Computer-Aided Detection of Covid-19 from X-Ray Images using Machine Learning Techniques

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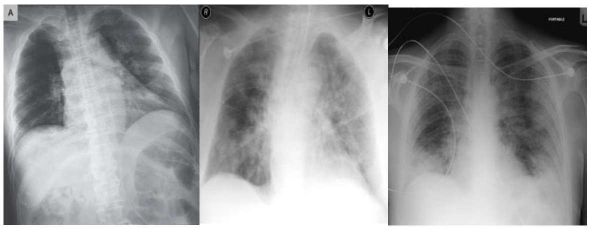
Abstract **- Corona Virus Disease (COVID-19), triggered by novel coronavirus, is a pandemic that spread across the globe, taking millions of lives. Even after a year of its first occurrence, the disease is not under control. COVID-19 is re-emerging in various countries, making it a serious concern. Early diagnosis and containment can prevent large scale transmission of COVID-19. The gold standard for COVID-19 detection is RT-PCR. However, the facility to carry out RT-PCR test is insufficient in most part of the world. Research has proved the effectiveness of X-Ray in the discovery of COVID-19. X-Ray, being an easily available and cheaper modality could serve as an alternative to RT-PCR tests, where there is a deficiency of RT-PCR test facility. Machine intelligence techniques could extract features from X-ray images and can efficiently classify the X-ray images as COVID-19 and non-COVID. Convolutional Neural Network (CNN) is the most widely used machine intelligence technique for the prediction of diseases from images. This study compares COVID-19 detection using various pre-trained CNNS.**

Keywords - COVID-19; Automatic detections; X-ray ; Machine intelligence techniques

I. INTRODUCTION

The World Health Organization (WHO) on March 11, 2020, has stated the novel coronavirus eruption a universal pandemic. It is caused by the highly infectious virus named severe acute respiratory syndrome corornavirus-2 (SARS-COV-2). According to the reports, the virus mainly infects the human respiratory tract results in severe pneumonia with dry cough and fever. In severe cases death can occur. There is no 100% effective medication or vaccine available to overcome the disease and stop the spread. The standard clinical test for COVID-19 detection reverse transcription-polymerase chain reaction (RT-PCR) is time consuming, painful and complex. The facility to carry out RT-PCR test is insufficient in most part of the world as there is a shortage of the test kits. Also, the diagnostic method RT-PCR is painful and its facility is low in village areas. Chest X-Ray is one of the prominent clinical diagnoses that plays an inevitable role in detecting various pulmonary abnormalities. X-ray images are readily available in such areas, which is the least expensive compared to CT scan. CT scan exposes the patient to a relatively high radiation dose (thus should not be performed on pregnant women). Some organs are more sensitive to radiation than others thereby it tends to do more damage to cells that grow and divide quickly so X-ray is preferable. In order to find an alternative method to fight against COVID-19 pandemic, the prevailing machine learning techniques can be incorporated for the development of a computer-aided diagnosis system. Therefore, deep learning method using pretrained CNN can be considered as an alternative for covid-19 diagnosis. Deep Learning is a combination of machine learning procedures largely focused on the automatic feature extraction and classification from images. Its applications are generally met in either object detection or medical image classification tasks. Machine learning and deep learning have become established disciplines in applying artificial intelligence to mine, analyze, and recognize patterns from data. Transfer learning is a preferable approach to train the deep CNNs. Transfer learning is a study in machine learning that concentrates on preserving information achieved while solving one problem and applying it to different but linked problem.



Pneumonia/Viral/COVID-19   Pneumonia/Viral/SARS   Pneumonia/Fungal/Pneumocystis

Fig. 1. Different Chest X-ray images used in the project.

