Convolutional Neural Network (CNN) in COVID-19 Detection: A Case Study with Chest CT Scan Images

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***Abstract*—Deep Learning, especially Convolutional Neural Networks (CNN) have been performing very well for the last decade in medical image classification. CNN has already shown a great prospect in detecting COVID-19 from chest X-ray images. However, due to its three dimensional data, chest CT scan images can provide better understanding of the affected area through segmentation in comparison to the chest X-ray images. But the chest CT scan images have not been explored enough to achieve sufficiently good results in comparison to the X-ray images. However, with proper image pre-processing, fine tuning, and optimization of the models better results can be achieved. This work aims in contributing to filling this void in the literature. On this aspect, this work explores and designs both custom CNN model and three other models based on transfer learning: InceptionV3, ResNet50, and VGG19. The best performing model is VGG19 with an accuracy of 98.39% and F-1 score of 98.52%. The main contribution of this work includes: (i) modeling a custom CNN model and three pre-trained models based on InceptionV3, ResNet50, and VGG19 (ii) training and validating the models with a comparatively larger dataset of 1252 COVID-19 and 1230 non-COVID CT images (iii) fine tune and optimize the designed models based on the parameters like number of dense layers, optimizer, learning rate, batch size, decay rate, and activation functions to achieve better results than the most of the state-of-the-art literature (iv) the designed models are made public in [1] for reproducibility by the research community for further developments and improvements.**

***Index Terms*—COVID-19 detection, chest CT scan, Convolutional Neural Networking (CNN), Deep Learning (DL), chest radiography images.**

I. Introduction

Since the outbreak of COVID-19, it has been spreading rapidly with a drastic mortality rate of 2 - 5% of the infected patients [2]. For the alarming rate of spread and severity, World Health Organization (WHO) characterized COVID-19 as a global pandemic on 11 March 2020 [3]. However, detecting and isolating SARS-CoV-2 (virus responsible for COVID-19) virus carrying individuals at an early stage of infection can normalize the spread of this virus. For early detection nasopharyngeal (NP) swab or oropharyngeal (OP) swab is often suggested [4]. Collection of an NP/OP swab specimen can cause discomfort and also if the specimen is not collected properly, it may affect the result. This method of collecting specimens may also generate a theoretical risk of transmitting COVID-19, as airborne transmission is verified COVID-19 outbreak [5]. For detection of infected patients by these methods, we require adequate testing apparatuses, and these methods are also time consuming. Bronchoalveolar lavage fluid or sputum sampling and fibro-bronchoscope brush biopsy are carried out on the patients who are severely ill or using mechanical ventilation [6]. These methods of testing have generated the highest viral loads for diagnosis of COVID-19 infection [7]. WHO listed two COVID-19 tests for emergency purposes i.e. genesig Real-Time Polymerase Chain Reaction (RT-PCR) COVID-19 testing and cobas SARS-CoV-2 Qualitative assay to use on the cobas® 6800/8800 Systems [8]. Genesig Real-Time PCR COVID-19 test is suitable for laboratories consisting of moderate sample testing capacity, but the cobas® SARS-CoV-2 with cobas® 6800/8800 Systems is suitable for larger laboratories.

To reduce social panic due to scarcity of test kits, and to get faster results with higher accuracy and less effort & cost, extensive researches have been going on in detection of COVID-19 from chest radiography images, i.e. CT and X-ray images as SARS-CoV-2 attacks the epithelial cells of respiratory tract [9] [10]. Computer-aided diagnostic system is also easily accessible, reduces dependency on proper medical facilities and trained medical personnel, and can diagnose the virus infection in a short time with more efficiency than human detection. Though extensive research is going on in detecting COVID-19 from chest X-ray images, chest CT images have also become a popular choice [11] [12]. Singh et al. suggested the usage of chest CT images over chest X-ray images as CT images provide 3D representation which may detect the infection better [13].

