COVID-19 Diagnosis using Machine learning

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ABSTRACT

Over 4 million individuals have already died as a result of the deadly contagious viral COVID-19 worldwide. The infection can seriously harm the lungs, increasing the chance of fatal health effects. The only way to lower the mortality rate due to this deadly illness and to halt its growth is through early detection. Deep learning has recently come to light as one of the most useful methods for computer aided diagnosis for helping clinicians make correct illness diagnoses. However, deep learning models require a lot of processing, so hardware with TPUs and GPUs is required to execute these models. To create machine learning models that can be used on mobile and peripheral devices, experts are currently working. In this context, the goal of this study is to create a concise Convolution Neural Network-based computer-aided diagnostic system that can be used on devices with limited processing capacity, such as mobile phones and iPads, to identify the presence of the Covid-19 virus in x-ray pictures. On the basis of various assessment parameters, the findings plainly show that the suggested model outperforms other transfer learning models such as Resnet50, Inception, and Xception. According to various evaluation parameters, the findings definitely show that the proposed model outperforms other transfer learning models like Resnet50, Inception, and Xception.

Keywords—Deep learning; CNN; COVID-19; Transfer learning; Image enhancement

INTRODUCTION

In 2019, the coronavirus illness (COVID-19) [1] that has infected more than 600 million individuals worldwide was discovered in Wuhan, China. Middle East Respiratory Syndrome (MERS), Severe Acute Respiratory Syndrome (SARS), and numerous other fatal consequences are all brought on by the virus. Cough, temperature, exhaustion, headaches, and sore tongue are the most frequent signs and symptoms [2]. Droplets of breath can spread the infection from one individual to another. The sudden increase in cases during previous COVID-19 waves made it challenging for the labs to use RT-PCR, which takes a long time, has a high incidence of false-negative cases [2][3], and is also expensive, to validate positive or negative cases. The key to halting the proliferation of the virus in society is early diagnosis of COVID-19.

One of the most promising methods, deep learning [4], is used frequently in the medical industry to identify serious illnesses at an early stage and yields accurate results in the accurate identification of diseases from pictures. An input layer, concealed levels, activation functions, and an output layer make up a deep neural network [6]. Finding better outcomes may be aided by using mathematical equations with feed forward and feed backward functions at each stage [5]. The output of a node is essentially defined by an activation function, which is used to engage and inhibit neurons. Convolution Neural Networks (CNN) [7] are a type of deep learning neural network made up of neurons that, over time, self-optimize. These networks are mainly used by scientists who study the detection of diseases from images. CNN's ability to autonomously learn functions from domain-specific images is credited with being the primary reason for its popularity. Additionally, transfer learning models [8] store information from one issue and allow it to be applied to another. However, the traditional CNN models, such as Resnet50, Alex Net, Inception and Xception, etc., cannot be used for real-time apps because they cannot be operated on devices with limited computing capacity, such as tablets, mobile phones, or embedded processors. These traditional models require a lot of training time and are also very complicated. To solve these drawbacks, compact and lightweight CNN models are being created, which have fewer parameters than conventional CNNs and can be run on hardware with less powerful processors and memory needs [9].

The paper is organized into the following sections. Section 2 of the paper discusses the literature survey, section 3 describes our proposed model. Section 4 describes dataset. Section 5 describes experimental results and discussion part. Section 6 discusses conclusion and future work.

LITERATURE SURVEY

In recent times, a lot of research has been going on in the domain of disease diagnosis using CNN from images. This section summarizes some of the existing works for disease diagnosis.

Litjens et al. [10] proposed application aspects in deep learning. The different deep learning techniques extracted the spatial features from sophisticated image data i.e. CT, X-ray images, color Fundus images, ultrasound image and implemented models, which can be helpful in hospitals to detect severe diseases such as diabetic retinopathy, skin lesion, bone fracture and breast cancer at their early stages.

Kermany et al. [11] used optical coherence tomography images dataset to detect viral pneumonia and macular degeneration and diabetic retinopathy. Cao et al. [12] introduced the basic concepts of deep learning, and the image analysis is done by deep learning architecture such as CNN, RNN, and Stacked machine auto encoder. With these models, the detection of pediatric pneumonia using chest x-ray images can be done. The authors also presented the challenges in handling unlabeled data, privacy issues in the medical field, and many more.

