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Novel Comparative Study of Covid-19 Detection from X-ray and CT Scan Images Using CNN and MLP Neural Networks

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Abstract: The coronavirus has caused the deaths of millions of people and has endangered the entire healthcare system. In order to count positive cases and stop the disease from spreading, Rapid clinical results may prevent the COVID-19 from spreading and help medical professionals treat patients while working under challenging circumstances.. Normal disease diagnosis using a laboratory test requires equipment and takes some time with the use of X-ray and chest CT Scan images, artificial intelligence techniques are extensively used to categorize the COVID-19. In this study we present an automatic detection approach for COVID-19 infection based on Chest CT and X-ray images using a Multilayer Perceptron (MLP) Neurons Network and a Convolutional Neural Network (CNN). The two models are evaluated in two classes, COVID-19 and normal images, for detection by Chest X-ray images we obtained 95,7% accuracy using MLP model and 90% accuracy using CNN model. For detection by Chest CT image we obtained, 80,60 % accuracy using the MLP model and 88,49 % accuracy using the CNN. The experimental results indicate that the proposed approach can achieve high accuracy in detecting COVID-19 from X-ray images, demonstrating the potential of using machine learning techniques in medical diagnosis.

Keywords: COVID-19, MLP Neural Network, X-rays images, CT Scan image, Machine learning, CNN.

Introduction

In 2019, the tale coronavirus (COVID-19) Begin to spread in China as the starting point, and also in many other countries across the world (Scudellari, M (2020). Early automatic diagnosis of this disease could be very helpful in limiting its spread. Machine Learning is one artificial intelligence method that can help in the detection of COVID-19 infections in medical images like chest X-rays. An X-ray is an imaging technique used to investigate fractures, bone displacement, pneumonia, and tumors. X-rays have been used for many decades and provide an impressively fast way of seeing the lungs, making them a useful tool in the detection of COVID-19 infections [3 (Boudrioua et al., 2020)- (Narin et al., 20201). They are capable of producing images that depict lung damage, such as that caused by Coronavirus (COVID19) pneumonia (Apostolopoulos , I. D et al, 2020).

CT scans make use of the principles of X-ray in an advanced manner to examine the soft structures of the body. It is also used to get clearer images of organs and soft tissues (Wang, 2020) – (Kroft Ljm et al., 2019). Changes in chest radiography pictures such as X-ray and CT scan were detected even before clinical signs of COVID-19

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appeared in several studies (Chan et al., 2020). We need an expert radiotherapist to examine the x-rays because they contain very small details. Even if some cases are a failure due to poor vision (Belhia et al., 2022)

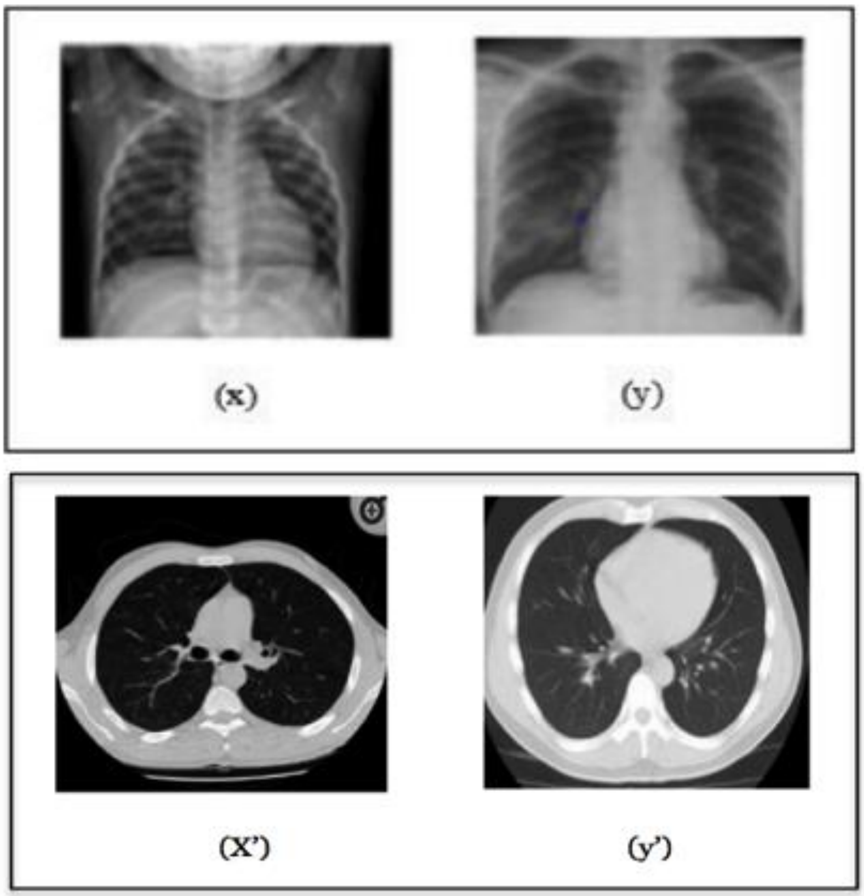


Figure 1**.** (x) Normal chest image and (y) Covid 19 affected chest image (x') Normal CT scan image and (y') COVID-19 affected CT scan image.