II. RELATED WORKS

In this section, we describe some remarkable works presented in the literature. The first work we are going to describe was presented by Abraham et al. [2] in 2020. The technique uses a combination of features extracted from multi-CNN with correlation-based feature selection (CFS) technique and Bayes Net classifier for the estimation of COVID-19. The process was tested using two public datasets and achieved excellent results on both the datasets. The dataset consisting of 453 COVID-19 images and 497 non-COVID images, the experiments, proved the efficacy of pre-trained multi-CNN over single CNN in the detection of COVID-19. Pereira et al. [3] proposed a Classification schema based on multiclass classification and hierarchical classification. Also put forward the use of resampling algorithms in the schema in order to re-balance the classes distribution. Texture is one of the core visual traits of CXR images, classification schema extract features using some renowned texture descriptors and also using a pre-trained CNN model. Early and late fusion techniques are examined in the schema in order to leverage the strength of multiple texture descriptors and base classifiers at once. A database, termed RYDLS20[3] (1144) containing CXR images of pneumonia caused by different pathogens as well as CXR images of healthy lungs were created to evaluate this method. 802 and 342 images were used for training and testing respectively. Rahimzadeh et al. [4] Using two open-source datasets, trained various deep convolutional networks with new training strategies for classifying X-ray pictures into three classes: normal, pneumonia, and COVID-19. The data contains 180 X-ray scans of people infected with COVID-19. The suggested neural network is a concatenation of the Xception and ResNet50V2 networks. By combining several features collected by two robust networks, proposed network was able to attain the highest accuracy. The network was evaluated using 11302 photos in order to reflect the actual accuracy achieved in real-world situations. Ozturk et. al [5] suggested a model that comprises an end-to-end architecture that does not use any feature extraction approaches and returns the diagnosis using raw chest X-ray pictures. This model was trained using 125 X-ray images of the chest that were not in a regular format and were taken on the spur of the moment. Diagnostic tests performed after 5–13 days in recovered individuals are found to be positive. COVID-19 was diagnosed using X-ray pictures taken from two separate sources. On the basis of this successful architecture, the Darknet classifier is used. This is an effective strategy that can aid specialists in diagnosis. In Ioannis D et. al [6] there is a collection of 1427 X-ray scans, with 224 photos showing verified Covid-19 disease, 700 photos showing confirmed common bacterial pneumonia, and 504 photos showing normal conditions. Second, a dataset comprising 224 photographs of Covid-19 illness, 714 photos of bacterial and viral pneumonia, and 504 photos of normal circumstances. The information was gathered from publicly available X-ray scans in medical repositories. Transfer learning is the preferred method for training deep CNNs. The current research advances the possibility of a low-cost, quick, and automatic Coronavirus illness detection. A Deep Convolutional Neural Network model called CoroNet was presented to detect COVID-19 infection from chest X-ray pictures automatically was proposed by khan et. al [7]. X-ray pictures from two publicly available sources. On the prepared dataset, CoroNet was trained and tested. The preliminary results appear good, and when more training data becomes available, they can be enhanced further. CoroNet produced promising results on a small prepared dataset, implying that with more data, the suggested model can produce better results with less pre-processing. In April 2020 Ucar F et. al [8] implemented SqueezeNet decision making system for the COVID-19 diagnosis from X-ray images. SqueezeNet with much less model size is a state-of-the-art deep learning model, which is inspired by the well-known AlexNet. The SqueezeNet is preferred in embedded applications due to its practical structure and generalization performance. To develop a stable and long-term learning model, the Bayes optimization process was used to optimize the SqueezeNet structure. With a validation dataset, Bayesian optimization helps us to create the best-performing model. Marques et [9] proposed automated medical diagnosis of covid-19 through EfficientNet convolutional neural network. The stratified 10-fold cross-validation method was used to train the suggested CNN model. Table I shows the detailed analysis of the literature papers,

TABLE I. LITERATURE ANALYSIS

METHOD	PERFORMANCE	PROS	CONS
[2] For COVID-19 prediction, a mixture of features collected from multi-CNN with (CFS) methodology and BayesNet classifier is used.	AUC .963 Accuracy 91.16% AUC .911 Accuracy 97.44%	Showed the effectiveness of multi CNN over single CNN	Limited dataset
[3] Use of a multiclass classification and hierarchical classification,	Macro avg F1-score 0.65 (multiclass) 0.89(hierarchical	Best rate obtained in an unbalanced environment with 3 class. Helps in the screening of patients in emergency	Lack of larger database
[4] The suggested neural network is a concatenation of the Xception and ResNet50V2 networks.	99.50% Average accuracy	The best accuracy is achieved by combining two robust networks' retrieved features.	Dataset is limited. The covid-19 class has a poor level of precision.
[5] Based on this effective architecture, the DarkNet classifier is used.	Accuracy 98.08% (binary classes) 87. 02% (multi-class cases.)	Employed to assist radiologist	Less reliability
[6] transfer learning with convolutional neural networks for x-ray image detection	96.78%Accurracy 98.66% sensitivity 96.48 specificity	Low cost Rapid Automatic diagnosis	Need more data
[7] On the prepared dataset, CoroNet has been trained and tested.	89.6% Accuracy (4) 93% Precision (4) 98.2% Recall (4) 95% Accuracy (3)	Promising results. very useful tool for clinical practitioners and radiologist	Lack of data
[8] COVID-19 diagnosis from X-ray pictures using a deep Bayes-SqueezeNet decision-making system	98.04%accuracy	Finetuned and augmented dataset gives good result. Better result	Dataset limitation
[9] 10-fold cross-validation was used to verify the approach.	99.62 % (binary) 96.70%(multiclass)	Rapid diagnosis	Need more data