Jaiswal et al. [13] developed a Mask-Region based Convolution neural network model for detecting pneumonia from X-rays images of the chest. The model contains the region of interest, align convolution layer and pixel-wise segmentation of disease. Toğaçar et al. [8] proposed a minimum redundancy maximum relevance (mRMR) model for the detection of pneumonia. The three transfer learning models, namely, Alex Net, VGG-16, and VGG-19, are used in the proposed model architecture. The stochastic Gradient Descent (SGD) optimization technique is used for better results. Moreover, decision tree, k-nearest neighbor, linear Discriminant analysis, and support vector machines are used for classification using features generated by transfer learning model.

Singh et al. [14] proposed multi-objective differential evolution (MODE) model for the classification of the COVID-19 disease. An exponential crossover algorithm is used. The proposed model gives high accuracy as compared to artificial neural network, Adaptive Neuron Fuzzy Inference System, and CNN models.

Das et al. [15] designed an Xception model to detect COVID-19 infection using chest X-ray dataset containing three classes pneumonia andCOVID-19 negative, COVID-19 positive, and other infections except forCOVID-19. The features are extracted by using different masks applied to the convolution layer. The cross-entropy is used as a loss function.

Brunese et al. [16] built two models for the detection of COVID-19 from dataset images. The first model determines if the image belongs to a healthy patient or a patient with generic pulmonary disease. If the patient belongs to a generic pulmonary disease, then the X-ray image is transferred to the second model, which checks whether it is a COVID-19 patient or pulmonary disease only. Liu et al. [5] proposed a model for the diagnosis of dental disease by using mask region based convolution neural network with the classification of seven different dental diseases. The model uses an IoT platform for patients to upload their dental images. A broad-level prototype is also given in the paper for dental image acquisition.

PROPOSED MODEL

A convolution neural network's design is influenced by the quantity of layers, filters, activation functions, optimizers, and group sizes [17,18]. The suggested design for the covid-19 diagnosis system is depicted in Figure 1.

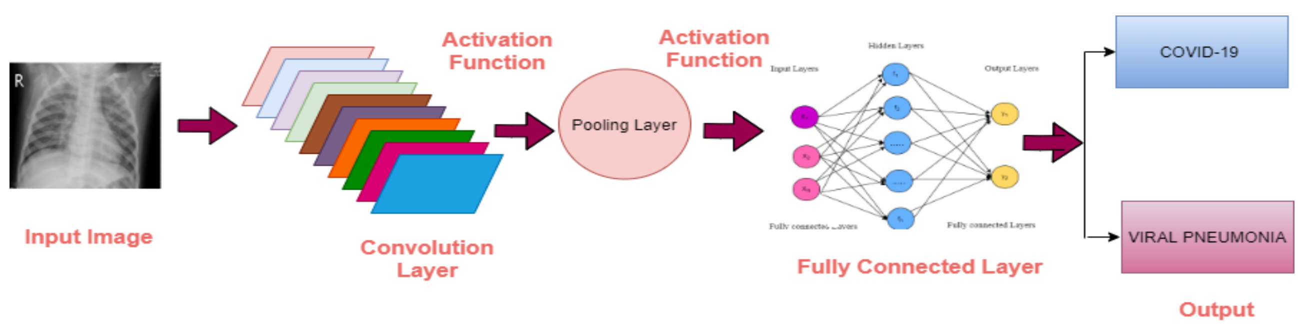


Figure –1. Proposed Model architecture

The foundational Efficient Net model [18] served as the basis for the suggested model. Instead of using the more intricate structures, the objective is to create a brief CNN model that can recognize image modification. The Conv layer is replaced with a Conv2D layer in the layers of the effective Net model, and the filter values in the layers are updated as well. The dropout layer is introduced with a 0.4 value to lessen overfitting and add regularization. A sequential paradigm underlies the suggested design. The layers are also put in the correct order to create the CNN design. Conv2D, Maxpooling2D, Dropout, the Relu activation function, and a dense/fully linked layer are all components of the suggested CNN architecture. The suggested model has three convolution layers, three maxpooling layers, three Relu layers, two dense layers, one dropout layer, and a completely linked layer.

