Early Detection of Lungs Abnormality with Chest X-Ray Using Deep Learning Approach for COVIOD-19 Patients

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***Abstract*—** Coronavirus disease is frequent throughout the world, especially in developing countries. The year 2019 experienced an unprecedented pandemic called COVID-19, which impacted the whole world leading to one of the most disruptive disasters in the current century. It threatens human life, public health, and productivity. Researchers from engineering fields have tried to develop automatic COVID-19 detection toolkits to deal with this state of affair. Chest X-rays are predominantly used for the prognosis of these diseases. However, even for an expert radiologist, it is a tedious task to examine chest X-rays of patients. So, to recuperate the prognosis accuracy an efficient model for the detection of COVID-19 trained on digital chest X-ray images has been proposed, which can improve the decision-making process. This proposed work represents a robust deep-learning framework developed to detect lung diseases like Covid-19, reliably from chest X-ray images using image pre-processing, data augmentation, and deep-learning classification techniques. Discrete public databases were used to create a database of 2800 Covid-19 infected, and 1200 normal chest X-Ray images for this study. Three different deep CNN algorithms (CNN, ResNet152 V2, and Inception V3) were used and were trained, validated, and tested for classifying affected and non-affected normal cases. However, classification using InceptionV3 images has outperformed with its accuracy of 98.21%. An efficient intelligent decision support system can be developed using those approaches to assist radiologists in the future field in making the befitting assessment in terms of computer-aided faster diagnosis.

***Keywords*—** Deep Learning, Chest X-Ray, COVID-19, CNN, ResNet152 V2, Inception V3.

INTRODUCTION

Coronavirus disease 2019 (COVID-19) is a drastic infectious disease of the respiratory system caused by novel coronavirus infection, which is mainly transmitted through direct contact and droplets. COVID-19 has the characteristics of rapid transmission, strong infectivity, and general susceptibility among people. Since the outbreak of COVID-19, it has mutated and evolved in the process of transmission resulting in multiple variants. According to the World Health Organization around 767,750,853 confirmed cases of COVID-19, including 6,941,095 deaths is caused by the mass destruction COVID-19 in recent years. Airborne diseases spread so fast that doctors face a lot of issuesto handle that huge patient crowd suddenly at once. Presently, researchers mostly rely on deep learning approaches due to high performance in automatic feature extraction and data accuracy. Detecting COVID-19 is a difficult task due to various types of manifestations such as large opacities, aggregation, focal lesions, cavities etc. Due to its clinical significance, a variety of deep learning architectures are proposed to diagnose a variety of lung abnormalities. These works consider chest X-Ray images for analysis and classification and detection. Deep learning is a type of machine learning where the machine learns from a large amount of data which involves artificial intelligence, neural networks and algorithms inspired by the human brain. Biomedical image diagnosis that uses the techniques of deep learning and computer vision has proven to be very helpful to provide a quick and accurate diagnosis of the disease. Researchers have proposed several computer algorithms to analyse X-ray images. Also, several computer-assisted diagnosis tools have been developed to provide an insight of X-ray images. However, these tools are not able to provide sufficient information to support doctors in making decisions. From the earlier research works, it can be noted that traditional DL architectures and their modified versions are widely adopted by researchers to solve a variety of image classification problems. Earlier workalso confirms that, if an adequate number of pictures are used, then it is possible to train the DL architecture in an efficient manner to attain better accuracy. Hence, this work investigates the classification of lung abnormalities using CNN, Inception V3 and Resnet152V2 deep learning techniques.

