Enhanced CT-image for Covid-19 classification using ResNet 50

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Abstract
Disease caused by the coronavirus (COVID-19) is sweeping the globe. There are numerous methods for identifying this disease using a chest imaging. Computerized Tomography (CT) chest scans are used in this study to detect COVID-19 disease using a pre-train Convolutional Neural Network (CNN) ResNet50. This model is based on image dataset taken from two hospitals and used to identify Covid-19 illnesses. The pre-train CNN (ResNet50) architecture was used for feature extraction, and then fully connected layers were used for classification, yielding 97%, 96%, 96%, 96% for accuracy, precision, recall, and F1-score, respectively. When combining the feature extraction techniques with the Back Propagation Neural Network (BPNN), it produced accuracy, precision, recall, and F1-scores of 92.5%, 83%, 92%, and 87.3%. In our suggested approach, we use a preprocessing phase to improve accuracy. The image was enhanced using the Contrast Limited Adaptive Histogram Equalization (CLAHE) algorithm, which was followed by cropping the image before feature extraction with ResNet50. Finally, a fully connected layer was added for classification, with results of 99.1%, 98.7%, 99%, 98.8% in terms of accuracy, precision, recall, and F1-score.
Keywords
COVID-19; CNN; Resnet50; BPNN; CLAHE; CT-scan.

1 Introduction

The Coronavirus (COVID-19) has been a serious and ongoing threat to global health, Since its discovery in Wuhan, People's Republic of China, in December 2019. According to WHO data, the deadly Coronavirus has killed 5,127,696 people and infected 255,324,963 more. Coronavirus has a direct impact on the lungs, causing illness and perhaps causing death [1].

In the diagnosis, care, and follow-up of patients with COVID-19 pneumonia, radiologic imaging, particularly thin slice CT, plays a significant role. Chest CT can detect early stages of infection and allow patients to be isolated sooner [2].

The application of artificial intelligence (AI) in diagnostic medical imaging is currently being researched. AI has demonstrated outstanding sensitivity and accuracy in the detection of imaging abnormalities, and it has the potential to improve tissue-based detection and characterization [3].

Deep learning is a subset of machine learning and artificial intelligence, therefore it may be thought of as an artificial intelligence function that mimics the human brain's data processing [4].

The deep neural network is a term used to describe deep learning. The use of a convolutional neural network to extract features reduced the need for manual intervention. The input to a convolutional neural network is known as a feature vector. Without the help of a programmer, deep learning models and neural networks extract features. For image classification, image prediction, and natural language processing, transfer learning is utilized to reuse the pre-trained model. Pre-trained models can be transferred to a new dataset, rather than creating a new model from scratch. This is a frequent method used instead of creating a new model from scratch [5]. Learning goals and existing knowledge can be used as a basis for transferring information from existing models and data to learn new skills. Transfer learning is now widely employed in a wide range of machine learning applications [16]. Various CNN models can be used as a pre-trained model such as VGG16, VGG19 and ResNet50 [7], [8]. It is customary to employ feature extraction and fine-tuning simultaneously in many applications to improve the results of transfer learning from a pre-trained CNN model. The convolutional part of the pre-trained model is preserved in its original form and then used to train a new classifier part that is more suited to the new application rather than the original classifier.

A contemporary and effective approach to overcoming the vanishing gradient problem is Resnets. Neural networks that feature skip or residual connections are called ResNets. This information can be transferred between levels by building "highways" of information, where the output of a previous layer is linked to the output of an even deeper layer. This permits data from early sections of the network to be passed on to later areas of the network, allowing signal

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propagation to continue even in deeper networks. Skip connections were a key component in allowing deeper neural networks to be successfully trained. Simply by reinstating outputs from deeper layers in the network to compensate for the vanishing data, ResNets produced less training error (and test error) than their shallower counterparts. ResNets are a collection of relatively shallow nets that overcome the vanishing gradient problem by combining ensembles of several short networks [9], [10].

