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COVID-CNNnet: Convolutional Neural Network for Coronavirus Detection

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ABSTRACT

The coronavirus disease (COVID-19) is the most recent severe diseases that has spread globally at an exponential rate. During this crisis, any technological approach that allows highly precise early detection of COVID-19 infection will save many lives. The main clinical technique for COVID-19 recognition is the reverse transcription polymerase chain reaction (RT-PCR). However, the RT-PCR testing tool is time-consuming, inaccurate and requires skilled medical staff. Therefore, auxiliary diagnostic tools should be developed to stop the spread of COVID-19 amongst people. Chest X-ray imaging is a readily available method that able to serve as an extremely good alternative for RT-PCR in identifying patients with COVID-19 diseases because it provides salient COVID-19 virus information. In this study, the COVID-CNNnet model proposed based on a convolutional neural network (CNN) deep learning (DL) algorithm, to detect COVID-19 cases rapidly and accurately based on patient chest X-ray images. The proposed COVID-CNNnet model aims to provide an accurate binary diagnostic classification for COVID-19 cases versus normal cases. To validate the proposed model, 3540 chest X-ray images were obtained from multiple sources, including 1770 images for COVID-19 cases. Results show that the COVID-CNNnet model can identify all classes (COVID-19 cases versus normal cases) with an accuracy of 99.86%. The proposed method can assist doctors diagnose COVID-19 cases effectively using chest X-ray images.

1. Introduction

The COVID-19 disease was originated in Wuhan, China in the end of 2019 when pneumonia cases with unknown causes rapidly spread within 30 days from Wuhan to most parts of the country. COVID-19 quickly became a pandemic and posed a serious public health issue worldwide [1]. This disease is induced by the SARS-CoV-2 virus, which is related to two separate coronaviruses, namely, Middle East respiratory syndrome viruses and severe acute respiratory syndrome (SARS) [2]. The worldwide prevalence of COVID-19 has quarantined many individuals and damaged many businesses. This pandemic negatively affected the quality of human life. Based on the World Health Organization report, the estimated number of approved COVID-19 cases everywhere in the world at the time of writing this paper is 75,479,471, including 1,686,267 deaths [3]. Given the high transmissibility of the disease, early diagnosis plays an important role in COVID-19 control [2]. The first step in the detection of any virus is to identify the usual clinical features of a virus and use these features as special symptoms to obtain accurate diagnosis. The symptoms of COVID-19 comprise cough, cold with fever, tiredness, headache, sore throat, muscle pain and acute respiratory syndrome. COVID-19 can also affect other important body organs, such as the liver [4][5]. At present, RT-PCR is the most popular testing tool used to diagnose COVID-19 cases [6]. However, the RT-PCR process is manual, complex, laborious, and time-consuming. The process takes 4–6 h to achieve results, and the positivity rate is only 63% [7]. Consequently, the timely location of infected patients is difficult, and thus can lead to the contamination of healthy patients. Therefore, finding alternative early diagnosis methods is necessary to mitigate the inefficiency and scarcity of RT-PCR test kits and an early identification of the disease to decrease the COVID-19 infection incidence amongst people.

According to [8][3], one of the major indicators of COVID-19 infection is respiratory difficulty, which can be easily recognised using X-ray images. X-ray is an imaging test tool that serves as a promising alternative for RT-PCR in diagnosing COVID-19 cases because of its ability to reveal numerous white patchy shadows in the lungs of a COVID-19 infected person [9]. Utilising chest X-ray images can solve the problem regarding the unavailability of diagnostic RT-PCR kits and the limitations of their manufacturing. In addition, radiological image systems are available in every hospital. Considering that this diagnostic method is simple and easy to use, doctors can use the images to detect the infection in suspected individuals even if the common symptoms are not yet present [1].

Recently, DL and computer vision are used to identify many biomedical problems, such as tumour detection in the lungs [10] and brain [11], skin lesion classification [12]. The CNN is one of the important and common DL techniques that demonstrate excellent performance in the medical imaging field. The CNN methodology exhibits such a satisfactory performance because it does not rely on handcrafted feature engineering but learning features from the data automatically. The aim of this research is to propose a DL model by based on the CNN algorithm to achieve an effective and rapid identify of COVID-19 patients. The developed model, called COVID-CNNnet that only uses chest X-ray images to identify the COVID-19 patients. The dataset comprised 3540 images that obtained from various sources. The efficiency of the proposed model was measured and validated through the accuracy metric and confusion matrices.

