Deep Convolutional Neural Networks For Accurate Coronavirus Detection Through Chest CT Screening

ABHISHEK NAGRECHA[1], RAJESH AYTHA[2] AND
DR. THIAGO E. ALVES DE OLIVEIRA[3], (Assistant Professor(PhD), Lakehead University)

[1]Student, Lakehead University, Thunder Bay, Ontario, Canada P7B 5E1 (email: nagrechaa@lakeheadu.ca)
[2]Student, Lakehead University, Thunder Bay, Ontario, Canada P7B 5E1 (email: raytha@lakeheadu.ca)
[2]Department of Computer Science, Lakehead University, Thunder Bay, Ontario, Canada P7B5E1

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ABSTRACT The communicable disease caused by the extreme acute respiratory syndrome is Coronavirus (COVID-19). More than thirty-four million people around the globe have tested positive for the disease and in access to a million people have lost their lives. To this end, CT imaging has been suggested as one of the primary screening methods which can be adopted as a substitute to the testing of RT-PCR. Compelled by this, we contemplate to precisely segment lung lesions with computing-time accuracy and reliability from healthy lung fields using CT scans and implement a deep convolutional neural network architecture during this analysis that is designed to detect novel cases of coronavirus pneumonia from chest CT scans. In addition, COVID-CTset is the dataset we will be using.it contains 48260 CT scan images from 282 normal persons and 15589 images from 95 patients with COVID-19 infections. We want our research to demonstrate a high-speed and accurate fully-automated method to detect COVID-19 from the patient's CT scan images. In contrast with other state-of-the-art standards, we firmly presume that our research studies would reveal the optimal effectiveness of the theorized architecture.

INDEX TERMS Coronavirus, Deep Learning, Transfer Learning, Chest, Lung CT Scan

I. INTRODUCTION

The coronavirus infection (COVID-19) is a global pandemic that first emerged in December 2019, in Wuhan, China, the capital city of mainland China's Hubei province [1]. There is no authorised human vaccine at present to prevent it. When individuals are in close vicinity, the transmission of COVID-19 is quicker and the disease has been declared a pandemic by the World Health Organisation (WHO). Studies have shown that more than 60 % of patients lose their lives as soon as they advance to the stage of serious or critical illness [2] Thus, the WHO has strictly indicated that travel precautions will control the progression of the virus, and it has been reiterated to keep our hands sanitized regularly for avoiding possible virus infections.

Most of the federal governments around the globe, including Canada have imposed travel restrictions and sealed their borders to stop any further spread.To add to that, a set of rules have been established for travellers entering a new territory under the Quarantine Act. The most prominent illness signs, are fever and cough. There may be other effects, including chest pain, growth of sputum, and a stuffy nose that appears to have a significant effect on patients and health services around the world. There is indeed an urgent need for quick and reliable screening methods to classify patients afflicted with COVID19 to ensure prompt isolation and care in the battle against this unusual disease. Digital technology applications, such as contact tracing apps, have been used since February 2020 to curb the possible risk of infection.if someone is infected by the virus, the smart Cell phone applications warn consumers to self-quarantine and contact the local health department.They also track infected individuals and the hindmost individuals with whom they were in close contact [3] .However,the fast spread of COVID-19 is one of the major threats, with an average of 1-3 individuals getting infected by the disease upon contact with an infected person [4].This advocates that they are more likely to infect 15-35 other individuals if 10 individuals are COVID-19 positive.However,WHO is still reviewing ongoing studies on the forms in which COVID-19 is being transmitted and therefore will continue to post certified data for more information.Furthermore, unless intervention steps are enforced, COVID-19 could infect a very large number of ethnic groups in the coming days since transmission from individual to individual has been clearly identified [5].

Besides, a new gene close to the virus causing SARS and MERS is caused by COVID-19. While the spread of COVID-19 has a lower mortality rate than the SARS and MERS outbreaks [6],but it spreads more quickly and has infected larger inhabitants than the SARS and MERS outbreaks [6]. The reverse transcription polymerase chain reaction (RT-PCR) research method [1] is currently the main diagnostic technique for the primary means of screening for COVID19, a laboratory protocol that interacts with other ribonucleic (RNA) and deoxyribonucleic acids (DNA) to determine the volume of specific ribonucleic acids using fluorescence.While RT-PCR is capable of identifying the strain of severe acute respiratory syndrome SARS-CoV-2 that causes COVID-19, in some instances it gave negative testing results even though sufferers showed improvement on follow-up chest computed tomography (CT) scans [6] and its susceptibility is also varied, depending on the method of sampling and the period after symptom onset [7] [8].