Deep Learning (DL) is a branch of Machine learning which has shown promising performances in extracting and classifying images due to its high learning capabilities of features in an incremental pattern. Thus, over the last decade, it has been one of the most popular and reliable choices in medical

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image classification. It also has a great prospect in detection of COVID-19 and it has already drawn the attention of both academia and industry in this aspect. Even though CT images perform better in segmentation and 3D representation, it still lags in achieving better classification accuracy in comparison to the Chest X-ray images. This work addresses the challenges of fine tuning, optimizing, and designing of CNN models to achieve better accuracy with Chest CT images. The aim of the work is to contribute to the continuing effort of the research community to fight against COVID-19. Based on the study of the state-of-the-art literature, four different models have been designed to explore the potentiality and to achieve a better prospect. One of these four models is a custom designed CNN model and other three are transfer learning models based on (i) InceptionV3 (ii) ResNet50 and (iii) VGG19. Though a lot of researchers have taken both of these approaches to custom CNN and transfer learning, due to the lack of fine tuning and optimization most of the research efforts were unable to achieve accuracy of more than 98%. Thus, this work is also going to contribute to filling that void in the state-of-the-art literature.

The following sections of this research paper are organized as follows: section II: Related Research and Our Contribution, section III. Dataset Description and Pre-processing, section IV. Designed CNN Models, section V. Results and Comparative Analysis, and section VI. Conclusion.

II. Related Works and Our Contributions

Researchers have been developing deep learning techniques amid the COVID-19 outbreak to diagnose the viral infection from chest clinical images: CT scans, and X-ray images. Fang et al. compared the sensitivity of DL based COVID-19 detection with Chest CT and RNA based test RT-PCR. He concluded the DL based CT image test to have higher performance sensitivity which is 98% in comparison to the 78% of the RT-PCR [14]. Another research study done by Xie et al. also proved the less sensitivity of initial RT-PCR testing [15]. He et al. analyzed 349 COVID-19 and 397 non-COVID chest CT scan images with ResNet-50 and DenseNet-169 [16]. The highest accuracy found in this research work is 86% using model DenseNet-169. Mishra et al. produced 88.34% accuracy using decision fusion matrix (approach to correctified the mistakes of individual models via majority voting approach) on five different deep CNN based models,i.e., VGG16, Inception V3, ResNet 50, DenseNet [17]. This work used a dataset with 360 COVID-19 and 397 non-COVID chest CT scan images. Loey et al. used 345 COVID-19 and 397 non-COVID chest CT scan images for five different deep CNN models: AlexNet, VGGNet16, VGGNet19, GoogleNet, and ResNet50 with Conditional Generative Adversarial Networks (CGAN) [18]. This investigation suggested ResNet 50 as the most appropriate deep learning model with the highest accuracy at 82.91% among five deep CNN models for a small dataset.

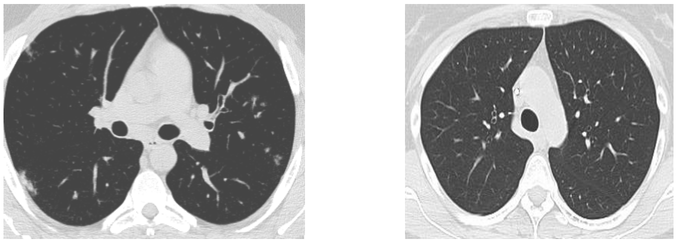
Gifani et al. used a collection of fifteen CNN architectures (EfficientNets(B0-B5), NasNetLarge, NasNetMobile, InceptionV3, ResNet-50, SeResnet50, Xception, DenseNet121, ResNet50, and Inception_ResNetV2) for screening of COVID-19 disease using 349 COVID-19 positive and 397 normal or other lung diseases chest CT scan images [19]. Compare to the other architectures, EfficientNetB0, EfficientNetB5, and InceptionV3 had the highest accuracy at 82% and considering other metrics (precision and recall) this research suggested EfficientNetB0 model is the best pre-trained CNNs model for their dataset. They found 86% accuracy with majority voting of five deep transfer learning architecture method using EfficientNetB0, EfficientNetB3, EfficientNetB5, Inception_resnet_v2, and Xception architectures.

Song et al. used a chest CT scan dataset of 777 COVID-19 and 505 bacterial infected images with four deep CNN models (VGG16, DenseNet, ResNet, and DRE-Net) [20]. This research generated 86% accuracy with DRE-Net model which has been constructed from pre-trained ResNet-50 model. Shi et al. collected large-scale COVID-19 and community acquired pneumonia (CAP) Chest CT data-set (2,685participants) and developed a machine learning method with 90.7% sensitivity for COVID-19 detection [21].

