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A Comparative Study of Deep-Learning Models for COVID-19 Diagnosis based on X-ray Images

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Abstract.
Background: The rise of COVID-19 has caused immeasurable loss to public health globally. The world has faced a severe shortage of the gold-standard testing kit known as RT-PCR (Reverse Transcription Polymerase Chain Reaction). The accuracy of RT-PCR is not 100%, and it takes a few hours to deliver the test results. An additional testing solution to RT-PCR would be beneficial. Deep learning's superiority in image processing is characterized as the most effective COVID-19 diagnosis based on images. The small number of COVID-19 X-ray images in existing deep-learning methods for COVID-19 diagnosis may degrade the performance of deep-learning methods for new sets of images. Our priority for this research is to test and compare different deep-learning algorithms on a dataset consisting of many COVID-19 X-ray images.
Methods: We have merged the publicly available image data into two groups (COVID and Normal). Our dataset contains 579 COVID-19 cases and 1773 Normal cases of X-ray images. We have used 145 COVID-19 cases and 150 Normal cases to test the deep-learning models. Deep-learning models based on CNN, VGG16 and 19, and InceptionV3 have been considered for prediction. The performance of these models is compared based on measurements of accuracy, sensitivity, and specificity. In the deep-learning models, the SoftMax activation function is used along with the Adam optimiser and categorical cross-entropy loss. A customised hybrid CNN model found in literature is considered and compared to explore how the inclusion of many COVID-19 X-ray images could impact the model's performance.
Results: The accuracy of the considered deep-learning models using InceptionV3, VGG16, and VGG19 algorithms achieved 50%, 90%, and 83%, respectively, in predicting the X-ray images of COVID-19. We have shown that number of COVID-19 X-ray images does have a significant

impact on the model's performance. A customised hybrid CNN model found in the literature failed to perform well on a dataset consisting of a large number of COVID-19 X-ray images. The customised hybrid CNN model reached an accuracy of 71% on many COVID-19 X-ray images. In contrast, it achieved 98% accuracy on a small number of COVID-19 X-ray images. It is also observed from the experiments that the VGG16 performs well with an increased number of images.
Conclusions: A maximized number of COVID-19 X-ray images should be considered in building a deep-learning model. The deep-learning model with VGG16 performs the best in predicting from the X-ray images.

Keywords: Coronavirus (COVID-19) · RT-PCR · Machine Learning (ML) · Deep Learning (DL) · X-ray images.

1 Introduction

The COVID-19 pandemic is caused by the novel coronavirus known as Severe Acute Respiratory Syndrome coronavirus (SARS-COV-2) found in Wuhan city, China, at the end of 2019 [21]. SARS-COV-2 and other viruses from the corona family known as MERS COV 2 are responsible for causing respiratory disease in humans. The death and the transmission rate by this virus are very high, and it can survive a few hours to few days in the environment. The primary symptoms of COVID-19 are fever, cough, headache, muscle pain, and shortness of breath [13,17,24]. It spread so fast from Wuhan china to the whole world that it declared it a global pandemic [18,21]. Around 2.9 million people had died due to covid infection by the 8th of April 2021 [6]. On the contrary, some countries are now facing the third wave and, the virus is changing its variant and spreading so fast that it is hard to imagine what will happen shortly [5]. Therefore, the early detection of a corona virus-infected person is of great importance to slow down the spread and death [11,17]. The gold standard diagnostic technique for COVID-19 is the reverse transcription-polymerase chain reaction (RT-PCR) [7]. However, RT-PCR is not fast enough for the diagnosis of COVID-19 because RT-PCR takes about 4-6 hours to provide an outcome which is time-consuming. Also, the shortage of RT-PCR kits creates another challenge [11,12]. Furthermore, RT-PCR's implementation and standardisation were hampered in many countries due to the cost, availability and technology. Therefore, many lower- and middle-income African, Asian, and Latin American countries have failed to implement RT-PCR testing at the beginning of the pandemic. It was also confirmed that in China, the CT chest findings sensitivities as high as 98% compared to 71% for RT-PCR [1,8].