III. METHOD

X-ray images of various patients were correctly labelled with "COVID-19" or "Non COVID-19" for computer aided COVID19 detection as part of this work. Every epoch, Image Data Generator changes the original images (i.e., rotation, zooming, etc.) and then uses them for training. This will not only make the model more reliable, but it will also reduce memory usage. To identify x-ray pictures as "COVID-19" or "Non COVID-19," a convolution neural network transfer learning approach will be used. VGG16, RESNET50 VGG19, Xception, Densnet121 EfficientnetBo, and other Keras-trained CNNs were employed. To assess and analyse the performance of the CNN model, we calculated precision, recall (or sensitivity), and the F1- score in this paper. Significant biomarkers associated to COVID-19 disease can be extracted using deep learning and X-ray imaging. Architecture of the method is shown below in the fig.2

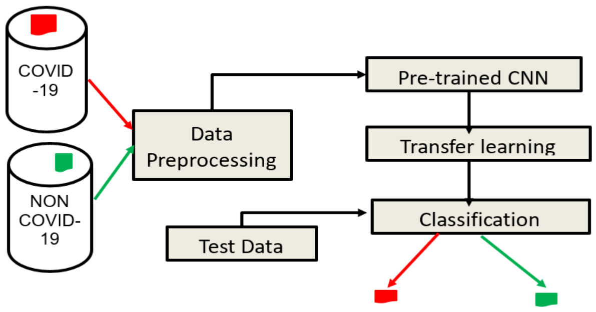


Fig.2. Architecture of the proposed method

The various steps in the method are explained in the following sections.

A. Dataset

The dataset created by Cohen et al. consists of 783 chest X-ray images. The 783 chest X-ray images were composed of 504 COVID-19 and 279 non-COVID images. To solve the data imbalance problem, 263 pneumonia images are taken from paul mooney's dataset and added up with non- covid images. Thereby forming 542 non-Covid images. Total of 1046 chest x-ray images are utilized for the transfer learning model.

B. Pre-processing

The major challenge with above-mentioned datasets are data imbalance. The number of COVID-19 images are predominantly greater than that of non-COVID images. In such cases, the classifier tends to get biased towards the class with a greater number of instances. To solve the data imbalance problem, we used Image Data Generator method like random rotation flipping, horizontal and vertical shift of the images.

C. TRANSFER LEARNING

Convolutional Neural Networks (CNNs) feature representations are more efficient than traditional hand-crafted features. To train a CNN from scratch, a significant number of images are necessary. However, due to ethical considerations, it is difficult to get a large number of x-ray photographs of patients in medical diagnostic applications such as the detection of COVID-19 from X-ray images. Because the data in the proposed public dataset is minimal, it is difficult to train a CNN from scratch. Pre-trained CNNs trained on a large number of natural photos, such as the Imagenet database, can be utilized to extract features from the data at hand in this case. Transfer learning is a deep learning methodology that involves training a neural network model on a problem that is similar to the one being solved. Transfer learning provides the advantage of shortening a learning model's training time and lowering generalization error. VGG16, RESNET50 VGG19, Xception, EfficientnetBo, and other Keras-trained CNNs were investigated. In this experiment, we used the learning rate annealer. If the error rate does not change after a particular number of epochs, the learning rate annealer reduces the learning rate. This methodology is used to assess validation accuracy, and if it appears to have reached a plateau after 5 epochs, the learning rate is reduced by 0.01. Dense layers, Global Average Pooling layers, Droupout layers as well as activation and batch normalization were added. Unfrozen a few of the top layers of a frozen model base and trained both the newly inserted classifier levels and the base model's final levels simultaneously. This allows us to "fine-tune" the underlying model's higher-order feature representations to make them more relevant for the task at hand.