From Figure1 it is very difficult to detect COVID-19 infection. But artificial intelligence techniques can classify them by training with labeled data. Thus, we use machine learning (Kishore et al., 2018). In this work, we present an automatic detection system to classify chest X-ray and CT Scan images as from COVID-19 patients or normal patients using perceptron neural network (MLP) compared with Convolutional Neural Network (CNN). The research findings indicate that COVID-19 can be detected more accurately through X-ray images than CT scan images, with a detection rate of over 90%, demonstrating a superior diagnostic performance. With the same methods (CNN and MLP).

This study is structured as follows:. Section II describes the technique's suggested methodology (Multi-layer Perceptron MLP) and Convolutional neural network (CNN), including the dataset, classification processes, and metrics used to evaluate the approach. The results are discussed in Section III. The conclusion and future prospects are presented in Section IV.

Methodology

In most cases, we always require a medical diagnosis based on multiple expert medical opinions. several medical opinions help to reach a more reliable conclusion. Following the same principle, two models MLP and CNN have been adopted in our proposed work.

Model Architecture

Three main modules are distinguished in this architecture (Figure 2). Each one has a distinct role and task that will act and interconnect in the order listed below:

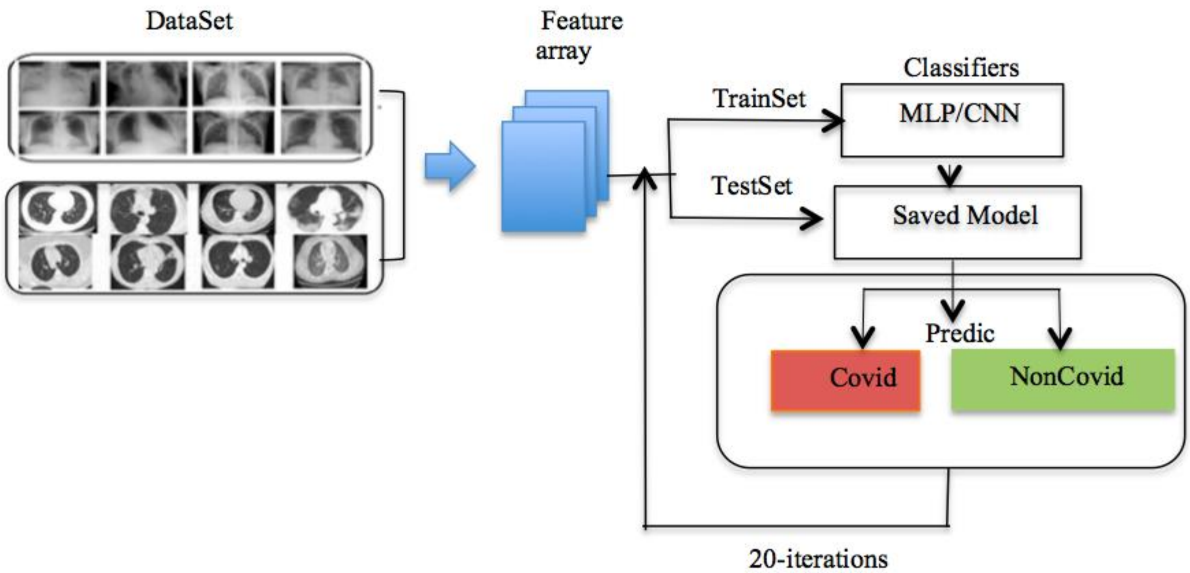


Figure 2. A description of the COVID 19 detecting system

Perceptron Neural Network

A Multi-layer perceptron (MLP) is a feed forward neural network that has been supplemented. The three types of layers depicted in Figure. 3 are input, output, and hidden layers. The first layer receives the information that is going to be processed. Tasks like prediction and classification are under the output layer's purview. The multilayer perceptron has between the input layer and the output layer one or more so-called "hidden" layers. The number of layers correlates to the network's weight matrices. A multilayer perceptron is therefore better suited to deal with nonlinear types of functions. Similar to a feed forward network, data flows forward from the input to the output layer to train the neurons, the back propagation learning technique is utilized. MLPs are meant to approximate any continuous function and can handle issues that aren't linearly separable (Abirami et al., 2020)

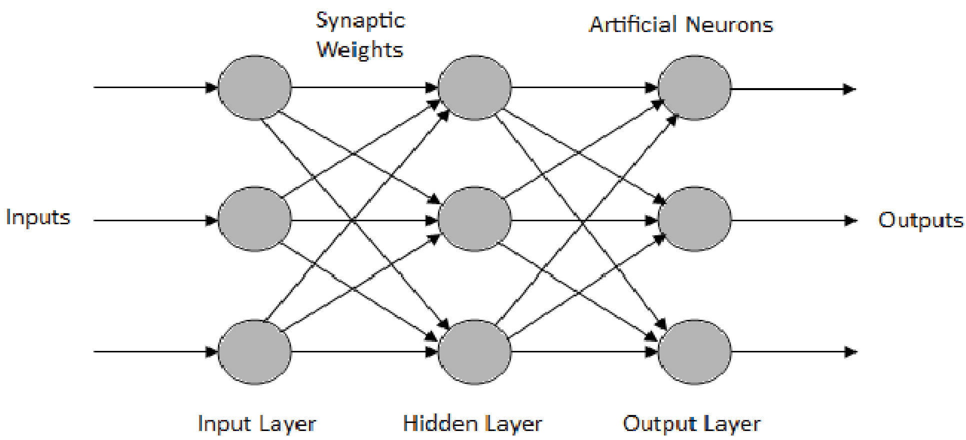


Figure 3. Basic architecture of multilayer neural network.

