Deep Learning approach to detect COVID-19 from X-ray Images

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Abstract : COVID-19 is a highly contagious viral infection that has a major impact on worldwide health. It also had a tremendous influence on the world economy. If positive cases are discovered early, the pandemic disease's spread can be hindered. Fever, cough, dyspnea, breathing issues, and viral pneumonia are among the flu-like symptoms experienced by COVID-19 patients. These signs, however, are negligible by themselves. Many individuals are asymptomatic yet have a positive COVID-19 chest CT scan and pathogenic test. As a result, in addition to symptoms, positive pathogenic tests and positive chest CT/X-Rays are used to diagnose the condition. In medical picture categorization, Deep Learning (DL) techniques, notably Convolutional Neural Networks (CNN), have been found to be successful. This study presents CNN and ResNet50 models for COVID-19 prediction from chest X-ray images. The findings achieved in COVID-19 prediction using CNN and ResNet50 with training and testing accuracy of 99.5 percent and 94 percent, respectively, highlight the applicability of Deep Learning models in illness prediction.

Index Terms - X-ray images of chest, Prediction, COVID-19, CNN, ResNet50**.**

I. INTRODUCTION

The requirement for effective COVID-19 detection has risen considerably as the epidemic spreads. In rural locations with fewer equipped hospitals or clinics, the shortage of COVID-19 viral and antibody test kits, as well as the time required to receive test results (in the order of days to weeks) pose a significant obstacle. In many developing countries, for example, hospitals do not have enough COVID-19 test kits, so they must seek the help of more advanced medical institutes to collect, transport, and test the samples. This creates a bottleneck in COVID-19 bulk testing. As a result, an automated and accurate COVID-19 detection methodology is required to meet the daily need for a massive number of new test cases.

In locations where viral/antibody testing is unavailable, the use of radiograph images for first COVID-19 screening could be critical. CT scans were employed in various investigations to analyse and detect COVID-19 characteristics because they had a higher resolution of ground glass opacities and lung consolidation than chest X-ray images. CT scan is not a feasible approach for identifying COVID-19 because of infection control concerns connected with patient transfer to CT suites, the relatively high cost (for procurement, operation, and maintenance of CT equipment), and the limited availability of CT machines in developing/rural areas. On the other hand, because X-ray imaging equipment is widely available in hospital ERs, public healthcare facilities, and even rural clinics, a chest X-ray can be used to identify COVID-19 or other pneumonia cases as a more practical and cost-effective solution. Even for experienced radiologists, distinguishing between symptoms of COVID-19 and community-acquired bacterial pneumonia can be difficult. Furthermore, during a pandemic, the flood of patients into hospital ERs, manual evaluation of radiograph data, and accurate decision making might result in a difficult tradeoff between detection time and accuracy, which might overburden the radiologist department. As a result, an automatic classification method must be devised. The abovementioned difficulty is addressed in the following part, and a deep learning-based technique is shown to effectively tackle the problem.

II. RELATED WORKS

In this section some of the related works for the prediction of pneumonia, COVID-19 and some other chest related diseases is presented.

Using only image processing techniques, a novel method is proposed for detecting the presence of pneumonia clouds in chest X-rays (CXR) by analysing 40 analogue chest CXRs from patients with normal and Pneumonia-infected lungs. Cropping and extraction of the lung region from photos is developed using indigenous techniques. Otsu thresholding is employed to detect pneumonia cloud, which separates the healthy section of the lung from the pneumonia-infected hazy regions. To detect the presence of Pneumonia, research recommended calculating the ratio of the area of healthy respiratory organ region to the entire respiratory organ region [1].
In Detection of pneumonia in chest X-ray images [2] work, an unsupervised fuzzy c-means classification learning method is employed to detect pneumonia infection. Chest X-rays are also used to diagnose disorders such as emphysema, lung cancer, line and tube installation, and tuberculosis. DWT, WFT, and WPT are examples of feature extraction methods. This strategy outperforms the others in terms of results. Because each resultant pixel in fuzzy c-means has a weight associated with it, each resultant pixel offers an accurate value.