The rest of the paper organized as follows. Section 2 discusses several related works. The design and architecture of COVID-CNNnet are presented in Section 3. Experimental results and discussion presented in Section 4. The comparison of the proposed method with other state-of-the-art methods is discussed in Section 5. Lastly, in Section 6 conclusion and future research directions are provided.

2. Related Works

The diagnosis of COVID-19 infection through different types of medical images is a fast-growing research topic. Machine learning-based methods, along with manual feature extraction algorithms, are used in few studies to diagnose the disease [7] [5]. To rapidly identify COVID-19 cases, many studies utilised DL approaches that use chest X-ray images to diagnose infected patients. Their findings present encouraging results in terms of accuracy. However, these studies used a small dataset that includes few samples of COVID-19 chest X-ray images [1] [13]. Therefore, the existing findings cannot be generalised, and the maintenance of the reported model performance when evaluated on a large dataset is uncertain.

Wang and et al. [14] introduced COVID-Net to recognise COVID-19 cases from a dataset comprising 266 COVID-19 chest X-ray images. The maximum accuracy obtained by this method is 83.5%. Ioannis et al. [1] used the transfer learning method to classify a dataset with 1427 chest X-ray images, which consists of 224 COVID-19 cases. The authors used five DL models, namely, Inception, VGG19, Xception, MobileNet and Inception-ResNet-v2, to identify infected patients by using chest X-ray images. The dataset was divided for training and testing through the 10-fold cross-validation method. The VGG19 method was selected as the primary DL model, which obtained an accuracy of 96.78. Afshar et al. conducted a method called COVID-CAPS. They reached an accuracy of 95.7% from the approach without pretraining and 98.3% from the pretrained COVID-CAPS. However, the sensitivity values that they obtained are not as high as the general accuracy [15]. Sahinbas and Catak [16] used five different pretrained models, namely, VGG16, VGG19, ResNet, DenseNet and InceptionV3 to study 70 COVID-positive and 70 COVID-negative data. They achieved an accuracy of 80% by using VGG16 as their binary classifier. Narin et al. [6] used the ResNet50 DL model to recognise 50 COVID-19 cases from 50 normal chest X-ray image data. They reached a maximum accuracy of 98%. However, this study does not reflect the model performance in multi-class classification. Ucar et al. [9] adopted transfer learning methods to automatically identify COVID-19 cases from 284 chest X-ray images of COVID-19 ceases and 310 chest X-ray images of normal individuals. The best performance reached an accuracy, precision and recall of 89.5%, 97% and 100%, respectively. However, this research is not completely tested using different machine learning methods, and the experimental method was not explicit. The DarkNet model, which comprises 17 leaky rectified linear unit (ReLU) convolution layers with leaky ReLU activation feature, was developed by Ozturk et al. [13]. This model was tested on binary and multi-class cases and achieved an accuracy of 87.02% and 98.08% respectively.

A concatenated CNN depend on the Xception and ResNet50V2 models was created by Rahimzadeh et al. [17] to distinguish COVID-19 cases through chest X-ray images. Authors used a dataset containing 180 of COVID-19 and 8851 of chest X-ray images normal cases. This model attained an accuracy of 99.56%. A DL approach that uses ResNet50 to extract the feature and support vector machine for classification was developed by Sethy and Behera. [4] to identify COVID-19 patients through chest X-ray. A total of 158 of non-COVID-19 and COVID-19 chest X-ray images were obtained, and the propose method reached an accuracy of 95.38.

Many researchers considered inadequate amount of COVID-19 data. In the present study, the differentiation performance of 1770 COVID-19 data with respect to each other was investigated using three CNN DL architectures.

3. Proposed Methodology

This study propose a new model for COVID-19 identification, called COVID-CNNnet, depend on chest X-ray images. The proposed method consists of four major steps: (1) dataset gathering, (2) data preprocessing and labelling, (3) model training and (4) model validation and analysis. Figure 1 shows the complete flowchart of the COVID-CNNnet model for COVID-19 detection.