LITERATURE SURVEY

Lopes and Valiati [1] used different pre-trained CNN models to classify the chest radiographs into TB positive and TB negative classes. The performance of the system was evaluated on two publicly available chest X-ray datasets (CHN and MC) and achieved an accuracy of 80%. Wang et al. [2] addressedthis issue and prepared a new database ChestX-ray8 with 108,948 front view X-ray images of 32,717 unique patients. Each of the X-ray images could have multiple labels. They used deep convolutional neuralnetworks to validate the results on this data and obtained promising results. They mentioned that the chestX-ray8 database can be extended by including more disease classes and would be useful for other research studies. Evalgelista and Guedes [3] reported a computer-aided approach based on intelligent pattern recognition using CNNs for TB detection from chest X-ray images with an accuracy of 88.76%. Nguyen et al. [4] evaluated the performance of a pre-trained model, DenseNet, to classify normal and tuberculosis images from Shenzhen (CHN) and Montgomery County (MC) databases using fine-tuned model, and reported the Area Under the Curve (AUC) values of 0.94 and 0.82 respectively. Hernández et al. [5] proposed a method for the automatic classification of TB from X-Ray images using an ensemble of CNN models with an accuracy of 86%. Meraj et al. [6] used four different CNN models (VGG-16, VGG-19, RestNet50, and GoogLeNet) and explored the limits of accuracies for small-scale and large-scale CNNmodels in the classification of TB from chest X-rays. Ahsan etal. [7] proposed a generalized pre-trained CNN model for TB detection and achieved accuracies of 81.25% and 80% with and without the application of image augmentation respectively. Khatri et al. [8] proposed the use of EMD (earth mover's distance) toidentify infected pneumonia lungs from normal non-infected lungs. Kallianos et al. [9] presented a state ofart review stating the importance of artificial intelligence in chest X-ray image classification and analysis. In 2020, Yasin Yari et al. used transfer learning particularly ResNet50 and DenseNet121 combined with adeep classifier to discriminate between normal, viral pneumonia, and COVID-19 radiographs. The proposed architecture achieved 97.83% accuracy using a small dataset with augmentation [10]. Lacruz et al. compared the performance of six different pretrained architectures namely VGG16, Xception, ResNet50, ResNet101, DenseNet201, and InceptionResNetV2. They used the Kaggle dataset, they augmented the data because of the unbalanced nature of the dataset. The goal was to discriminate betweenhealthy people, COVID-19, and viral pneumonia. The best performance was obtained by Xception with anaccuracy of 97.34% [11]. Alquran et al. utilized the texture features from the enhanced Chest-X-Ray images to distinguish between two pulmonary disease classes alongside the normal case with 93.2% accuracy [12]. Finally, Alsharif et al. focused their research on pediatric Chest-X-Ray images and employed deep learning techniques, they created a light CNN to discriminate between causes of pulmonarydiseases whether it is viral or bacterial, their model achieved a near 96.79% accuracy [13].

METHODOLOGY

The proposed techniques are used in this work, for detecting various types of pulmonary diseases. The comparisons are made for different deep learning algorithms such as CNN, Inception V3 and Resnet152 V2 to determine which algorithm suits best and can be adapted to detect different lung abnormalities.

Following are the algorithm steps to be followed-

Algorithmic steps:

- Step 1: Collect data and prepare the dataset.
- Step 2: Data Pre-processing is done on the data set to make it balanced.
- Step 3: Divide the dataset into two parts i.e., Train dataset and Test dataset.
- Step 4: Feature selection is applied for the proposed models.
- Step 5: Accuracy and losses have been identified to know the efficiency for different algorithms.
- Step6: Then retrieve the best algorithm based on efficiency for the given dataset.

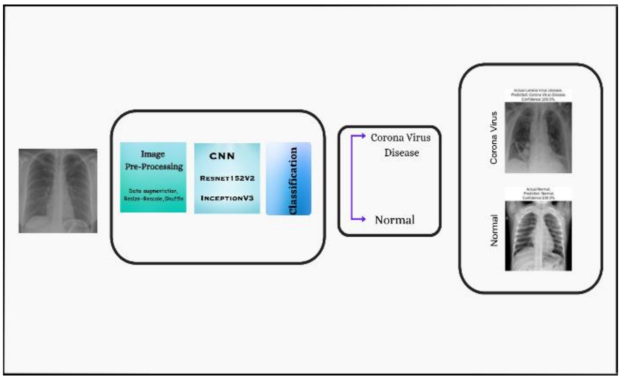


Fig 1: Block Diagram of the Proposed System

A. *Dataset*- In this classification study, a dataset of X-Ray images from www.kaggle.com have been collected and the final dataset of 3982 images containing three types of X-ray images i.e. Bacterial pneumonia,Coronavirus Disease and Normal have been prepared. The entire dataset folder was mounted in google drive to fetch datain future using Google-Colab.

B. *Data Pre-processing*- Adequate training of a neural net requires big data. With less data availability, parameters are undermined, and learned networks generalize poorly. So, to get a perfect result with great confidence we have to pre-process the data to organize it in proper format. For that reasons we have taken 125 batches ofimages each containing 32 (batch_size) images.

1. **Resizing and Rescaling:** A parameter is created as resize_rescale to make all the image_sizeas 224*224 pixels and all the images are shuffled within the dataset and within the batches so that model can extract each and every possibility from an image.