Main Contributions of Our Work: From the above literature, it is evident that most of the designed models could not achieve very high accuracy even though the pre-trained models they used performed with higher accuracy for other medical image classification like brain tumor detection, cancer detection, lung disease detection, etc. There might be several reasons for this lower accuracy which include– lack of fine tuning of the designed models, selection of the unsuitable base model for transfer learning, lack of optimization of the training parameters, lack of augmentation of the gathered datasets, and smaller datasets. This work addresses this crucial issue by exploring the above mentioned probable reasoning. The main contributions of our work are the followings. We designed a custom CNN model and three transfer learning models based on InceptionV3, ResNet50, and VGG19 to classify COVID-19 from CT images. These three models are chosen based on the performances from the study of the state-of-the-art literature. The models are trained and validated based on a comparatively larger dataset having 1252 COVID-19 images and 1230 non-COVID CT images. Fine tuning and optimization of the designed models are done based on the parameters like number of top layers, fully connected layers, optimizer, learning rate, batch size, decay rate, and activation functions. This ultimately resulted in achieving the accuracy of 98.38% with VGG19 and 98.19% with ResNet50. The designed models are made public in [1] for clarity and reproducibility by the research community for further developments and improvements.

III. Dataset Description and Pre-processing

In this work, the dataset from [22] is used which is publicly online and has been collected from real patients from Sao Paulo Brazil. The dataset is divided into two classes: COVID and non-COVID which are respectively of COVID-19 patients and non-COVID patients. Fig. 1 shows two samples– one of COVID-19 and another of non-COVID-19 chest CT scan



(a) COVID 19 sample (b) non-COVID 19 sample

Fig. 1. (a) is the chest CT scan of COVID-19 positive patient and (b) is of normal people

representing each class of the dataset. This dataset has total of 2482 CT scans images, out of the 1252 CT scan images are of SARS-CoV-2 infected patients, and 1230 CT scan images of non-infected SARS-CoV-2 patients. The non-infected SARS-CoV-2 patients have other pulmonary infections. This dataset was collected from 120 patients, of which there are 60 SARS-CoV-2 infected and 60 non infected patients.

TABLE I
DATASET DESCRIPTION OF CT SCAN IMAGES

Dataset	Number of Images	Number of Patients	Training Set	Validation set
COVID 19 infected	1252	32 male 28 female	1002	250
Non infected	1230	30 male 30 female	984	246

All CT scan images are converted to 120 × 120 pixels to maintain image size and quality same for all the images. With this image size, the number of trainable parameters was optimum to achieve the desired accuracy with a reasonable training burden. Our preliminary tests suggest that the higher pixel size does increase the number of parameters exponentially but that did not have any effect on improving the performance of the models. The dataset is split into training and validation sets with a ratio of 80% and 20% respectively as depicted in Table I. However, seed number is added while splitting to have the randomization and reproducibility at the same time. Moreover, besides reshaping the images, all the images are normalized to have a similar pixel distribution in all the images which eventually reduces the computational burden and helps to converge faster. Even though the dataset is larger than most of the earlier discussed work, the larger the dataset, the easier it is for the Neural Network to learn. Thus, both the training and validation sets are augmented based on random rotation, horizontal shift, vertical shift, zoom, & flipping input horizontally and vertically. To have a faster training period and to reduce the memory usage as well, the data is direly fed from the data generator.

IV. DESIGNED MODELS

CNN is based on the principle of the human nervous system especially human brains which are formed of billions of neurons. CNN is formed of artificial neurons which have

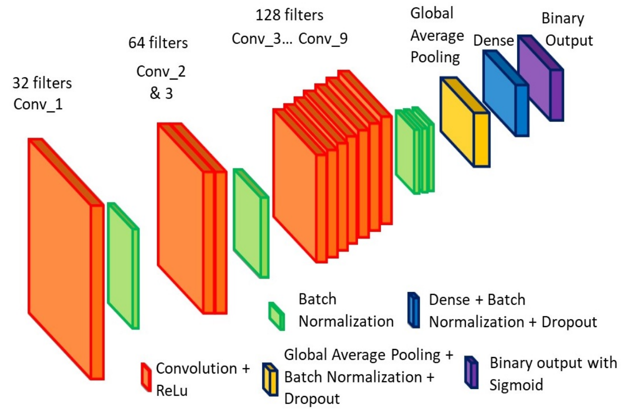


Fig. 2. Time-series graph of world-wide total confirmed cases and deaths due to COVID-19