Each neuron in the output and hidden layers computes the following:

$$A(x) = F(n(2)+E(2)j(x)) \qquad (1)$$

$$Z(x) = F(x)=d(n(1)+E(1)x) \qquad (2)$$

With the parameters as shown in Table 1 (Abirami et al., 2020).

Table 1. Summarize network parameters.

Parameters	Description
$n(1), n(2)$	Bias vectors
E(1) , E(2)	Weight matrices
F , d	Activation functions
$q = \{E(1), n(1), E(2), n(2)\}$	is the set of parameters to be learned.
$\tanh(a) = \frac{e^a - e^{-a}}{e^a + e^{-a}}, sigmoid(a) = \frac{1}{1+e^{-a}}$	Are two common choices ford

Our model consists of four Multilayer Perceptron layers in a Dense layer, followed by a Rectified Linear Unit (ReLU) and sigmoid activation function:

- (ReLU): a deep neural network's classification function that is utilized as an activation function for a multi-layer perceptron MLP learning network (Yamashita et al 2018). We accomplish this by taking the activation of the penultimate layer *hn1* in a neural network, then multiply it by weight parameters θ to get the raw scores *oi* (2)

$$T(O) = Max(O, o_i)$$ Where

$T(O)$ is the ReLU function

- Sigmoid is an activation function that receives a real value as input and returns a probability between 0 and 1..It appears to be in the shape of a 'S'.

$$S(Z) = \frac{1}{1+e^{-Z}}$$

The data is moves from the input layer to the hidden layers. Each layer simply multiplies the inputs by the weights, adds a bias, and applies an activation function to the result before passing the output to the next layer. We keep going till we get to the last layer (Xavieret al., 2020). The activation functions ReLU and Sigmoid were used in our study.

A multi-layer neural network was created for the classification task, with the first layer having 128 neurons (the number of nodes varies depending on the size of the data), two hidden layers with 64 neurons each, and a final layer to divide cases into COVID-19 and no-COVID-19 categories. For this layer, we used a binary classifier (0 and 1): 0 for COVID-19 cases and 1 for normal cases.

Convolutional Neural Network *(*CNN*)*

A CNN or ConvNet convolutional neural network is a type of acyclic (feed-forward) artificial neural network, in which the connection pattern between neurons is inspired by the visual cortex of animals. CNN is a mathematical construction generally composed of three types of layers: (Convolutional layer), the pooling layer (Pooling layer) and the fully connected layer (Fully-connected layer).

The role of the convolutional layer consists in extracting the relevant information from the image (characteristics) thanks to a convolution operation the rectified linear unit layer (ReLU) is an activation function that is used on all elements of the volume to eliminate all negative values and keep positive values. It aims to introduce non-linear complexities to the network. The pooling step is a down sampling technique. Generally, a pooling layer is inserted regularly between the correction and convolution layers. By reducing the size of the feature maps, and therefore the number of network parameters, this speeds up the computation time and reduces the risk of over-fitting.

Fully-connected layer FC Fully-connected layer This layer is at the end of the network. It allows the classification of the image from the characteristics extracted by the succession of processing blocks. It is entirely connected, because all the inputs of the layer are connected to the output neurons of this one (Yamashita et al 2018), (Belhia et al, 2022)**.**

Nonlinear Activation Function

The rectified linear unit (ReLU) is presently which is used as a activation function, which simply computes the function: $g(x) = max(0, x)$ as seen in Figure 4, and then is forwarded through a nonlinear activation function sigmoid in the final layer (output layer).

