positive.

Since the ratio of positive and negative samples is roughly 1:1.5, to better deal with bias, we use Adam Optimizer in neural network training, which adds bias-correction and momentum based on RMSprop.

3. Experiment

3.1 Data Set and Feature Engineering

The original data set came from the data set disclosed by KAGGLE and COSWARA. There are 1,934 pictures to use. The data set is divided into the training set, validation set, and test set according to the ratio 6:2:2. We preprocess original data in some methods such as normalization, centralization, and so on. The following takes picture Negative_0_308 as an example for analysis:

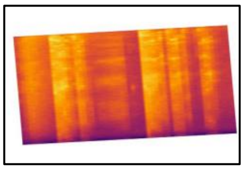

Fig. 2. Original spectrogram picture of one person's cough**.** We preprocess the original data: normalization, centralization.

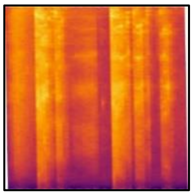

Fig. 3. Processed spectrum picture of **Fig.2.**

We use the supervised learning method, so the labels of the data are very important for us to improve the accuracy rate. Because of the limited data sets provided by open-source data sets, to improve the generalization ability of the model and to better extract features of images. We know the increase in the number of data sets is an essential tool to increase the accuracy of the model. So do Data Augmentation is an important method. Data Augmentation of the image is shown in the following figure:

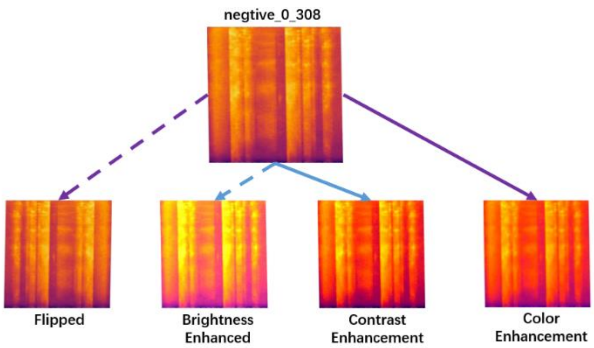

Fig. 4. Data Augmentation of negative_0_308. There are 4 main augmentation methods used: flip the original picture, enhance brightness on the original picture, enhance contrast on the original picture and enhance color on the original picture.

3.2 Evaluation Indicators

The evaluation indicators of the experiment results are accuracy on the test set and the validation set. Loss on the test set and the validation set is also an important indicator. The method used in this paper is the binary classification technique. If people belong to COVID-19 patients, they are set as positive cases and those not belong to COVID-19 patients, they are set as negative cases. Then results can be divided into true-positive cases, false-positive cases, true-negative cases, and false-negative cases according to the combination of real type and predicted type of the model. And let TP, FP, TN, and FN respectively represent the corresponding number of classifications. Then the formula for calculating accuracy is as follows

$$\frac{TP+TN}{TP+FP+TN+FN}$$

Another important evaluation indicator is loss, which can be obtained from formula $H_p(q)$ mentioned in 2.2.

3.3 Experiment Design

Through the previous preprocessing, the parameters of the convolutional neural network can be continuously designed and adjusted. Finally, the appropriate parameters can be obtained. For example, the input image was normalized and the input size of the image was adjusted to 200*200 pixels. And to better learn the characteristics of COVID-19 patients and normal people and reduce training concussion, epochs were adjusted to 150 times, and batch size was adjusted to 32. To make the absolute error proportional to the magnitude that needs to be adjusted, the loss function used is the binary cross entropy loss function. The optimizer used in the training process is the Adam Optimizer mentioned in 2.2. Then we can start training our model on the computer.

3.4 Analysis of Result

In the identification and classification of COVID-19 patients and normal people, the accuracy rate of recognition of our model CoughNet can reach 99% in both the training set and validation set. And loss is very small in both the training set and validation set. The loss is less than 0.1 in the end. So, we can find this model can identify COVID-19 patients very well. The following figure shows the change of accuracy in the training set and validation set with the increase of epoch.

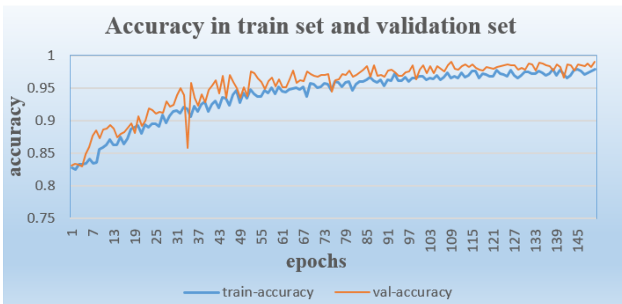

Fig. 5. The variation of accuracy in training and validation set. We do 150 epochs, and the blue line shows variation in the training set and the yellow one in the above picture shows the variation in the validation set.

Similarly, we can obtain the change of loss in the training set and the validation set with the increase of epoch as follows:

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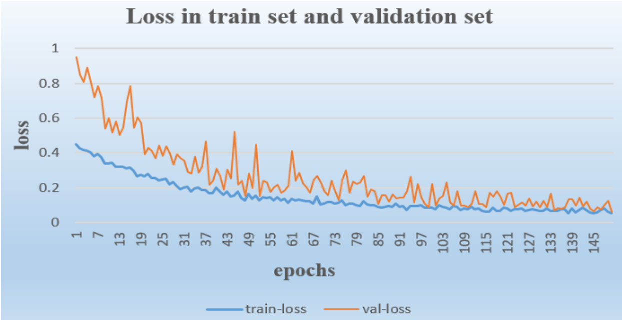

Fig. 6. The variation of loss in training and validation set. We do 150 epochs, and the blue line shows variation in the training set and the yellow one in the above picture shows the variation in the validation set.

This experiment design has some advantages as follows. I find that traditional patient recognition focuses on the deep learning of CT images. Or they may focus on machine learning based on speech recognition where their model needs to learn features based on the patient's speech (including cough, exhalation, and so on). However, the model CoughNet designed by me first converts the patient's cough into the spectrogram, and further, the model can extract main features from the spectrogram, which can greatly improve the accuracy, and greatly reduce the time and space cost of training. For 150(EPOCHS)*100(STEPS)'s training. The training time on GPU (using Google Colab) is about 20min. Meanwhile, in the process of identifying COVID-19 patients and normal people, we obtained a relatively high accuracy rate and relatively low loss, which indicates that our model has relatively high generalization and reliability.
The experiment results are compared with those got from other methods, as shown in the table below.

Method	CoughNet	VGG16	SVM
Classification Accuracy Rate	99.13 %	92.65 %	82.58 %

Table. 1. The contrast between CoughNet and the other two machine learning methods.

Just in terms of the accuracy rate of identifying patients, CoughNet can be compared to the following teams. Compared with Jordi Laguarta's team, their model achieves 98.5% of COVID-19 sensitivity with a specificity of 94.2% [2]. In contrast to Ahmed Fakhry's team, the sensitivity and specificity of detecting COVID-19 are 85% and 99.2% respectively [4]. Compared with the Yu-Huan Wu group, their model can achieve an average sensitivity of 95.0% and specificity of 93.0% on the classification test set, and 78.5% Dice score on the segmentation test set of their COVID-19 dataset [5].

4. Conclusion

The CoughNet model is proven to be effective and could make a difference in the future identification of COVID-19 patients.

4. References

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