DATASET DESCRIPTION

The proposed model for detection of COVID-19 disease has been tested on the publicly available standard chest X-ray images dataset [19]. The dataset consists of 3616 COVID-19 positive cases along with 10,192 Normal, 6012 Lung Opacity (Non-COVID lung infection), and 1345 Viral Pneumonia images. Out of the four mentioned classes, we have considered only two classes of images in our experimental setup, i.e., COVID-19 positive and Viral Pneumonia.

EXPERIMENTAL RESULTS AND DISCUSSION

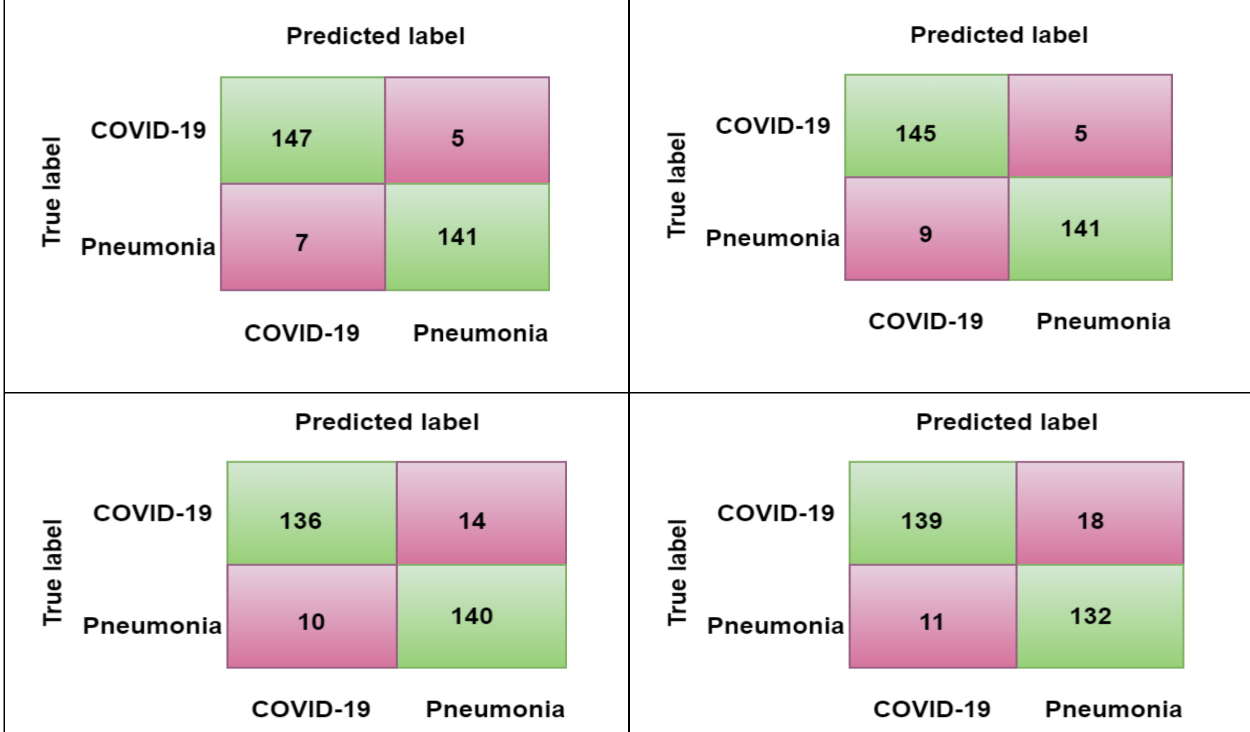
This section represents and analyze the results obtained after performing experiment with 70:30 dataset splitting. The proposed approaches have been executed with python using Tensor flow and Keras libraries [20].

A. Experimental Results

The following results are based on dataset ratio of 70:30 in which 70 percent of images belong to the training set and 30 percent belong to the testing dataset. The proposed model is compared with other models based on accuracy, precision, recall and f1-score value.

(a) Proposed model

(b) Inception model



(c)Resnet50 model

(d) XCeption model

Figure – 2. Confusion matrix

Figure 2 shows the confusion matrix of bifurcation of the dataset. Moving ahead, table 1 shows the performance metrics obtained in this experiment, containing the value of precision, recall and F1-score.

