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DETECTION OF COVID-19 VARIANT USING X-RAYS

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ABSTRACT

The outbreak of coronavirus disease 2019 (COVID-19) has had an immense impact on world healthand daily life in many countries. Sturdy observing of the initial site of infection in patients is crucial to gain control in the struggle with COVID-19. The early automated detection of the recent coronavirus disease (COVID-19) will help to limit its dissemination worldwide. Many initial studies have focused on the identification of the genetic material of coronavirus and have a poor detection rate for long-term surgery. The first imaging procedure that played an important role in COVID-19 treatment was the chest X-ray. Radiological imaging is often used as a method that emphasizes theperformance of chest X-rays. Recent findings indicate the presence of COVID-19 in patients with irregular findings on chest X-rays. There are many reports on this topic that include machine learning strategies for the identification of COVID-19 using chest X-rays. Other current studies have used non-public datasets and complex artificial intelligence (AI) systems.

Keywords: Analysis, Investigation, Research.

I. INTRODUCTION

Coronavirus illness is a disease that comes from Severe Acute Respiratory Syndrome (SARS) and Middle East Respiratory Syndrome (MERS). A novel coronavirus, COVID-19, is the infection caused by SARS-CoV-2 (Zhang, 2020). In December 2019, the first COVID-19 cases were reported in Wuhan city, Hubei province, China (Xu et al., 2020). World Health Organization (WHO) declared COVID-19 a pandemic (Ducharme, 2020) on March 11 2021, up to July 13 of 2021 there are 188,404,506 reported cases around the world, which have caused 4,059,220 deaths (Worldometer, 2020).

These diseases cause respiratory problems that can be treated without specialized medicine or equipment. Still, underlying medical issues such as diabetes, cancer, cardiovascular and respiratory illnesses can make this sickness worse (World Health Organization, 2020).

Reverse transcription Polymerase chain reaction (RT-PCR), gene sequencing for respiratory or blood samples are now the main methods for COVID-19 detection (Wang et al., 2020). Other studies show that COVID-19 has similar pathologies presented in pneumonic illness, leaving chest pathologies visible in medical images. Research shows RT-PCR correlation with Chest CT (Ai et al., 2020), while others study its correlation with X-ray chest images (Kanne et al., 2020).

Typical opacities or attenuation are the most common finding in these images, with ground-glass opacity in around 57% of cases (Kong & Agarwal, 2020). Even though expert radiologists can identify the visual patterns found in these images, considering monetary resources at low-level medical institutions and the ongoing increase of cases, this diagnostic process is quite impractical. Recent research in Artificial Intelligence (AI), especially in Deep Learning approaches, shows how these techniques applied to medical images performed well.

There are only a few large open access datasets of COVID-19 X-ray images; most of the published studies use as a foundation the COVID-19 Image Data Collection (Cohen et al., 2020),which was constructed with images from COVID-19 reports or articles, in collaboration with a radiologist to confirm pathologies in the pictures taken. Although computed tomography (CT) scans have proven to be more effective, the increasing number of patients and the consequent rise in radiological examinations are making it impossibleto continuously rely on chest CT scans for each individual patient from diagnosis to discharge. Also, a high reliance on CT scans will impose a significant burden on radiology departments, thus rendering chest X-rays (CXRs) a more feasible option for COVID-19 detection . Although CXRs are deemed less sensitive in diagnosing early-stage pulmonary involvement in COVID-19, it is beneficial to track the gradual development of lung anomalies . Previous studies have observed and identified various radiological manifestations of COVID-19, such as consolidation, reticular interstitial thickening, ground-glass opacities (GGO), pulmonary nodules, and pleural effusion.

With the rapid global spread of COVID-19, researchers have begun using state-of-the-art deep learning techniques for the automated detection of COVID-19 within patients. The onerousness of obtaining COVID-19 data in its initial stages has forced researchers to create their own model using pretrained networks. However, the bulk of these experiments used a limited dataset comprising just a few COVID-19 samples. This renders the stated results in these studies are difficult to generalize and does not ensure the reported output would be retained when these modelsare evaluated on a larger dataset.

Finally, the visualization of heatmaps for different images provides helpful information about the regions of the images that contribute to the prediction of the network, which in ideal conditions should focus on the appearance of the lungs, backing the importance of lung segmentation in the preprocessing stage. After this section, the paper follows the next order: first, the Methodology applied for these approaches, followed by the experiments and results obtained, a discussion of the products, and lastly the conclusions.

