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COVID-19 & Pneumonia Detection using Multi Model Fusion

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Abstract
COVID-19 is a pandemic that has affected the healthcare system and the global economy. The symptoms of COVID-19 and pneumonia are very similar, so it is a challenging task to differentiate between the two diseases. Available Test Methods such as Real-time Reverse Transcription-Polymerase Chain Reaction (RRT-PCR) and Rapid Diagnostic Tests (RDT) are costly, time-consuming, with high false detection rates and limited availability. Therefore, the research community should come forward with other alternative methods that can detect these diseases faster and prevent the spread of COVID-19 and hence, Chest X-ray (CXR) has emerged as a very popular solution as it is cheap and very easily available everywhere. This paper proposes an automated COVID-19 detection model based on chest X-rays. The proposed model developed a fusion of multiple pre-trained convolutional neural networks to extract deep and high-level features from CXR images. This model is tested for three different classes on two different data sets and achieves an accuracy of 94.05% and 92.25%, respectively. These classes are: COVID-19, Pneumonia, and Normal (Healthy).

Keywords: CNN, COVID-19, Fusion, Multi Model, Chest X-rays

1. Introduction

After almost a century, a deadly pandemic has knocked the whole world. The disease belongs to the family of a rare novel CoronaVirus (CoV) hence, also known as Severe Acute Respiratory Syndrome CoronaVirus 2 (SARS-CoV-2) [1]. The World Health Organization (WHO) named the disease COVID-19 in February 2020 and declared it a pandemic in March 2020 in view of its outbreak. According to the data obtained from the WHO site, today on 20 September 2021, 229 million people have been affected by this deadly virus and 4.2 million people have lost their lives [2]. The most prominent symptoms of COVID-19 are cough, fever, loss of smell, and drop in oxygen level in the body. Apart from these symptomatic cases, asymptomatic cases are also increasing, resulting in the rapid spread of COVID-19. Along with this, it is a rapidly spreading disease that infects the respiratory system through contact with a person or during exposure to the virus in the person's lungs. Hence rapid detection is essential to containing the increasing spread of COVID-19. The RT-PcR test being used to detect COVID-19 is based on the swab test and gives results in 2 hours to 48 hours with a high false rate and limited availability [2,3]. Therefore, some other methods have to be explored, which can detect COVID-19 with high accuracy in less time. Chest X-ray (CXR) is an inexpensive diagnostic method for lung screening, readily available everywhere, to detect large numbers of COVID-19 patients at the earliest [4,5]. Examples of CXR show clear lungs, pneumonia lungs, and lungs suffering from COVID-19, respectively, as shown in Figure 1.

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In this work, a Deep Learning (DL) based model has been developed, to detect COVID and pneumonia on the input of CXR images. Transfer learning, which works to transfer the weights of a pre-trained CNN model, can be used effectively in developing a multi-model [6].

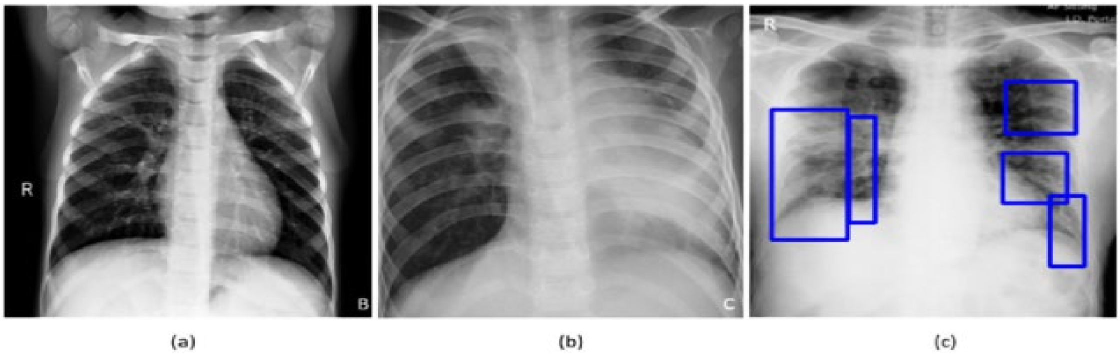

Figure 1: Chest X-rays image: (a) Normal lungs; (b) pneumonia infected lungs; and (c) COVID-19 infected lungs

However, deep learning models are heavy to compute and require massive data sets. Therefore, the studies done in [7-9] prove that the fusion of multiple models gives promising results as compared to a single model in extracting discriminatory information for the classification of CXR images. In this fusion, a combination of Google's Inception Convolutional Neural Network (InceptionV3) [10], Residual Network (ResNet50) [11], and Densely Connected Convolutional Network (Xception) [12], produced good results as compared to other art of algorithms.

