Original Article

AUTOMATED DEEP LEARNING-BASED NETWORK FOR DETECTING COVID-19 FROM A LUNG CT SCAN

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Abstract

The COVID-19 disease is a threat to public health around theworld. Early diagnosis and detection will be critical factors in preventing the spread of COVID-19. Computed tomography has a significant role in COVID-19 detection because it gives both fast and best results. Hence it is very significant to develop an accurate and rapid computer-assisted tool for helping clinical experts to identify COVID-19 patients from CT scan images. The project's main objective is to develop an artificial intelligence-assisted tool for predicting the severity of COVID-19 with the help of CT scan images. We introduce a new dataset that contains 47,144 CT scan images from 292 normal persons and 14,346 images from 92 patients with COVID-19 infections. In the first stage, the system runs our proposed image processing algorithm that analyses the view of the lung to discard those CT images inside the lung that are not properly visible. This action helps to reduce the processing time and false detection. Then those chosen images from the CT selection algorithm will be fed to the ResNet50V2 model, so the model becomes able to investigate different resolutions of the image and does not lose the data of small objects. Apart from 152 patients,47 patients have been detected with COVID-19, and 105 patients have been detected as Normal. It shows that the model obtained 97.89% correctness overall and 95.45% along with class with COVID-2019 sensitivity.

Keywords: Artificial Intelligence, CT scan images, Image processing algorithm, ResNet50V2

1. INTRODUCTION

The sort of illness that interferes with lung function is a chest infection. The causes of the lung infection and the affected person's overall health affect how severe the lung infection is. Lung cancer, bronchitis, asthma, chronic obstructive pulmonary disease, and pneumonia are the most prevalent lung infections. The COVID-19 coronavirus illness is well-known. The world is facing a problem, and the number of infected cases was rising rapidly. On December 31, 2019, The United Nations Agency received the first update about COVID-19. The United Nations Agency proclaimed the disruption of COVID-19 an international well-being crisis on February 10, 2020. Over 130 million individuals have been afflicted since March 10th, 2021, and 2 million have perished. A virus called the coronavirus first infected animals and then humans. After meeting animals, the virus was transferred from people to humans. When a person coughs, sneezes, or exhales near others, respiratory droplets can spread the coronavirus to those nearby. This can happen when an infection triggers the respiratory system to release inflammatory substances called cytokines into the blood, which can destroy human organs and tissues.

The new coronavirus is currently causing a severe outbreak, quickly spreading throughout China and subsequently to other nations. The COVID-19 side effects as symptoms begin 2 to 14 days after one becomes ill. The incubation period is this time frame. Results that are positive or exhibit symptoms are kept under medical supervision in isolation wards or quarantine. Fever, a rapid heartbeat, a sore throat, a cough, chest pain, and shortness of breath are further disease-related symptoms.The virus can survive on surfaces for up to 72 hours. Many infected people were found to have pneumonia in both lungs, ranging in severity from moderate to severe. Extreme acute respiratory syndromes and kidney failures were also discovered in the worst infected individuals, leading to death. The primary approach for diagnosing COVID-19 and many other disorders is a reverse transcripts-polymerize chain reaction, one of the numerous techniques for making a firm COVID-19 diagnosis. Recent researchers have developed new and more straightforward methods to identify the disease. Another issue is the inadequate quantity of diagnostic kits in all contaminated locations worldwide. Scientists examine X-rays and CT scans to find COVID-19 illnesses because of the accessibility of envisaging medical technology at the maximum diagnosing hub.

The growth rate has been investigated by deep learning with the examination of Expert system-based COVID classification techniques of COVID- 2019 through which we can discover where structured-based learning plans might give promised outcomes of categorizing COVID-19. As of detailed analysis of the state of the COVID-19 diagnosis field, it can be inferred that CT scans will be the best practical method for the identification of COVID-19. Tomography of computation was much more dependable, quicker, and helpful automation of categorization and examination for COVID-19.

Every hospital has Scanning CT Images, so the CT images could be exercised for the advanced identification of persons affected by COVID-19. In contemporary circumstances, the test outcomes of COVID-2019 proceeding excess of 28 hours in predicting the inflammations in the human body. Hence, that place might have a desperate requirement to see the sickness in the premature stage because no specific drugs are available for COVID- 19. The CT images were considered the systematic system for accommodating circumspection recognition by medical experts. Automation of the identification of the inflammations assists those clinical experts in quicker and better authentic accountability.

1.1 MOTIVATION

In March 2020, Corona Virus be formally proclaimed by the United Nations Agency. SARS-2 was the reason. The highly contagious COVID- 19 virus may have contributed to the development of acute respiratory distress syndrome. Controlling the spread of COVID-19 will depend critically on early diagnosis and detection. In diagnosing COVID-19, driven data approaches will be of tremendous interest. To analyze COVID-19, researchers used deep convolutional neural networks like DenseNet. Since convolutional neural networks include many parameters, deep learning networks need a lot of training data because small datasets are readily overfitted. Due to the difficulty and expense of obtaining medical image data, the datasets will be modest.