Several studies including [7] have advocated the use of chest computed tomography (CT) scans rather than RT-PCR , because its available in all major public health facilities, including hospital emergency rooms (ERs), and even at rural clinics, and its sensitivity is also high ,more importantly considering the limitations of RT-PCR research and the time required to obtain data. The method of CT scanning has a quicker processing time than the RT-PCR test and can offer more detailed pathology-related details and explain the extent of lung involvement [9]. Additionally, the exposure of COVID-19 symptoms in the lower parts of the lungs has a higher accuracy when using CT scans than that when using RT-PCR [10].Likewise, radiological imaging is also considered an important screening method for COVID-19 diagnosis [9]. Ai et al. [11] demonstrated the consistency of the radiological history of COVID-19-associated pneumonia with the clinical nature of the condition. When examined by CT scans, almost all COVID-19 patients have exhibited similar features including ground glass opacities in the early stages and pulmonary consolidation in the latter stages. In fact, the morphology and peripheral lung distribution can be rounded.

Also, deep learning models can be employed to initially evaluate a COVID-19 patient as an alternative solution to traditional approaches that are time-consuming and labour intensive. However, they cannot exclusively address the whole problem due to the high volume of re-examinations of infected people who wish to know the progression of their illness. In this study, we want to develop a fully-automated method for detecting COVID-19 cases from the images of the lung HRCT scan device. For this, we intend to use the new dataset that called COVID-CTset that contains 15589 COVID-19 CT slices from 95 individuals and 48260 normal CT slices from 282 individuals [12]. Besides, we also want to investigate the infected areas of the COVID-19 classified images by segmenting the infections using a feature visualization algorithm. Our primary goal will be to do a exploratory work that can assist the radiologists in finding COVID-19 using the chest CT scans, which would allow them to concentrate all their energies in right direction and would also be useful for optimum resource allocation.

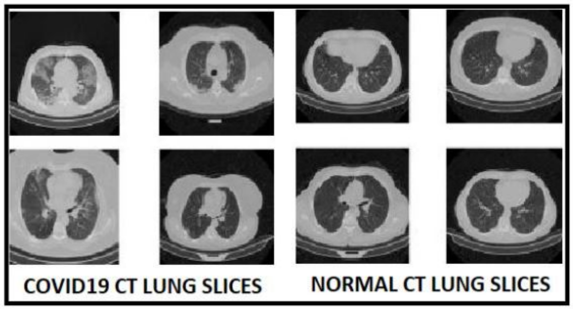

FIGURE 1. Computed tomography (CT) slices of lung in axial view: left-to-right infected lung with COVID-19, and Normal lung,from COVID-CTset.

II. LITERATURE REVIEW

When it comes to doing research, the most important resource is the availability of good data.one might have path-breaking solutions but until and unless its been tested on real time data, its of no use. For this research the data was discovered from Kaggle, a subsidiary of Google LLC, which is also considered as an online community of data scientists and machine learning practitioners. The data is named COVID-CTset and is derived from the paper [12] . COVID-CTset is constructed of two main sections. The first section with the name of (TrainingValidation) contains the Ct slices for training and validating the networks, and the second section contains the entire data for all the patients. We founded only the first section of the dataset on Kaggle which itself was large enough to be used for training and testing deep classifiers. The data had nearly 12.1 thousand CT scans of patients belonging to two classes namely covid and normal. However, upon further contact with the author we got the access to the whole dataset.

In [12] they propose a high-speed and accurate fully-automated method to diagnose COVID-19 from CT scan samples of the individual. They released a new dataset containing 48260 CT scan images from 282 normal persons and 15589 images from 95 patients with COVID-19 virus. They enforced their method using the ResNet50V2 network and a modified feature pyramid network. alongside their designed architecture for classifying the selected CT images into COVID-19 or normal with higher accuracy than other models. After running these two phases, the system was able to determine the condition of the patient using a selected threshold. But, one thing which we found surprising was that they had not done much pre-processing on the CT scans and actually fed the un-processes scans to the networks for classification. Several research papers, including [13], have recapitulated chest computed tomography (CT) as a useful tool in the assessment of suspected SARS-CoV-2 infection patients. Furthermore, they included the number, height, and density of lesions, as well as the total lung parenchyma, lung injury, and residual lung reserve as lesion characteristics, and also tested the hypothesis as to whether an AI method can be established using both clinical data and CT parameters to produce an reliable clinical prognostic model that can succor clinicians to prepare for early surveillance.