the property of self optimization with learning like the brain neurons. Due to this self optimizing property, it can extract and classify the features extracted from images more precisely than any other algorithm. Moreover, it needs very limited preprocessing of the input data though it yields highly accurate and precise results. Four different CNN model is designed to better understand the effect of number of convolutional layers, activation function, and optimizers in performance parameters. A sequential CNN is built from scratch with only 10 convolutional layers with batch normalization and Rectified Linear Units (ReLu) activation function in each layer and Sigmoid activation function in the output layers. The designed model is depicted in fig. 2 which shows the main architecture and number of filters used in each layer. This model is referred to as Model 1 in later part of the paper. However, Global Average Pooling (GAP) is used instead of Flatten layer which converts the multi-dimensional output tensors of the convolutional layers to a single dimensional tension which eventually creates fully connected layer. With GAP, instead of adding these fully connected layers on top of the feature map generated by the convolutional layers, average of each feature map is taken to form a vector which is then directly fed to the final activation layer which is Sigmoid in this case. Optimizers play an important role in optimal training of the designed model. The preliminary tests with three popular choices of optimizers: Adaptive Moment Estimation (Adam), Stochastic Gradient Descent (SGD), and Root Mean Squared Propagation (RMSProp) suggests better performance with Adam optimizer. Adam is based on the principle of using the exponential moving averages which are computed based on the gradient evaluated on the current mini batch as presented in equation (1) & (2).

$$m_t = \beta_1 mt - 1 + (1 - \beta_1) g_t \tag{1}$$

$$v_t = \beta_2 vt - 1 + (1 - \beta_2) g_t^2 \tag{2}$$

As this model is quite shallow, it is also needed to study

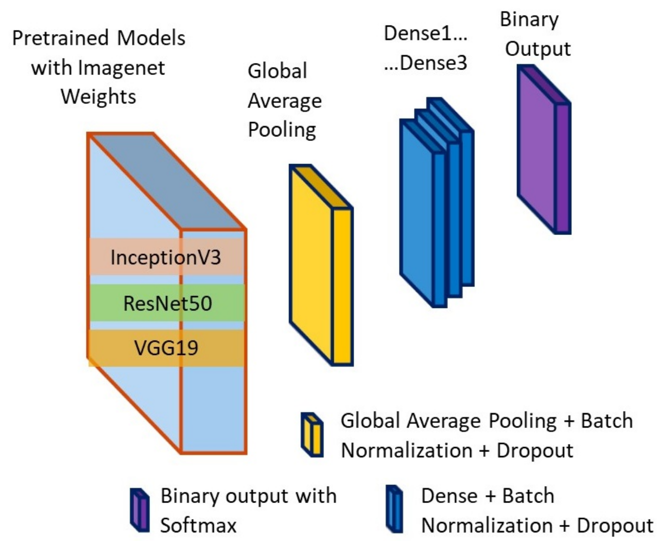
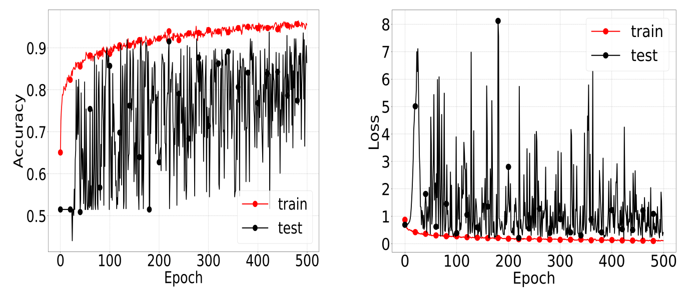


Fig. 3. Time-series graph of world-wide total confirmed cases and deaths due to COVID-19

the models with much more depth in convolutional layer. For this, instead of building models from scratch, it is much more efficient to utilize transfer learning in importing the pre-trained models with 'imagenet' weights. An extensive study on the state-of-the-art literature suggests us to choose InceptionV3, ResNet50, and VGG19 which also performed excellently in other medical image classifications including COVID-19. The basic architecture of the models with transfer learning remains the same as the earlier designed CNN model. But instead of using the 10 convolutional layers as earlier, one of these mentioned pre-trained models is used with the 'imagenet' weights. Top layers of these models are discarded to change them as per our input image shapes. Moreover, unlike the custom designed CNN model Softmax activation function is used in the final layer as the preliminary tests suggested better performance with this one. The designed models with transfer learning are depicted in fig. 3.

