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Covid-19 Detection using Optimized CNN from Chest X-Ray

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Abstract: *With the exponential rise in cases, the COVID- 19 outbreak has wreaked havoc and suffering all across the world. Priority demands isolationand social seclusion, the only measures that canstop the disease from spreading. It has been noted that COVID-19 RT-PCR testing takes a long time and yields a lot of false positive results. Therefore, given the disease's extensive distribution across all continents, quick and accurate COVID-19 testing is crucial. Alternative methods of detection are urgently needed to fight the disease. In this study, a convolutional neural network-based automated detection system for COVID-19 is developed using chest X-ray images (CNN). The accuracyrate for detection according to the CNN model is 98%.*

Keywords: Herbal Drug

I. INTRODUCTION

It may be possible to significantly slow the globalspread of the novel coronavirus (COVID-19) like diseases with the use of early automaticdiagnosis. In this study, we use deep learning to redo the identification of COVID-19 from chestX-ray pictures.

The newly discovered coronavirus (COVID-19)began to spread in China in December 2019before moving on to other nations. In order to stop the spread of this disease, an early automaticdiagnosis may be very helpful. When we have a small image dataset and want to detect COVID-19 infections from medical images like X-ray images, deep learning is one artificial intelligencetechnique that can be useful.

Artificial intelligence has been used to automate the diagnosis of numerous diseases. Through various machine learning techniques, AI has demonstrated its effectiveness and high performance in automatic picture classification challenges. Additionally, machine learning describes models that may learn from and decide based on a significant amount of examples in the input data. In order to execute tasks that require human intellect, such as speech recognition, translation, visual perception, and more, artificialintelligence bases its calculations and predictionson an analysis of the incoming data.

II. BACKGROUND

The use of chest X-ray and computed tomography (CT) images in the identification of COVID-19 is suitable in the majority of nations since patients can easily obtain them and the procedures are inexpensive. Three separate convolutional neural network models, ResNet50, InceptionV3, and Inception-ResNetV2, were employed in another method to analyze chest X- ray radiographs to identify individuals with coronavirus pneumonia. There was no need for afeature extraction or selection phase. Using the ResNet50 model, they were able to classify objects with an accuracy of 98%, 97%, and 87% for InceptionV3 and InceptionResNetV2,respectively. They ran about 30 epochs for each model during the training phase to prevent overfitting. However, they used only a few photographs from the time that they could use them in their study.

A deep learning-based method was created by Fei et al. in their work to automatically segment all lung and infection locations using chestcomputed tomography (CT) . Using lung CT images and deep learning techniques, Xiaowei etal. set out to create an early screening model to separate COVID-19 pneumonia and Influenza-A viral pneumonia from healthy cases.

[1] In a study by Apostolopoulos et al.published in springer,the effectiveness of cutting-edge convolutional neural network architectures previously developed for medical image classification was assessed using a collection of X-ray pictures from patients with pneumonia, proven COVID-19 disease, and normal occurrences. According to the study, transfer learning can be used to identify important biomarkers for the COVID-19 disease.

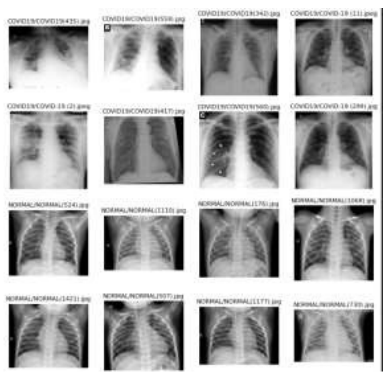
[2] A method by J. D. L. Lovenia, D. Darling Jemima, R. Raghhul and E. Kingsley published on *2021 International Conference on Computational Performance Evaluation* uses Four distinct pre-trained convolutional neural networks (CNNs) were employed toautomatically discriminate between COVID-19 and pneumonia patients using digital X-ray images: ResNet18, AlexNet, SqueezeNet, and DenseNet201. A 20-fold training set of COVID- 19 images was created using image augmentationtechniques, specifically rotation, scaling, and translation. The models' outcomes both with and without augmentation were obtained. The photoswere pre-processed in order to resize them to a particular size and in order to improve the detection accuracy. As a collection of three publicdatabases that were just recently released in the literature, a public database was finally introduced. The database includes 1340 regular chest X-ray photos, 1343 viral pneumonia images, and 191 COVID-19 images. They achieved a 98% accuracy rate.

