2023-06

A comparative study of Detecting Covid 19 by Using Chest X-ray Images– A Deep Learning Approach

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Draft Version

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Abstract-SARS-CoV-2's COVID-19 pandemic has quickly spread over the world, inflicting a sizable number of illnesses and fatalities. Stopping the virus's spread depends on correctly and rapidly identifying infected people. Although RT-PCR assays, for example, are thought to be the most accurate way to identify COVID-19, their cost and availability may be restricted in places with limited resources. In this study, we propose some deep-learning methods for predicting COVID-19 detection using chest X-ray images. Chest X-ray imaging has become an essential diagnostic tool in the management of COVID-19, as it is non-invasive, widely available, and cost-effective. However, the interpretation of chest X-rays for COVID-19 detection can be challenging, as the radiographic features of COVID-19 pneumonia can be subtle and overlap with other respiratory diseases. In this study, the performance of different deep learning models, notably VGG16, VGG19, DenseNet121, and Resnet50, was examined for their ability to distinguish between coronavirus pneumonia and cases of pneumonia. 4649 chest X-ray images of patients with pneumonia (3526) and COVID-19 (1123) were employed in the study, and performance measures were used to assess each model. Confusion metrics were also used to evaluate each model's performance. The study's findings demonstrated that DenseNet121 performed better than the competing models, with an accuracy rate of 99.78%.

Keywords: COVID-19, X-RAY, Pneumonia.

I. Introduction

The COVID-19 pandemic has posed significant challenges for the global healthcare system, necessitating the urgent need to identify affected people accurately and quickly. This study focuses on using chest X-rays to find COVID-19 in patients with symptoms or illnesses that have been diagnosed. To control the transmission of the virus, it is essential to identify COVID-19-affected individuals as soon as possible. The most effective approach for COVID-19 detection is RT-PCR, although, in areas with limited resources, it may not always be available or economical. The identification of distinctive radiographic characteristics connected to COVID-19 pneumonia using chest X-ray imaging has been proposed as an alternative, affordable, and non-invasive approach to COVID-19 detection.

However, the sensitivity and specificity of chest X-rays in COVID-19 detection are highly variable, and the interpretation of radiographic findings requires expertise and may be subject to interobserver variability. Deep learning, a subset of machine learning, has shown significant promise in image analysis and has the potential to aid in the detection of COVID-19 pneumonia on chest X-ray images. Deep learning algorithms can automatically learn and identify image patterns and features without prior knowledge of specific radiographic features associated with COVID-19 pneumonia. Detecting COVID-19 through radiological means can be challenging because its appearance on radiographs is like that of viral pneumonia. Distinguishing between the two requires specific expertise, which may not always be readily available, especially with the high number of suspected cases daily [1,3]. As a solution, researchers have turned to automation and machine learning to bridge this gap [2,4]. In this study, we aim to review the current state of knowledge on the use of deep learning algorithms in the detection of COVID-19 pneumonia on chest X-ray images. We will discuss the performance of deep learning algorithms and their potential clinical implications for COVID-19 detection in resource-limited settings. The results of this study could have important consequences for the creation of precise and affordable methods for detecting COVID-19. The use of deep learning algorithms in radiological imaging could significantly enhance the accuracy of diagnosis for this virus.

II. Literature review

Taher et al [6]. This study focuses on the use of chest X-ray (CXR) pictures to categorize instances as viral pneumonia, normal pneumonia, or Covid-19 pneumonia. The technique requires computing the Discrete Cosine Transform (DCT) for each smaller subblock created from the CXR pictures. The DCT makes it possible to create compressed copies of each CXR image, which is helpful for energy compaction. The final feature vectors' dimension is decreased by using average pooling windows after the images have been compressed. A small number of spectral DCT components that are chosen as features for each image make up these vectors. The photos are split into three categories using a multilayer artificial neural network. The accuracy of the suggested method is 95% on average.

Huynh et al [7]. The authors recommend applying transfer learning models to chest X-ray pictures to detect pneumonia brought on by COVID-19. As a result, the dataset's size rose, and prediction precision increased. They used both privately generated and publicly available datasets to test six different transfer learning architectures. The experiment's findings showed that the DenseNet121 transfer learning model beat the competition on the enhanced dataset with accuracy, precision, recall, F1-score, and AUC values of 98.51%, 98.54%, 98.51%, and 98.51%, respectively. Additionally, most algorithms performed better while analyzing fresh data.