We also studied another similar research to [14] which used the same data and discovered some discrepancies. we felt that there was a need for doing additional analysis of the explainability results for coming to an acceptable outcome. Identification of key patterns in the CT images was also missing which would have aided clinicians in manual screening. In addition, by using a mixture of CT and clinical criteria, they imparted prognostic signs for patients with NCP, with the goal of offering another instrument to assist physicians, According to [15], the lack of polished radiologists risks the availability and adequacy of COVID19 screening facilities in affected countries. Suspicious patients anywhere, especially in developed countries, have fair access to the correct diagnosis, appropriate treatment, and isolation through the implementation of AI diagnostic algorithms. With 10,250 CT scans from three centers in China and three publicly accessible databases, they developed clinically representative large-scale datasets. They developed both CT-based and CXR based diagnostic systems and tested them using paired data to explain the relative efficiency of CT and CXR for the identification of COVID-19 [16].

DeepPneumonia was developed to help doctors diagnose the pneumonia-causing COVID-19 and localise the key lesions. Three key measures have been developed for their fully automatic lung CT diagnostic method. Although, after going through their research we found their pre-processing steps highly debatable, specifically their selection of libraries. Also, the data which was used for this experiment was relatively small, having only 88 COVID-19 patients. To extract the top-K information in the CT images and corral the image level predictions, and Information Relation Extraction neural network (DRE-Net) was developed. Both two-dimensional local and 3D global model characteristics were being collected. As the backbone, the COVNet the structure consisted of RestNet50, which took as input a set of CT slices and created functionality for the corresponding slices [17].Nevertheless, there were few inconsistencies in this research, such as the random choice of CAP from Aug'16 to Feb'20, and the analysis relied only on whether one sample was of COVID19 or not, but the classification of the virus into various levels of severity were not discussed. Also, we have seen a variety of papers which have put-to-use well-known convolutional neural networks to separate COVID-19 infection from Non-COVID19 classes, including [18], [19], and [20].. We checked several papers for some detailed studies on CT image pre-processing and found the methodology of [21], [22] and [23] useful. [21] proposes a recent and realistic deep, completely convolutional neural network architecture named SegNet for semantic pixel-wise segmentation. This central trainable segmentation system consists of a network of encoders, a corresponding network of decoders preceded by a classification stage pixel-wise.SegNet 's innovation lies in the fact in which the decoder up-samples its function map with lower resolution information. Besides, the submitted cadre was contrasted with the commonly accepted FCN [24].

We were very impressed by the pre-processing steps proposed by [22], since they were aligning with our methodology and hence we might include them in our research. These steps allowed them to distinguish the limits of the lung from its underlying thoracic tissue. Histogram thresholds were used to separate the the backdrop of the Ct scan by thresholding the sensitivity values by the average value of each CT slice independently. The shortcomings of the segmentation process were then resolved by eliminating all minor components. As a result, a binary mask of those representing the lung and zeros representing the backdrop was multiplied by the initial CT lung scan to remove only the useful pulmonary areas. In [25] they applied several random on-the-fly data augmentation strategies during training, including cropping of square patches at the center of the input frames, random rotation and horizontal reflection etc.But one impediment of this research would be the way they handled their classification task, that is, they failed to distinguish CAP from COVID-19.Keeping this in mind we decided to use more advanced backbone architectures, such as ResNet50V2 and DenseNet169. They had described a fully convolutional network (FCN) when it comes to [23], trained end-to-end, pixels-to-pixels on semantic segmentation. Since their redefinition of classification networks, generates output maps for inputs of any size, the output parameters are generally decreased by subsampling.Sub-sampled classification networks to retain low philters and fair computing requirements.

Now, when it comes to standard criteria in this domain, we want to validate our architecture's output with [26] as well as [21] as we described above, which is a deep learning-based approach that captures local and contextual information to segment the ONH's individual neural and connective tissues. As we mentioned before that data availability plays a critical role for the performance of deep learning systems and this challenge is especially acute within the medical image domain, particularly when pathologies are involved, due to two key factors: (1) limited number of cases, and (2) large variations in location, scale, and appearance. In [27], they investigate whether augmenting a dataset with artificially generated lung nodules can improve the robustness of the progressive holistically nested network (P-HNN) model for pathological lung segmentation of CT scans.

