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Covid-19 Prediction Using Deep Convolutional Neural Networks

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Abstract: *The currently available methods such as RT-PCR for the detection of the novel coronavirus disease fail due to restricted supply of test kits and few favourable signs of illness in the early phases, requiring the use of alternative solutions. The use of an Artificial Intelligence (AI) tool, could assist the world in developing an additional disease prevention regulation. An automatic detection technique is provided in this method, which leverages information from Computer Tomography (CT) images to train the deep learning model CNN architecture. CNNs are the best deep learning model option due to its promising accuracy for biomedical images and availability of fewer samples, which satisfies the need for CNN training. The presented paper aims to discuss the various aspects of the system, beginning with a brief summary and gradually progressing to explain the various implementations, which include the datasets used, the use of the State of the Art (SOTA), and a discussion of the various metrics used for evaluation. Finally, a user-interactive system is presented that employs the qualified model in the area.*
Key Word*: COVID-19; CNN Model; VGG16; Deep Convolutional Learning*

I. Introduction

The Severe Acute Respiratory Syndrome Coronavirus 2 has resulted in novel coronavirus disease also known as COVID-19, which is a globally transmitted epidemic. The virus first appeared in Wuhan, China in December 2019 and has since spread across the world[1]. Although some instances are asymptomatic, the vast majority are accompanied by symptoms such as fever, dry cough, and fatigue. Majority of the people have symptoms such as aches and pains, runny noses, sore throats, nasal congestion, and diarrhoea. The pandemic spread quickly due to airborne spread, prolonged contact with objects, and respiratory transmissions of the disease from one person to another. According to the epidemic estimates as of June 20, 2020, there are 88, 04,268 people worldwide who have been infected, 4, 63,510 people who have died, and 46,56,912 people who have recovered. Many technologically sophisticated nations are battling to sustain their medical care systems, as the demand for Intensive Care Units grows as patients with the most severe illness symptoms seek treatment.

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RT-PCR detection methods had a low positive rate in the early stages of the illness, suggesting a reduced sensitivity value for COVID-19 samples. However, as compared to all other viral pneumonias, the markers of computed tomography pictures have revealed distinct characteristics. Because of this, physicians have chosen CT scans as one of the first diagnostic tools for this disease. A case study with 1014 afflicted individuals conducted in China found that using chest CT scans to diagnose the condition was more successful than original RT-PCR research. The testing has shown to be less sensitive than chest CT in detecting the disease. Out of 1014 cases, 59% were found to be positive using RT-PCR, while 88% were found using chest computed tomography images.

Huang et al. looked at the clinical effects of 41 people who had COVID-19. All 41 patients were confirmed to be infected with pneumonia, with abnormalities identified by a chest CT scan, in addition to common beginning symptoms such as cough, fever, and tiredness. CT scans indicated serious respiratory diseases, chronic heart disease, and various secondary contaminations. The restricted availability of RT-PCR test kits, the time required to perform the test, the low positive rates in the early phases, and the requirement for substantial human knowledge all demand an advanced technique for the diseases' detection. Alternative options should be discussed in such a -unprecedented situation in order to find less expensive alternatives to understanding, monitoring, and handling this global pandemic. Furthermore, the proposed approach should aid researchers in fully comprehending the disease's fundamental causes and progression. Image processing and cutting-edge machine learning algorithms may aid in the identification of landmark features and lesions, allowing the input sample to be categorised as a normal or disease-affected event. Computed Tomography (CT) photographs of the chest are one of the techniques used to diagnose pneumonia. We proposed using advanced deep neural network architecture, VGG-Net, to categorise input samples as common, having some sort of viral pneumonia or Covid affected cases using chest CT images.

In the present era of machine learning and artificial intelligence, CNN has shown to be the most beneficial and popular image processing method. We've gone through some of the many CNN algorithms and techniques that have been utilised in recent years to analyse various illnesses utilising medical pictures such as chest X-rays and chest CT scans.