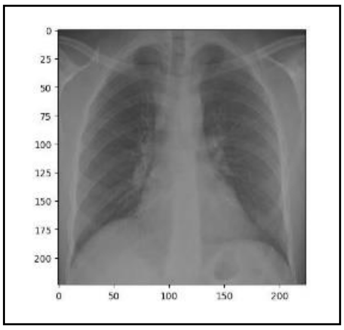


Fig 2: X-ray Image after Rescaling

2. **Data Augmentation:** After rescaling, the Data augmentation part comes in and solves the problem by utilizing existing data more efficiently. It aids in increasing the size of the existing training dataset and helps the model not to overfit this dataset. As the images are shuffled, therefore, we have donedata augmentation on the X-Ray images with a random rotation of 0.2 to get the numpy array value perfectly from every pixel of the image.\

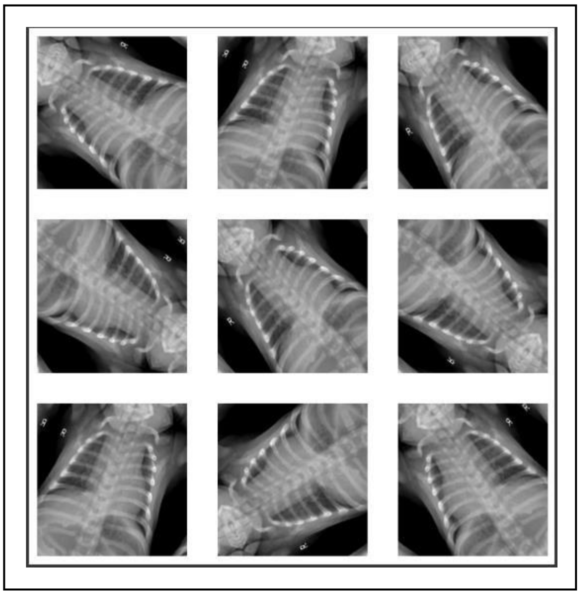


Fig 3: Data Augmentation

3. **Splitting of the dataset:** To fit a model architecture, it is needed to split the dataset into two parts. One is for the training purpose that is to make the model learn by extracting all the features from the training dataset and another is to test the model's accuracy by giving the test dataset as input. In this proposed work, the dataset have been split into 3 parts i.e. 80% for training set, 10% for test set and 10% for validation.

C. *Training & Fitting the Model*- After pre-processing the image dataset, three different deep learning algorithms have been proposed which are Convolutional Neural Network, Inception V3 and Resnet 152V2 to train the model to reach thedesired aim. Each model is made of neurons that are extracting every value including (r,g,b) in the form of a numpy array to set features and recognize the differences among every single image.

D. *Evaluation*- The classified outputs are get after fitting the models of CNN, InceptionV3 and ResNet152 V2 models. Later, a comparative study has been done among these three models using the confidence and accuracy of the result. Evaluation of a model's best performance was made according to its test set accuracy. After, fitting the model into the dataset, the train accuracy and test accuracy has been evaluated.

CNN- Convolutional Neural Network has three layers namely, convolutional, pooling and a fully connected layer. CNN is very useful as it minimizes human effort by automatically detecting the features. CNNs are a class of Deep Neural Networks that can recognize and classify particular features from imagesand are widely used for analysing visual images. It is a class of neural networks and processes data havinga grid-like topology. The convolution layer is the building block of CNN carrying the main liability for computation. Normally, in multi-layer neural networks (MLNN), the inputs are in vector form. For Medical Images, the neighbouring pixels or voxels are another source of information. When using MLNN the vectorization process discards the voxel and neighbouring pixel information, and thus CNNs are used. When using convolutional layers coupled with pooling and finally fully connected layers, the spatial information in the voxels can be much better utilized. For this proposed work, 2D convolutional layer and max pooling layer have been used and 'relu' and 'softmax' have been used as activation functions for computing the data loss and optimized the model with 'adam' optimizer.

ResNet152V2 Resnet is a neural network that allows the model to skip one or more layers. ResNet is short for Residual Network which is used to facilitate the training of networks that are deep. This module provides the feature map of input image and the data compression using Discrete Wavelet Transform. Using ResNethas significantly enhanced the performance of neural networks with more layers. It is a Convolutional Neural

Network (CNN) architecture designed to support hundreds or thousands of convolutional layers.