A dataset comprising X-ray images from patients suffering with respiratory disorders, COVID-19, and other diseases from public repositories are taken for the automated detection of Corona Virus [3]. Transfer learning with CNN is utilized to detect any abnormalities in medical X-ray image datasets, and the results are remarkable. Concluded that deep learning from X-ray pictures can successfully identify key biomarkers linked to Corona Virus.
Pneumonia Detection through X-Ray Using Deep Learning [4] uses Deep Learning web application that detects the presence of Pneumonia in a sample of chest X-rays. Methods that primarily rely on transfer learning approaches or classic handcrafted procedures are used to produce remarkable classification results. Convolutional neural network (CNN) model is used which extracts

information from a chest X-ray image and classifies it to identify if a person has pneumonia. This paradigm helps with issues like reliability and interpretability, which are common when working with medical images.

The use of a convolutional neural network (CNN) for the categorization of ILD patterns is presented and analysed in Lung Pattern Classification for Interstitial Lung Diseases Using a Deep Convolutional Neural Network [5]. In a challenging dataset, a comparative analysis confirmed the usefulness of the suggested CNN vs earlier approaches. In analysing lung patterns, a classification performance of 85.5 percent is achieved in this work. To see how expert-crafted rules, a Bayesian network, and a decision tree perform when it comes to automatically detecting chest X-ray findings that suggest acute bacterial pneumonia, A Comparison of Classification Algorithms to Automatically Identify Chest X-Ray Reports That Support Pneumonia was proposed [6]. When the Bayesian network's binary output is compared to that of two physicians, there are differences. There is a discrepancy between the decision tree and one physician when the probabilistic output is compared to physicians. The expert systems performed similarly for the probabilistic output, but the binary output yielded different metrics of sensitivity, precision, and specificity. All three expert systems outperform physicians in the same way.

III. EXPERIMENTAL DETAILS

The proposed approach addresses the problem as follows: given a chest X-ray, determine if it belongs to a healthy patient, a patient with COVID-19, or a patient with viral pneumonia. The methodology used in this work is as shown in figure 3.1.

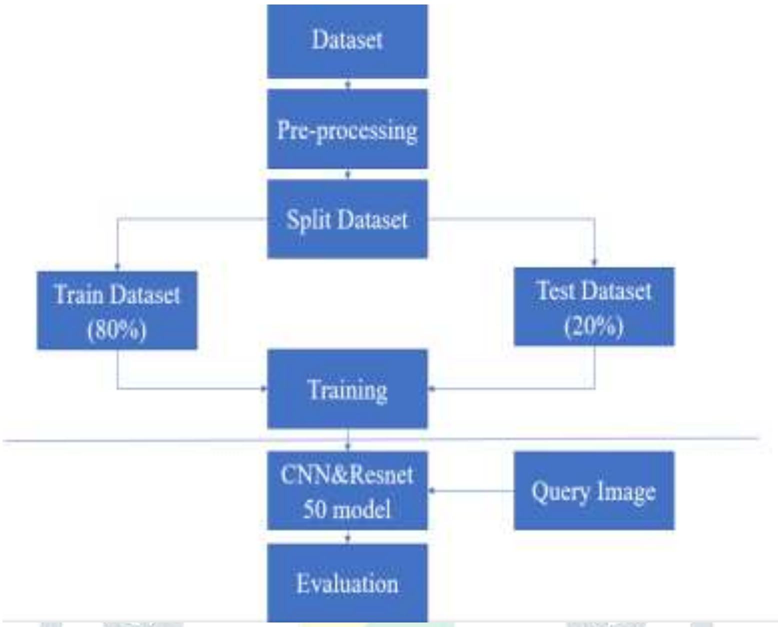

Figure. 3.1. Methodology

Dataset: The dataset utilized in this study is open to the public. This data collection contains 3000 chest x-ray radiographs of healthy people, viral pneumonia patients, and COVID-19 patients, each with 1000 images. The representative chest x-rays of normal, viral pneumonia, and COVID-19 patients are shown below in figures 3.1, 3.2, and 3.3.