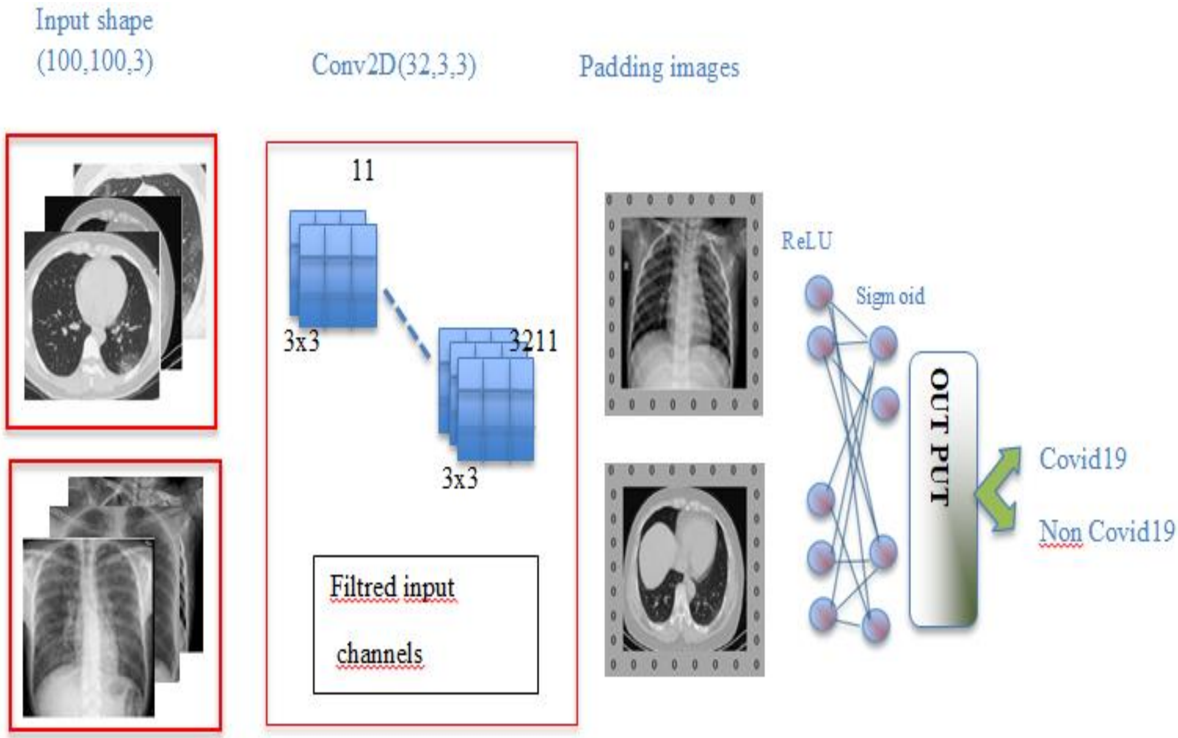


Figure 4. Diagram of the pretrained models for COVID-19 detection.

The planned CNN design will be presented in this part. As previously stated, this network is made up of an input layer, 8 layers of hidden blocks, and then a classification layer. The input images of this network are sized as (100, 100, 3), while the output can be one of two different classes: COVID-19, or normal. The proposed model consists of 8 convolutional layers and 6 pooling layers. Filters of (3x3) size with padding are applied to each convolutional layer, and each pooling layer implements a max-pooling window of (2 x 2) size. The terms "Conv2D," "MaxPool2D," and "FC" refer to the convolution, pooling, and fully connected layers, respectively, in the following. (The filter has dimensions of 3 height and 3 width, Convolution over volume (color image — 3 channels) with a filter of 3 x 3, The models were trained using the Adam optimizer and the cross-entropy loss function. and the table 2 explains the architecture of our suggested CNN.

Table 2. The architecture of our suggested CNN

Layers	Layers type	Output shape
Image-input	Input-layer	[(None, 100, 100, 3)]
Layer-1	Conv2D	(None, 100, 100, 32)
Layer-2	Conv2D	(None, 100, 100, 64)
Layer-3	MaxPool2D	(None, 50, 50, 64)
Droput-0	Dropout	(None, 50, 50, 64)
Layer-4	Conv2D	(None, 50, 50, 64)
Layer-5	MaxPool2D	(None, 25, 25, 64)
dropout-1	Dropout	(None, 25, 25, 64)
Layer-6	Conv2D	(None, 25, 25, 128)
Layer-7	MaxPool2D	(None, 12, 12, 128)
droput-2	Dropout	(None, 12, 12, 128)
Flatten	Flatten	(None, 18432)
Layer-8	Dense	(None, 64)
Droput-3	Dropout	(None, 64)
Predictions Dense	Dense	(None, 2)

Dataset Preparation

X-Ray Images COVID-19 and Normal Individuals

For this research, we worked on different data-sets (Joseph ,P C et al , 2020).these open source public data-sets contain X-ray images of COVID-19 positive patients, patients having bacterial pneumonias (MERS, SARS, and ARDS.) Also the data-set used has been taken from two different sources Kaggle and GitHub making our data contains X-ray images of different patients from two data-set.