Many deep learning models are currently being used experimentally to detect COVID-19 from X-ray and CT imaging [6,17,26]. In our previous study, "Deep Learning models for the diagnosis and screening of COVID-19: A systematic review (accepted)", in Google Scholar and PubMed, we found a total number of 188 titles in September 2020, whereas a recent search at the 12th of April, 2021 with the exact keywords have found 646 titles. Through our analysis, we have observed that X-ray mainly was used for the theoretical implementation of deep learning as CT images pose several challenges in detecting COVID infected region using deep learning algorithms. The challenges imposed by CT images are less applicability, slower image acquisition, high cost, limited sensitivity [24]. On the contrary, chest x ray-based ML models for COVID-19 diagnosis has become the popular early detection technique recent days because of its various salient features like it can be used in emergencies using portable device [25], cheaper, faster and reliable method [24]. An automated, faster, and reliable COVID-19 diagnosis method algorithm with better performance can save the RT-PCR kits [20]. Therefore, there is increasing interest in deep learning models in many publications in the last several months.

We have also observed the cost and availability between the RT-PCR and X-ray to diagnose COVID-19. X-ray imaging is painless and cheap compared to RT-PCR [15, 30]. In the UK, we have noticed that the lowest cost of an X-ray is £79, but the maximum cost is £140 compared to the PCR test is £185 [29]. However, RT-PCR kits are widely available in high-income countries, whereas, in Bangladesh, an X-ray cost is from 450 BDT to 1200 BDT, but RT PCR is 3000 BDT [10, 16]. In India, X-ray images' cost is a minimum of RS183, and the maximum is RS 1370. On the other hand, RT-PCR has a RS 980 to RS 1800 [15,30]. X-ray images in South Africa cost approximately R2500. RT-PCR, on the other hand, has a minimum price of R1150 [9, 27]. Furthermore, many low- and middle-income countries (LMICs) struggle to cope with the shortages of the RT-PCR testing kits and the technology, and we need an alternative testing solution to RT-PCR [14].

Researchers are trying to investigate the power of AI or ML techniques in diagnosing COVID-19 based on medical imaging and are restructuring the system to alleviate this problem. Therefore, deep learning with X-ray images is gaining popularity to use available data and technology [3]. But the main concern with most of these ML models is that they are trained and tested with smaller size dataset, and practical implementation is limited. Therefore, considering all the above scenarios, we have decided to progress our research to inspect some of the published literature and models based on the chest X-ray image.

In healthcare services like ML-based automated diagnosis systems, performance depends on the reasonable amount of dataset used during the training phase. Generally, a large dataset enhances the classification performance of the predictive model. Still, a small dataset leads to an overfitting problem [2]. More specifically, CNN based ML models require a large dataset to work correctly [4]. Since most of the models' design for x-ray based COVID-19 diagnosis includes the CNN model, it is a significant issue to analyse their performance in various dataset sizes.

To overcome this issue related to the dataset, we have collected the dataset used in various papers by emailing the corresponding authors. Combining all the datasets, we have prepared a dataset of 2352 images containing 1773 standard images and 579 COVID images. In particular, we have taken a hybrid deep learning model proposed in [17] and reimplemented it with the paper's dataset for training and testing. The proposed model used DarkNet to detect and classify COVID-19 patients as binary classification and multiclass classification using CXR images. The dataset used for this model includes 125 COVID-19 cases, 500 normal and 500 pneumonia cases. COVID sample dataset is very low in number for training the deep model. We also tested the model based on our prepared dataset. We have also considered VGG16, VGG19, and InceptionV3 algorithms and used our training and testing dataset. Furthermore, we have compared these models' performance in terms of performance metrics like accuracy, sensitivity, and specificity.