KARHAN et al [8]. In this work, they proposed Chest radiographic images are extremely important in the diagnosis and identification of COVID-19 in addition to the RT-PCR test. We used the ResNet50 model, a convolutional neural network architecture, to categorize chest X-ray images for COVID-19 detection. Chest X-ray scans may be quickly analyzed using artificial intelligence, allowing the identification of sick people. The results of the experiment show promise in the field of pathology with the aid of computer-aided techniques. This approach can be beneficial in situations where resources and RT-PCR tests are inadequate.

Umri et al [9]. This study aims to analyze a dataset of 100 chest X-ray photos of COVID-19 patients and 100 images of typical chest X-rays make up the dataset used in this study. The dataset is processed using the Contrast Limited Adaptive Histogram Equalization (CLAHE) and Convolutional Neural Networks (CNN) approaches, and two situations are considered to produce the detection results. The findings indicate that the accuracy of COVID-19 detection using CNN is affected by the implementation of CLAHE. Moreover, the basic CNN model performs better than the VGG16 transfer learning model.

Channa et al [10]. In this paper, Researchers propose using deep learning to analyze chest X-rays retrospectively and detect COVID-19. The study suggests that the proposed approach can achieve a 91.67% accuracy in diagnosing COVID-19 and a 100% accuracy in predicting the survival rate. This could be a valuable tool for healthcare providers to diagnose COVID-19 patients and determine the severity of the disease quickly and accurately.

Podder et al [11]. The need for intensive care unit (ICU) treatment for COVID-19 patients was predicted by the authors using a variety of ML classifiers. The hospital Israelita Albert Einstein in Brazil provided the dataset for the study, which included 5644 samples with 111 variables. 57 variables were employed for COVID-19 detection and 67 for ICU prediction following preprocessing. Based on the dataset's responses to base and ensemble classifier applications, it was determined that stacking ensembles of random forest (RF), Boost (XGB), and logistic regression (LR) led to COVID-19 detection accuracy of 94.39% and recall of 92%. The stacking ensemble with RF, additional trees, and LR produced an accuracy of 98.13% and a recall of 99% for ICU prediction.

III. Methodology

This section provides an explanation of the VGG16 deep-learning model that was used in this investigation. It consists of 16 layers, including 13 convolutional layers and 3 fully connected layers, and it accepts inputs with a preset size of 224 × 224 RGB pictures. The image size is reduced via max-pooling, and a SoftMax classifier is applied after the final fully linked layer. However, as shown in Figure 1, a specially created classifier was used in place of the last fully linked layer with SoftMax activation in this investigation.

a) VGG 16

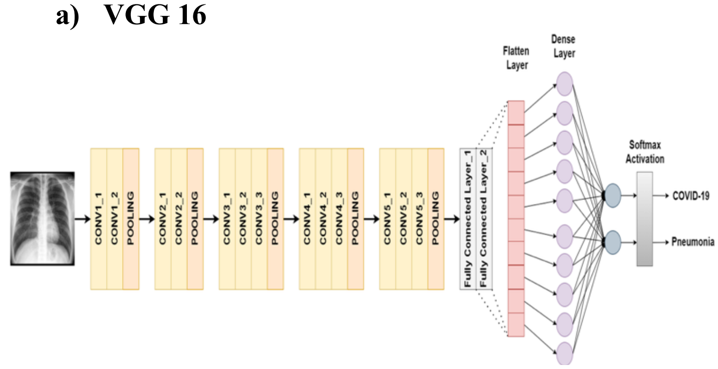

Fig 1: VGG 16 for binary Classification

b) VGG 19

This paragraph explains the VGG19 model used in the study. The model used in this study comprises a total of 19 layers and takes as input RGB images with 224 x 224-pixel dimensions. 16 convolutional layers and 3 fully linked layers are among them. The output size is decreased using max-pooling, and the final fully connected layer is subjected to a SoftMax classifier. However, as indicated in Figure 2, a custom-made classifier is utilized in this study as opposed to the final fully linked layer with SoftMax activation.