To achieve this goal, they developed a 3D generative adversarial network (GAN) that effectively learns lung nodule property distributions in 3D space. As a result, their system provided a promising means to help overcome the data paucity that commonly afflicts medical imaging. Now, since we have scrutinized a lot about the segmentation and augmentation frameworks, let's move towards the classification aspect for the CT scans. For this we came across limited papers since the disease is very nascent.

We found [28], [29], [30] useful for our project framework and hence we studied them in detail. [28] recommended the use of an attentive fully convolutional network that could concentrate on contaminated areas of the chest, allowing a more detailed forecast to be made. They trained the model on a relatively a small dataset comprising of roughly 2000 CT images and also presented a diagram of their prototype attention maps and demonstrated how close they were to the board-certified radiologists' manually identified infected regions as we would be actually working extensively with images, it was important for us to have one survey paper in our literature, so we could navigate to the availability easily. for this purpose we chose [29] which discusses the approach and performance of the computer vision CT-based pathological condition diagnosis, having selected some recent representative works to provide an overview of their effectiveness. Based on their role in contagion management, they grouped the approaches listed into 3 categories: computed tomography (CT) scans, X-ray imaging, and control and prevention.

Last but not the least, [30] implemented a computer-aided diagnosis (CAD) web site for online identification of COVID19.In this research, a public chest CT scan database was utilized, including 746 participants. To identify the most effective model for the hybrid system, a range of very well-known deep neural network architectures consisting of ResNet, Inception and MobileNet were inspected. To differentiate between COVID19 and safety controls, a variation of the Tightly connected convolutional network (DenseNet) was chosen to minimise image dimensions.Nevertheless, the limited data set size they have chosen will have to be a big drawback because the training phase for deep neural networks demands a significant number of samples and such limited samples trigger over fitting.

III. PROBLEM DESCRIPTION AND FORMULATION

The most significant thing about the current coronavirus, as we have described before, is it's rapid and wide-spreading ability. The virus is spread primarily from individuals with the disease to others and its transmitted indirectly by the surfaces and air in the atmosphere in which it comes into contact with the sick people. As a consequence, properly recognizing and quarantining the effects of patients with illness plays an important part in stopping the disease. [6] There are many approaches, including reverse transcriptase-polymerase chain reaction (RT-PCR), isothermal nucleic amplification test, antibody test, serology test, and medical imaging, for conclusive detection of COVID-19.

The primary method of diagnosing COVID-19 and other viral diseases is RT-PCR. [1] [12]. For some of the experiments, however, the methodology is restricted as higher skills and exploration are needed to create new therapeutics. Besides, in most infected regions around the world, the shortage of diagnostic kits is encouraging scholars to come up with innovative and simpler approaches to make an accurate diagnosis. [10] [11].Researchers are analyzing CT scans and X-rays to diagnose COVID-19 thanks to the availability of medical imaging equipment in most healthcare facilities. Infections in the lungs of people with new coronaviruses that may help detect the disease are present in most patients with COVID-19. Pneumonia caused by the new coronavirus was seen in the study of CT scans of COVID-19 patients. [14] [13]

IV. SYSTEM OVERVIEW

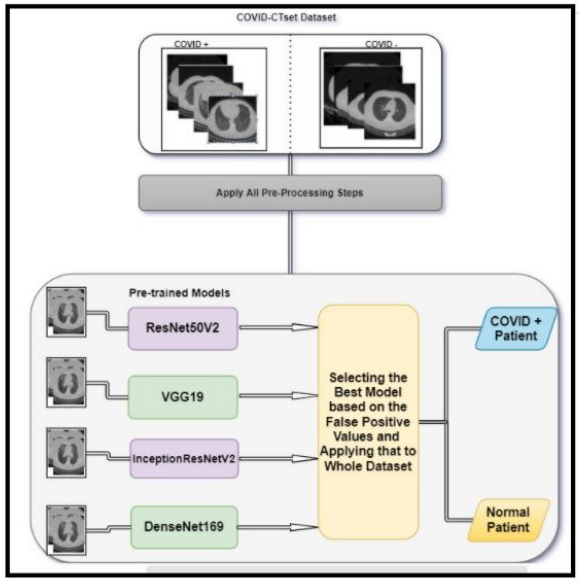

FIGURE 2. Scheme of our architecture, a deep learning framework based on series of lung CT slices for the classification of COVID-19 and Normal.