This paper is written in the following manner. In Section 2, a survey on existing literature was done. The problem statement and research contribution are presented in Section 3. In Section 4, a description of the proposed Fusion Multimodal, proposed new dataset, and methodology is presented. The obtained results and related analysis are represented tin Section 5. Finally, Section 6 concludes the paper.

2. Literature review

Recently, several classical Image Processing and machine or deep learning methods have succeeded in automatically classifying diseases with CXR images. Therefore computer-aided diagnosis (CAD) has been successfully used as an auxiliary tool for the diagnostic process of radiologists since the 1980s [13].

Wang et al. [14] proposed COVID-Net, the first open-source architecture for detection of COVID-19 from CXR, and achieved an accuracy of 83.5% for the four classes. In [15] the authors used the features of various pre-trained CNN models and classified them into two classes based on SVM, in which the ResNet50 model with SVM got accuracy of 95.38%. Narin et al used transfer learning on five pre-trained CNN models Inception V3, ResNet152, ResNet50, ResNet101 and Inception-ResNetV2 for the classification of COVID-19 and pneumonia, with the ResNet-50 model gave the best results among them [16].

In [17] the authors proposed a CNN model and compared it with 6 pre-trained CNNs (DarkCOVIDNet, VGG19, COVID-Net, Xception, Inception, ResNet) for the multi-class classification (Normal, COVID-19, and pneumonia). This model achieved a sensitivity and specificity of 93.15% and 97.86% respectively for the binary classification, and a sensitivity of 91.78% for the three-class classification (Normal vs. COVID-19 vs. viral). In [18] the authors presented a deep learning model that applied depth convolutions with varying dispersion rates to incorporate local and global features extracted from diverse receptive fields.

The pre-trained CNN models Xception and ResNet50V2 were concatenated to form a new model to classify CXR into three different classes (general, pneumonia, and COVID-19), presented in [19]. The paper [20] shows a comparative study of various pre-existing CNN models for COVID-19 detection, including VGG16, DenseNet201, VGG19, Inception, InceptionV3, ResNetV2, Resnet50, and MobileNetV2.

3. Problem formulation

In previous studies, deep learning-based COVID-19 diagnosis using X-ray images has shown significant improvement. But due to limited datasets and lack of completeness in algorithms, the detection of COVID-19 suffers. Consequently, previous results present low accuracy and high false detection rates. Therefore, there is a growing need to build new algorithms or new CNN models to control this pandemic situation and Our motivation is to develop a rapid and accurate testing system that can help radiologists to detect COVID-19, Normal and Pneumonia classes from chest X-ray images.
The contributions of the paper are as follows:

- Developed a novel model by fusing various pre-trained models to achieve higher accuracy in detection of COVID-19 than previously available methods.
- Two enriched datasets have been used to evaluate the performance of the proposed model.
- The new dataset was proposed by combining two publicly available dataset.
- The performance of the proposed model is compared with the baseline model and is represented by various evaluation metrics such as Confucius Matrix, ROC curve.

4. Method of analysis

A CNN model was introduced for rapid and accurate detection of COVID-19, pneumonia and normal cases. This model was learned from the weights of various pre-trained models using transfer learning and fusion of pre-train CNN model. Additionally, the deep features of the pre-trained model were extracted and concatenated. This model was trained and tested on two different datasets. The details of the pre-trained model and dataset are given in the subsection below.

4.1. Dataset Information

In this experiment two datasets were used to measure the classification accuracy of the model. The first dataset given in Kagal [20-21] is publicly available and includes COVID-19 cases: 3616, Normal: 10,192 and Pneumonia: 1345 CXR images.
The second dataset was created using a combination of two publicly available datasets. First dataset [22] included 4265 pneumonia and 1575 normal CXR images. The second datatset [23] contains CXR images of pulmonary diseases, in which we have taken 946 COVID-19 X-ray images. This new database contains a total of 6,786 chest X-ray images to compare our study to other state-of-the-art findings.

4.2.Fusion Model

This research used a features fusion of various pre-trained models of deep learning to detect respiratory diseases such as COVID-19, pneumonia and Normal. In this feature fusion, deep features are extracted from the various pre-trained models and concatenate to form a new deep learning model. The experiment was performed on different combination of pre-trained models, for which the fusion of ResNet50, InceptionV3, and Xception gave the best results. in the proposed works transfer learning method was used to overcome the problem of scarcity of large datasets. By transfer learning method, pre-trained models were initialized to weights of ImageNet (heavy datasets) to enhance the accuracy. The proposed model architecture is shown in Figure 2. A brief description of all the three CNNs used in our multi-model structure is given below.