Although rapid point-of-care COVID-19 tests are expected to be used in clinical settings at some point, for now, turnaround times for COVID-19 test results range from 3 to more than 48 hours, and probably not all countries will have access to those test kits that give results rapidly. According to a recently published multinational consensus statement by the Fleischner Society, one of the main recommendations is to use chest radiography for patients with COVID-19 in a resource-constrained environment when access to computed tomography (CT) is limited. The financial costs of the laboratory kits used for diagnosis, especially for developing and underdeveloped countries, are a significant issue when fighting the illness. Using X-ray images for the automated detection of COVID-19 might be helpful in particular for countries and hospitals that are unable to purchase a laboratory kit for tests or that do not have a CT scanner. This is significant because, currently, no effective treatment option has been found, and therefore effective diagnosis is critical.

AI tools have produced stable and accurate results in the applications that use either image-based or other types of data. Apostolopoulos and Mpesiana[2] performed one of the first studies on COVID-19 detection using X-ray images. In their study, they considered transfer learning using pre-trained networks such as VGG19, MobileNet V2, Inception, Xception, and Inception ResNet V2, which are the most frequently used. Several evaluation metrics were used to evaluate the results obtained from two different datasets. MobileNet V2 and VGG19 achieved 97.40% and 98.75% accuracy, respectively, for two-class experiments (COVID-19/Normal and COVID-19/Pneumonia), and 92.85% and 93.48% for three-class experiments (COVID-19/Pneumonia/Normal). The final conclusion was made by the authors using the obtained confusion matrices, not the accuracy results because of the imbalanced data.

II. METHODOLOGY

Our Architecture consists of three main experiments to evaluate the performance of the models and assess the influence of the different stages of the process. Each experiment follows the workflow. The difference between experiments is the dataset used in all instances, the same images for COVID-19 positive cases were used. Meanwhile, three different datasets for negative cases will be used. In that order, Process 1 and 2 consists of evaluating positive vs. negative cases datasets, and Process 3 involves Pre-COVID era images (images from 2015-2017).

Datasets

A total of 9 Chest X-ray images datasets were used in different stages:

COVID-19 classification datasets

This dataset consists of CXRs from different individuals with COVID-19, 1341 CXRs from healthy individuals, and 1345 CXRs from individuals with other types of viral pneumonia. All theimages are in the Portable Network Graphics (PNG) file format, and with a resolution of either 1024-by-1024 pixels or 256-by-256 pixels. It must be noted that the dataset is divided into 3575 training and 311 test images, as outlined in Table 1. In the training phase, the dataset was preparedand verified as reliable by reviewing it with chest specialists. In addition, cases of viral pneumoniashould be free from any instances of COVID-19. Before passing the images into a pretrained model for feature extraction, we resized all images to a size of pixels. All images were normalized according to the pretrained model standards. CXR images within thetraining set that were used in this study.

Classify a lung region into small sub-regions

To mask all possible of small pneumonia regions, the masking equation needs to control the minimum number of pixels in each region and classifies sub-regions into two classes by using the proposed fractional threshold correction

Training Set

A training dataset is an initial dataset that teaches the ML models to identify desired patterns or perform a particular task. A testing dataset is used to evaluate how effective the training was or how accurate the model is.

Features Extraction

Feature extraction refers to the process of transforming raw data into numerical features that can be processed while preserving the information in the original data set. It yields better results than applying machine learning directly to the raw data of covid.

Convolutional Neural Network Model

Xception is an improvement of Inception V3, replacing its convolution operation with depthwise separable convolution, which divides traditional convolution into the steps of depth wise and point wise convolution.

The InceptionResNetV2 model is a **CNN** with top accuracy on the ILSVRC image classification benchmark. It is based on **Google's Inception V3 model** and draws on the ideas of ResNet , a 152-layer neural network successfully trained by using the **ResNet** Unit. The error rate on Top5 is 3.57%. It has fewer parameters than **VGGNet**, and the effect is outstanding. It introduces the idea of residual learning, which effectively solves the problem of network degradation.

The VGG family is used in face recognition and image classification, where VGG19 has better performance. VGG19 has 19 hidden layers, consisting of 16 convolutional layers and three fully connected layers. The input is set to 224 × 224 RGB images. The RGB average of all images calculated on the training set image, and the image is passed as input and enters the VGG19 convolutional network.