This study is divided into four main sections; in section 2, we have described our methodology's detailed procedure, including data preparation, preprocessing, model training, and testing. In section 3, we discussed the results found from the experiment and compared the results. Finally, section 4 concludes this paper.

2 Methodology

2.1 Dataset Preparation

We have considered all the papers included in our previous systematic review work. We have emailed all the authors to request their dataset and received seven datasets in response. Three of the datasets are used here (of the others, one was CT images and three were corrupted). The datasets for this study are represented in the below table. The dataset contains 2352 images, consisting of 1773 normal images and 579 COVID images. The training dataset consists of 2057 images, which contains 1623 normal images and 434 COVID images. In contrast, the test dataset consists of 295 images containing 150 normal images and 145 COVID images.

Table 1: Dataset considered for this study

Ref	COVID	Non-COVID	Pneumonia	MERS	SARS	Streptococcus	Varicella	Augmented
[26]	271	65	98	×	×	×	×	×
[17]	125	500	500	×	×	×	×	×
[11]	183	208	1525	×	×	×	×	912
[19]	0	1000	11	10	11	12	10	×

2.2 Data preprocessing

Data preprocessing has been carried out in several steps. Firstly, the image sizes were reduced and image augmentation was performed. Since the images in the training sample were of different sizes, they had to be resized before being used as inputs to the algorithm. Square images were resized to 256×256 pixels in resolution. Rectangular images were resized to 256 pixels on their shortest line, and then the image's middle 256×256 square was cropped. Image data training augmentation was used to have 224×224 images.

2.3 Models

The models that are considered for comparison are VGG16 and VGG19 [22]. VGG16 and 19 are the variants of the VGG machine learning model, which focuses on the CNN's depth feature. This model consists of the input layer, hidden layer, convolutional layer, fully connected layer. Besides VGG, we also considered the InceptionV3 [23] model, whose underlying architecture is also CNN. This version improves several features like label smoothing. Finally, the customised CNN model was proposed in [17] to detect COVID-19 patients from chest X-ray images. We have re-implemented this model and compared it with the models mentioned above.

2.4 Model training and testing

The environment for implementing our models comprises Intel Core i9-10885H (8 Core, 16MB Cache, 2.40 GHz to 5.30 GHz, 45W,vPro), 32GB RAM, NVIDIA Quadro RTX 5000 w/16GB GDDR6. We used the train and test dataset mentioned in Section 2.1 for training and testing our models. The loss function used was categorical cross-entropy loss with Adam optimiser. The target size of the image and batch size was 224×224 and 32, respectively. Finally, the epoch size was taken as 50 for each of the models.

2.5 Performance Metrics

We have considered three metrics to evaluate and compare the models that we have considered: accuracy, sensitivity, and specificity. They are defined as follows in terms of true positive (TP), true negative (TN), false positive (FP), and false negative (FN).

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

The accuracy of the model is the proportion of the total dataset that is classified correctly.

$$Sensitivity = \frac{TP}{TP + FN}$$

The sensitivity defines the model's ability to generate a correct positive result for people with COVID-19.

$$Specificity = \frac{TN}{TN + FP}$$

The specificity defines the model's ability to generate a correct negative result for people who do not have COVID-19.

3 Results and discussion

We have considered various datasets initially to inspect the models. First, we have run all the models with the smaller dataset to see the performance and actual data. For this review, we present only the results of the final datasets to understand the performance.

Table 2 compares the models' image quantity, accuracy, sensitivity, and specificity. We have compared and evaluated the models using these metrics, where VGG16 performed well in all three categories compared to all other models. VGG16 gained 90% accuracy compared to 83% for VGG19, 71% for Customised CNN [2] and 50% InceptionV3. VGG16 achieved 90.90% in the sensitivity parameters, whereas VGG19 achieved 76.92%, InceptionV3 and Customised CNN [2] achieved 69.93% and 70.71% respectively. VGG16 achieved 89.04% for specificity parameters, whereas VGG19 achieved 88.43%, Customised CNN [2] achieved 70.32%, and InceptionV3 achieved 28.57%.