Figure. 3.2

Figure. 3.3

Figure. 3.4

Data Preprocessing: As illustrated in figure 3.5, all photos in the jpg or jpeg format are fed into the preprocessing unit and resized at a 1:1 ratio (244/244).

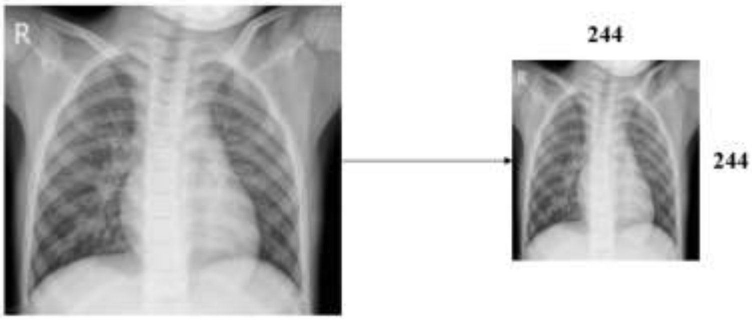

Figure 3.5: Pre-processing data

Data Splitting: The 80:20 ratio is used to split the dataset into training and testing sets. 2400 records are utilized for training and 600 are utilized for testing.

Training:
In this paper Convolutional Neural Network and ResNet-50 approach is used.

CNN algorithm: As illustrated in Figure 3.6, the CNN network is built up of three convolutional layers. There are 32-3 x 3 filters on the first layer, 64-3 x 3 filters on the second layer, and 128-3 x 3 filters on the third layer. There are also three max-pooling layers, each measuring 2 x 2. The network is trained for 50 epochs with a batch size of 32. Convolutional layer with Conv2D() is inserted initially, followed by max-pooling layer with MaxPooling2D(), which lets the network learn non-linear decision boundaries with Leaky ReLu activation function (). Lastly, there is a dense layer with softmax activation, which is required for multi-class classification.

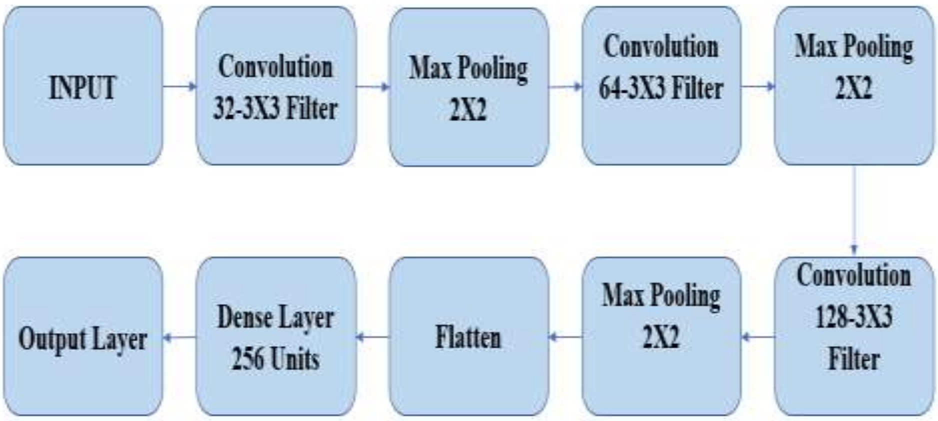

Figure.3.6. Architecture of CNN model

The preprocessed image of size 244 × 244 is fed to the network once the model is constructed. It's made with the Adam optimizer, which is one of the most widely used optimization techniques. Also mentioned is the loss type, which is sparse categorical cross entropy, which is utilized for multi-class classification. Finally, accuracy is supplied as a measure that will be used to examine the model while it is being trained for 50 epochs with Keras fit().