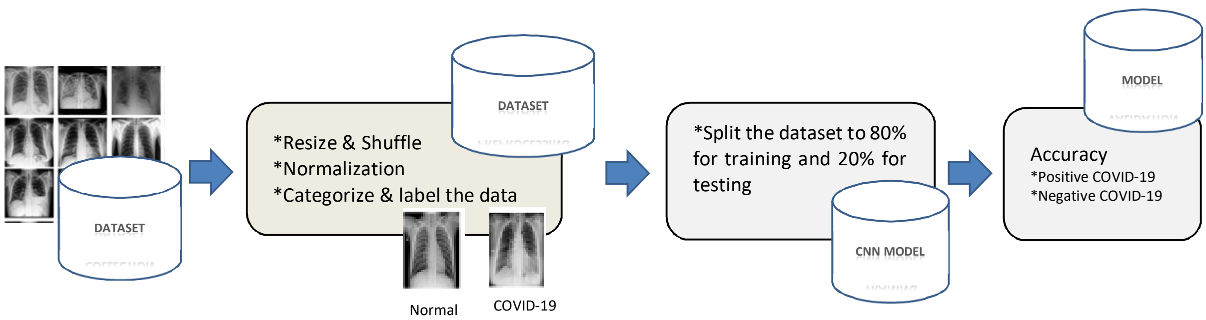


Fig. 1 The flowchart of the COVID-CNNnet model

3.1 Dataset Collection

Given that COVID-19 is a recent and novel disease, no large repository contains a large amount of relevant data. Therefore, various sources were utilized to collect the dataset. The COVID-19 images were gathered from publicly available datasets, whereas the normal non-COVID-19 images were generated from the publicly accessible Kaggle database (Table 1). The combination of two GitHub repositories [18] [19] provided 1770 COVID-19 data items, which were then used to test and train the COVID-CNNnet proposed model. The repositories have different chest X-ray images for different diseases, such as SARS, Escherichia coli, influenza and other types of pneumonia from various patients, but only the images with positive COVID-19 infection were considered. The ages of the patients varied from 12 years to 93 years. We also collected 1770 standard chest X-ray images of non-COVID-19 data items, which were randomly acquired from a Kaggle dataset called "Chest X-ray Images (Pneumonia)" (the number of non-COVID-19 images is the same as the number of COVID-19 images to prevent the imbalanced data issue during performance analysis) [20]. Figure 2 visualises a sample of chest X-ray Images from COVID-19 and non-COVID-19 cases.

Table 1. Characteristics of the COVID-19 dataset

Dataset	COVID-19	Normal	Total	Dimension	Depth	Training	Test
COVID-19 chest X-ray	1770	1770	3540	(224,224)	1	80%	20%

(a) Normal cases

(b) COVID-19 cases

Fig. 2 COVID-19 dataset (a) normal cases (b) COVID-19 cases

3.2 Dataset Preprocessing and Labelling

Data preprocessing is important to remove noise from the data before feeding them to the network. All chest X-ray images were recorded in a single dataset. The original resolution of the images ranges between 916 × 673 and 2000 × 2000 pixels. To fit the experimental configuration and ensure the uniformity and image quality, all images were converted into greyscale and subsequently normalised and downsized to 224 × 224 pixels to perform real-time classification and prevent resource exhaustion and decrease RAM usage. The greyscale colour space conversion allows operating in one channel only rather than processing in the three RGB channels. The number of parameters of the first convolutional layer would be decreased twice by this conversion, and the computational time would be also reduced. To introduce randomness, the dataset was shuffled to avoid bias towards certain parameters. One-hot encoding is perform to the image data labels to indicate if the image is a COVID-19 positive case or a normal case.

3.3 COVID-CNNnet Model Architecture

CNNs have achieved several breakthroughs as a basic DL technique in image classification problems [21][22]. This method has become increasingly common in many benchmark datasets under different domains, such as human activity recognition and object and image detection [23][24][25]. The CNN algorithm uses three kinds of layers, these are, convolutional layers, pooling layers and fully connected layers. The full CNN architecture is built through numerous stacks of the above mentioned layers.

