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A Comparative Study of Multiple Neural Network for Detection of Covid 19 on Chest X-Ray

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Abstract

Coronavirus disease of 2019 or Covid-19 is a rapidly spreading viral infection that has affected millions all over the world. With its rapid spread and increasing numbers it is becoming overwhelming for the healthcare workers to rapidly diagnose the condition and contain it from spreading. Hence it has become a necessity to automate the diagnostic procedure. This will improve the work efficiency as well as keep the healthcare workers safe from getting exposed to the virus. Medical image analysis is one of the rising research areas that can tackle this issue with higher accuracy. This paper conducts a comparative study of the use of the recent deep learning models (VGG16, VGG19, DenseNet121, Inception-ResNet-V2, InceptionV3, Resnet50, and Xception) to deal with detection and classification of coronavirus pneumonia from other pneumonia cases. This study uses 7,165 chest X-ray images of Covid-19 (1536) and Pneumonia (5629) patients. Confusion metrics and performance metrics were used to analyze each model. Results show DenseNet121 (99.48% of accuracy) showed better performance when compared with the other models in this study.

Index term Artificial neural networks, Deep Learning, Transfer Learning, Multi-task Learning, Covid-19, Classification, DenseNet121

1. Introduction

The novel coronavirus or simply known as the Covid 19, affects the respiratory tracts and the lungs leading to severe cases of pneumonia. The usual symptoms include fever, dry hack cough, body ache, and loss of taste or smell. In extreme cases the patient may experience shortness of breath, multiple organ failure and could be fatal in 3.4% of the cases (<https://www.worldometers.info/coronavirus/>). While the world pharmaceutical companies are trying to develop vaccination to prevent the spread of this pandemic, the current medical practice to control the spread of Covid-19 is focused on early detection and isolation of the patient. The current gold standard for Covid 19 detection is the real-time reverse transcription-polymerase chain reaction (rRT-PCR), where the short sequences of DNA or RNA are reproduced or amplified

and analyzed [1]. [2] reported that the RT-PCR testing has a low sensitivity of 71% while [3] reported that the sensitivity of a single RT-PCR test in hospitalized patients is 82.2%.

Perceiving the limitations of rRT-PCR, there is a need for cross-verification examination by using radiological images. Radiography scanning was proposed to detect pathological effects of COVID-19 by examining chest radiological images of lungs of patients [4]. Several studies have shown that changes in chest radiography images such as X-ray and CT scan were noticed even before the appearance of clinical features of COVID-19 [5]. Interpretation of chest X-ray (CXR) and CT scans have widely been done by radiologists to find some visual indicators for COVID-19 infection as an alternative method for rapid screening of infected patients.

Chest radiography, particularly chest X-ray, is one of the most frequently performed examination in radiology due to its cost-effective diagnostic procedure and high availability in medical facilities. Due to its low cost and easy to operate, X-ray equipment are also accessible to underdeveloped areas. There are certain highlights or feature can be found on X-ray images, for example in the early stage, reciprocal, multi-focal, ground glass opacities with a fringe or back dissemination, primarily found in the lower projections, while in the late stage, pulmonary consolidation can be found [6]. Since the studies have shown that the abnormalities caused by COVID-19 are visible in chest X-rays, these abnormalities, especially the opacities, should further be used to detect COVID-19.

In terms of early detection, although X-ray diagnosis has some benefits over the current RT-PCR method, however, the biggest challenge encounter here is that this method requires medical expert to comprehend the X-ray images and the extraction of important findings take a lot of valuable time[7]. In the current pandemic situation when everyday there is huge amount of people to be screened, it would be a huge burden to radiologists. Furthermore, X-ray images of COVID-19 pneumonia look similar to other common viral pneumonia, the features might overlap with other infectious and inflammatory lung diseases. This makes radiologists struggle to identify COVID-19 images from other viral pneumonia images. At times where medical facilities are overburden and radiologists are overwhelmed with uncountable examinations, incorrect diagnosis could happen which will result in wasting the medical resources on false positive patients or deferring in treatment with resulting costs, exertion and danger of presentation to positive COVID-19 patients. Hence, there is a need of automated methods to accelerate the X-ray diagnosis with high accuracy.