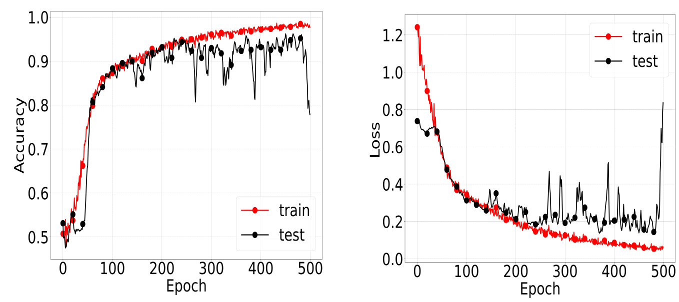
V. Results and Analysis

Model 1 is trained for 500 epochs with a batch size of 128 and 15 steps per epoch. The training has been carried out with and without early stopping which corresponds to the same results with a definite seed number. The overall accuracy and F-1 score achieved by this model are 93.56% and 94.05% respectively. However, the performance improved significantly with the pre-trained models. The InceptionV3 is trained with a batch size of 256 and for 500 epochs with 7 steps per epoch. However, ResNet50 and VGG19 are trained for 800 epochs as it took more iterations to converge. The training and validation accuracy and loss of these models would depict a better idea of this convergence which are presented in fig. 4- 7



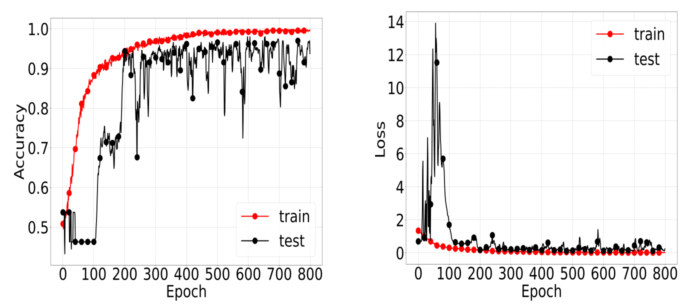
(a) accuracy (b) loss

Fig. 4. The training and validation accuracy & loss with the corresponding epochs for Model 1 (Custom CNN).



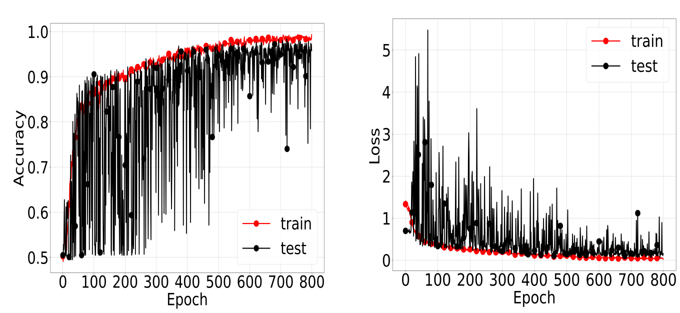
(a) accuracy (b) loss

Fig. 5. The training and validation accuracy & loss with the corresponding epochs for InceptionV3.



(a) accuracy (b) loss

Fig. 6. The training and validation accuracy & loss with the corresponding epochs for ResNet50.