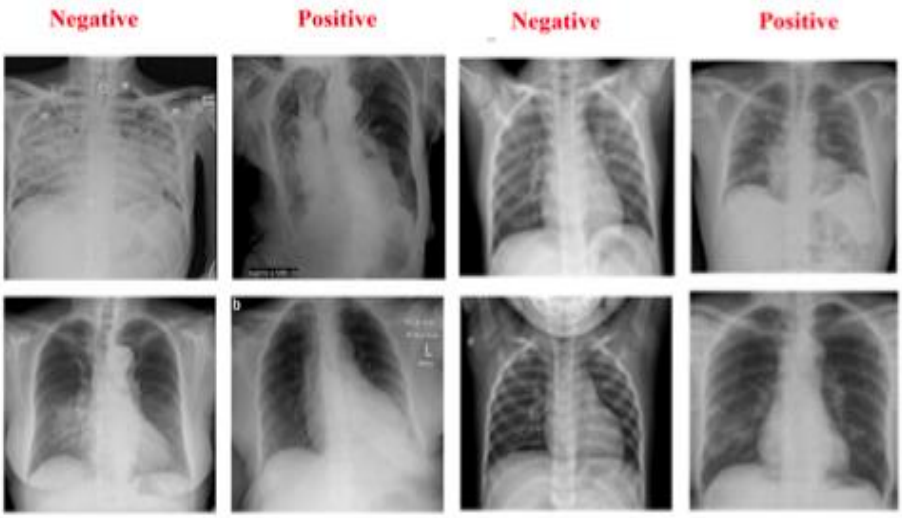


Figure 5. Illustrates some of the dataset's examples. Normal cases are on the first row, whereas COVID-19 cases are on the second. (Xavier et al., 2020).

In this study, we used a dataset which contains 538 of COVID-19 and 180 Normal X-ray images. The COVID-19 X-ray and normal X-ray images are collected from the GitHub repository and Kaggle repository. The dataset was examined in the proposed model. We use this dataset for the proposed machine learning architectures MLPNN and CNN for detection of COVID19 cases.

Chest CT Scan Dataset COVID-19 and Normal İndividuals

This is a large public COVID-19 (SARS-CoV-2) chest CT scan dataset, containing a total of 8439 CT scan, including 7495 positive cases (COVID-19 infection) and 944 negative cases (normal and not COVID-19). The data is available as 512×512 pixel PNG images and was collected from real patients at the radiology centers of University Hospitals in Tehran, Iran. Which 718 of CT Scan images are used in this work including 538 positives case and 180 negatives cases (Mustafa et al., 2021). In order to create a consistent and robust model, the same number of samples with a total of cases must be guaranteed for each class. In this study, we used the chest X-Ray and CT scan images available in the Github and Kaggle (Joseph, P. C ,2020) repositories. The publicly accessible database contains X-ray and CT scan for both classes, , i.e.Non-COVID-19 images and COVID-19 infected images. Figure 6 and 7 show X-ray and CT scan for COVID-19 and non-COVID-19. The sample images involved in this comparative analysis are listed in Table 3.

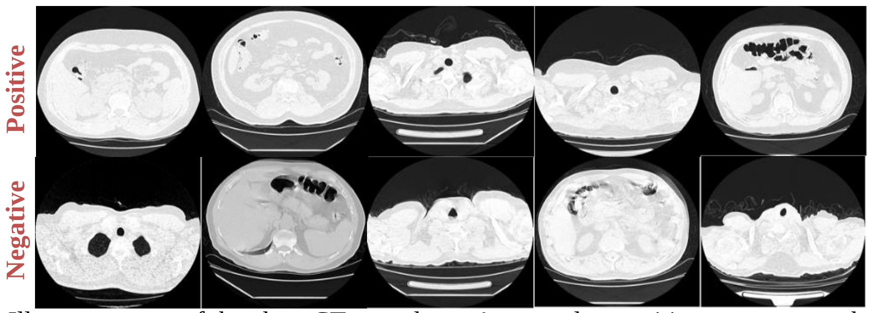


Figure 6. Illustrates some of the chest CT scan dataset's examples. positive cases are on the first row, whereas negative cases are on the second.

Table 3. Dataset and class.

Dataset	Class	Train data	Test data	Type
X-Ray images	COVID-19 /Non-COVID-19	501	217	jpg, png , jpeg
CT images	COVID-19 /Non-COVID-19	501	217	png

Classification Module

Module, which specializes exclusively in image classification. The module's output must be a single probability value between 0 and 1 indicating the presence or nonappearance of Covid19 internationally, — for example as a function of the entire image as a whole. For starters, this module will allow us to globally classify the sample into two classes: images with Covid cases and images without any trace of Covid19, and its output will have a direct influence on the detection module's predictions (Belhia,S,2022).

Evaluate the Results

Model Validation

There are several ways to validate model performance. The confusion matrix is one of the most widely used techniques. The diagonal values of the matrix represent correct predictions for each class, while other cell values represent a number of incorrect predictions. The performance of deep transfer learning models was measured using Performance Metri Criteria. They are as follows:

Performance Metric

For the performance of deep transfer learning models, criteria were utilized. These are the following:

Table 4. Performance metric

Equation	Number
Accuracy = (VB + VA) / (VB + VA + FB + FA)	(1)
Recall = VA / (VA + FB)	(2)
Specificity = VB / (VB + FA)	(3)
Precision = VA / (VA+ FA)	(4)
F1-Score = 2x((Precision x Recall)/(Precision + Recall))	(5)

In Equation (1) and (5), VA, FA, VB, and FB denote the number of True Positives, False Positives, True Negatives, and False Negatives, respectively. Given a test dataset and model, VA is the proportion of positive (Covid-19) that the model correctly labels as Covid-19; FA is the proportion of negative (normal) that the model incorrectly labels as positive (Covid-19); VB is the proportion of negative (normal) that the model correctly labels as normal, and FB is the proportion of positive (COVID-19) that the model incorrectly labels as negative (normal) (Narin et al., 2021).