The COVID-CNNnet model consists of four convolutional layers activated with ReLUs activation function, three pooling layers, one dropout layer and one fully connected layer that is also activated with ReLUs. This model ends with an output layer that has a softmax activation function to yield the distribution of the probability over classes (Figure 3). Table 2 lists the detailed dimensions of each layer and operation. The first and second layers are convolutional layers that contain 64 feature maps and have a kernel size of 3 × 3. Both layers are activated with ReLUs. The third layer is a 2 × 2 max pooling layer. The objective of this layer is to decrease the number of parameters to minimise overfitting and decrease the computation time. The next layer is the third convolutional layer, which has kernel size of 3 × 3 and 64 feature maps. This layer is also activated with ReLUs. Another 2 × 2 max pooling layer follows the third convolutional layer. This max pooling layer is followed by the fourth convolution layer activated with ReLU and has 3 × 3 kernel size and 64 feature maps and follow by another 2 × 2 max pooling layer.

The proposed network architecture of the COVID-CNNnet ends with a fully connected layer consisting of a flatten layer, a fully connected layer, a dropout layer and an output layer. To process the final output through standard completely connected layers, the flatten layer transforms the 2D matrix data into a vector. The second layer is a fully connected layer that comprises 64 neurons, which are activated with ReLU. The next layer is a dropout layer that excludes 40% of the neurons and the last layer is the output layer, which contains two neurons and is activated with a softmax activation function.

Two additional CNN models with six and eight convolution layers were developed for the comparative analysis instead of using the four layers of the proposed model. These models are respectively referred to as 'CNN_Model2' and 'CNN_Model3'. CNN_Model2 has six convolution layers with ReLU activation function. Each layer has 64 channels and a fixed 3 × 3 kernel. In addition, CNN_Model2 comprises three 2 × 2 max pooling layers, two fully connected layer and one dropout layers. On the other hand, CNN_Model3 has eight convolution layers that have 64 channels each with a fixed 3 × 3 kernel and a ReLU activation function, four 2 × 2 max pooling layers, four fully connected layer and one dropout layer.

Table 2. Configuration and parameters of the COVID-CNNnet model

#Layer	Type	Layer Configuration			#Parameter
		#Filters	Kernel size	Activation function	
1	Convolution2D	64	3x3	ReLU	640
2	Convolution2D	64	3x3	ReLU	36928
3	Pooling (Max)	-	2x2	-	0
4	Convolution2D	64	3x3	ReLU	36928
5	Pooling (Max)	-	2x2	-	0
6	Convolution2D	64	3x3	ReLU	36928
7	Pooling (Max)	-	2x2	-	0
8	Flatten	100352 Neurons	-	-	0
9	Fully connected	64		ReLU	3211328
10	Dropout	0.4	-	-	-
11	Output	2 classes		Softmax	130
		Total Parameters			**3,322,882**
		Trainable parameters			**3,322,882**
		Non-Trainable parameters			**0**

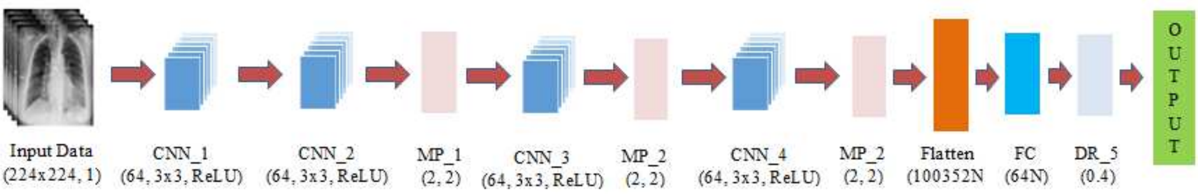


Fig. 3 COVID-CNNnet model architecture and layer configuration for COVID-19 detection

3.4 Assessment and Validation Measures

Different metrics can be used to evaluate the efficiency of DL algorithms for image classification. These metrics include precision, F1 score and accuracy. The most important metric for assessing a CNN model is the accuracy, which defines how similar the generated result is to the real value. Equation (1) defines the accuracy metric (A) utilized to measure the efficiency of the COVID-CNNnet model, where TC and FC represent the number of instances that are correctly and incorrectly classified, respectively.