(a) accuracy (b) loss

Fig. 7. The training and validation accuracy & loss with the corresponding epochs for VGG19

The performance of the models is more evident from the metrics like precision, recall, and F-1 score. These performance metrics are calculated from the possible outcomes of the validation dataset which is obtained by the confusion matrix. A confusion matrix has four different outcomes: True Positive (TP), True Negative (TN), False Positive (FP), False Negative (FN). In this case, TP denotes the number of Coronavirus positive patients detected as positive, TN denotes the number of negative cases detected as negative, FP presents the number of cases that are actually negative but detected as positive and FN gives the cases which are actually positive but detected as negative. Accuracy defines how close the generated result is close to the actual value whereas precision measures the percentage of the relevant results. Recall or sensitivity is another important factor for evaluating a CNN model. It is defined by the percentage of the total relevant results that a model can correctly classify. F1-score combines both precision and recall and it is designated as the weighted average of these two. Equation 3-6 represents accuracy, precision, recall, and F-1 score respectively.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{3}$$

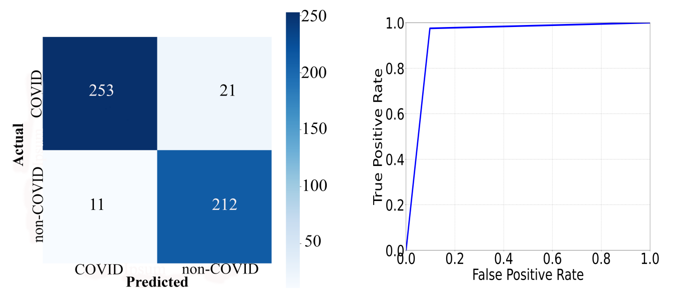
$$Precision = \frac{TP}{TP + FP} \tag{4}$$

$$Recall = \frac{TP}{TP + FN} \tag{5}$$

$$F1\ Score = 2 \times \left(\frac{Precision \times Recall}{Precision + Recall} \right) \tag{6}$$

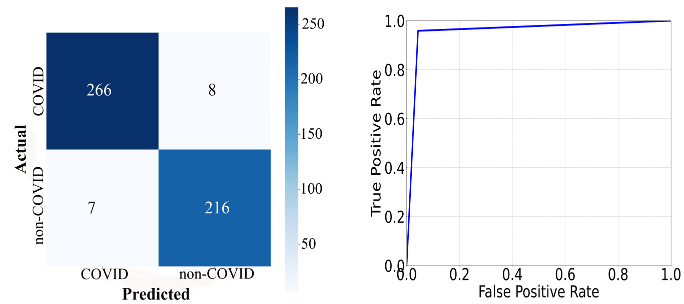
Receiver Operating Characteristics (ROC) curve represents the performance of the classifier at different threshold values which plots the TP rates vs. FP rates. The confusion matrix and the ROC curve of the Model 1, InceptionV3, ResNet50 and VGG19 are presented in fig. 8 - 11

The results show that VGG19 performs with the highest accuracy of 98.39% which is followed by ResNet50 with an accuracy of 98.19% whereas the InceptionV3 has an accuracy of 96.98%. The corresponding F-1 score, precision, and recall of the best performing model– VGG19 are 98.52%, 98.89%, and 98.16% respectively. The performance metrics of all the designed models are tabulated in table II



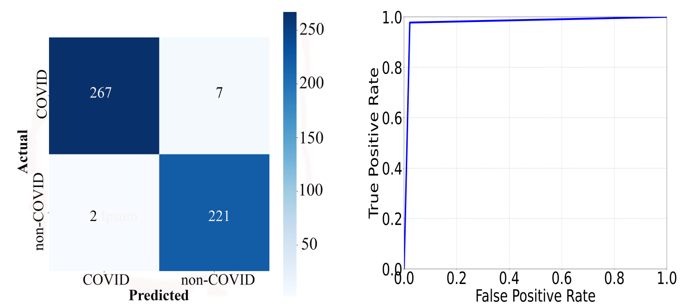
(a) Confusion matrix (b) ROC curve

Fig. 8. (a) Confusion matrix and (b) ROC curve for Model 1.



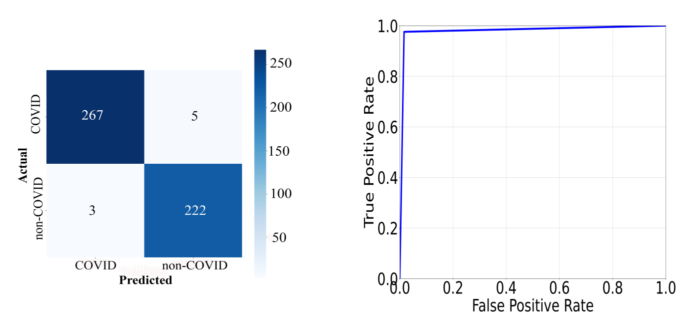
(a) Confusion matrix (b) ROC curve

Fig. 9. (a) Confusion matrix and (b) ROC curve for InceptionV3.