In this paper, a novel model for detecting COVID-19 is introduced. This new model uses pre-trained CNN ResNet50 with an image enhancement.

The rest of this paper is arranged as follows: Section 2 focuses on the preliminaries and basics, whereas Section 3 explains the suggested model in detail. Furthermore, Section 4 describes the experimental results and analyzes the results and performance of the suggested model. Finally, Section 5 has the conclusion and highlights future work.

2. Preliminaries

2.1Contrast limited adaptive histogram Equalization (CLAHE) technique

CLAHE (Contrast Limited Adaptive Histogram Equalization) is a method for improving low contrast in pictures, particularly medical images. CLAHE is preferable to Adaptive Histogram Equalization (AHE) and regular Histogram Equalization in medical imaging because of its superior results (HE).

CLAHE works by limiting the contrast enhancement that standard HE typically performs, which leads in noise enhancement as well. As a result, desired outcomes were attained in circumstances where noise became excessively noticeable by enhancing contrast, such as medical imaging, by restricting contrast augmentation in HE [11],[12].

2.2 Convolution Neural Network

Traditional artificial neural networks have evolved into CNNs, which are network architectures for deep learning. They are used for item and picture categorization. Convolutional layers are followed by fully connected layers in CNNs, which are similar to multilayer neural networks. Each layer provides a high-level abstraction of the input data, known as a feature map, that preserves crucial unique information. Using a very deep hierarchy of layers, contemporary CNNs can reach incredible performance [13]. It is possible to employ as many as a thousand layers in DL.

Feature extraction and classification are the two primary layers of the CNN architecture [14]. Convolution and max-pooling are the feature extraction layers.

Convolution Layer: Feature maps from preceding layers are concatenated using kernels that can be learned. Non-linear activation functions such as sigmoid, Softmax, rectified additive, and sameness functions are used to build feature maps from kernel output. It is possible to conjunct more than one input feature map with each of the output feature maps.

suppose $LR_i^l = f(\sum_{j \in Mi} LR^{l-1} * \ k_{ji}^l + B_i^l)$ (1)

LR_i^l is the product of the current layer, The previous layer's product is represented by LR^{l-1} , k_{ji}^l is the kernel for the current layer, and B_i^l are biases for the presentation layer. For each input map, Fi denotes a subset. Each output map is given an additional bias B.

Max-pooling Layer: The distribution of this mattress is flawless. Filler in a land distribution mask affects the size and shape of the feature maps [14].

Convolutional layers are used to extract characteristics for the classification layer. There is a complete interconnectivity between the layers of the categorization layer. A vector of scalar values representing the final layer is sent to the connected layers. In the fully linked feed-forward neural layers, the softmax classification layer is being misused [14].

2.3 Transfer learning

For transfer learning, a network is first trained on an initial dataset before being repurposed or moved to another network for training on another dataset and new task. If the characteristics are adequate for both the base and target jobs, this approach will work.. This approach has worked well for image classification applications that use similar datasets. Models such as the Oxford VGG Model, Google Inception Model and Microsoft ResNet model require weeks of training on modern hardware. They can be downloaded and integrated with new models that take images as input to improve their performance.

Model weight and bias are learned during training in deep learning. This is done using a vast amount of data. For testing, these weights are applied to various network models. You can get started with weights that have been pre-trained in the new network model [15].

2.4 ResNet 50 architecture

Using deep convolutional neural networks, researchers have been able to make significant advances in picture identification and categorization. An increasing number of people are going deeper in their efforts to tackle more difficult problems and to enhance classification or identification accuracy. The vanishing gradient problem and degradation problem have made it difficult to train more complex neural networks up to this point. Both of these issues are addressed by residual learning.

For any given task, each layer of the neural network can be trained to pick up low-level features or high-level features. Instead of attempting to learn features, the model uses residual learning to attempt to learn some residual. The activation takes place after the input 'x' has been added as a residue to the weight layer output. There are reluctance activations in ResNet. These additional variations, such as the 50-layer residual network ResNet101 and the 150-layer ResNet152 are also available. Using ResNet as a pre trained medical image classification model yielded promising results [15], [16].