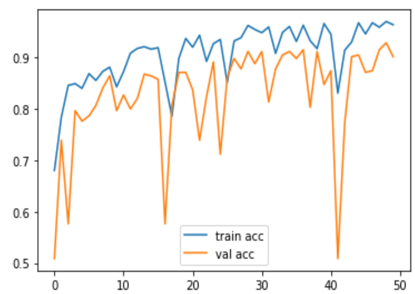
Table 2: Performance comparison

Models	Image Quantity	Accuracy	Sensitivity	Specificity
InceptionV3	2352	50%	69.93%	28.57%
VGG16	2352	90%	90.90%	89.04%
VGG19	2352	83%	76.92%	88.43%
Customized CNN [17]	2352	71%	70.71%	70.32%

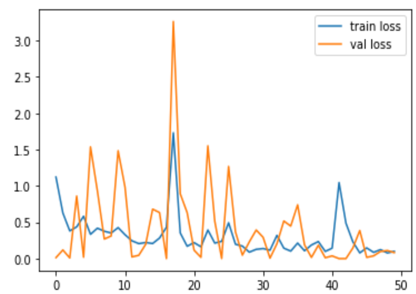
Table 3 compares the models' performance using our dataset and the actual dataset of Ozturk et al. [17], showing how the performance varies with the image quantity. The Customised CNN achieved 98% accuracy, where it contains only 125 COVID images. With our dataset of 579 COVID images, the Customised CNN accuracy was 71%. The model with the VGG16 algorithm shows the same performance with our dataset as the Ozturk et al. dataset. The model with the VGG16 algorithm failed to match the sensitivity and specificity on Ozturk et al. compared with the 125 COVID images. However, the model with the VGG16 algorithm gained the correct balance between sensitivity and specificity with our dataset, which contains 579 COVID images.

Table 3: Comparison based on image quantity

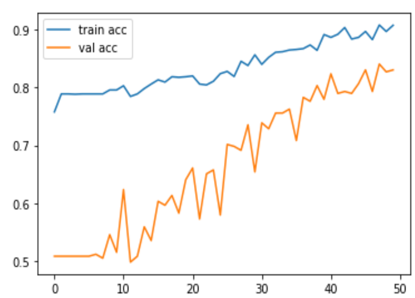
Models	Image Quantity	Accuracy	Sensitivity	Specificity
Customised CNN [17]	1127	98.08%	95.13%	95.30%
VGG16	1127	98%	62.50%	100%
Customised CNN [17]	2352	71%	70.71%	70.32%
VGG16	2352	90%	90.90%	89.04%