With the recent advancement in computing power, hardware and availability of medical image datasets; artificial intelligence and machine learning have taken a boom over the past few years. Over the last year, scientists and researchers are globally working on the automated methods that used contemporary AI technologies, particularly deep learning, to enhance the performance of X-ray imaging with the goal to reduce the workload of radiologists[7]. Studies have been conducted to use neural networks to differentiate Covid-19 X-ray from that of pneumonia and normal X-ray. This study aims to compare different deep neural networks that can differentiate coronavirus pneumonia from a bacterial pneumonia on chest X-ray.

In this study we have fine-tuned existing models (VGG16, VGG19, DenseNet121, Inception-ResNet-V2, InceptionV3, Resnet50, and Xception) based on our classification requirements. The models have been trained and tested on Covid-19 and Pneumonia CXR images from multiple datasets to avoid any biases. The models are then compared based on their performance metrics and computational time taken. The results are carefully analyzed and best model is chosen for this binary classification.

2. Related Work

The global pandemic, covid-19 has become a prevalent research topic in all the scientific areas. Various techniques and methods are implemented to bring a more effective way in controlling it. Researchers have explored various deep learning techniques to bring an effective way of diagnosis with existing tools and modalities available today. Due to limited availability of data, pretrained models are utilized with the help of transfer learning techniques to distinguish Covid-19 radiographs from other forms of pneumonia.

Jain et al. [8] implemented ResNet-101 in the classification of COVID-19 and viral pneumonia, achieving accuracy of 97.78%. Che Azemin et al. [9] used pretrained ResNet-101 to detect COVID-19 in CXR with accuracy of 71.9% as their training dataset was based on airspace opacity instead of confirmed COVID-19 cases. Ismael et al. [10] also used ResNet-50 architecture but only for feature extraction. The extracted features were classified using SVM classifier with the Linear kernel function and produced high accuracy of 94.7%. Makris et al. [11] fine-tuned several CNN models and compared their performances in classifying COVID-19, pneumonia and normal images. VGG16 turned out having the best performance with overall accuracy of 95.88% in their study. Abbas et al. [12] proposed a new method to classify COVID-19, SARS and normal CXR which is called DeTraC (stands for Decompose, Transfer and Compose). It is done by adding a class decomposition layer to the pretrained models than can partition each image class into sub-classes, but assemble back during prediction. By using VGG19 with DeTraC approach, the model has achieved classification accuracy of 93.1%.

Asif et al. [6] trained Inception-V3 using transfer learning techniques to distinguish COVID-19 from viral pneumonia and normal CXR. In this study, the model gives a classification accuracy of more than 98%, proving the effectiveness of transfer learning and easily deployable approach for COVID-19 detection. Inspired by DarkNet architecture, Ozturk et al. [13] developed a deep learning network named DarkCovidNet for automated COVID-19 diagnosis. The model achieved accuracy of 98.08% for binary (COVID-19 and normal) and multiclass (COVID-19, pneumonia and normal) classification. Shelke et al. [14] worked in segregation of COVID-19 and normal pneumonia using DenseNet-161 and achieved an accuracy of 98.9%. Minaee et al. [15] fine-tuned 4 pretrained networks (ResNet18, ResNet50, SqueezeNet, and DenseNet-121) and compared their performance. Different cut-off thresholds for probability score were experimented in this study. SqueezeNet turned out to be the best models with sensitivity of 98% and specificity of 92.9%.