(a) Confusion matrix (b) ROC curve

Fig. 10. (a) Confusion matrix and (b) ROC curve for ResNet50.



(a) Confusion matrix (b) ROC curve

Fig. 11. (a) Confusion matrix and (b) ROC curve for VGG19.

TABLE II
PERFORMANCE METRICS OF THE MODELS

Model	Accuracy (%)	Precision (%)	Recall (%)	F-1 Score (%)
Custom CNN	93.56	95.83	92.33	94.05
InceptionV3	96.98	97.43	97.08	97.25
ResNet50	98.19	99.26	97.44	98.34
VGG19	98.39	98.89	98.16	98.52

It is evident from the results and study that, the dataset performs best with the optimum number of convolutional layers. The Model 1 (custom CNN) model is too shallow, thus it underfits slightly and misses the deep features which reflect in comparatively lower accuracy of 93.56%. On the other hand, InceptionV3 and ResNet50 both have 48 convolutional layers and thus tend to overfit. However, VGG19 with 19 convolutional layers fitted most perfectly with better accuracy than that of other designed models.

VI. Conclusion

Convolutional Neural Network (CNN) is a kind of machine learning approach being used to analyze visual imagery. Computer-aided diagnostic system can be easily accessible and provide rapid diagnosis of the virus which can contribute to COVID 19 detection and isolation of patients. CNN has been used widely to diagnose COVID-19 from X-ray images compared to CT scan images. Though CT scan images have benefits like providing three dimensional (3D) volumetric data, elimination of superimposed structures, better image quality and ability to differentiate small differences, using CT scan images for COVID-19 detection is still underdeveloped. In this work, a custom CNN model and three transfer learning based models (InceptionV3, ResNet50, VGG19) are used for COVID-19 diagnosis with CT scan images. Even though, the custom made CNN model didn't perform with high accuracy as that of the pre-trained transfer learning models because of its shallow convolutional layers, transfer learning models achieved quite good performances. The analysis achieved the highest accuracy of 98.39% for large dataset with VGG19 model using proper image pre-processing, fine tuning, and optimization of the models, which is a promising outcome of COVID-19 detection from CT scan images.

References

[1] K. F. Haque and K. N. Hafiz, "Github," 2022. [Online]. Available: http://github.com/Foysal1565/COVIDCT

[2] Y.-C. Wu, C.-S. Chen, and Y.-J. Chan, "The outbreak of covid-19: An overview," *Journal of the Chinese medical association*, vol. 83, no. 3, p. 217, 2020.

[3] D. Cucinotta and M. Vanelli, "Who declares covid-19 a pandemic," *Acta Bio Medica: Atenei Parmensis*, vol. 91, no. 1, p. 157, 2020.

[4] L. Zou, F. Ruan, M. Huang, L. Liang, H. Huang, Z. Hong, J. Yu, M. Kang, Y. Song, J. Xia *et al.*, "Sars-cov-2 viral load in upper respiratory specimens of infected patients," *New England journal of medicine*, vol. 382, no. 12, pp. 1177–1179, 2020.

[5] Q. Li, X. Guan, P. Wu, X. Wang, L. Zhou, Y. Tong, R. Ren, K. S. Leung, E. H. Lau, J. Y. Wong *et al.*, "Early transmission dynamics in wuhan, china, of novel coronavirus–infected pneumonia," *New England journal of medicine*, 2020.

[6] W. Wang, Y. Xu, R. Gao, R. Lu, K. Han, G. Wu, and W. Tan, "Detection of sars-cov-2 in different types of clinical specimens," *Jama*, vol. 323, no. 18, pp. 1843–1844, 2020.

[7] F. Yu, L. Yan, N. Wang, S. Yang, L. Wang, Y. Tang, G. Gao, S. Wang, C. Ma, R. Xie *et al.*, "Quantitative detection and viral load analysis of sars-cov-2 in infected patients," *Clinical Infectious Diseases*, vol. 71, no. 15, pp. 793–798, 2020.