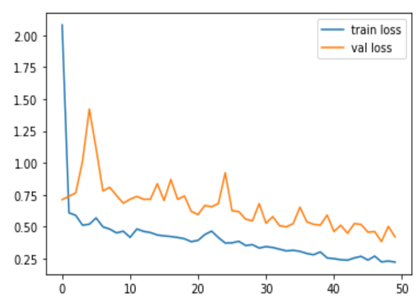
(a) VGG16 Accuracy



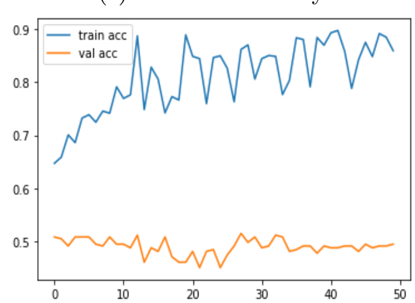
(b) VGG16 Loss



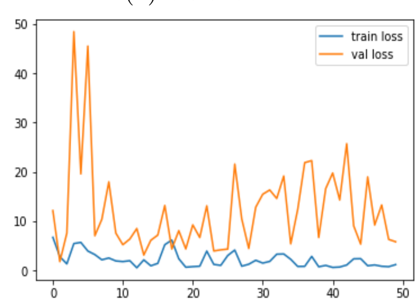
(c) VGG19 Accuracy



(d) VGG19 Loss



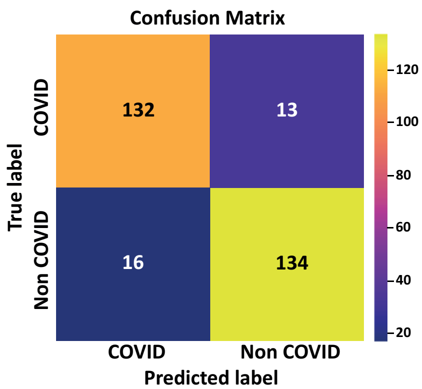
(e) InceptionV3 Accuracy



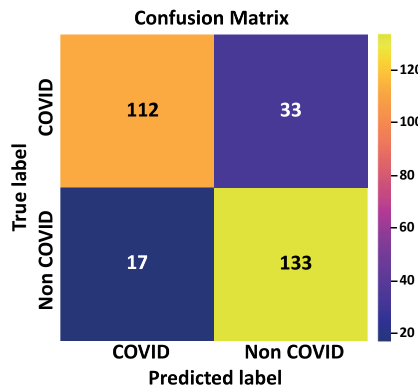
(f) InceptionV3 Loss

Fig. 1: Training loss, validation loss, training accuracy, and validation accuracy for VGG16, VGG19, and InceptionV3.

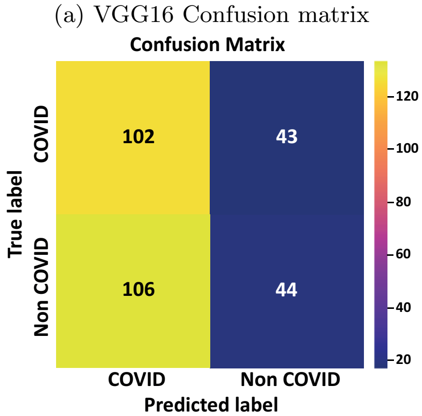
Figures 1a and 1b show the accuracy and loss curve of VGG16 respectively, where the training and test data almost overlap each other, showing the satisfactory performance of this model. Figures 1c and 1d show the accuracy and loss graph of VGG19 respectively, where the training and test data are separated from each other, showing worse performance compared with VGG16. However, InceptionV3 performed very poorly compared with both VGG16 and VGG19. Figure 1e and 1f shows the accuracy and loss graph of InceptionV3, where the training and test data are widely separated.



(a) VGG16 Confusion matrix



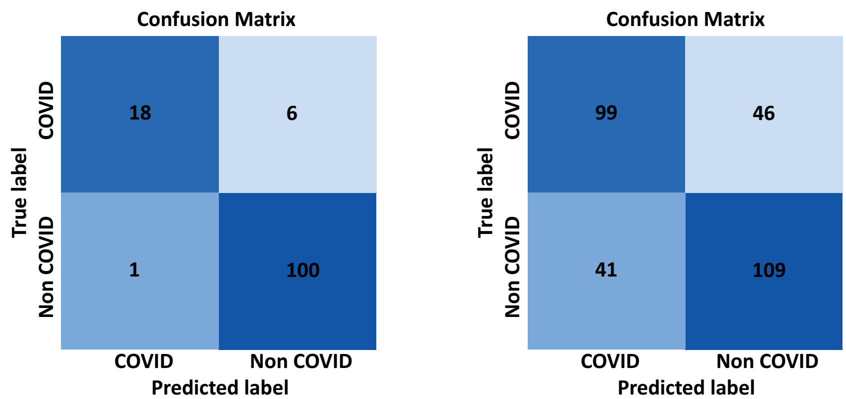
(b) VGG19 Confusion matrix



(c) InceptionV3 Confusion matrix

Fig. 2: Confusion matrices of the experimental models.