DenseNet builds a connection relationship between layers, makes full use of features, and further alleviates the problem of gradient disappearance. The use of a bottleneck layer, translation layer, and smaller growth rate makes the network narrower, reduces the parameters, effectively suppresses overfitting, and reduces calculation. Pre-trained networks have very deep architectures, they have been trained by using millions of different kinds of images, and the saved final weights are intended to be transferred to similar or different applications. Recent research, however, aimed to develop light ConvNets to reduce the computational cost of pre-trained networks; and, as mentioned above, networks with less deep architectures become preferable for classification problems, even with a huge number of images and a high number of output classes. The obtained results also demonstrate that architectures may begin to deepen more in connection with the increased number of images and output classes. For this reason, some pre-trained neural networks have been found to have difficulties in learning one class successfully while learning another class with high accuracy.

COVID-19 data used in this study have been collected by pulling images from publications and websites. Therefore, they have come from different institutions and different scanners. X-ray imaging parameters might be different for some of the scans, which might result in different image quality, and this is common when multisite studies are mixed, or one database has multiple characteristic flaws like different imaging protocols. Therefore, pre-processing of the data to make the radiographic images more similar and uniform is important in terms of providing more efficient analysis and consistency. This is a complex procedure, however, including co-registration, standardization, and so on to obtain the same image size and pixel size along the same spatial orientation and to make the images' resolution uniform and isotropic. We believe that, as more pre-processed datasets on COVID-19 become publicly available, more accurate studies will be conducted.

Nevertheless, the current limited dataset has led researchers around the globe to develop methods to aid in facilitating the diagnosis of COVID-19. Although this study shows that CNNs can be used for automated detection of COVID-19 and for distinguishing it from pneumonia, we believe applying artificial neural networks

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to COVID-19 detection more accurately requires clinical trials. Another limitation of this study is the small sample size of COVID-19 images, which restricts the appropriate cohort selection and might result in a biased conclusion. At the time of writing, there is no other reliable publicly available dataset. To have a more accurate and robust model, a larger COVID-19 dataset is needed. Furthermore, because of the use of a relatively small number of COVID-19 images, clinical information about the patients, such as risk factors and medical history, is not available at this time.

III. MODELING AND ANALYSIS

To demonstrate the results qualitatively, we generate saliency maps for our model's predictions using RISE . In this approach **1000 randomly** masked versions of a given **X-ray** image are queried and their classification scores are used to create a weighted mask corresponding to each output class. The core idea behind the RISE approach is that masks which preserve semantically important parts of the image will lead to a higher classification score and hence a higher weight in the final mask for the respective class.