Using X-ray images, Baltruschat et al.[3] evaluated several deep learning techniques methods in identifying different illnesses. This paper discusses the understandings of the influential ResNet-50 architecture and its enhanced variants. Along with diseases visible in X-ray pictures such as cardiomegaly, nodule, and pneumonia, a few non-image characteristics such as gender, age, and acquisition technique are also included for categorization.

Nicolas Coudray et al.[4] advocate for assistance in lung cancer detection. Using Google's CNN - Inception v3, the two common forms of lung cancer – LUAD and LUSC – are automatically identified from normal tissues. The suggested technique was evaluated on full slide pictures and found to have 89%, 93%, and 97% sensitivity, precision, and accuracy, respectively, as well as validation of the model for different frozen tissues.

A CNN was described by Anthimopoulos et al.[5] for the classification of six Interstitial Lung Disorders. To avoid overfitting, the proposed CNN employs five convolutional layers with the Leaky Rectified Linear Unit (RELU) activation feature, followed by max pooling and soft-max classification. A total of 14,696 image patches were created from 120 CT scans gathered from two local hospitals. The loss function was minimised using cross entropy, with an overall accuracy of 85.61 percent recorded by the author.

Wanli Xue et al.[8] devised a system for keeping people and/or officials updated if they come into contact with someone who has tested positive for the virus. However, one of the constraints is that an active internet connection was needed. Another field where the approach was found to be missing was the lack of explicit directions for communicating with individuals who could make a mistaken conclusion. Android apps were also tested in preparation for a next-generation software architecture that would allow for better tracing and security efficiency. These android applications can be used to track down contacts all around the globe.

Michael. J. Horry et al.[9] pioneered the use of drones for public surveillance to validate quarantine. However, such an IoT implementation can be very expensive. Furthermore, it was unable to track down each and every person. On the input sensor values, data processing was done. Monitoring methods and an IoT-based architecture were used to limit the dissemination of Covid-19.

Krishna Kumar et al.,[11] used ML algorithms that can learn and improve in accuracy and reliability over time. This enables them to make more informed choices. However, this ML technique requires a significant amount of time to allow the algorithms to learn and improve sufficiently. Techniques such as SVR, LSTM, and DNN were used. NLP was used to exclude peripheral vein illness-related watchwords from clinical notes, and they have noted that further future analysis is needed to ensure that everybody communicates and interacts together in a way that avoids losing any basic targets.

Domenico Gaglione et al.[12] created a technique that used the Naive Bayes algorithm, but it took fewer training data, performed easily, and saved a lot of time. When applied to actual data from the Lombardy region of Italy and the United States, the proposed approach accurately calculated infection and recovery parameters, as well as tracked and predicted the epidemiological curve. While an inference was made, Naive Bayes believed that all predictors (or features) are independent, which seldom occurs in real life. This constrained the algorithm's applicability in real-world use cases.

Shuo Wang et al.,[14] suggested an approach based on the use of AI techniques, claiming that CT scans and CXR have the ability to easily analyse large quantities of data. This method made use of artificial intelligence (AI) to do predictive processing on imaging data. For diagnosis and care, CT, positron emission tomography - CT

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(PET/CT), lung ultrasound, and magnetic resonance imaging (MRI) were used. This procedure, however, did not identify those that were asymptomatic.

II. Material and Methods

For image classification, the suggested approach uses transfer-learning from a VGG16 convolutional neural network. The top layers used for classification have been replaced by 2 Dense fully connected layers of 4096 and 1072 neurons each with ReLU activation, 1 Dropout layer for regularisation to prevent overfitting, and 1 Flattening layer for output vectorization, followed by another Dense layer of 3 neurons corresponding to the total number of classes with a softmax activation function. The Adam Optimizer with a learning rate of 1e-3 and a categorical cross entropy as a loss function is also used. The model has a total of 24 layers.

The dataset used is a compilation of five separate datasets obtained from kaggle. The dataset is over 5GB in size and is divided into three classes: Covid positive, Normal, and Pneumonia. The dataset includes 4,317 chest X-Ray images of patients infected with the SARS Cov2 virus, 13,358 images of patients who are fully normal and have no signs of the disease, and 9,973 images of patients with other types of pneumonia. Thirty percent of the images in the dataset were used for testing and validation, while the other seventy percent were used for training.
Since all of these images were of different formats and sizes, they first needed to be made of the same format, and an automated function was used for this purpose to format all of the images to a.PNG format. The VGG16 network accepts (224,224,3) as input, which corresponds to the height, width, and channels. During the data augmentation process, this was also addressed.