As long as the extra layers can accommodate a hypothetical identity mapping H(x) = x, the performance of a shallow network optimized for image recognition should not be affected by the addition of additional layers. It is true, however, that the degradation problem will arise in such networks, which makes it impossible to match the identity mapping with numerous nonlinear layers. Because of this, there came the introduction of residual learning. As a result of residual learning, the new layers instead fit another mapping F(x): = H(x) x, which indicates that H(x) was transformed to F(x) + x and it was actualized by "shortcut connections" [17].

A deep convolutional network called ResNets [18] has a basic idea of employing shortcut connections to skip blocks of convolutional layers. If the feature map size is halved, the number of filters is doubled in the basic blocks known as "bottleneck" blocks. These blocks follow two simple design criteria. Convolutional layers with a stride of 2 execute downs sampling and batch normalizing after each convolution and before activation of the ReLU. The identity shortcut is utilized when the dimensions of the input and output are the same. Using the projection shortcut, dimensions can be matched using convolutions of 1X1. Stride lengths of 2 are used in both cases where the shortcuts traverse feature maps of different dimensions. The network concludes with a softmax-activated layer of 1,000 fully-connected (fc) nodes.

In comparison to Approaches VGG16 and VGG19, we discover that the number of parameters is lower (25,636,712, against 138,357,544 and 143,667,240 in Method VGG16 and VGG19, respectively), and thus the storage area is lower (98 MB) [19].

2.5 Back Propagation Neural Network(BPNN)

Artificial neural networks (ANNs) are empirical modeling tools that mimic the behavior of biological brain structures. Neural networks are powerful tools that can identify underlying highly complex relationships from input-output data only. A BPNN model is one of the most commonly used neural networks. The neurons in the BPNN model are organized in layers and connected so that neurons in one layer receive input from the previous layer and transmit output to the next layer. At the first layer, external inputs are applied, and system outputs are taken at the last layer. Hidden layers are the intermediary layers. Back propagation using a single hidden layer has been shown to generate accurate approximations to any continuous function if there are enough hidden units.

Back-propagation In order for neural networks to learn, they are fed a series of examples of similar input and output values. A nonlinear transfer function is used to process the total of each input and output utilizing a hidden and hidden output unit's weighted sum.

The process of learning begins with the distribution of weights at random. The network tries to match the outputs to the intended goal values during training. After that, the output is calculated, and the error is calculated. Until the ending criterion is reached, this error is used to update the weights [20].The mathematical model for BPNN is defined as follows.

$$Y = f\left[v_0 + \sum_{j=1}^{m}\left(\lambda_i + \sum_{i=1}^{n} x_i w_{j)}\right)v_j\right] \quad (2)$$

Where Y denotes the network output and f denotes the activation function's output layer. The number of hidden units m is given by the output bias $v0$ = output, h is the hidden layer of the activation function, and λi is the hidden unit bias such that j = 1,…,m. Given the weight wij from input unit i and hidden unit j, the number of input units is n for xi= input vector such that i = 1,...,n, and the weights from hidden unit j to output are vj such that j = 1,...,m [21].

3. CT-image chest enhancement for Covid-19 classification using ResNet 50 proposed model

The proposed model as seen in Fig. 1 starts with image acquisition and then manipulates the following phases:

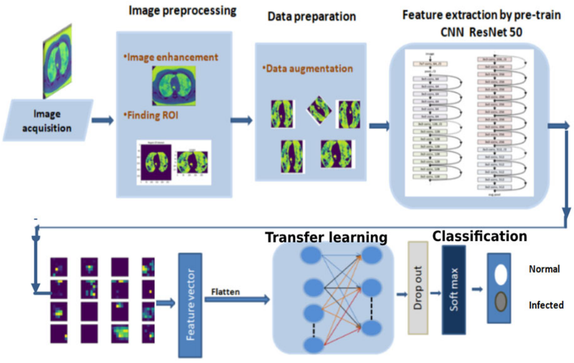


Fig. 1: CT-image chest enhancement for Covid-19 classification using ResNet 50 proposed model

3.1 Image processing

Image Preprocessing focuses on extracting the region of interest, in this case, the lunges. Preprocessing starts with CLAHE to improve features, then selecting contours that match the lunges' properties and finally isolating them from the background.