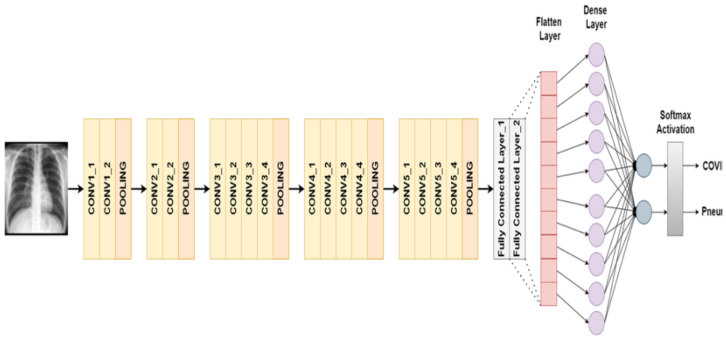

Fig 2: VGG 19 for binary Classification

An equal number of samples were chosen at random for both training and validation to create a dataset for pneumonia that is balanced. 20% of these samples were utilized for validation, while the remaining 80% were used for training. To achieve better testing outcomes and avoid overfitting to the pneumonia cases, the other samples were preserved [5]. Regardless of the cases in the test dataset, the balanced training and validation tests were conducted to attain the best accuracy because prior research has demonstrated the need for a balanced training set for obtaining accurate results [13].

c) Dense Net 121

An RGB image with a particular size of 224x224 is required to use the DenseNet121 model. More than 8 million parameters make up the model's 121 layers. The core components of DenseNet121, known as Dense Blocks, maintain the feature map dimensions while changing the number of filters. The Transition layers use batch normalization for downsampling and are positioned in between the blocks. As shown in Figure 3, a custom-made classifier is employed in this study in place of the final fully linked layer with SoftMax activation.

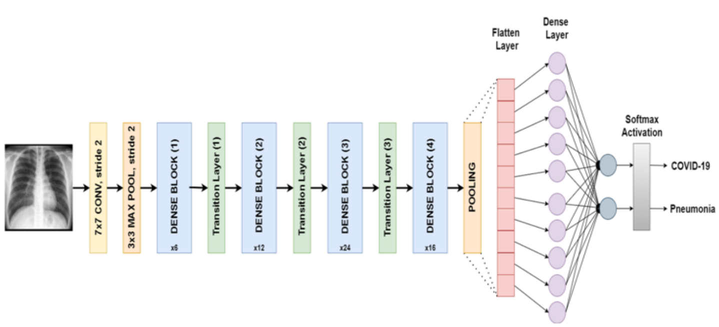

Fig 3: Dense Net 121 for binary Classification

d) Resnet 50

One Max-Pool layer, one Average Pool layer, and 48 Convolutional Layers make up the ResNet50 design for residual networks. ResNet50 features three convolutional layers of each convolution block ResNet50 contains one identification block and three convolutional layers. Over 23 million different parameters in the model can be trained. Figure 4 shows how the ResNet50 model was altered in this study to account for COVID-19 and pneumonia categorization.

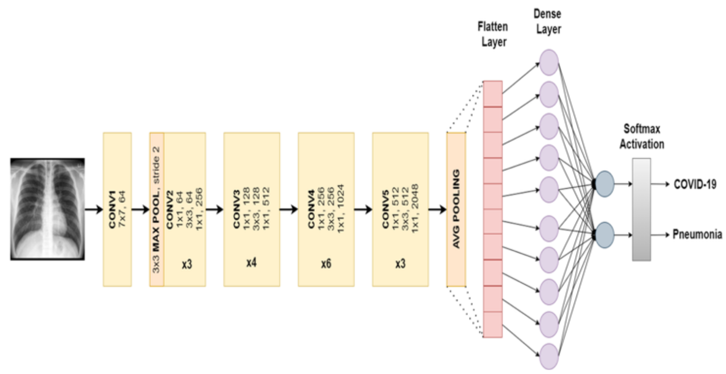

Fig 4: Resnet 50 for binary Classification

Model Training and validation

In this study, four deep learning models were used in the study (VGG16, VGG19, DenseNet121, and ResNet50), and for consistency, all images in the dataset were scaled down to 224 × 224 pixels. TensorFlow 2.4 and the Keras API were used to design the algorithm and implement CNN. The models were trained using a 12 GB NVIDIA Tesla K80 GPU. The performance of the models was evaluated during training based on their ability to accurately predict ground truth probabilities using the categorical cross-entropy loss function.