Many patients with COVID-19 signs have X-rays and CT scans of their lungs at least four days apart, revealing infections that indicate the presence of a new coronavirus in their body. [6] [15].While medical imaging for the correct diagnosis of COVID-19 is not approved, but it can be used as a secondary diagnostic tool for quarantining the suspect and preventing the virus from being spread to others during the onset of symptoms. [29].Our primary objective in this research will be to employ the deep-learning methods to accurately diagnose the virus from the CT scans due to its ability to derive rich features from multimodal clinical databases. Also deep learning applied technology has recently seen considerable progress in the field of medical data processing. [25] [19].Deep learning-based methods for chest CT data processing and classification have been developed effectively in the ongoing COVID-19 pandemic. [17] [16] [15] In addition, deep learning algorithms for COVID-19 tracking, scanning, and hospital stay prediction has been suggested. [25].The system could also reliably differentiate COVID-19 cases from CAP and NP patients. The precise location of the lesions or inflammations caused by COVID-19 can now be known, and would also therefore theoretically include guidance on patient severity to direct the triage and care that follows [13].

To further support our approach we have studied numerous papers which demonstrated the use of deep learning in other domains including accurate diagnoses of tumors and infections caused by various diseases.This approach has also been used for numerous medical images, such as neuro and skin lesion segmentation [12], Breast Applications Lesions and pulmonary nodules [4], and automated identification using X-ray images of coronavirus disease [10]. On the other hand, it has been agreed that it is far more effective to accurately determine COVID19 by using deep learning methods when compared to the radiologists. [29]

V. PROPOSED SOLUTIONS AND COMPARISON TO THE LITERATURE

For the above-mentioned problems related to the RT-PCR and other testing methods we came up with a solution to work with CT scan images of both patients with Covid related pneumonia and Normal scans. We propose to use four deep learning based deep Convolutional neural network architectures including VGG-19, DenseNet169, ResNet50V2, and InceptionResNetV2 to accurately predict the status of the patient through the lung HRCT radiology Scans given as the input. For this we want to use the COVID-CTset which is made available by [12] through Kaggle datasets.

Below in Figure 3 you can see the Flowchart of our proposed methodology.

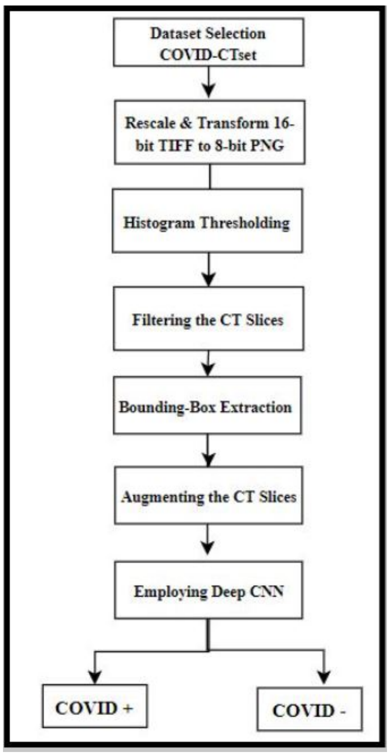

FIGURE 3. Proposed Flowchart of our Research.

A. DATA SET INFORMATION

The dataset that we will use in this research work is the COVID-CTset. It was retrieved from Negin radiology from March 5 to April 23, 2020, located at Sari in Iran. A SOMATOM Scope model and a Syngo CT VC30-easyIQ software versions are used by this medical center to collect and visualize patients' lung HRCT radiology images. The specification of the exported radiology images was a 16-bit DICOM grayscale with a resolution of 512*512 pixels. The dataset consists of 15589 CT scans belonging to 95 patients infected with COVID-19 and 48260 scans of 282 normal patients. Each patient has three different folders, which includes the CT scans captured from the CT imaging device with a three different thickness types namely SR_2, SR_3, and SR_4. As the patient's CT slices were originally available in DICOM format, it was converted to TIFF format by [12], which retains the very same 16-bit grayscale data but does not infer the private information of the patients.

The below table shows the COVID-CTset data distribution

Covid-19 Patients	Normal Patients	Covid-19 Scans	Normal Scans
95	282	15589	48260

B. CT LUNG SCAN PRE-PROCESSING

As a part of this,since we are given with a 16-bit data format we will be converting it to 8-bit data, which may help us improve the method's results. Additionally, we will be converting the scans to PNG format from the original DICOM format. Also, we will be resizing the scans to 256*256 pixels from the original 512*512 size.Below we have identified four essential pre-processing steps which will speed up the deep Convolutional Neural Networks training process and improve the classification performances.