Result

The experimental setup and detail as well as the experimental results are presented in this section. In the "Experimental details" subsection, we explain the MLP and CNN implementation specifics, including the data used, the architectures, and the training and testing procedures. In the "Experimental results" subsection, we report on the performance of the suggested method (MLP) and compare it to a CNN.

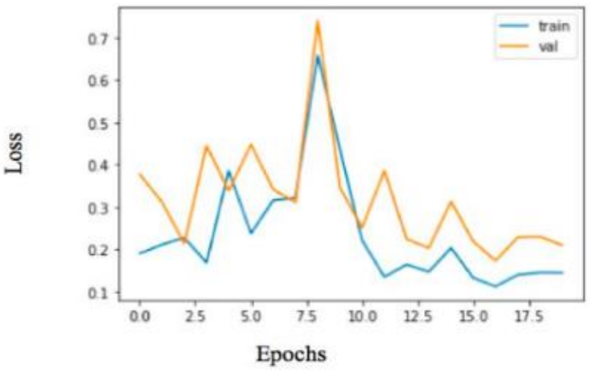
Experiment Setup

Python 3.8.8 programming language has been used to develop The MLP and CNN architecture and it is executed on intel®core™ i5-6200GHz processor with 8.00 GB of RAM. All experiments were performed on a jupyter notebook.

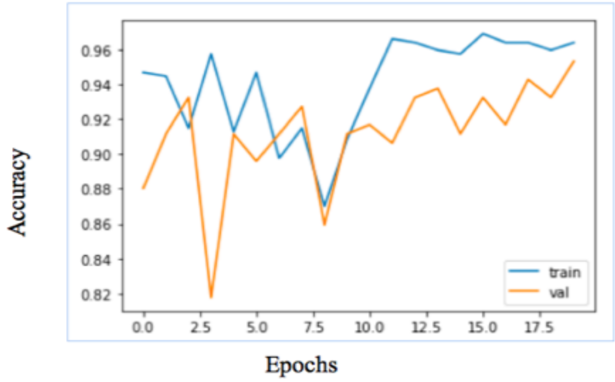
Experiments Details Using (MLP and CNN) for X-Ray Images

For MLP model we used the Adam optimizer to optimize model weights and minimize the categorical cross-entropy loss function, after training the model for 20 epochs. We also employed the Early Stopping technique to avoid overfitting by stopping training after the validation score stopped improving (Early Stopping callbacks (patience = 10 epochs)). Our network is good, as our training history graphic demonstrates, based on our training data:

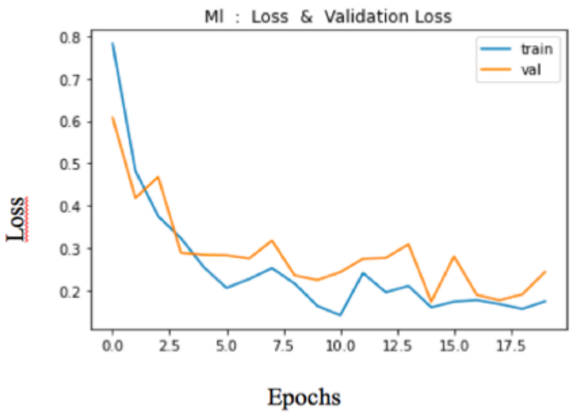
(A.1)



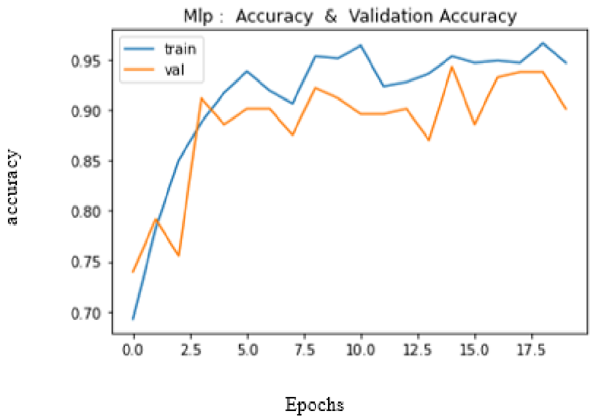
(A.2)



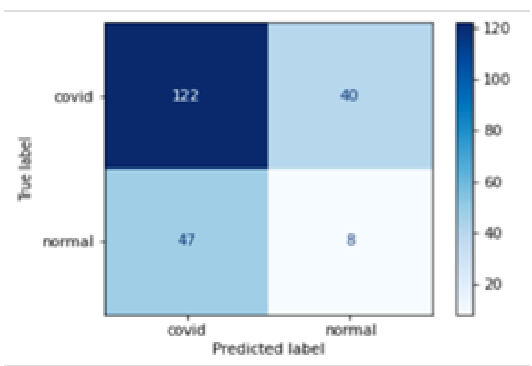
(A.3)



(A.4)