ResNet50: Instead of attempting to learn features, the model tries to learn some residual in residual learning. As shown in figure. 3.4, the input 'x' is being added as a residue to the output of the weight layers and the activation is carried out. In the ResNet model, ReLu activations are employed. ResNet50 is a 50-layer residual network with ResNet101 and ResNet152 as variations. For x-ray picture categorization, the ResNet pretrained model is utilized. The picture is fed into the ResNet50 layer, which will include the pretrained weights, and the final layer is a fully linked dense layer. The proposed model has two layers: a dense layer and a pre-trained ResNet layer. Weights that have been pre-trained for the ResNet50 model is imported. The dense layer is the sole layer that learns via back propagation, and the input data is taught using pre-learned weights. The network is trained for 50 epochs with a batch size of 32.

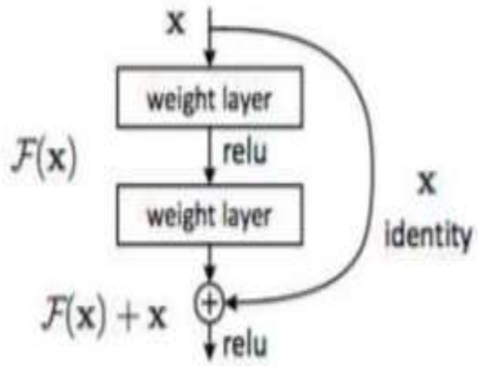

Figure 3.7. Residual Learning

Once trained, real- time images are fed to the model and the trained system takes decisions based on CNN model and ResNet50. Finally, the image is classified as normal, viral pneumonia or COVID-19.

IV. EXPERIMENTAL RESULTS

The model is trained for classifying normal, viral pneumonia and COVID detection using CNN and ResNet50 with the dataset divided as 80% training data and 20% testing data. The images of the dataset are resized to (244,244). Some hyperparameter which are useful for the better performance of the model during the training process are noted as shown in table 4.1 and 4.2 for both the models.

Table 4.1 Hyperparameter Values of CNN model

Epoch No.	Batch Size	Learning rate	Loss	Training Accuracy	Validation Accuracy
1	32	0.1	0.95	69	72.5
5	32	0.1	0.51	81	91.3
10	32	0.1	0.44	97	91.3
15	32	0.1	0.35	98	92
20	32	0.1	0.38	99	92
25	32	0.1	0.45	99.6	91.3
30	32	0.1	0.40	98	93.1
35	32	0.1	0.45	99	92.6
40	32	0.1	0.50	99.3	90.1
45	32	0.1	0.40	99.5	92.8
50	32	0.1	0.40	99.5	92.8

Table 4.2 Hyperparameter Values of ResNet50

Epoch No.	Batch Size	Learning rate	Loss	Training Accuracy	Validation Accuracy
1	32	0.1	0.63	73	73
5	32	0.1	0.37	88	82
10	32	0.1	0.31	90	87
15	32	0.1	0.29	92	88
20	32	0.1	0.28	93	88
25	32	0.1	0.30	93.6	87
30	32	0.1	0.35	93	84
35	32	0.1	0.29	93.6	87
40	32	0.1	0.29	93.2	87.3
45	32	0.1	0.26	94	88
50	32	0.1	0.29	94.3	88

All the values are tuned in order to improve the performance of model. After training the CNN model training accuracy of 99.5% and validation accuracy of 92.8% is achieved, and training accuracy of 94% and validation accuracy of 88% is achieved for ResNet-50 model.