D. Evaluation Measures

Specific metrics were recorded for the CNNs' classification task: correctly identified diseased cases (True Positives, TP), incorrectly identified diseased cases (False Negatives, FN), correctly identified healthy cases (True Negatives, TN), and, incorrectly classified healthy cases (False Negatives, FN) (False Positives, FP). Based on those metrics, we compute the accuracy, sensitivity, and specificity, precision, f1 score of the model with the help of equation (1), (2), (3), (4), (5) respectively.

$$\text{Accuracy} = (TP + TN)/(TP + TN + FP + FN) \quad (1)$$

$$\text{Sensitivity} = TP/(TP + FN) \quad (2)$$

$$\text{Specificity} = TN/(TN + FP) \quad (3)$$

$$\text{Precision} = TP / (TP + FP) \quad (4)$$

$$\text{F1 Score} = 2TP / (2TP + FP + FN) \quad (5)$$

IV. RESULTS

We used 80% of the images for training and 20% for testing. The best result was achieved in transfer learning employing EfficientnetB0 pre-trained CNN. The confusion matrix for COVID-19 detection using EfficientnetB0 is displayed in fig. 3. In the above matrix 11 normal and 27 Non covid images are misclassified as Covid and non-Covid respectively. It can be seen that 98 normal and 74 COVID-19 images are correctly classified. Also, fig. 4 indicates a graph showing model accuracy and model validation accuracy for 20 epochs. 81.9 % validation accuracy is obtained.

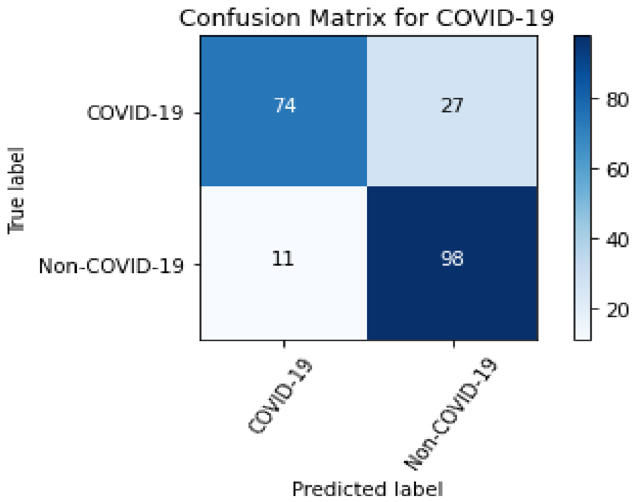


Fig.3 Confusion matrix of EfficientNetBo

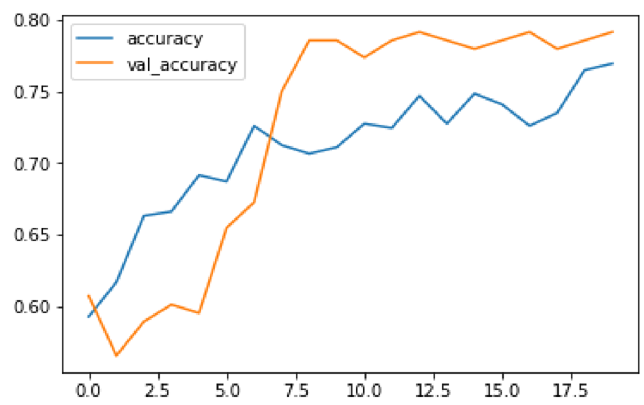


Fig.4. Graph represents model accuracy and model validation accuracy for 20 epochs

Below table II shows the computed accuracy, sensitivity, specificity, precision andf1 score of the model.

TABLE II. RESULTS

MEASURE	VALUE (%)
Accuracy	81.90
Sensitivity	87.06
Specificity	78.40
Precision	73.27
F1 Score	79.57

In order to compare the efficiency of proposed model few CNNs like VGG16, VGG19, Xception, were studied and the validation accuracy obtained by transfer learning is plotted in fig.5. Validation accuracy obtained for VGG16, VGG19 and Xception are 73.81, 58 and 77 respectively. This pie chart clearly indicates that EfficientNetBo has comparatively better validation accuracy.