Several studies have used ensemble techniques and stacking techniques to build a model from multiple CNN architectures in order to further boost the performance in COVID-19 detection. Das

et al. [16] has developed a new model with weighted average ensembling method, the model comprises of three pre-trained CNN models - DenseNet201, Resnet50V2 and Inceptionv3. This approach has achieved accuracy of 95.7% and sensitivity of 98% in the classification of positive and negative COVID-19 cases. Ridhi et al. [17] proposed a new method to classify COVID-19, pneumonia and normal CXR by using stacked of DenseNet and GoogleNet as feature extractor, then the features were classified by the ensemble of XGB, RF and SVM classifiers. The classification accuracy obtained in this study is 91.7%. Gupta et al. [18] proposed an integrated stacked deep convolution network called InstaCovNet-19 which makes use of InceptionV3, NASNet, Xception, MobileNetV2 and ResNet101. The proposed model achieved accuracy of 99.53% in binary (COVID vs Non-COVID) classification, and accuracy of 99.08% in 3-class (COVID-19, pneumonia, normal) classification.

A 22-layer CNN architecture was proposed by Hussain et al. [19] for automatic COVID-19 detection using raw CXR and CT scan images. A classification accuracy of 99.1%, 94.2% and 91.2% were obtained for binary, 3-class and 4-class classification respectively. The result of 4-class classification outperforms other state-of-the-art methods used for COVID-19 detection. Canayaz et al. [20] developed a model called MH-COVIDNet that used VGG19 as feature extractor and BPSO meta-heuristic algorithm (MH algorithm) for feature selection. After that, the selected features were classified using SVM classifier. This approach obtained classification accuracy of 99.38%. Khuzani et al. [21] performed feature extraction using different techniques such as Texture, FFT, Wavelet, GLCM and GLDM. In the study, a multilayer network was created with 2 hidden layers of 128 and 16 neurons and a final classifier. The 3-class classification (COVID-19, pneumonia and normal) has achieved an accuracy of 94%.

3. Materials and Methods

3.1. Dataset

A total of 1536 COVID-19 and 5629 pneumonia images were for training, validation and testing of the models. Table 3.1 tabulates the various databases and the number of images used in this study.

Table 1 List of databases used in this study

	Dataset	Covid-19	Pneumonia
1	CoronaHack-Chest X-Ray-Dataset [22]	19	4118
2	Covid_Data_GradientCrescent [23]	69	158
3	Covid-19 Radiography Database [24]	1143	1345
4	Covid-chestxray-dataset [25]	142	-

5	Figure1-COVID-chestxray-dataset [26]	35	-
6	Actualmed-COVID-chestxray-dataset [27]	58	-
7	COVID-19-x-ray-10000-images [28]	70	-
8	ChestXRay2017 [29]	-	8
	Total	1536	5629

3.2. Data Preprocessing

Initially a python script was created to extract the images from the CSV file of the database into separate folders such as COVID-19, pneumonia and normal. The algorithm was assembled from Kaggle and this was achieved by using Pandas high level data manipulation tool and Shutil module that enables high-level operations on collection of files. After extracting the images in respective folders, data splitting was done using “splitfolder” script of python. Images were randomly split in training, validation and test set. Utilizing the ImageDataGenerator the images were preprocessed and resized to 224x224x3 in their respective directory.

3.3. Pretrained transfer model

This study compares various neural networks that has successfully distinguished Covid-19 from other forms of pneumonia. Models such as VGG16, VGG19, DenseNet121, Inception-ResNet-V2, InceptionV3, Resnet50, and Xception were used for this comparative study. Due to limitation of large training datasets this study has adopted transfer learning technique where the last layer of pretrained CNNs were modified for classification purpose and previous parameters and layers remained intact. All the models were instantiated with pretrained weights of ImageNet dataset. The last fully-connected layer along with softmax activation function were replaced by flatten layer, 0.5 dropout rate and dense layer that applies softmax activation on previous layers and produce 2 outputs of probability for “COVID-19” and “Pneumonia” classes.