The training process was split into two phases in which the VGG16 model was used in two different configurations, one without fine tuning in which all of the pretrained layers were set to be non-trainable and the second in which, with the exception of the last two layers, each and every layer was trainable, resulting in a much finer tuned model with a greater number of trainable parameters.
The fine-tuned solution was chosen after several iterations and optimizations. The architecture of the final network has been shown below.

The architecture begins with an input layer, which takes in an image of arbitrary size. This image is either a chest x-ray of the patient or a CT scan. As the VGG16 architecture has a strict input size requirement of (224, 224), the input image tensor first needs to be pre-processed which is done by using the *preprocess_input* function present in keras. Further feature extraction is performed on it, by passing it through a series of convolutional layers.

The convolutional layers apply different filters on the inputs that they receive and produce corresponding feature maps in the output which are used further by different convolutional layers for feature extraction or fully connected layers for prediction or classification tasks. The most important parameters related to a convolutional layer are the input shape, the filter size which corresponds to the output feature maps generated, the kernel size which corresponds to the width and height of the convolutional filter mask, the padding which helps in making the input and output to be of the same dimensions, finally the activation function to introduce some non-linearities.

In the case of a VGG16 network, the input image tensor will be first passed through 2 convolutional layers. The first convolutional layer has an input size of (224, 224, 3) which corresponds directly to the shape of the input image tensor, 64 output filters, a kernel size of (3,3) and ReLU activation. The output feature maps are then taken as a input to the second convolutional layer, the input shape of this layer is the output shape that was obtained from the previous operation, the output filters are kept the same in this layer too as well are the other parameters. Finally, the output of this layer is then passed to a MaxPooling layer which helps in reducing the size of the output feature map obtained previously. Further this obtained feature map is again passed through 2 more convolutional layers, however, in these layers only the output filters are increased by a factor of 2. That is these 2 layers will have 128 filters instead of 64. Again, the output feature maps formed are passed through a MaxPooling layer to reduce the feature map size. Further, the number of convolutional layers is increased to 3 instead of 2 with each one of them having output filters increased by a factor of 2 such that the consecutive set of convolutional layers will have 256, and 512 output filters. Finally, the output feature map formed after all the convolutional operations are performed is passed through a MaxPooling layer and a matrix of all convoluted features is obtained.

This feature matrix is then flattened into a vector of features and passed through a two fully connected layers of 4096 and 1072 neurons each. A dropout layer with a drop rate of 20% is also added to avoid overfitting. Finally, the output vector is passed through a dense layer with units corresponding to the number of classes that need to be classified with *softmax* activation for getting the probability predictions for each class. All the dense layers except the final layer for classification use ReLU as their activation function. The number of units in each dense layer were decided on the basis of trial and error. The Adam optimizer with a learning rate of 1e-3 is used, whereas a *categorical crossentropy* function instead of *sparse categorical crossentropy* was chosen for performance optimization purposes. The total number of parameters were 121,874,435, whereas the trainable parameters amounted to 109,519,555 and non-trainable parameters amounted to 12,354,880 when the network was used in the fine tune mode.

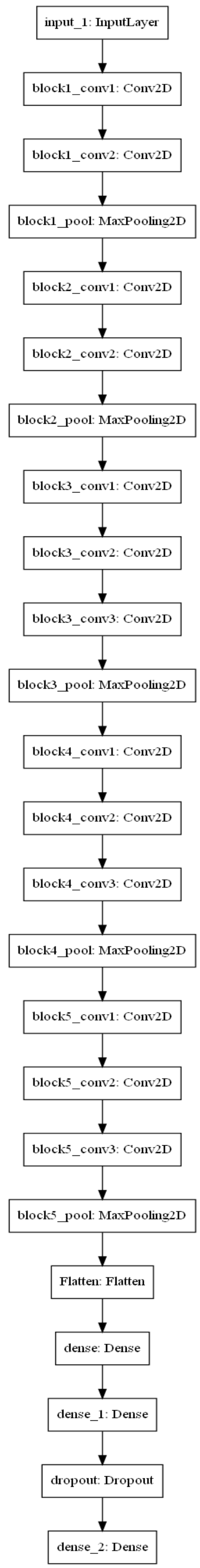

Figure no 1: VGG16 CNN network.