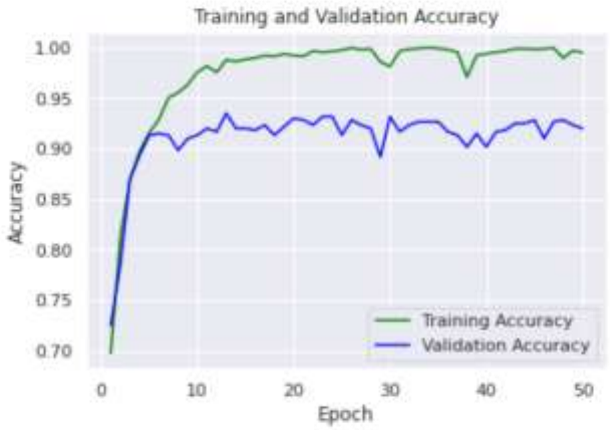

Figure 4.1. Graph of Training and Validation Accuracy

Figure 4.1 shows the plots of training and validation(test) accuracy. Figure 4.2 and 4.3 represents the graph for Testing loss v/s accuracy and Training loss v/s accuracy. It is observed that the accuracy increases as the loss decreases at each epoch.

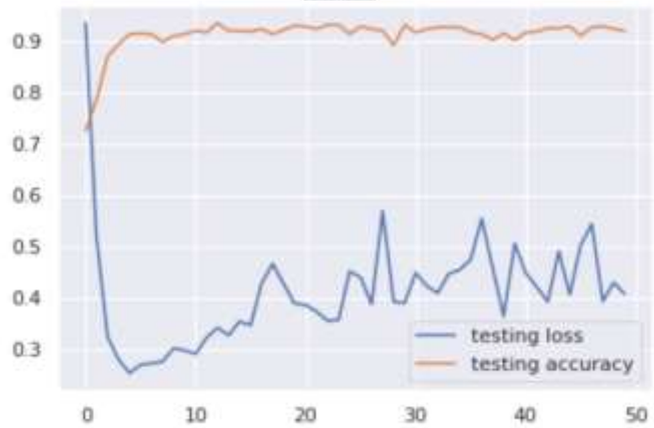

Figure 4.2. Graph of Testing loss v/s testing accuracy

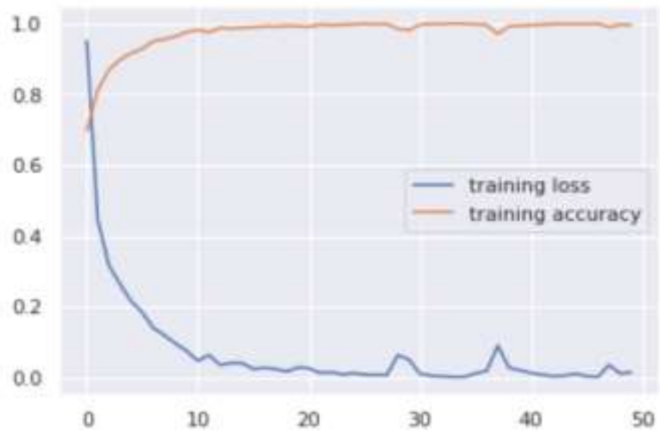

Figure 4.3. Graph of Training loss v/s training accuracy

From the graph in figure 4.1 it is observed that there is minimal change in value of training accuracy and testing accuracy from epoch 18. And from figure 4.2 and 4.3 it is observed that there is increase in loss after 18 epochs. So in order to avoid overfitting and in order to avoid the increment in loss, the number of epochs for this model can be optimally selected as 18 for CNN model.

V. CONCLUSION

A method for predicting COVID-19 infected, Pneumonia, and normal cases from patient chest X-ray pictures is provided in this research. Demonstration of how deep learning techniques may be used to predict COVID-19 in a unique way is shown in this work. These models can be used to diagnose COVID-19 from patients' chest X-rays quickly and accurately. Trained model is able to obtain a training accuracy of 99.5% and testing accuracy of 92.8% with CNN and training accuracy of 94% and testing accuracy of 88% with ResNet50. Primary health care providers in rural areas where experienced practitioners are unavailable can use this computerized COVID-19 prediction method. This work could be expanded to create a large collection of X-rays of COVID and non-COVID patients with various Pneumonia diseases in order to enhance specificity and sensitivity.

VI. Acknowledgment

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