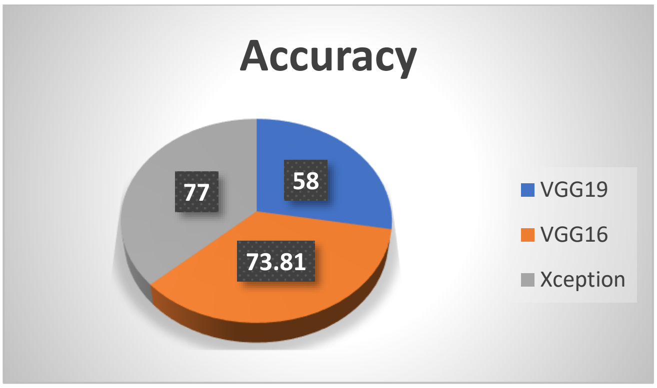


Fig.5. Validation accuracy by transfer learning

Few other experiments related to classification are carried out. Features were extracted using pre-trained CNNs and classified using SVM. Results show that EfficientnetB0 outperforms the other techniques. Fig 6. and Fig 7. compares the performance of EfficientnetB0 against other techniques.

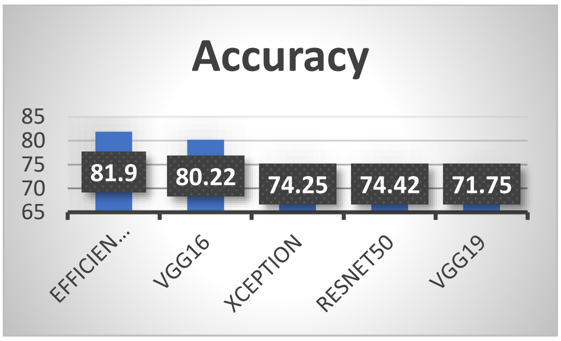


Fig.6 Comparing accuracy obtained by transfer learning using EfficientnetB0 against feature extraction using VGG19, VGG16, Xception and Resnet50 and classification using SVM.

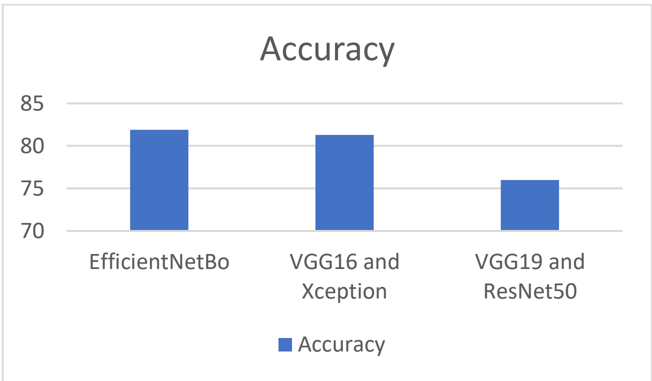


Fig.7 Comparing accuracy of EfficientnetB0 against accuracy of the models concatenated and classified using SVM.

After concatenated models were classified using SVM, principal component analysis (PCA) was done. In terms of accuracy, the EfficientNetBo outperforms other concatenated models, and it is thus recognized as a useful model for classification.

V. CONCLUSION

The results show that pre-trained CNNs can be used for the detection of COVID-19. Transfer learning model can be used as an alternative method for diagnosis of COVID-19. Data augmentation techniques to get more data from limited datasets can be done. We performed a comparative analysis of various pre-trained CNNs used for COVID-19 detection. To evaluate the performance of transfer learning we have extracted features using CNN and performed classification using SVM also concatenated features extracted from multi-CNN and classified using SVM. Transfer learning using EfficientNetBo outperformed the other methods. Some of the study's weaknesses can be addressed in future research. A more in-depth investigation, especially for people suffering from Covid-19, necessitates a lot more patient data. Future study should focus on separating patients with moderate symptoms from those with pneumonia symptoms, as these symptoms may not be recognized accurately on X-rays, or may not be recognized at all. Future study focuses on multi-class classification of COVID-19 and various types of pneumonia. As a future work to solve the data imbalance problem, Generic Adversarial Network (GAN) technique can be used. Combining pre-trained CNN features with handcrafted features (GLCM texture features, GLRLM, GLSZM, and NGTDM features) has yet to be investigated.

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