3.4. Training and classification

For this study, deep learning models such as VGG16, VGG19, DenseNet121, Inception-ResNet-V2, InceptionV3, Resnet50, and Xception are chosen and trained on 12GB NVIDIA Tesla K80 GPU. All the images of the dataset were resized to 224x224 pixels. For the algorithm development and implementation of CNN, the deep learning library – TensorFlow 2.4 with Keras API was used. The model was compiled by using “categorical_crossentropy” for the loss function, while the optimizer used was “Adam” with a learning rate of 0.001. Tensorflow Keras built-in callback was used for early stopping of the training. Validation loss was used as performance measure to terminate the training. The number of epochs with no improvement (patience) was set to 20, meaning that the training will be terminated as soon as the performance measure has no improvement for the 20 consecutive epochs. Besides, the model weights from the epoch with the best value of validation loss will be stored and used for final prediction.

3.5. Performance Metrics

After the models finished training, they were tested on test set to evaluate the model accuracy. The models were tested on 156 COVID-19 images and 4249 pneumonia images. To evaluate the performance of the models, the metrics adopted include overall classification accuracy, recall (also known as sensitivity), precision and F1-score. The metrics are defined as follow:

Accuracy:

$$\frac{TP+TN}{TP+TN+FP+FN} \quad \text{Equation 1}$$

Precision:

$$\frac{TP}{TP+FP} \quad \text{Equation 2}$$

Recall:

$$\frac{TP}{TP+FN} \quad \text{Equation 3}$$

F1-score:

$$\frac{2 \times (\text{Recall} \times \text{Precision})}{(\text{Recall} + \text{Precision})} \quad \text{Equation 4}$$

where TP, TN, FP and FN stand for True Positive, True Negative, False Positive and False Negative. In this study, if the COVID-19 image is correctly classified, it is counted as TP, while incorrectly classified as pneumonia, is counted as FN. On the other hand, if a pneumonia image is classified correctly, it is counted as TN and the one wrongly classified as COVID-19 is FP. A confusion matrix was plotted to depict the number of correctly classified images. Lastly, a classification report was created using scikit-learn metrics function.

4. Experimental results and discussions

In result analysis, typical pneumonia chest X-ray images have been compared with Covid-19 images. VGG16, VGG19, DenseNet121, Inception-ResNet-V2, InceptionV3, Resnet50, and Xception were analyzed based on accuracy, precision, recall and F1-score.

4.1. Accuracy and Loss During Training and Validation

The accuracy and loss values in training and validation process are listed in the Table 4.1. When comparing the number of epochs taken by each model to reach the minimum validation loss, it is observed that InceptionV3, ResNet50 and Xception reached minimum loss at just 3, 4 and 4 epochs respectively. With few epochs, they are able to achieve validation accuracy of 99% and above. This indicates that these models are able to learn the distinctive features between COVID-19 and

pneumonia very quickly. However, when loss and accuracy are taken into consideration it is observed that the training accuracy is highest for DenseNet121 and ResNet50, however the DenseNet121 has the lowest training loss. For the validation set VGG16, VGG19, DenseNet121 and Inception-ResNet-V2 have higher accuracy, however DenseNet121 has the lowest validation loss. Hence from this data, it can be summarized that DenseNet121 model exhibits higher training and validation performance among the seven models.

Table 2 Accuracy and Loss During Training and Validation

	Best Epoch	Training Loss	Training Accuracy	Validation Loss	Validation Accuracy
VGG16	21	0.0100	0.9990	0.0000e+00	1.0000
VGG19	22	0.0122	0.9994	0.0000e+00	1.0000
DenseNet121	20	6.1363e-09	1.0000	7.2103e-07	1.0000
Inception-ResNet-V2	9	0.0022	0.9993	0.0011	1.0000
InceptionV3	3	0.0472	0.9943	0.0554	0.9963
ResNet50	4	1.1188e-04	1.0000	0.0633	0.9982
Xception	4	0.0430	0.9951	0.0325	0.9926

4.2. Confusion Matrix

The confusion matrix displays numbers of images identified correctly and incorrectly by the model. Confusion matrix was generated for both validation dataset and test dataset. Validation dataset comprised of 276 Covid-19 and 276 Pneumonia images whereas the test dataset comprised of 157 Covid-19 and 4250 Pneumonia images. Table 4.2 below summarized the confusion matrix for all the seven model. It can be observed that though multiple models performed well during the validation but DenseNet121 has the lowest False Positive and False Negative. Indicating that the DenseNet121 model made the least number of error while predicting the image was Covid-19 or pneumonia.