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III. Result

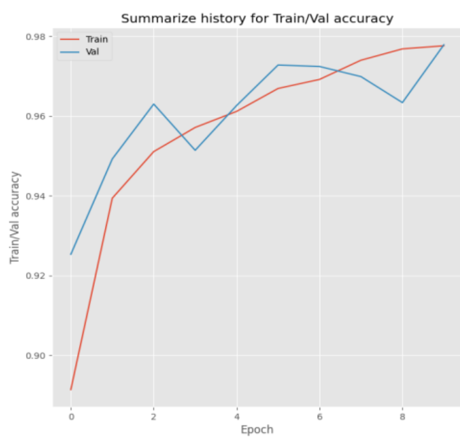
The network was trained for ten epochs and achieved 97.77 percent training set accuracy with a loss of 0.07 and 97.79 percent validation set accuracy with a loss of 0.08. The classification report below includes all of the other metrics.

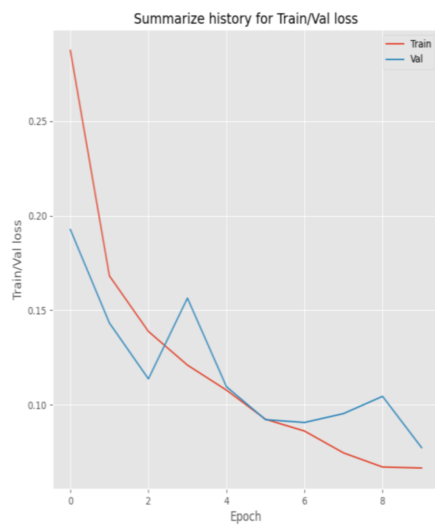
VGG16 Model Accuracy with Fine-Tuning: 97.49%
Area Under Curve (AUC) score: 0.9972098240765179

	precision	recall	f1-score	support
0	0.96	0.91	0.93	863
1	0.96	0.99	0.98	2671
2	1.00	0.98	0.99	1994
accuracy			0.97	5528
macro avg	0.97	0.96	0.97	5528
weighted avg	0.97	0.97	0.97	5528

Figure no 2: Classification with various metrics.

The training, and validation set loss and accuracy graphs can also be seen below.





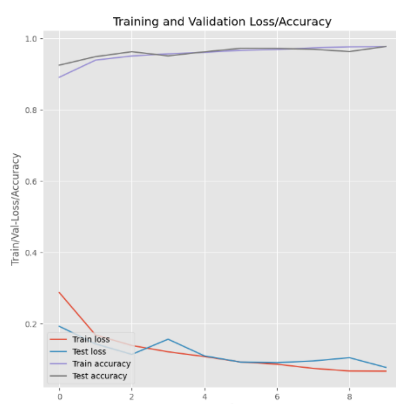


Figure no 3: Training and validation graphs for losses and accuracies.

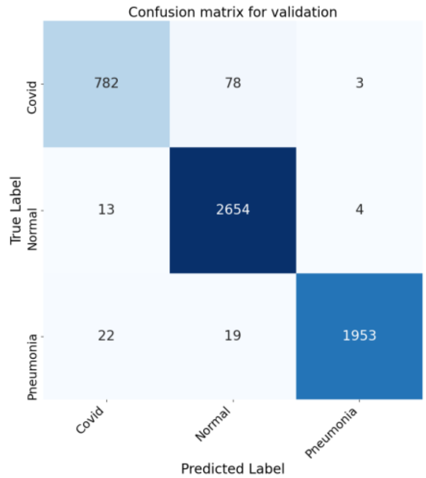


Figure no 4: Confusion matrix for validation made on the test set.