3.2 Data preparation

In the data preparation step, data augmentation is performed. Data augmentation will raise the dataset's size to several times that of the original when training on very little data, preventing over-fitting. The method facilitates in the design of more generalizable, simpler, and more stable models. The training dataset was enlarged in size by repeating the available with data rotation of 30 sheer range of 0.1 width shift range of 0.2 height shift range of 0.2 zooms rang = 0.3 horizontal, which improved performance and regularization while avoiding the over-fitting problem.

3.3 Feature extraction using pre train network (ResNet 50)

To extract features from CT scan pictures, the pre trained model (ResNet 50) is employed as standalone software. The extracted features of an image could be a vector of numbers that the model uses to represent the image's individual features. These characteristics can then be used in the classification phase as input.

3.4 Transfer learning

ResNet-50 was used to propose Transfer Learning. A ResNet-50 model is followed by extra task-specific layers in the suggested model for our task. It is loaded with pre-trained weights from ImageNet. The model was fine-tuned and transfer learning was used to classify images (ct-scan images) for COVID-19 detection in this work. The ResNet-50's completely connected layer is replaced with the additional layers. They're two dense layers with a Rectified Linear Unit (ReLU) activation layer between them. The next layer is a dropout layer with a 30% dropout probability, which randomly eliminates 30% of the parameters and reduces overfitting.

3.5 Classification

Finally, a classification layer with two neurons and a "Softmax" activation function determines if the image is normal or diseased. Transfer learning

4. Experimental Results, Discussion and Analysis

4.1 CT-Scans Covid-19 Dataset

we got this data from Kaggle. Union Hospital (HUST-UH) and Liyuan Hospital (LH) provided the data for this study (HUST-LH) of which this paper [22] provides a thorough explanation. Non-informative CT (NiCT) images were divided into three categories: positive CT (pCT) images where imaging features associated with COVID-19 pneumonia were collected (4001 photos), and negative CT (nCT) images where imaging features in both lungs were irrelevant to COVID-19 pneumonia (9979 images).

4.2 Experiment setup

The experiments were performed using tensor flow and Keras with TPU google colab environment. There are three scenarios in the experimental section: the first is to use the suggested model, the second is to use Resnet50 without image preprocessing, and the third is to utilize a BPNN (see Fig. 3).

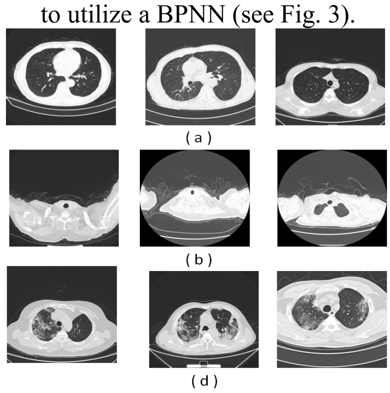


Fig. 2 Sample images from CT-Scans dataset, (a) negative case, (b) non-informative case and (c) positive case.