Table 3 Confusion Matrix

Model	Validation				Testing			
	TP	TN	FP	FN	TP	TN	FP	FN
VGG16	276	276	0	0	157	4210	40	0
VGG19	276	276	0	0	157	4214	36	0
DenseNet121	276	276	0	0	156	4228	22	1
Inception-ResNet-V2	276	276	0	0	156	4172	78	1
InceptionV3	276	274	2	0	155	4206	44	2
Resnet50	275	276	0	1	156	4221	29	1
Xception	274	274	2	2	155	4179	71	2

4.3. Performance Metrics

This study compares seven different pre-trained model according to accuracy, precision, recall F1 score and training and testing time as tabulated in Table 4.3. It is observed that DenseNet121 gave good classification performance with accuracy of 99.48%, followed by ResNet50 with 99.32% accuracy. Table 4.3 also compares the computational times taken by each model for training and testing. It is seen that the InceptionV3 takes the least time for training however the it is slow during testing. Whereas DenseNet121 was bit slow during training but it was the fastest during testing with highest accuracy.

Table 4 Performance Metrics

Model	Accuracy (%)	Precision (%)	Recall (%)	F1 (%)	Training time (sec)	Testing time (sec)
VGG16	99.09	99.28	99.09	99.14	1353	1012
VGG19	99.18	99.34	99.18	99.22	1344	946
DenseNet121	99.48	99.54	99.48	99.49	1200	936
Inception-ResNet-V2	98.21	98.79	98.21	98.38	899	1083
InceptionV3	98.96	99.17	98.96	99.02	710	974
ResNet50	99.32	99.42	99.32	99.35	783	1056
Xception	98.34	98.83	98.34	98.49	750	865

From the above result we recommend DenseNet121 (99.48% accuracy, 99.54% precision, 99.48% recall and 99.49% of F1 score) for classification of Covid-19 from pneumonia cases on chest X-ray.

4.4. Comparison with existing research

Comparing our best model with the works that also performed binary classification, particularly COVID-19 and pneumonia images, DenseNet-121 obtained the highest classification accuracy. Shelke et al. [14] used a deeper network, DenseNet-161 but the accuracy obtained is lower, might be due to the lower number of training images. Compared with other works that worked on binary classification of CXR images, our model has the second highest accuracy. The highest binary classification accuracy is obtained by Gupta et al. [18] using their proposed network called InstaCovNet-19. In summary, our experimented model DenseNet-121 using transfer learning technique, has achieved very good performance in binary classification and has used the highest number of images among the methods mentioned above.

Table 5 Comparison with other related work that performed binary classification on CXR images.

Author (Year)	CNN Architectures	Image Classification	Total Dataset	Accuracy
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Nayak, et al. [30]	ResNet-34	COVID-19 and Normal	COVID-19: 775 Normal: 775	98.33%
Ismael and Şengür [10]	ResNet50 feature + SVM	COVID-19 and Normal	COVID-19: 180 Normal: 200	94.7%
Ozturk, et al. [31]	DarkCovidNet	COVID-19 and No-findings	COVID-19: 177 No-findings: 500	98.08%
Amit Kumar, et al. [32]	Ensembling method: three pre-trained CNN models - DenseNet201, Resnet50V2 and Inceptionv3	COVID-19 Positive and COVID-19 Negative	COVID-19 +ve: 538 COVID-19 -ve: 468	95.7%
Gupta, et al. [33]	InstaCovNet-19 (Integrated stacking of InceptionV3, NASnet, Xception, MobileNetV2 and ResNet101)	COVID-19 and Non-COVID	COVID-19: 361 Normal: 365	99.53%
Hussain, et al. [34]	CoroDet	COVID-19 and Normal	COVID-19: 2843 Normal: 1108	99.1%
Shelke, et al. [14]	DenseNet-161	COVID-19 and Pneumonia	COVID-19: 500 Pneumonia: 500	98.9%
Jain, et al. [8]	ResNet-101	COVID-19 and Viral Pneumonia	COVID-19: 440 Viral Pneumonia: 480	97.78%
Best experimented model in this study	DenseNet-121	COVID-19 and Pneumonia	COVID-19: 1536 Pneumonia: 5629	99.48%