$$A = TC / (TC + FC) \times 100 \tag{1}$$

4. Results and Discussion

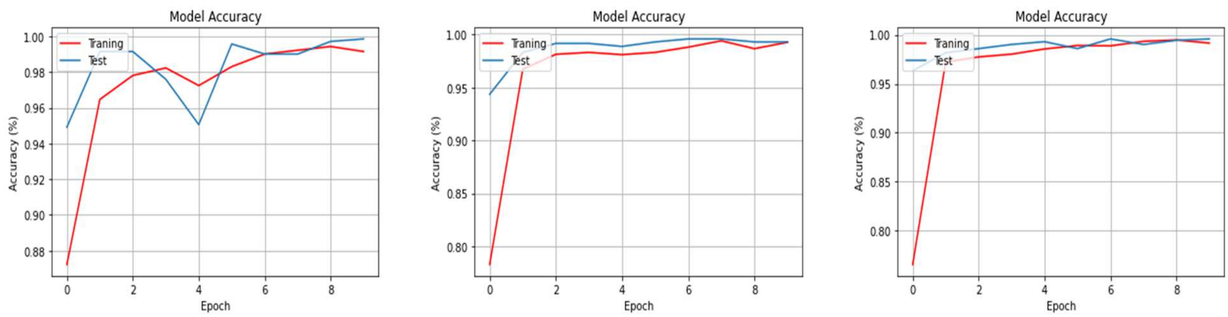
The dataset was divided into two sets to test and train the performance of the developed COVID-CNNnet model. The first collection consists of 80% from the dataset, representing 2832 images that are randomly selected for training; 20% (708 images) of the images are randomly selected for testing. For all experiments, the batch size, learning rate and number of epochs were set to 128, 0.0001 and 10, respectively. The COVID-CNNnet model is trained in a completely supervised way, and its parameters are optimised by minimising the role of the binary-entropy loss function and Adam was used for learning. The architectures of the three CNNs models (i.e. COVID-CNNnet model, 'CNN_Model2' and 'CNN_Model3') are described in Table 3. All DL models were trained using SGD because of its high convergence and fast running time and executed using Keras libraries and Python programming language that run based on TensorFlow 2 backend. The models were trained on Google Colaboratory, which has an NVIDIA K80 graphics processing unit, 64 GB RAM, 12 GB memory and 100 GB solid-state drive. Image data augmentation was not implemented in this study.

The COVID-CNNnet proposed model was evaluated along with CNN_Model2 and CNN_Model3. The results are summarised in Table 3. Given the powerful GPU capabilities, the runtime of all models is relatively short (3.1–1.7 min). The results show that the COVID-CNNnet model reaches the highest testing accuracy (99.86%) amongst the other two models after 10 learning epochs.

Table 3. Architectures and performances of COVID-CNNnet model, CNN_Model2 and CNN_Model3

Models	Number and types of Layers				#Epochs	Accuracy %	Testing loss	Training Time
COVID-CNNnet (proposed model)	**4 (CL)**	**3 (PL)**	**1 (FC)**	**1(DL)**	**10**	**99.86**	**0.013**	**2.2 m GPU**
CNN_Model2	**6 (CL)**	3 (PL)	2 (FC)	1(DL)	10	99.29	0.01	3.1 m GPU
CNN_Model3	**8 (CL)**	4 (PL)	4 (FC)	1(DL)	10	99.58	0.02	1.7 m GPU

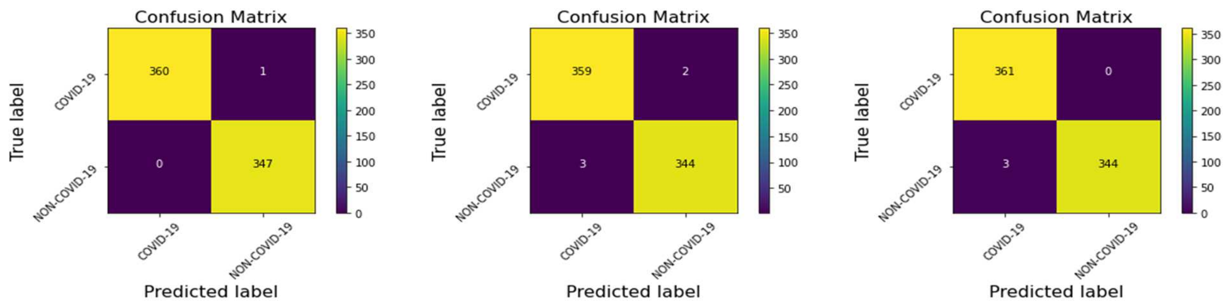
Table 3 indicates that the increase in the number of hidden layers does not reflect any improvement in the test accuracy. On the basis of the obtained results, the best design for the proposed system is to use four convolutional layers. The comparison of the training and testing accuracies of the COVID-CNNnet proposed, CNN_Model2 and CNN_Model3 is illustrated in Figures 4a, 4b and 4c.