1) Visualize the scans and Histogram thresholding

We had scans in the raw TIFF format which were not visible on our screen therefore to make these images visible on any normal display, we transformed them to float by averaging the pixel value of every scan to the maximum pixel value of that scan. As a result, the output images had 32-bit float pixel-type values that could be visualized by standard monitors, and the quality of the photos was good enough for our preliminary analysis. Below are the images before and after being transformed.The histogram thresholding would be used for Isolating the background of the CT lung slices by thresholding the intensity values by the mean value of each CT slices. [22]

2) Data Augmentation

Throughout training our network, we want to incorporate multiple data augmentation techniques because we firmly believe that these approaches can make learning more successful and avoid over-fitting of the network,such as (a) resizing rectangular regions at the middle of the input frames with a randomly chosen scaling factor from 0.7 and 1, and

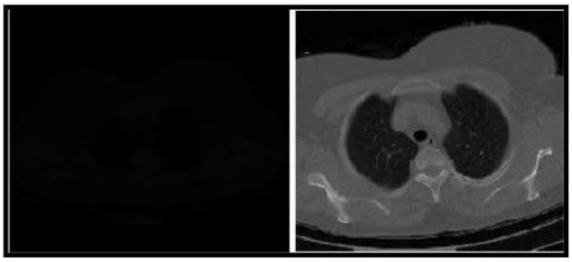

FIGURE 4. left-to-right CT scan before and after transformation

resizing the crops to 256*256 resolution; (b) doing both horizontal and vertical reflection at random, i.e. rotating the images in the left-right direction with a probability of p = 0.5; and (d) Doing a zoom_range of around 0.05 and rotation range of 360. We will also be looking into width and height shift range, for this purpose we will be referring the steps performed by [25].

3) Bounding Box Extraction

We've seen researchers exploiting image augmentation with only 8 initial source images to create production-ready prototypes for production processes. Bounding box augmentation takes this concept and moves a stage farther, for instance, varying an object's light or darkness compared to its context. Or for tasks that frequently record fast moving objects, maybe blur an object relative to its backdrop.For this, we will be exploring libraries like Numpy and OpenCV. By just altering the content of the bounding boxes of an input scan, bounding box level generates new data points. In doing so we will have better control over generating training data that are more important for our environment . We can't claim credit, however, being the first one to suggest Bounding box Augmentation.This concept was first stated by [31] and many google based alumni were associated in this valuable contribution. Researchers demonstrated in this paper that only modifications to the bounding box yielded structural changes, particularly for models that were small datasets.

4) Filtering the CT scans

In this research, since we do not have an expert radiologist to assist us in selecting the right CT scan, we decided to make the patient lung analysis fully automated.Let us presume that we have a deep convolutional neural network that is qualified to identify COVID-19 cases based on the data extracted from the lung. If we evaluate the network on every segment of the CT scan present in a series that belongs to one patient, there are very high chances that the network may malfunction, since the lung is closed at the start and end of each CT scan image sequence, as seen in Fig 5.

Therefore, when training, the network has not seen these cases; it will result in inaccurate detections, and then it does not perform well. We recommend some other technique to eliminate the images inside the lungs that are not noticeable in them in order to get a solution. Using this also decreases computing time, since only certain chosen scans are used by the network. First, for analysis of the pixel values in them, we set a region in the middle of the scans. In all the scans, this area should be at the core of the lung, so that the variations in this area are shown by the open and closed lungs.

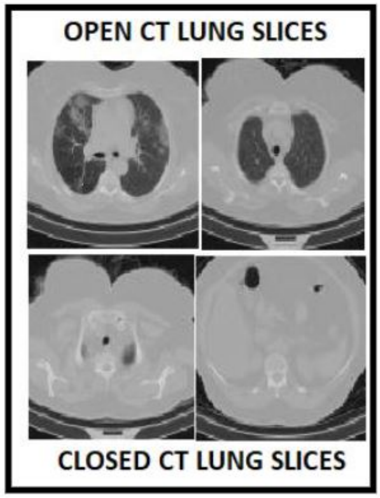

FIGURE 5. top-to-bottom CT slices of open and a closed lung.