Model	**Labels**	**Precision**	**Recall**	**F1-score**	**Time(sec)**
InceptionV3	COVID-19	0.96	0.89	0.92	8779
	Viral_pneumonia	0.90	0.96	0.93	
Resnet50	COVID-19	0.90	0.89	0.89	7265
	Viral_pneumonia	0.85	0.88	0.86	
Xception	COVID-19	0.90	0.86	0.88	10273
	Viral_pneumonia	0.92	0.91	0.91	
Proposed model	COVID-19	0.97	0.95	0.96	4353
	Viral_pneumonia	0.95	0.97	0.96	

Table (1) - Model results

In this table, the proposed model shows the highest value of precision, recall and F1-score for class COVID-19 and viral pneumonia.

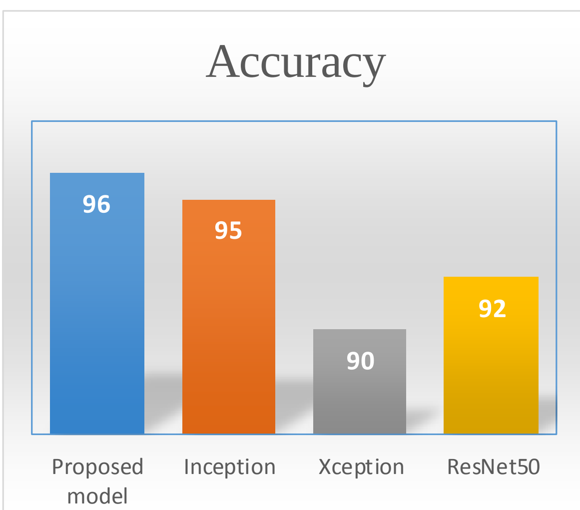


Figure – 3: Testing Accuracy with 500 epochs

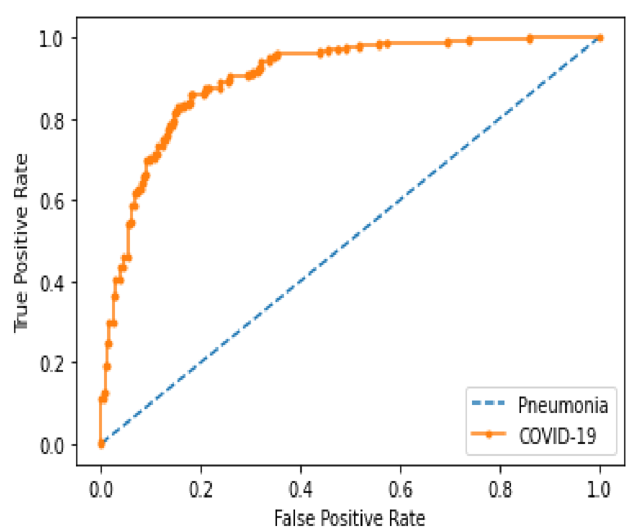


Figure –4: ROC of Proposed model

Figure 3 depicts the success rate of each transfer learning model and the proposed model for classifying COVID-19 dataset in 500 epochs. The proposed model gives 96 % accuracy which is better than other models. The ROC graph representation in figure 4 of the proposed model. In

ISSN: 2229-6913(Print), ISSN: 2320-0332(Online), Web Presence: http://ijoe.vidyapublications.com

Table 1 the Time column show the execution time of all models, additionally proposed model takes less time as compared to other models because it is lightweight and used fewer parameter which makes it faster than other models.

CONCLUSION AND FUTURE WORK

In current times, deep learning models have come into existence and are playing a massive role in the development of various computer aided disease diagnosis systems. In this research, an attempt has been made to develop a concise CNN model by using lesser number of parameters (no. of layers, kernel size, optimizer, activation function) so as to reduce the execution time while obtaining a better classification accuracy for the diagnosis of COVID-19. The experiments have been performed on various x-ray images. The performance of the proposed model is also compared with existing transfer learning models viz. Xception, Resnet50 and inception. The results clearly indicate the outperformance of the proposed model in terms of various parameters (accuracy, loss rate, precision, recall and f1-score). In near future, various image enhancement methods and hyper parameter tuning can be used in the future to improve the precision of the suggested model. The proposed model can also be used to diagnose various other illnesses and datasets from COVID-19.

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