[8] W. H. Organization, "Who lists two covid-19 tests for emergency use, https://www.who.int/news/item/07-04-2020-who-lists-two-covid-19-tests-for-emergency-use," Apr 2020. [Online]. Available: https://www.who.int/news/item/07-04-2020-who-lists-two-covid-19-tests-for-emergency-use

[9] C. Huang, Y. Wang, X. Li, L. Ren, J. Zhao, Y. Hu, L. Zhang, G. Fan, J. Xu, X. Gu *et al.*, "Clinical features of patients infected with 2019 novel coronavirus in wuhan, china," *The lancet*, vol. 395, no. 10223, pp. 497–506, 2020.

[10] M.-Y. Ng, E. Y. Lee, J. Yang, F. Yang, X. Li, H. Wang, M. M.-s. Lui, C. S.-Y. Lo, B. Leung, P.-L. Khong *et al.*, "Imaging profile of the covid-19 infection: radiologic findings and literature review," *Radiology: Cardiothoracic Imaging*, vol. 2, no. 1, p. e200034, 2020.

[11] K. F. Haque and A. Abdelgawad, "A deep learning approach to detect covid-19 patients from chest x-ray images," *AI*, vol. 1, no. 3, pp. 418–435, 2020.

[12] K. F. Haque, F. F. Haque, L. Gandy, and A. Abdelgawad, "Automatic detection of covid-19 from chest x-ray images with convolutional neural networks," in *2020 International Conference on Computing, Electronics & Communications Engineering (iCCECE)*. IEEE, 2020, pp. 125–130.

[13] V. K. Singh and M. H. Kolekar, "Deep learning empowered covid-19 diagnosis using chest ct scan images for collaborative edge-cloud computing platform," *Multimedia Tools and Applications*, vol. 81, no. 1, pp. 3–30, 2022.

[14] Y. Fang, H. Zhang, J. Xie, M. Lin, L. Ying, P. Pang, and W. Ji, "Sensitivity of chest ct for covid-19: comparison to rt-pcr," *Radiology*, vol. 296, no. 2, pp. E115–E117, 2020.

[15] X. Xie, Z. Zhong, W. Zhao, C. Zheng, F. Wang, and J. Liu, "Chest ct for typical coronavirus disease 2019 (covid-19) pneumonia: relationship to negative rt-pcr testing," *Radiology*, vol. 296, no. 2, pp. E41–E45, 2020.

[16] X. He, "Sample-efficient deep learning for covid-19 diagnosis based on ct scans," *IEEE transactions on medical imaging*, 2020.

[17] A. K. Mishra, S. K. Das, P. Roy, and S. Bandyopadhyay, "Identifying covid19 from chest ct images: a deep convolutional neural networks based approach," *Journal of Healthcare Engineering*, vol. 2020, 2020.

[18] M. Loey, G. Manogaran, and N. E. M. Khalifa, "A deep transfer learning model with classical data augmentation and cgan to detect covid-19 from chest ct radiography digital images," *Neural Computing and Applications*, pp. 1–13, 2020.

[19] A. Shalbaf, M. Vafaeezadeh *et al.*, "Automated detection of covid-19 using ensemble of transfer learning with deep convolutional neural network based on ct scans," *International journal of computer assisted radiology and surgery*, vol. 16, no. 1, pp. 115–123, 2021.

[20] Y. Song, S. Zheng, L. Li, X. Zhang, X. Zhang, Z. Huang, J. Chen, R. Wang, H. Zhao, Y. Chong *et al.*, "Deep learning enables accurate diagnosis of novel coronavirus (covid-19) with ct images," *IEEE/ACM transactions on computational biology and bioinformatics*, vol. 18, no. 6, pp. 2775–2780, 2021.

[21] F. Shi, L. Xia, F. Shan, B. Song, D. Wu, Y. Wei, H. Yuan, H. Jiang, Y. He, Y. Gao *et al.*, "Large-scale screening to distinguish between covid-19 and community-acquired pneumonia using infection size-aware classification," *Physics in medicine & Biology*, vol. 66, no. 6, p. 065031, 2021.

[22] P. Angelov and E. Almeida Soares, "Sars-cov-2 ct-scan dataset: A large dataset of real patients ct scans for sars-cov-2 identification," *MedRxiv*, 2020.