Inception V3 It is a deep learning model based on Convolutional Neural Networks, which is usedfor image classification. In the inception V3 model, in order to reduce the grid size efficiently the activation dimension of the network filters is expanded which is done using two parallel blocks of convolution and pooling later concatenated. The model itself is made up of symmetric and asymmetric building blocks, including convolutions, average pooling, max pooling, concatenations, dropouts, and fully connected layers. Batch normalization is used extensively throughout the model and applied to activation inputs. In this model, data loss has beencomputed using the 'softmax' activation method.

EXPERIMENTAL RESULTS

In this section, the experiments and evaluation techniques used in this work to test the efficiency of the proposed models are presented after successfully running 25 epochs on each model and plotting graphs denoting training accuracy and validation accuracy.

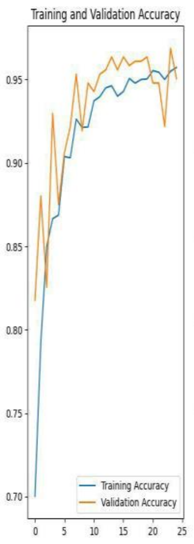
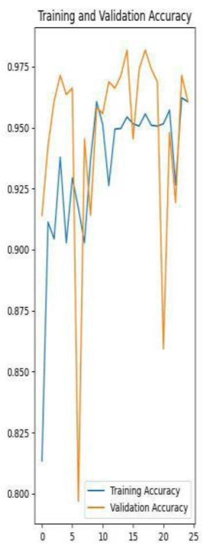
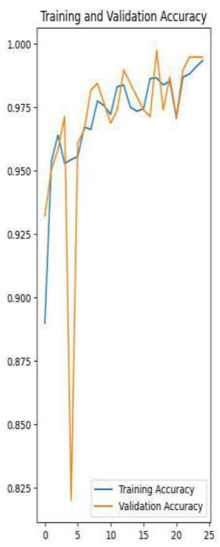
CNN	**ResNet152V2**	**Inception V3**
		

Fig 4: Graphs of Training & Validation Accuracy

As in the upper figure it can be seen that training accuracy and validation accuracy are increasing as moreepochs are running denoting the successful prediction of the models.

Classifiers	**Training accuracy**	**Testing Accuracy**
CNN	96.43%	95.63%
ResNet152 V2	97.03%	96.88%
Inception V3	98.75%	98.21%

Table1: Results for Different Machine Learning Algorithms used

This section illustrates the experiments held and corresponding outputs. In this work, three deep learningalgorithms have been developed to classify the chest X-Ray images of various respiratory diseases. After evaluating three classifiers, Inception V3 produced the best accuracy values with maximum confidence. Below, there are the ultimate result that shows how this model is classifying X-ray images of different categories and how much it's confident about it.

Fig 5: Final output results of Proposed Models

Author	Year	Models Used	Overall Accuracy
Lopes and Valiati [1]	2017	CNN	80%
Evalgelista and Guedes [3]	2018	CNN	88.76%
Nguyen et al. [4]	2019	DenseNet	94%
Hernández et al. [5]	2019	CNN	86%
Meraj et al. [6]	2019	VGG16, VGG19, ResNet50, GoogleNet	81.25%
Ahsan etal. [7]	2019	CNN	80%
Yasin Yari et al. [10]	2020	ResNet50	97.83%
Lacruz et al. [11]	2020	VGG16, Xception, ResNet50, ResNet101, DenseNet201, InceptionResNetV2	97.34%
Current Work	**2023**	**InceptionV3**	**98.21%**

Table 2: Comparison of findings of this study with other recent similar works

CONCLUSION

Lung diseases constitute a significant cause of morbidity and mortality. It accounts for a considerable number of adult hospital admissions, and a significant number of those patients ultimately die. Nevertheless, the majority of the global population lacks access to radiology diagnostics. Even when there is the availability of imaging equipment, there is a shortage of experts who can examine X-rays. Through this proposed work, the automatic detection of lung diseases in chest X-ray images using deep learning techniques has been proposed. The deep networks, which were used in our methodology, had more complex structures, but fewer parameters and, hence, required less computation power, but achieved higher accuracy. Data augmentation was used to solve the problem of overfitting. Further, three different classifiers were proposed. The experiments were performed and the classification accuracies are 95%, 96%and 98% for CNN, ResNet152V2 and InceptionV3 respectively. The relative comparison between the existing DL techniques confirms that Inception V3 gives the highest accuracy compared to other models. Though our model is 100%$ confident about its' prediction but as it is the question about human life or death doctors' supervision is very much necessary in serious conditions.

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