For this study, we collected images from multiple databases that were publicly available. 3525 photos of pneumonia and 1123 COVID-19 images were used in the study for training, validating, and testing the models. The photos were standardized by being resized to 224 by 224 pixels from their original range of sizes. 10% of the COVID-19 samples were chosen at random for testing, while the remaining samples were divided into 80% for training and 20% for validation.

IV. Result and Discussion

Table 3 and Figs. 5, 6, 7, and 8 demonstrate the accuracy and loss values of each fine-tuned model during the training and validation processes. ResNet50 achieved the minimum validation loss in just 4 epochs, with a validation accuracy of 99% or higher. According to the findings, the models can immediately recognize the distinctive features of pneumonia and COVID-19. However, it was shown that DenseNet121 and ResNet50 had the highest training accuracy when accuracy and loss were considered.

Model	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
VGG 15	99.10	99.10	99.06	99.06
VGG 19	98.30	99.00	99.16	99.12
Dense Net 121	99.44	98.72	99.38	99.42
Resnet 50	99.26	99.42	99.31	99.30

Table 1: Model performance

If we consider the combination of both training and validation accuracy and loss, then the DenseNet121 model achieved the lowest validation loss and the highest validation accuracy, indicating that it may have performed the best among the four models. It should be underlined that more testing and verification are required to ensure the comparative efficacy of the models shown in Table 1 before they can be used.