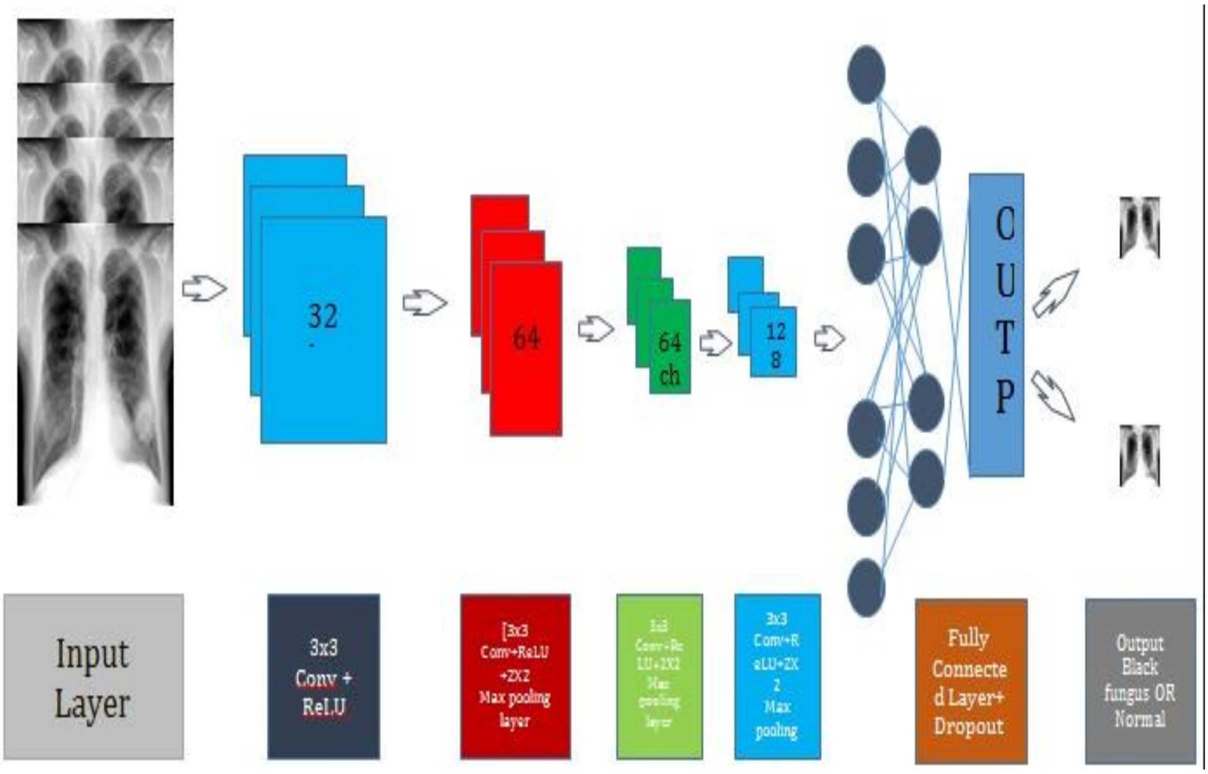

Figure 1: Step-wise process of Covid-19 Detection.

The purpose of these visualizations was to have an additional check to rule out model over-fitting as well as to validate whether the regions of attention correspond to the right features from a radiologist's perspective. architectures were also considered for all experiments to evaluate the model performance with different numbers of layers. Experimental results showed that the use of more convolutional and fully connected layers could not improve the model performance for the image database considered, because the differences between the mean ROC AUC scores of the ConvNet with minimized layers and the **ConvNet** with more layers were more than 1.7–5%, depending on the pre-processing technique. The minimum mean **ROC AUC** score of **ConvNet** with more layers in **APPN-applied images was 93.69%**, while ConvNet#1 achieved **95.41%**. The number of images used in the experiments has a direct effect on the number of layers and the architecture of the ConvNet, but the obtained results suggest that the use of minimized layer numbers can enhance detection of COVID-19 within the normal images. The highest result was obtained by using two convolutional layers and two dense layers with 160×120 image dimensions.

Then, statistical measurements and COVID-19 detection using several machine learning models were considered. The determination of the specific statistical measurements to be used is vital for this kind of classification approach; however, there are basic measurements that can be obtained from the images. In

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addition to the above-mentioned statistical measurements, the image pre-processing techniques were applied, and additional measurements were obtained from the images to make the knowledge for the machine learning models as similar as possible to that for the ConvNets. The machine learning models, however, could not achieve mean ROC AUC scores as high as those of the ConvNets, and there was a 4% difference between the highest mean ROC AUC score in ConvNet experiments and nB, which produced the highest result in statistical measurement experiments.

Similarly, machine learning classifiers were not able to produce higher results than ConvNets obtained, but general reduction was observed in the classification performance of machine learning models. This was caused by the complexity of images, the difficulty of differentiating COVID-19 from pneumonia images, and the increased number of training samples. It should be noted, however, that additional measured characteristics of images or significant statistical measurements, such as contrast level, brightness level, kurtosis, and so on, may help to improve the scores obtained by machine learning models.

IV. RESULTS AND DISCUSSION

Early detection of patients with the new coronavirus is crucial for choosing the right treatment and for preventing the quick spread of the disease. Our results show that the use of CNNs to extract features, applying the transfer learning concept, and then classifying these features with consolidated machine learning methods is an effective way to classify Xray images as in normal conditions or positive for COVID-19. For Dataset A and B, the VGG and other models of the CNNtheory will b used in the model for getting accuracy and fast result.

The proposed method has not undergone a clinical study. Thus, it does not replace a medical diagnosis since a more thorough investigation could be done with a larger dataset. Under those circumstances, our work contributes to the possibility of an accurate, automatic, fast, and inexpensive method for assisting in the diagnosis of Covid-19 through chest X-ray images.

V. CONCLUSION

Fast and timely detection of COVID +ve patients is necessary to avoid spreading the disease and keeping it in control. This research work has been done to detect the COVID +ve patients from Chest X-Ray images in a simple and inexpensive way. In the work proposed in this paper, three state-of-the-art deep learning models have been adopted and ensembled. The proposed model has achieved a classification accuracy of 91.62%. Even more important fact is it yields a sensitivity of around 95% for COVID +ve cases i.e., out of 100 COVID +ve patients, more than 95 can be correctly diagnosed by our proposed model. It is believed that this research work along with the GUI interface will help the doctors to detect the affected patients with the help of computer-aided analysis, that too within a few seconds. We believe that this will significantly add value to the medical field.

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