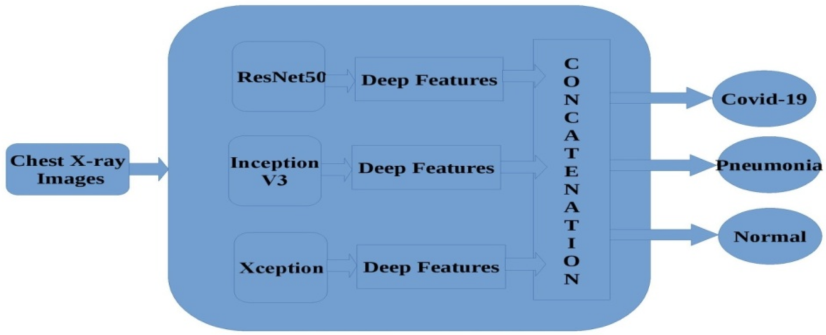

Figure 2: Fusion Model

4.2 ResNet50

The ResNet deep learning model is the first to introduce the concept of "skip connections". In the concept of "skip connection", a few convolutional layers are bypassed at once, allowing the model to be trained deeper in the network and through this the network can copy activations from one ResNet block to another ResNet block, and preserve the information as it flows through the data layers. In addition, batch Normalization is used in ResNet with non-linearity (ReLU) [24].

4.3 InceptionV3

The concept of the Inception module was introduced in InceptionV3, which was repeatedly stacked to form a larger network. It is being used as an alternative to sequential convolutional layers. Furthermore, factoring convolution and aggressive dimension reduction in the network showed relatively low computational cost while maintaining high quality [25].

4.4 Xception

F. Chollet [26] (Google) proposed the architecture of Xception. This architecture has 36 depth convolution layers, to extract deep features. It is upgraded version of Inceptionv3 and introduced Extreme Inception module in place of inception module.

5. Results and discussion

The performance of the proposed model was observed on two different data-sets. The experiment considered a total of 60% random images for training the model, 20% for validation, and the remaining 20% for testing the model. The model accuracy for training and validation is shown in Figure 3 and the model training and validation losses are presented in Figure 4.

The performance of the proposed model is compared with that of VGG19, RestNet50, InceptionV3, Xception, DarkCOVIDNet and COVID-Net as shown in Table 2. The proposed model achieved the highest accuracy of 94.05% for dataset DS-1 as compared to all other algorithms. Figures

7-8 show the ROC curve of the proposed model for data-set1 and data-set2. The model got ROC (0.97) for dataset DS-2 as compared to ROC (0.92) for dataset DS-1.

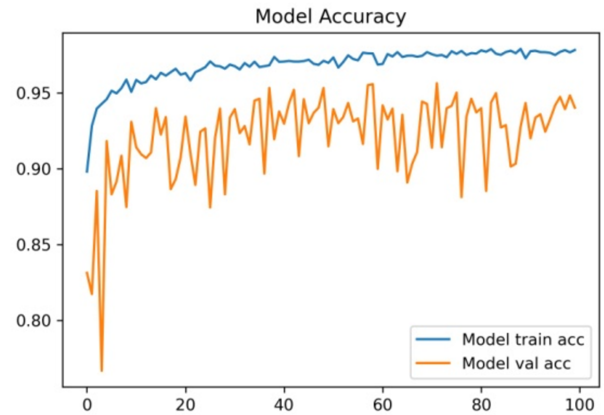

Figure 3: Training & Validation Accuracy

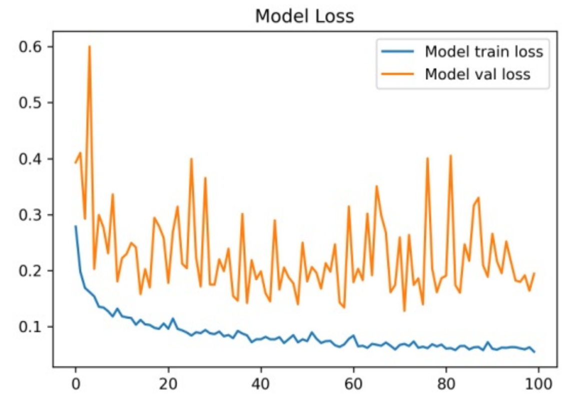

Figure 4: Training & Validation Loss

Table 1 shows the proposed model's precision, recall and F1-score for individual cases. It can be noted that precision, recall and F1-score of COVID-19 for DS-2 are better than that of DS-1.