[3] The Authors In M. P. Ayyar, J. Benois-Pineau and A. Zemmari published on *2021 CVF InternationalConference on Computational Performance Evaluation* presented a classification scheme for chest X-ray images that consists of a multiclass classification and a hierarchical classification forthe goal of identifying COVID-19 and pneumonia patients. The latter classification, which is organized hierarchically, includes pneumonia. The RYDLS-20 dataset was used to generate images of pneumonia and images ofhealthy lungs from chest X-rays. In the case of hierarchical classification, their strategy produced an F1-Score of 0.89 for the COVID-19identification, and a multiclass approach produced a 65% F1-Score. Using deep learning on a short dataset, a recent work identified COVID-19 from chest X-rays, as proposed by Ref. [36]. They employed 135 COVID-19 individuals who had chest X-rays obtained and 320 chest X-rays of pneumonia patients. The experiment's findings presented an accuracyof 91.24%

[4]]A model for COVID-19 detection in CXR and CT images utilizing transfer learning and Haralick features was put forth by varalakshmi perumal. Here, transfer learning technology can provide a speedy replacement to aid in the diagnosis and so stop the spread. The primary objective of this work is to provide radiologists with a less complex model that will aid in the early diagnosis of COVID-19. With 91% accuracy, 90% retrieval, and 93% accuracy utilizing VGG-16 and transfer learning, the recommended model outperforms other models utilized during this epidemic.

[5]In another mode developed by Wentao Zhao, Wei Jiang,Xinguo Qi was to detect only COVID-19 patients, CT scans were used instead of X-rayimages in order to use deep learning techniques to early detect the virus. These images show a variety of characteristics that set COVID-19 patients apart from those who have other pneumonias, like influenza-A. The samples, which total 618 CT samples and included 175 samples from healthy individuals and 224 samples from patients with influenza-A virus pneumonia, were obtained from three COVID-19 authorized hospitals in Zhejiang Province, China. Two three-dimensional (3D) CNN models were used to partition these images into many candidate image cubes. The initial version of CNN was the regular ResNet23, while the other was a modified version of the network structure created by concatenating the location-attention mechanism.

From the previously implemented models we cancome to the conclusion that each of the specifiedmodels have their own Pros and cons. Thus henceforth we are going to implement our modelwith CNN and chest X-Rays, since CNN is more advantageous when it comes to medical classification and X-Rays are considerably affordable in comparison to CT-Scans.



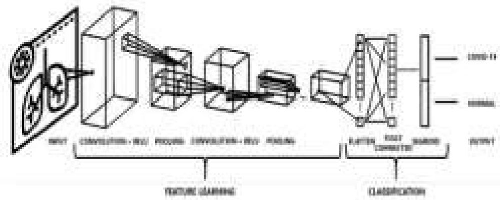
III. METHODOLOGY

There are various steps involved in the process starting from the importing of the required library functions necessary such as Conv2D, MaxPool2D,Dropout, Flatten, Dense, Adam, Sequential which are necessary for cleaning and for building the convolutional neural network(CNN).

The next step is to remove the outliers which arepresent in the images by preprocessing, Image preprocessing are the steps taken to format images before they are used by model training and inference. This includes, but is not limited to, resizing, orienting, and color corrections.

Once the unwanted attributes are removed. The features are then scaled to bring every feature in a single scaling criterion, Only then we perform dimensionality reduction on the features.

Convolutional and fully connected layers make up the two types of layers in the CNN model. In order to identify COVID-19 and standard x-ray pictures, a nine-layered CNN model is built here, consisting of sets of stacked convolutional and pooling layers, followed by Dropout layers



The layers present are as follows:

- Convolutional Layer-1
- Pooling Layer-1
- Dropout Layer-1
- Convolutional Layer-2
- Pooling Layer-2
- Dropout Layer-2
- Flattening Layer
- Dense Layer
- Dropout Layer-3
- Output Layer

As we go deeper into the layers, the receptive field of the CNN layer expands, making the first layers smaller initially because the lower layers only identify features in small portions of the images and can only find small patterns in the image. 3 × 3 is a common choice for the kernel size. Convolutional layers employ the activation of the Relu layer for non-linearity. We set the input size to 224 x 224 x 3 since this is the first layer. With Max Pooling, the layer's receptive field increases over the three pooling layers, eachof which has a filter size of 2 × 2 by default.

The first convolutional layer is modified to be 224 x 224 with three channels. When the imagesare examined closely, it becomes clear that the chest x-rays are RGB images rather than greyscale ones since some of the images have a blue or yellow tone. Two convolutional layers with a 3 x 3 kernel size have been employed in the first set of a stacked convolutional layer instead of one with a 5 x 5 kernel size. The model benefits from the use of two layers since it becomes more nonlinear and has fewer parameters, which reduces overfitting. Withdeeper model layers, the model can recognise more intricate elements in photos. every layer of pooling,To lessen the chance of overfitting with the 25% dropout rate, a dropout layer is introduced Convolutional and pooling layers must first be input, and then the output shape must be modified before moving on to the fully linked layers. Thus, the model is connected to a completely connectedlayer after being flattened from a two- dimensional layer to one dimension. The ReLU function is used for activation in the fully connected layer. Since we must differentiate between COVID-19 and standard chest x-ray images, just one filter is applied to the output layer. This is why the Sigmoid's activation function is employed.

The training dataset is run through the built-in Keras Image Generator library. The dataset is rescaled for normalization of RGB images by 1/255 to aid in data convergence. Additionally, the model is taught to use sheer and zoom augmentation, which enables the model to select random image cuts and zoom in by 20%. To obtain reliable findings, vertical flipping of the image has been prohibited. The Image Generator package is used to resize the images for

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normalization by 1/255 for the validation dataset.