Figures 2a, 2b, and 2c show the confusion matrix for VGG16, VGG19, and InceptionV3. VGG16 wrongly predicted 13 COVID cases and 16 normal cases. In contrast, VGG19 wrongly predicted 33 COVID cases and 17 normal cases. Finally, InceptionV3 wrongly predicted 43 COVID cases and 106 normal cases. Therefore, the performance of VGG16 is the best of the three.



(a) Confusion matrix Ozturk et al. (2020) (b) Confusion matrix for our dataset

Fig. 3: Confusion matrices of customized CNN models.

We have also compared the customised CNN (Ozturk et al., 2020) model with our dataset. Figure 3a shows the confusion matrix of their dataset, which can be compared with our dataset in Figure 3b. In the first run (a) 6 COVID cases and 1 normal case were wrongly predicted. In contrast, in the second run (b) 46 COVID cases and 41 normal cases were wrongly predicted. Therefore, this CNN model is not performing adequately when we ran an extensive dataset. We present some of the alternative models and their performance in this section. Table 4 represents the selected models with different datasets. We have observed that the proposed model by Toğaçar et al. [26] is a MobileNetV2 and SqueezeNet based COVID-19 diagnosis method based on X-ray images. The experimental phase of the proposed model shows a dataset that includes only 295 images.

Table 4: Selected models with different datasets.

Model Name	Image Quantity	COVID Images	Accuracy	Sensitivity	Specificity
VDSNet [26]	348	295	70.80%	64%	62%
Pruned [21]	14,979	268	99%	99%	99%
CNN+LSTM [11]	3363	613	99.20%	99.30%	99.20%
COVIDiagnosis-Net [28]	5949	76	98.3%	98.2%	99.1%
Panwar, Gupta [18]	529	192	97%	97.62%	78.57%

Rajaraman et al. [21] proposed an iteratively pruned deep learning model for COVID-19 diagnosis. Though the dataset contains 6761 normal, 5412 pneumonia and 2538 bacterial images, the COVID cases were only 268. Islam et al. [11] used the dataset of 613 COVID-19 cases, 1525 pneumonia and 1525 normal cases of X-ray images for training and testing their proposed combined CNN and LSTM-based deep learning model COVID-19 diagnosis. Although the dataset for that study contains more COVID images than our dataset, we could not confirm their performance with any of our experiments as we did not receive either their model or dataset to make a comparison. Ucar and Korkmaz [28] considered two large datasets for their experimental purpose but unfortunately, among 5949 images of one dataset, only 76 COVID cases were present. The other dataset comprises only 45 COVID cases. Panwar et al. [18] used a small dataset of 337 total images and 192 COVID X-ray cases. However, the authors performed image augmentation to increase the number of images. All the above studies have used limited datasets for their models, so their training and testing ML models may not perform well for a larger COVID dataset.

We have identified some high accuracy, sensitivity, and specificity models with the corresponding results compared with other papers. We can see that CNN+LSTM, pruned deep learning model, and COVIDiagnosis-Net achieved 99% results. However, the number of samples of COVID images considered for training and testing is small in size. If those models are trained and tested with a larger dataset, they might also show poor performance.

4 Conclusions and future work

This study has prepared a large dataset containing COVID-19 chest X-ray images and non-COVID-19 X-ray images, which has been achieved by combining publicly available data found in the existing literature. Comparative analysis of algorithms suggests that the model with VGG16 algorithms performs best and outperforms others in predicting COVID-19 from X-ray images. This study indicates that the number of COVID-19 X-ray images in the dataset plays a vital role in the model's performance. The maximum number of COVID-19 X-ray images should be considered for training and testing a reliable deep-learning model. We plan to increase the number of COVID-19 X-ray images in our dataset further, to allow a deeper investigation and comparison of the deep-learning methods' scope in detecting COVID-19 patients from X-ray images.

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