Table 1: Model performance on different evaluation matrices

	DS-1			DS-2		
	precision	recall	f1-score	precision	recall	f1-score
COVID-19	0.99	0.86	0.92	1.00	0.88	0.94
Normal	0.93	0.98	0.95	0.91	0.76	0.83
Viral	0.85	0.99	0.92	0.82	0.97	0.89

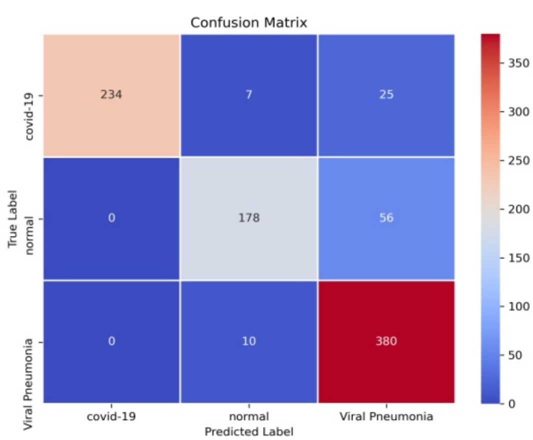

Figure 5: Confusion Matrix for DS-1

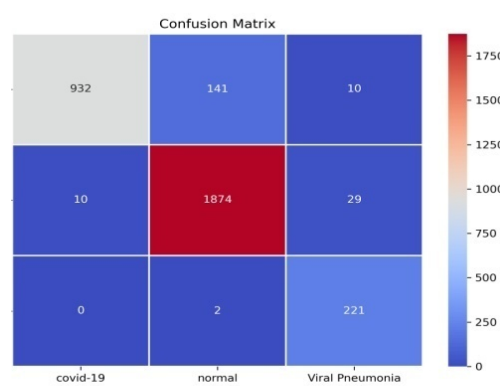

Figure 6: Confusion Matrix for DS-2

Figure 5 and Figure 6 present the confusion matrix for DS-1 and DS-2 respectively. Through this matrix it is clearly visible seen that the model achieved higher true positive and low false positive for data-set1 as compared to data-set2. This graphical and quantitative analysis proves that the proposed framework has significant potential for the detection of COVID-19.

Table 2: Comparison of accuracy for different models

Model	**Accuracy (%)**
DarkCOVIDNet [27]	87.02
VGG19 [29]	90.25
COVID-Net [28]	91.64
Xception [26]	91.85
Inception [25]	91.85
ResNet [24]	91.94
Proposed Model (for DS-2)	92.25
Proposed Model (for DS-1)	94.05

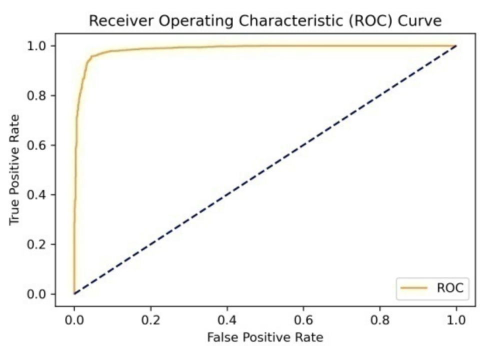

Figure 7: ROC for DS-1

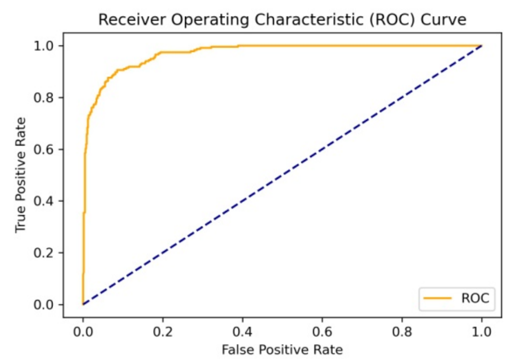

Figure 8: ROC for DS-2

6. Conclusion

This paper addresses the detection problem of current pandemic of COVID-19, where pulmonary diseases such as COVID-19, pneumonia, and Normal need to be detected rapidly and accurately. Therefore, a CNN model has been proposed from the fusion of pre-trained CNN model on CXR images. Transfer learning was used in the proposed model. ResNet50, InceptionV3, and Xception pre-trained models were concatenated to extract deep features. Furthermore, this model has proven to be accurate in detecting pulmonary diseases by comparing the results with other state-of-the-art of algorithms. In addition, it can be used in the healthcare industry as an inexpensive early detection diagnostic test. In the future, the accuracy of the model may be further enhanced by adding more chest X-ray images to enlarge its dataset.

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