Regrettably, the data set scans are not even on one scale, and the position of the lung varied for different patients; So after numerous experiments and assessment, since the images have a resolution of 512*512 pixels, we set the area between 120 and 370 pixels. for the x-axis and the y-axis was set to the range of 240 to 340 pixels. This region shall explain the fact that all items contain details on the center of the lung CT slice.During the next stage, we attempt to quantify the pixels of each CT scan in the indicated area that have a value just under 300, which we label dark pixels, to eliminate those images and pick the rest of them from an image series that corresponds to a patient. We count the number of pixels in a region with a value below 300 for all the images in the series. After that we will divide by 1.5 the variance between the maximum number counted and the minimum number counted. Our threshold is this estimated figure. The scan in the area with less dark pixels than the threshold is the one in which the lung seems to be almost closed, and the image with more dark pixels is the one that is visible inside the lung. We measured this threshold in such a way that the images in a series (a patient's CT scans) are evaluated together so the image size does not vary in one sequence. We discard all those scans that have fewer dark pixels counted than the measured threshold until that is completed. So, the images with more dark pixels than the computed threshold would be chosen for the classification task to be assigned to the network.

C. DEEP CONVOLUTIONAL NEURAL NETWORK FOR CLASSIFICATION

Deep learning models that are made available alongside pre-trained weights are Keras Applications. A pre-trained model is the one on a dataset that has already been trained and includes the weights and biases that reflect the characteristics of whatever dataset it was trained on. Now once we obtain the pre-processed CT scans our objective is to accurately classify the selected CT scan images exported from the CT scan filtering algorithm into normal or COVID-19. For that we want to train our model based on four different deep convolutional networks including VGG-19 ,DenseNet169 ,ResNet-50V2, and InceptionResNetV2.

1) VGG19

VGG19 uses 19 layers, including five convolutional blocks (16 convolutional layers) and fully connected layers of the tree (fc6-8). It is constructed by piling convolutions together but due to a problem called diminishing gradient, the depth of the model is restricted. This challenge makes it impossible to train deep convolution networks. [32] On ImageNet, the model was first trained to identify 1000 types of objects, and then the rest of the models were tested. It loads weights pre-trained on ImageNet by default. For other alternatives, we need to check 'weights'. This model can be built both with 'channels_first' data format (channels, height, width) or 'channels_last' data format (height, width, channels).

2) ResNet50V2

To address the problem of diminishing gradient, the Resnet model was proposed. The principle is to skip the connection and move the residual to the next layer so that it can begin to train the model. CNN models can go deeper and deeper with ResNet models.ResNet-50 is similar to ResNet18 but has different residual block scheme and different number (16) of residual blocks that contain in the network.The ResNet-50 contains 50 layers and ResNet50V2 is an upgraded version of the above and Optionally loads weights pre-trained on ImageNet. [33].

3) InceptionResNetV2

The third network, InceptionResNetV2, is a convolutional neural network that has already been trained on more than a million images of the imageNet dataset.The network is 164 layers deep and can divide images into 1000 clusters. It is conceived based on a combination of the architecture of Inception and the Residual connection. Multiple sized convolutional filters are paired with residual links in the Inception-Resnet block. The use of residual connections not only eliminates the issue of deterioration caused by deep systems, but also improves training time [34].

4) DenseNet169

The last network, DenseNet169, has many advantages: they mitigate the vanishing gradient problem, facilitate the propagation of features, encourage the reuse of features, and greatly reduce the number of parameters. DenseNet-169 was chosen because it is comparatively low in parameters compared to other models while having a depth of 169 layers, and the architecture tackles the vanishing gradient problem. Furthermore, some variations of ResNets have proven that many layers are barely contributing and can be dropped. In fact, the number of parameters of ResNets are big because every layer has its weights to learn. Instead, DenseNets layers are very narrow , and they just add a small set of new feature-maps [35].

VI. DISCUSSION

COVID-19 has caused significant public health and safety issues and has thus become a worldwide problem.Using CT images to screen patients can improve the early detection of COVID-19 and ease the pressure on RT-PCR testing.Also, when it comes to working with deep CNN, we claim that, based on his or her professional experience, an accomplished radiologist will make decisions on the probability of COVID-19; nevertheless, contextual considerations and human expertise could potentially impact those judgments.In conjunction, deep-learning-system based Screening models show more specific and consistent findings by means of digitizing and standardising the details from the lung CT slices. Consequently, they will help doctors make better and precise clinical choices.

To add to that, after studying the existing literature on this delving area, we were able to discover relevant loopholes, and managed to get detailed insights which would be extremely useful for us while going deeper into our approach. We intend to use four different deep convolutional neural networks VGG19, ResNet50V2, InceptionResNetV2 and DenseNet169 on our dataset once all the CT scans are pre-processed and augmented to find the best network for our task.