A5



A6

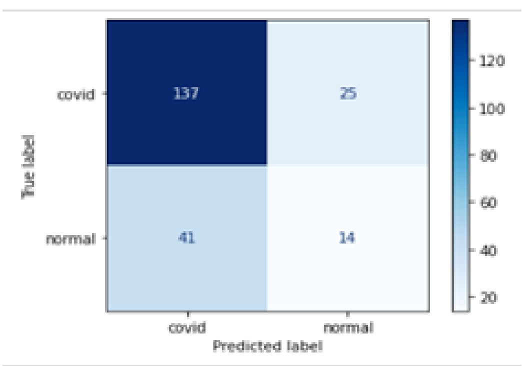


Figure 7. Experiments details using (MLP and CNN) for X-ray images

Figure A.1. depicts the examination of training and testing results with the loss. This Machine learning training history plot with accuracy curves shows that our model performs excellently on our Covid-19 X-ray training data, which was used in our Keras/TensorFlow model. Figure A.2. describes the training and testing result analysis with the Accuracy, which illustrates the model accuracy for our model as it improves with subsequent epochs. Figure A.3. and A.4. discuses the result analysis of training and testing with the Accuracy and loss for CNN Model (see Figure 7). Figure A.5 is Confusion matrix for the Ensembling (MLP) and Figure A.6.is Confusion matrix for the Ensembling (CNN).

In Figure A.5 The confusion matrix demonstrates that our proposed model successfully classified 122 of the Covid19 patients based on the X-ray pictures. Only 40 of the Covid19 patients were incorrectly classed as normal. Similarly, 8 cases were accurately identified based on X-ray pictures. Only 47 patients were misidentified as Covid19. In Figure A.6 We can examine the confusion matrix with model CNN, which shows that the model pre-trained model classified 137 of the Covid-19 as True Positive, while only 25 were incorrectly classified as normal. and 14 patients were accurately classified as Covid19, whereas 41 were incorrectly labeled as Covid19.

Experimental Results of X-Ray Images Data

From Figure (A.1) , we discuss the analysis of the results of training and testing with accuracy which shows the model accuracy for our model (MLP) as it improves with successive epochs and when comparing with the analysis of the CNN results in Figure (A.3) and (A.4), we deduce the MLP register of the model good results than CNN. In the second phase of our experiments, we compared the MLP to a standard CNN trained on the same data. The CNN architecture is presented in Table 5.

Table 5. Description a comparison of different models' performance in detecting Covid-19 from dataset X-ray images.

Method	Data	Loss	Accuracy	Validation loss	Validation Accuracy
MLP	X-ray img	0,144	0,957	0,209	0,957
CNN	X-ray img	0,174	0,90	0,244	0,901

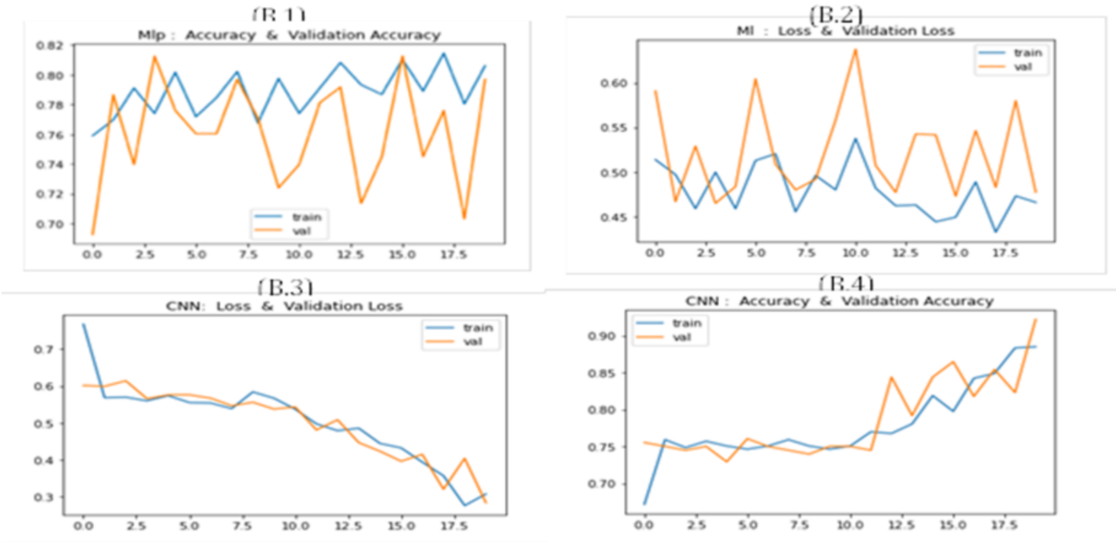
Experiments Details Using (MLP and CNN) Model for CT Scan Images

Experimental Results of CT Scan Images Data

Our model is perfect on the Covid-19 Chest CT Scan training data utilized in our Keras/TensorFlow model, as shown in Figure (B.1) Machine Learning Training MLP History Plot Showing Accuracy Curves. The result analysis of MLP training and testing with the loss is covered in Figure (B.2). Our network is robust, as shown by the training Covid-19 CT Scan data plot in our training history. Figures (B3) and (B4) display CNN result analysis of training and testing, and we reach the conclusion that the CNN record of the model performed MLP in terms of results.