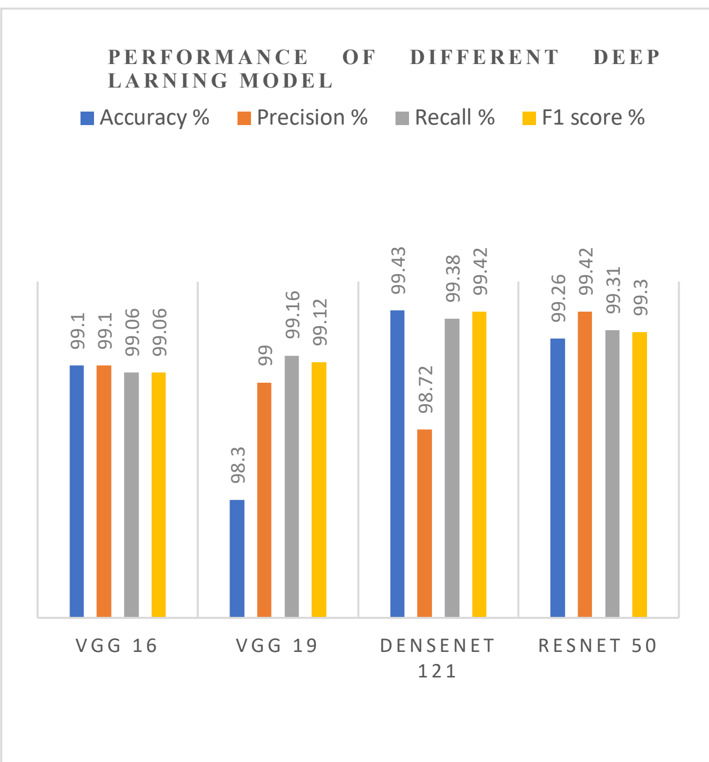

Chart 1: Performance Evaluation of Different Deep Learning Models

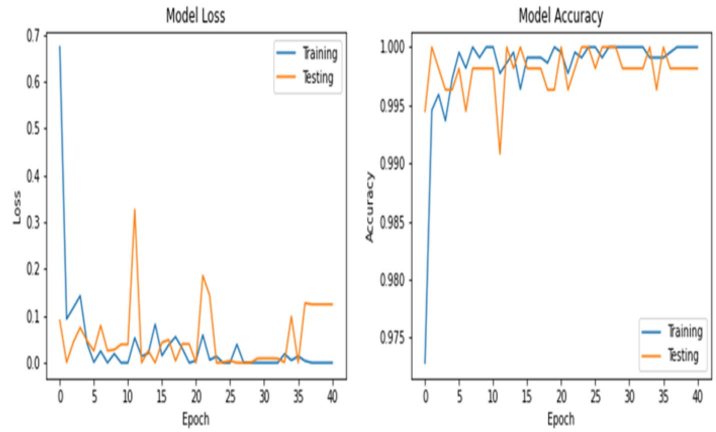

Fig 5: VGG 16 model accuracy graph

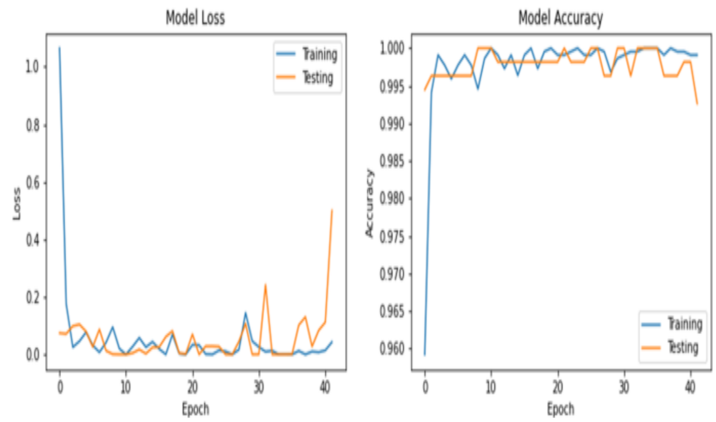

Fig 6: VGG 19 model accuracy graph

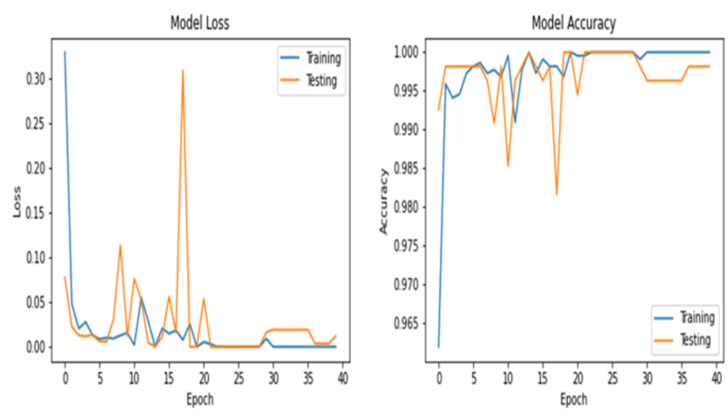

Fig 7: Dense Net model accuracy graph

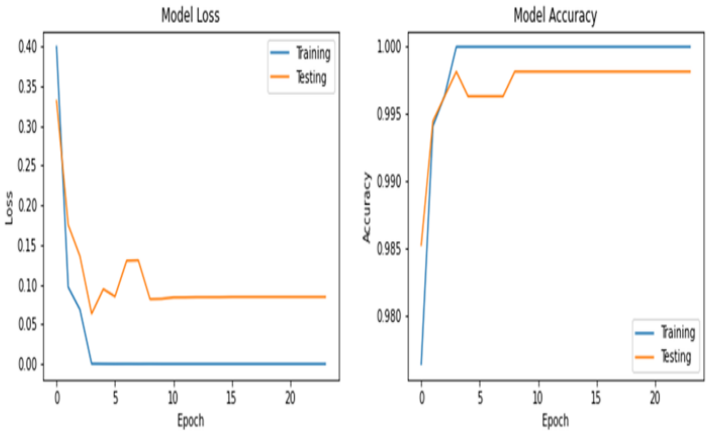

Fig 8: Resnet model accuracy graph

V. Conclusion And Future Work

Overall, DenseNet121 ability to accurately detect COVID-19 through chest X-rays is a testament to the power of machine learning in the healthcare and highlights the importance of continued research and innovation in this field. While further research is needed to validate the effectiveness of DenseNet121 in detecting COVID-19 on a larger scale, the results so far are very promising. The use of DenseNet121 in detecting COVID-19 through chest X-rays has the potential to revolutionize how we diagnose and manage this disease, particularly in areas with limited access to testing and medical resources.

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