While the training loss and accuracies were substantially uniform, the validation losses and accuracies showed considerable variance. This can be due to the lower number of training epochs used; however, the prediction accuracies have been substantially well-performing without overfitting, as shown by the confusion matrix plotted for the test set.

Simple functional block diagram to get predictions from the trained neural network has been shown below.

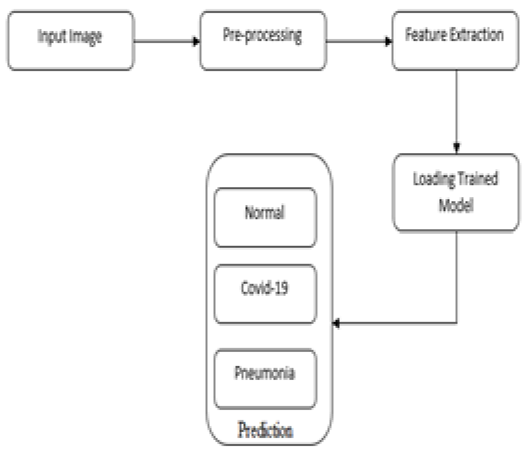
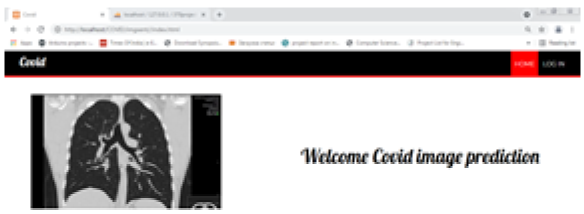
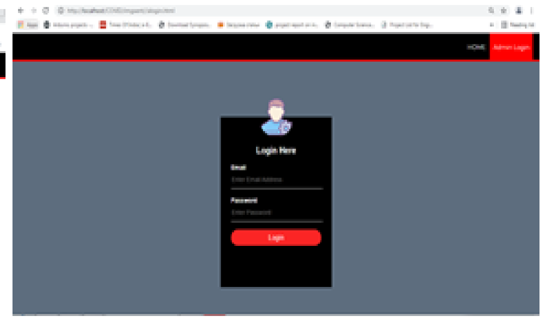


Figure no 5: Functional block diagram

Images of the User interface for ease-of-use for the user have been shown below.





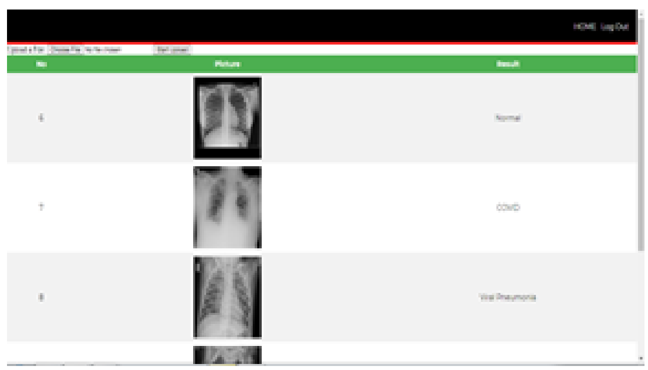


Figure no 6: User interface using the network for predictions.

IV. Conclusion

A user interface (UI) in the form of a website with database capabilities was developed. This user interface was designed with the intention of being used only by healthcare professionals for faster inference. This user interface can be greatly changed and rendered mobile-friendly.

Since the model was trained with a fine-tuned configuration, the total number of trainable parameters, and therefore the model scale, is currently enormous. The current implementation results in a model that exceeds 1 GB in size. As a result, it cannot be used in perfect manufacturing conditions. In the future, layer pruning and quantization techniques can be used to substantially reduce model size and thereby make it available in mobile devices without an active internet connection.

Furthermore, better techniques and models such as ResNets, Transformers, and MLP Mixers can be used for faster and more accurate training and prediction. The dataset can be improved further by using higher resolution images for better feature extraction and, as a result, higher prediction accuracies.

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