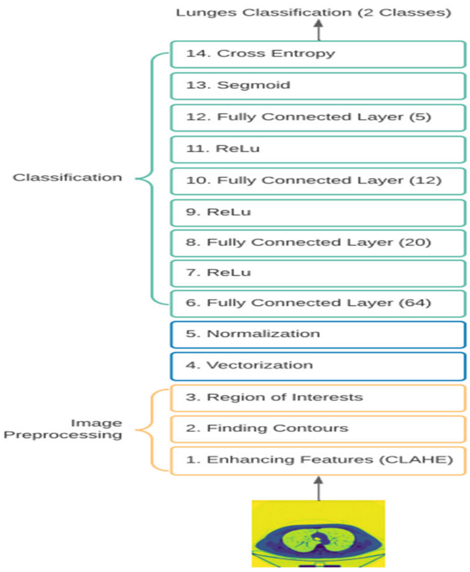


Fig. 3 Layer details of System based BPNN

4.3 Evaluation measures

The suggested approach's predict performance is evaluated using four assessment measures often employed in classification problems: accuracy, precision, recall, and F1-score. Accuracy is defined as the ratio of correct forecasts to total predictions, generally expressed as a percentage and determined using an Equ. 3. Precision is an equation that calculates a model's ability to correctly forecast values for a specific Equ. 4. The fraction of successfully recognized positive patterns is measured by recall, which is calculated as Equ. 5. The weighted average of precision and recall is the F1-score in Equ. 6 [23].

Accuracy= (Number of correct prediction)/(Total number of prediction) (3)

Precision= (particular category predicted correctly)/(all category predictions) (4)

Recall= (Correctly Predicted Category)/(All Real Categories) (5)

F1 Score=(2*(Recall*Precision))/((Recall + Precision)) (6)

4.4 Training models

4.1.1 Training the suggested model

In this section, the suggested model was trained after applying the data preprocessing and preparation. The training is done for 20 epochs using Adam optimizer. Adam is a stochastic optimization approach that just requires first-order gradients and uses little memory. The method uses estimations of the first and second moments of the gradients to calculate individual adaptive learning rates for distinct parameters; the name Adam comes from adaptive moment estimation. Adam adjusts the learning rate for each weight of the neural network using estimates of first and second moments of gradient [24]. Fig. 4 illustrates the training performance for the accuracy and loss.

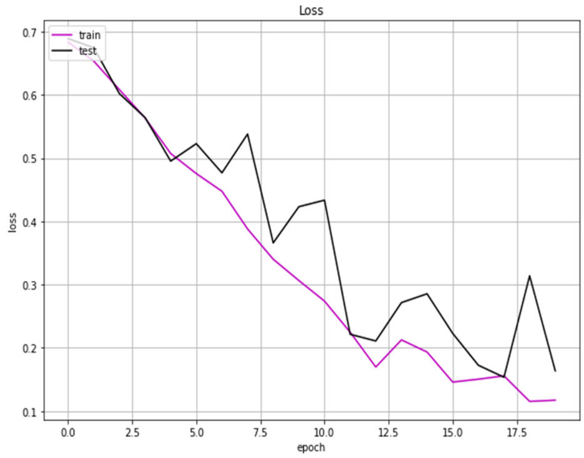
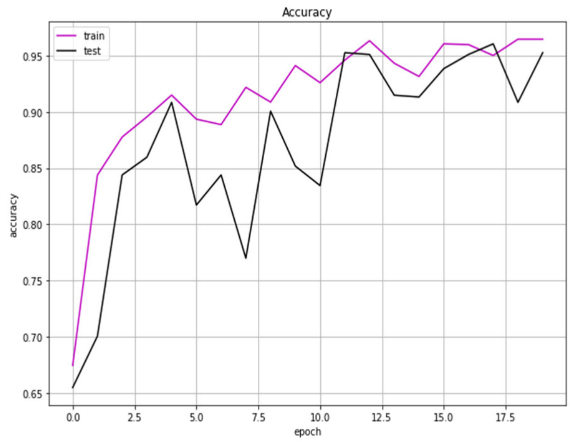


Fig. 4 progressive performance for the suggested model

4.1.2 Training the pertain CNN (ResNet50)

This section represented the training of using pre train CNN (ResNet50). In this model the preprocessing



phase didn’t applied, only data preparation is done. In the data preparation, the data augmentation techniques are implemented using Keras library’s Image DataGenerator function is also used to resize and rescale all the images in the training, validation and test sets.