5. Conclusion

Deep learning algorithm can aid healthcare workers for detecting COVID-19 with minimal processing of chest X-rays images. In this study, 2-class dataset were created which included COVID-19 and pneumonia images obtained from open sources. Several state-of-the-art pretrained neural networks that include ResNet50, DenseNet121, InceptionV3, VGG16, VGG19, Inception-ResNet-V2 and Xception were experimented using transfer learning technique. The best model turned out to be DenseNet-121 which accomplished an accuracy of 99.48%. ResNet50 also performed very well with a slightly lower accuracy (99.32%). This study has proven that the detection models built using CNNs with transfer learning technique are able to perform good

binary classification task on COVID-19 and pneumonia images. COVID-19 and pneumonia CXR images contain similar features which are challenging for the radiologist to interpret. However, the CNN model can easily learn the features in just few epochs of training and classify the images correctly. The high accuracies obtained suggest that the deep learning models could find something distinctive in the CXR images and that makes the deep networks capable of distinguishing the images correctly. These trained models can effectively reduce the workload of medical practitioners and increase the accuracy and efficiency of COVID-19 diagnosis.

Insufficient dataset is a limitation in this study. Unlike pneumonia disease which have large CXR database as many researches has been done for decades, COVID-19 is a newly emerged disease and it has limited medical image dataset. The availability of COVID-19 images on the open sources are very limited. Thus, in this study we have imbalanced dataset for testing. Besides, the number of trained images per class is only around 1400. It is assumed that with more training images, the performance of the model can be further improved.

Current study performs binary classification only on COVID-19 and pneumonia images. To make the trained model more practical to be deployed in the medical setting, the model can be trained on COVID-19 images and Non-COVID which is the combination of pneumonia and normal CXR images. By doing so, the model is still performing binary classification task, but now it can identify one more type of image which is the normal CXR image as Non-COVID. The drawback of this type of model is that the model will not label out the pneumonia image from the healthy image, so one information is lacking here, but in overall this model provides convenience to medical practitioners because it can detect COVID-19 images from 3 classes of images. To make the model even better, we can further train the model to perform 3-class classification (COVID-19, Pneumonia and Normal) or even 4-class classification (COVID-19, Viral Pneumonia, Bacterial Pneumonia and Normal).

ABBREVIATIONS

CNN: Convolutional Neural Network

Covid-19: Coronavirus disease of 2019

CT: Computed Tomography

CXR: Chest X-Ray

DeTraC: Decompose, Transfer and Compose

DNA: Deoxyribonucleic Acid

FFT: Fast Fourier Transform

FN: False Negatives

FP: False Positives

GLCM: Gray-Level Co-Occurrence Matrix

GLDM: Gray Level Dependence Matrix

RNA: Ribonucleic Acid

rRT-PCR: real-time reverse transcription-polymerase chain reaction

SARS: Severe acute respiratory syndrome

SVM: Support Vector Machine

TN: True Negatives

TP: True Positive

VGG: Visual Geometry Group

DECLARATIONS

A. ETHICS APPROVAL AND CONSENT TO PARTICIPATE

Not Applicable. All the database was obtained from literature that are publicly available.

B. CONSENT FOR PUBLICATION

Not Applicable

C. AVAILABILITY OF DATA AND MATERIAL

All the data are available upon request from the corresponding author

D. COMPETING INTERESTS

There is no conflict of interest reported by any authors

E. FUNDING

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F. AUTHORS' CONTRIBUTIONS

All the authors contributing equally in data collection, processing, experiments and article writing.

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