Table 6. Description a comparison of different models' performance in detecting Covid-19 from dataset CT scan images

Method	Data	Loss	Accuracy	Validation loss	Validation Accuracy
MLP	CT images	0,465	0,806	0,579	0,796
CNN	CT images	0,307	0,883	0,320	0,921



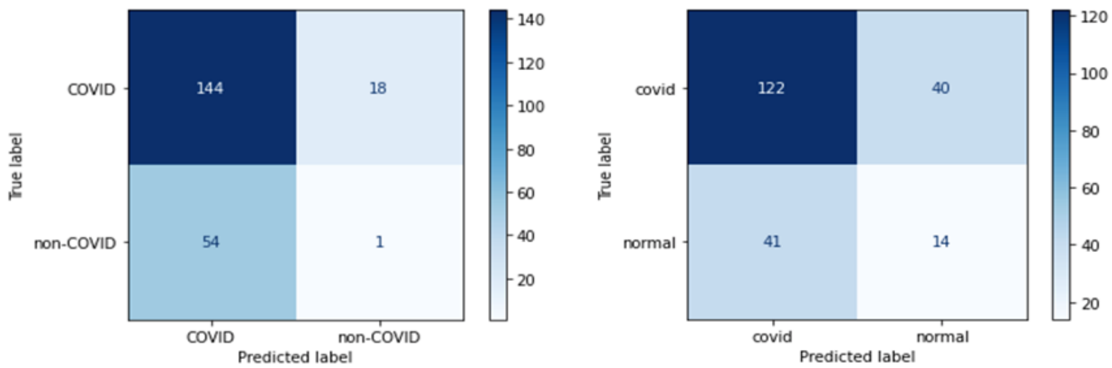


Figure 8. Experimental results of CT scan ımages data

Figure B.1. Machine learning training MLP history plot. Figure B.2. The result analysis of MLP training and testing with the loss. Figure B.3. Discusses the CNN result analysis of training and testing with the loss. Figure B.4 Show Accuracy Validation Accuracy with CNN model. Figure B.5. Confusion matrix for the Ensembling (MLP). Figure B.6. Confusion matrix for the Ensembling (CNN).

Figure B.5 of confusion matrix shows that 144 of the Covid19 patients were correctly identified using our suggested model and the CT images. 18 of the Covid19 patients were the only ones who were misclassified as normal. Similar to this, just 1 case could be correctly identified using CT images. Covid19 was mistakenly assigned to 54 patients.

Examining the confusion matrix with model CNN in Figure B.6 reveals that 122 of the COVID-19 were wrongly identified as True Positives, while 40 were accurately classified as normal. and however 41 patients were misclassified with Covid19, 14 patients had the correct classification.

Discussion

In this work we have studied the superior features and limitations of the suggested model compared to state-of-the-art models. It is, however, crucial to emphasize that due to differences in the datasets as well as the database size, simulation techniques and parameters, an individual comparison is not feasible. Despite the fact that both strategies MLP and CNN produced good outcomes with little difference, using X-ray and CT Scan images . As shown in the Table 5 and Table 6 , the MLP achieves an accuracy of 95,7% for X-ray images and 80.60% for CT scan images, while the CNN achieves an accuracy of 90% for X-ray images and 88.49% for CT scan images.

We noted that our proposed model MLP was perfect on X-ray images data However the CNN model performs better than the MLP on CT Scan images. It should be noted that the suggested model will be tested using the COVID-19 X-ray and CT Scan database. Given the amount of positive COVID-19 cases worldwide, one may claim that the database is insufficient. These results will definitely improve with the increased dataset. it is clear that the proposed model learned the COVID-19 infections very well leading to fewer false detections. Moreover, existing models are more complex than the proposed model.

Conclusion

This study examined the usefulness of pre-trained MLP in predicting Covid-19 from X-rays and CT scans. Another CNN model was used to evaluate the performance of the MLP model. For COVID-19 testing, these approaches can save RT-PCR test kits and costs and represent a rapid tool for RT-PCR testing. Our study uses personalized CNN and MLP approaches to support rapid diagnosis of people infected with COVID-19. Both models are evaluated in two classes, COVID-19 images and normal images. As a result, the COVID19 identification accuracy rate is 95.7% for X-ray images using MLP and 90% using CNN model, the Covid19 detection performance rate is 80.60% for CT Scan images with MLP and 88.49% with CNN.

Experimental results indicate that MLPs and CNNs can achieve high accuracy in detecting COVID-19 from X-ray images and CT images, demonstrating the potential of using machine learning techniques in the medical diagnosis. We also used chest X-ray images and CT images to train, test and compare the studied models and found that these models performed well for both types of images, there was no big difference in the performance rate. In the future, we will pay special attention to the classification of patients with other lung diseases.

Scientific Ethics Declaration

The authors declare that the scientific ethical and legal responsibility of this article published in EPSTEM journal belongs to the authors.

Acknowledgements or Notes

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