(a) COVID-CNNnet (b) CNN_Model2 (c) CNN_Model3

Fig. 4 Training and testing accuracies of the (a) COVID-CNNnet, (b) CNN_Model2 and (c) CNN_Model3

One of the precise metrics that offer insight into the accuracy of DL models is the confusion matrix. Figure 5 displays the confusion matrices of the test phase of the three models for COVID-19 virus identification. The diagonal elements represent the number of correctly labelled data, whereas the off-diagonal ones denote the mislabelled data. The higher the diagonal values, the higher the classification accuracy. Amongst the 708 images, only one image is misclassified by the COVID-CNNnet proposed model. Meanwhile, five images are misclassified by CNN_Model2, including two COVID-19 images and three images are misclassified by CNN_Model3. The high and robust true negative and true positive values and low false negative and false positive values of the COVID-CNNnet model suggest that it outperforms the other two model architectures. In conclusion, the proposed approach can effectively identify COVID-19 cases.



(a) COVID-CNNnet (b) CNN_Model2 (c) CNN_Model3

Fig. 5 Confusion matrices of (a) COVID-CNNnet, (b) CNN_Model2 and (c) CNN_Model3

5. Comparison of the proposed method With State-Of-The-Art Methods

DL-based systems are now commonly used to detect patients with COVID-19 infection. Numerous studies have been conducted on this subject (Table 4). In binary classification, COVID-19 positive cases are typically distinguished from negative ones through chest X-ray radiographs because of their ready availability. Chest X-ray radiographs are commonly used during this pandemic in health centres around the world. However, COVID-19 public image data are limited, and public sources are constantly supplemented with chest X-ray images. Several previous studies used chest X-ray images to differentiate individuals with COVID-19 infection but with limited number images [16] [26] [6]. To address the above issues, this study proposes a DL model called COVID-CNNnet for the identifying of COVID-19 cases. The proposed model has achieved highly and accurate results in detecting COVID-19 cases from normal cases based on automated chest X-ray image feature extraction. Compared with other methods, the proposed system can diagnose COVID-19 cases within a few seconds with a superior accuracy of 99.86% (Table 4).

Table 4 Comparison of the COVID-CNNnet proposed method With State-Of-The-Art Methods

Author	Methods used	#Sample	#Classes	Recognition rate (%)
Sahinbas and Catak [16]	VGG16, VGG19, ResNet, DenseNet, InceptionV3	50 COVID-19, 50 Normal	2	80.00
Hemdan et al. [26]	COVIDX-Net	25 COVID-19, 25 Normal	2	90.00
Ioannis et al. [1]	VGG-19	224 COVID-19, 504 Healthy	2	93.48
Sethy and Behra [4]	ResNet50+SVM	25 COVID-19, 25 Normal	2	95.38
Narin et al. [6]	Deep CNN ResNet-50	50 COVID-19, 50 Normal	2	98.00
Ozturk et al. [13]	DarkCovidNet	125 COVID-19, 500 Normal	2	98.08
Our approach	**COVID-CNNnet**	**1770 COVID-19, 1770 Normal**	**2**	**99.86**

6. Conclusion

Many countries are facing resource shortages due to the rising number of COVID-19 cases daily. To avoid the spread of the disease, a rapid diagnosis approach that can accurately detect positive cases is necessary. COVID-19 is usually associated with pneumonia symptoms and can be detected through genetic and imaging tests. This study introduces a DL model architecture called COVID-CNNnet to distinguish COVID-19 cases by using chest X-ray images. The COVID-CNNnet network architecture is fully automated and does not require manual feature extraction. The

COVID-CNNnet model can perform binary task classification with an accuracy of 99.86%. The results of this study can assist radiologists and other medical practitioners in making practical clinical decisions to detect COVID-19 within a limited period of time. Despite the large number of COVID-19 samples used to train and estimate the performance of the proposed model, the performance of the COVID-CNNnet model can be improved by further increasing the amount of data. To facilitate the accurate and cost-effective detection of COVID-19 infection using chest X-ray images, we intend to explore the possibility of using the proposed diagnostic approach on smart devices to utilise their high computational speed.

Conflict of Interest

The authors declare no conflict of interest.

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