In this training experiment, extracting the features of the images is done by using ResNet50, then classification phase come after that using SoftMax activation function with Adam optimizer. The Fig. 5

shows the performance of the training for accuracy and the model's loss through the training phase.

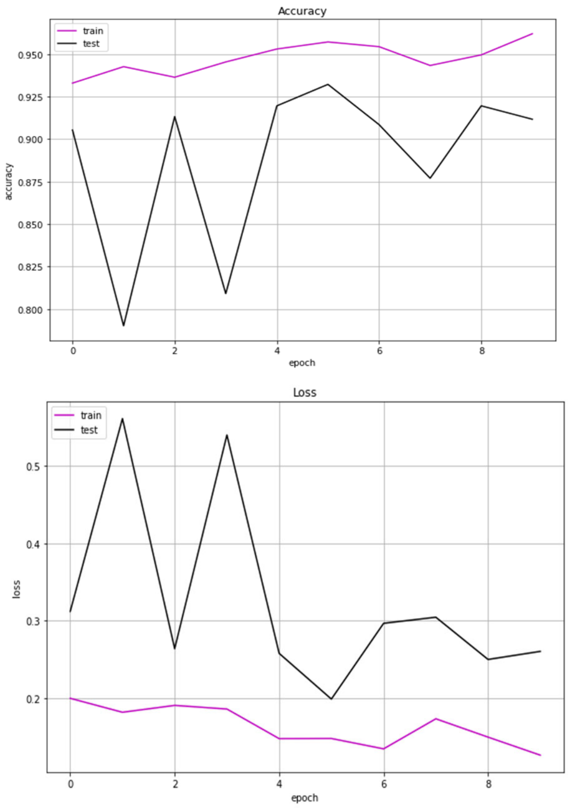


Fig. 5 progressive performance of the Resnet50 model

4.1.2 Training model based on BPNN

In the third experiment, main phases are executed, Image Preprocessing and classification. Image Preprocessing concentrate on extracting the region of interests, the lunges in this case. The preprocessing begins with features enhancement using Contrast Limit Adaptive Histogram Equalization, then finding contours that match the lunges attributes finally isolate them from the background and resize to 250*150 pixels. The extracted region was being vectorized and normalized, finally it was input into a BPNN for classification (see Fig. 6). The network includes 4 hidden layers. Fig. 7 shows the progressive performance through the training phase.