In order to discriminate between COVID-19 and Normal Chest x-rays for the training dataset, the flow from the directory function is used to reshape the picture with a goal size of 224 × 224, a batch size of 32, and binary classification. The validation dataset has undergone the same changes.For data scientists, 224 x 224 is a common input size selection. This input size is sufficient to fix the majority of ImageNet issues.If the input size were large, it would be difficult to train the model, and if it were small, it would be impossible to capture fine-grained features. Ten epochs with eight steps each are employed during the training procedure.

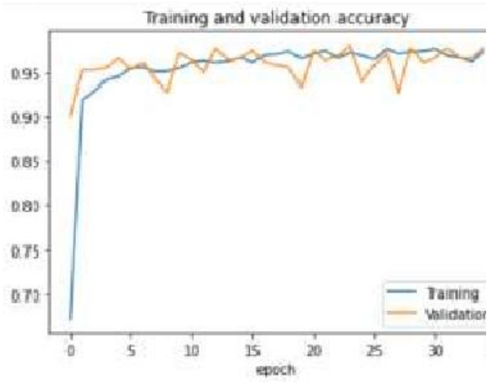
Given that it just employs a few parameters, this model is easier to understand than others like VGG16, ImageNet, and TransferNet. Due to theirover one million parameters, the other models won't produce satisfactory results. The models would need to be carefully adjusted with a number of alterations because the dataset comprises chest x-rays. Additionally, the dataset is too small, which would result in overfitting. For training, the other models need at least 3000 photos to achieve a high accuracy level.

IV. RESULTS

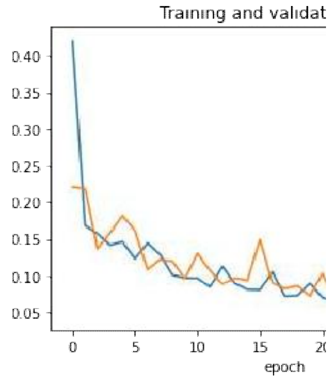
By following this methodology we are able to achieve an accuracy of 98.145% which is higher than any previously achieved accuracy by training a CNN model based on a limited dataset.

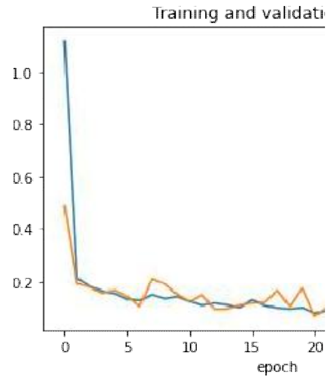
The gap between training and validation accuracyis an indication of overfitting if any. The larger the gap, the higher the overfitting. Overfitting is a modeling error in statistics that occurs when a function is too closely aligned to a limited set of data points. since the over lifting and under liftingis kept low.The model is useful in different datasets also.

A reasonable technique to assess the model's level of training is to plot the training loss vs. validation loss or training accuracy vs. validation accuracy over a number of epochs. This is crucial to avoid undertraining the model and overtrainingit to the point that it begins to memorize the training data, which would lower its predictive accuracy.



The training loss indicates how well the model isfitting the training data





V. CONCLUSION

To stop the disease from spreading to other people, early diagnosis of COVID-19 sufferers is essential.Since the virus is still quite young, there isn't an official vaccination yet. Therefore, it is important for humanity to act quickly to stop the spread of COVID-19. The detection of COVID-

19 depends heavily on chest X-ray pictures. Using chest X-ray pictures from COVID-19 patients and normal patients, a CNN Model was employed in this study to identify COVID-19. Highly representative and hierarchical local image characteristics can be directly learned from data using CNN. With the virus's recent origins, the model performance is a high accuracy score of 97%. Despite the fact that this study is solely intended for educational and research purposes and not for medical ones, the increased performance of the model will help doctors make better decisions in clinical practice. The largest problem in handling COVID19 instances from Chest X-ray pictures, however, continues to be the anomalies in annotated data. Due to the COVID-19 virus's recent discovery, there are a few limitations to this paper.

No medical advice was consulted when analyzing the project.

The following could be the future scope of this paper: To expand the dataset by making more data available. To include other infections, such as viral and bacterial pneumonia. To use Saliency maps and Gradient Class Activation Maps (Grad- CAM) to identify the areas where the illness has spread among the COVID Chest X-rays. The current research nevertheless raises the prospect of a quick, low-cost, and automatic diagnosis of COVID-19. Additionally, even though the proper course of treatment cannot be determined solely by an X-ray image, an initial screening of the cases would be beneficial for prompt application of quarantine measures in the case of positive samples until a thorough examination and particular course of treatment, or follow-up procedure, are followed. The minimization of exposure of nursing and medical staff to the outbreak is another benefit of automatic detection of COVID-19 using medical imaging.

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