VII. CONCLUSION

To conclude, in this research, we will be using a deep convolutional neural network for detection of COVID-19 using CT-scan images. We would be training our model on one of the largest publicly available dataset, and provide a detailed experimental study, by looking on model performance in terms of Accuracy sensitivity, specificity, precision-recall curve, ROC curve and confusion matrices. Furthermore, we want to achieve a high accuracy rate when compared to already existing works and try to obtain more features from the dataset not manually but by automating it with end-to-end structure. In addition, for the pre-processing part, we intend to apply one of the methods which we have described in our literature review in order for our network to work optimally.

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A. RESPONSIBILITIES

For this research, our main concern was to find a suitable dataset on which we could work to clearly classify novel COVID CT scans from that of normal patients. After extensive search by both me and Rajesh, we finally decided to go ahead with the COVID-CTset which Rajesh found on kaggle. Once that was done, we contacted the author to get the complete dataset along with the essential csv files and were successful in doing so. Next, we needed to study the data in detail and prepare it in such a way that different deep convolutional neural network models could be applied on it.After our initial research we clearly understood that we would have to invest some time in pre-processing the scans, therefore, we divided the pre-processing steps among ourselves. The first 2 steps of pre-processing that are histogram thresholding and data augmentation are the responsibility of Rajesh and he will be doing extensive research on that as explained before in the report and the rest two steps which are bounding box extraction and filtering the CT scans will be taken care by me. Now once our data gets ready to explore, Rajesh will work on VGG19 and ResNet50V2 and, in the meantime, I will focus all my energies in employing the deep convolutional neural networks InceptionResNetV2 and DenseNet169. We will also be exploring the Feature pyramid network(FPN) that was introduced by [12] for enhancing object detection. FPN might help the network better learning and detecting objects at different scales that exist in a scan.

As far as the project report is concerned Rajesh worked on the Abstract, introduction and the Project Management part whereas I focused on the Literature Review, problem formulation,proposed solution,System overview and Discussion/conclusion part of the report. In the end,I would just say that we are collaborating in a true sense to work on this research and it would not be possible to complete this without getting each other's constant motivation and support.

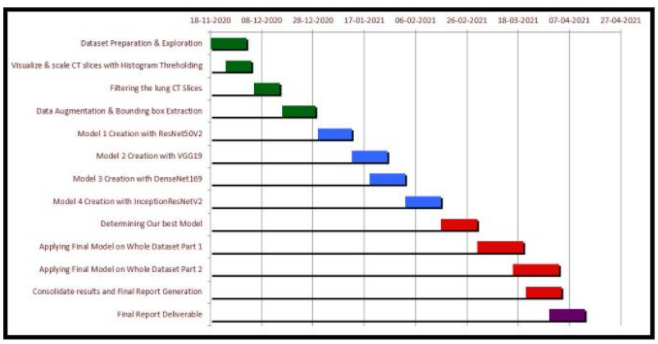
B. TASKS, TIMELINE, SPRINTS

Below we have identified 13 tasks for our project that will be starting from 18/11/2020 until 13/4/2021. Since its quite a long timeline there might be few adjustments made in the sprints but overall our goal will be do complete the research before the tentative End_Date.

Tasks	Start_Date	End_Date	Days
Dataset Preparation & Exploration	18-11-2020	01-12-2020	14
Visualize & scale CT slices with Histogram Threholding	24-11-2020	08-12-2020	10
Filtering the lung CT Slices	05-12-2020	15-12-2020	10
Data Augmentation & Bounding box Extraction	16-12-2020	08-01-2021	13
Model 1 Creation with ResNet50V2	30-12-2020	12-01-2021	13
Model 2 Creation with VGG19	12-01-2021	26-01-2021	14
Model 3 Creation with DenseNet169	19-01-2021	02-02-2021	14
Model 4 Creation with InceptionResNetV2	02-02-2021	16-02-2021	14
Determining Our best Model	16-02-2021	02-03-2021	14
Applying Final Model on Whole Dataset Part 1	02-03-2021	16-03-2021	18
Applying Final Model on Whole Dataset Part 2	16-03-2021	03-04-2021	18
Consolidate results and Final Report Generation	21-03-2021	05-04-2021	14
Final Report Deliverable	30-03-2021	13-04-2021	14

C. GANTT CHART

Based on the above mentioned tasks we created this chart and as it can be observed that some of our tasks are overlapping that means we will be looking into multiple tasks in few sprints.To do so we will be dividing this conjoining tasks among ourselves.



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