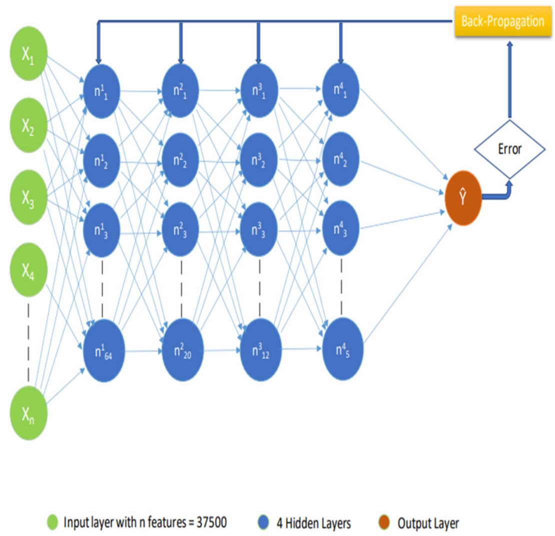


Fig. 6 progressive performance for the Resnet50 model

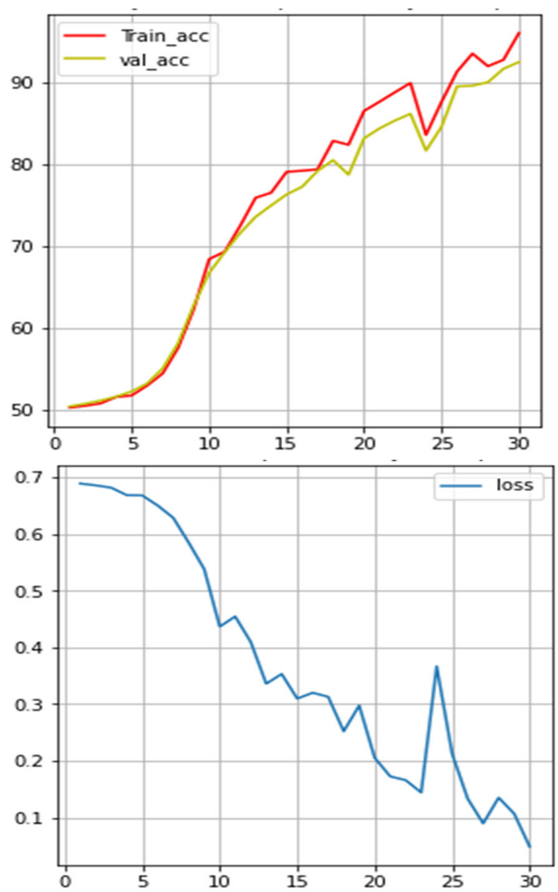


Fig. 7: progressive performance for BPNN model

4.4 The results

After training, the accuracy, precision, Recall and F1-score are measured for each experiment. As shown in Tab. 1, the results for the proposed model are 99.1, 0.987, 0.99, 0.988 of accuracy, precision, Recall and F1-score respectively. On other hand the results for the ResNet 50 model are 97, 0.96, 0.96, 0.96 of accuracy, precision, Recall and F1-score respectively. While the results for the BPNN are 92.5, 0.83, 0.92, 0.873 of accuracy, precision, Recall and F1-score respectively.

It was noticed that the F1-score is the highest for the proposed model, which is because using preprocessing methods may help the performance of ResNet50. Fig. 7 shows the predicted class probabilities for some images. we compare our proposed model outperforms with previous works that uses CT- scan images (see Tab. 2).

Table 1: Experimental Results

Model	Accuracy	Precision	Recall	F1-score
Proposed model	99.1	0.987	0.99	0.988
ResNet50	97	0.96	0.96	0.96
FFBN	92.5	0.83	0.92	0.873

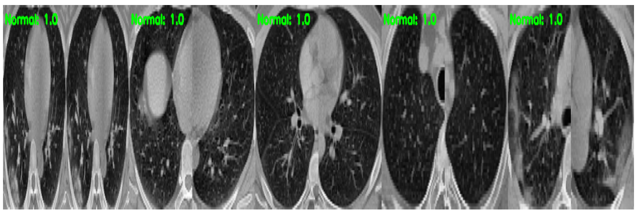


Fig. 7 The predicted class probabilities for some images

Table 2: Comparison of the proposed architecture to previous work in the CT-Scan Covid 19 classification

Researchers	Method	Acc.	P	R	F1
Y. Pathak et al.[25]	esnet50	96.2	97	-	-
H. Kang et al.[26]	eature xtraction+ ANN	93.9	-	-	-
X. Wang et al.[27]	egmentation(U Jet)+ 3D deep eural network	90.1	-	-	-
Samir Elmuogy et al [28]	VGG19	99,04	8.68	99,12	98,9
Kai Gao et al [29]	DCN	92.87	-	-	-
Edelson Damasceno Carvalho et al.[30]	CLACHE +CNN	97.88	97.77	97.94	0.978
Proposed model		99.1	98.7	99	0.988

5 Conclusion and Future Work

This paper showed enhanced CT scan images in order to improve ResNet 50's classification of COVID-19. The proposed model outperformed previous work in terms of accuracy, while in [28] gave better f1- score. Even though VGG19 outperformed our model in F1-score, our proposed model based on Resnet50 has far fewer parameters than VGG19; hence it is advisable to utilize our proposed model. It is suggested to optimize the hyper parameters of our proposed model which may improve the performance.

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