The lack of RTT-PCR kits during pandemic conditions causes tests on questionable cases to be delayed, which thus affects disease control and preventative actions. The radiology diagnosis-based setups, which identify the clinical changes in the lungs, will be cost-effective and time-consuming for early diagnosis. In addition, early diagnosis lowers the likelihood of COVID- 19 infection spreading during later therapies by increasing COVID-19 mortality rates. At that place, it seemed to be 10,04,346 established instances and 75,673 recorded deaths through March 31, 2020. COVID-19 clinical presentations vary from severe asymptomatic to less severe to intense illness. Elderly patients, in particular, may experience a higher rate of death when the disease progresses to an extreme stage. Therefore, the strategies that will be effective for saving lives and lowering the mortality rate are early detection and protection of patients due to the risk of higher advancement of future extreme cases of COVID-19. Accordingly, closely observing and appropriate diagnosing helps avoid those circumstances of acute position. As a result, artificial intelligence will greatly assist in COVID-19 detection.

Computed Tomography will provide essential information on COVID-19, particularly for COVID patients with lower to acute inflammations. Deep learning methods, a tool with automation, will be used to segment the semantics of regions in the lungs that are affected, which is also significant for recognising the prediction and severity of the disease. Accurate and rapid screening of COVID-19 is feasible by regulating. Computed tomography imaging mainly aims to differentiate the CT scan images of non-COVID-19 and COVID-19 CT by handling deep learning methods. The clinical experts will use automation of prediction of COVID-2019 from the images of CT scans will be the fast and best method for screening COVID-19. In the Medical field, CNN will be the best deep learning algorithm by filtering images of the CT scan to the particular exemplary to get desired output. With the method for classifying the images of CT scans of patients affected by COVID-19, Information may be derived by detecting COVID-19 patients from the images of CT scans, which helps the clinical experts to get the critical data accurately and quickly.

2. RELATED WORK

The primary objective of the research is to apply supervised learning models to identify COVID-19 utilizing lung computed tomography scan images. The network of super-residual neuronal density has improved and become habituated in combination with the effective lung CT scan. Benchmark data sets for COV2-SARS and COV-CT scans were created through experiments. The created CT scan uses pre-trained networks, such as DenseNet, ResNet50, VGG, XceptionNet, MobileNet, and InceptionV3, to label COVID-19 as favourable or unfavourable. This study investigates transfer learning models using the benchmark data sets COVID- CT and COV2-SARS. A quarter of the data set was used for testing, while the remaining seventy-five% was used for training. The data set of COVID-19 CT images includes 342 rare COVID-2019 patients along with 237 COVID-2019 CT images from 109 individuals. That dataset of 1131 COV2-SARS-infected individuals' 2335 COV2-SARS CT scan images. The Non-COVID-19 individuals listed the CT scans for 985 of the 2482 total images in COV2-SARS are positive for COVID-19. True-positive patients are those whose COVID-19 status has been altered; false-positive patients are those whose COVID-19 status has been wrongly identified as corona positive even though they are healthy. The COVID-19 negative subjects that have been appropriately identified as unfavourable are referred to as True Negative. The term "False Negative" has been used to describe COVID-19 positive patients who were mistakenly categorised as unfavourable. The Mobile Net model produced 82.21%, and 78% precision on the data sets Scans of Covid CT along with CT Scans of COV2 SAARS, respectively [1].

Many DL and ML algorithms are trained to address this supervised learning issue. The unsupervised learning technique is discovered to have a high potential measure at the same time. A thorough experimental validation is carried out to ensure the UDL-VAE approach performs proficiently to facilitate the method's efficient detection performance. With higher accuracy of 0.834 and 0.812 on the binary and multiple classes, the acquired experimental data demonstrated the effective outcomes of the UDL-VAE model. Future learning rate schedulers can be developed for hyperparameter sets via meta-heuristic optimisation [2].

Different datasets frequently offer images of differing quality, possibly from various CT machine types, reflecting the environments of the nations and places from which they originate. In this method, a voting system is used to group the images from a particular patient. The two most comprehensive COVID 2019 Computed tomography analysis information sets are segregated based on patients to test. For example, cross-data set analysis is also offered to assess models' resilience in a more real-world situation where data is gathered from different distributions. In the best evaluation scenario, the accuracy rate drops from 81.54% to 47.09%, showing that deep learning techniques have the generalisation power to be used as a clinical alternative for COVID-19 identification in CT images.

Additionally, more comprehensive data sets are needed to calculate the procedures in a practical framework. The SARS-CoV-2 CT-scan data collection includes 1147 CT scans of 55 SARS-CoV-2 infected individuals, including 28 men and 32 females, out of 1356 CT scans of 115 patients. Additionally, it contains 1125 CT scan images of 60 SARS-CoV-2-negative patients, including 27 men and 28 women. However, these images depict different pulmonary illnesses. 52 patients contributed a total of 352 images. To identify COVID-19 patterns in CT scans, the model Efficient Covid Net, a casting ballots approach, and a bridge set examination are recommended. The proposed voting-based approach promotes the identification of false positives and false negatives, enhancing accuracy. These results demonstrated that methodological development is necessary before COVID-19 identification in CT imaging can be considered a clinical substitute. Additionally, more comprehensive data sets are needed to calculate the procedures in a practical framework. [3]

This work uses Computed Tomography images to develop DLMMF, the Deep Learning Multi-Modal Fusion technique, for COVID- 2019 detection. Weiner Filtering (WF)-based pre-processing, feature extraction, and classification form the basis of the hypothesised DLMMF approach. For experimental validation of this DLMMF model, 680 CT scans from the open-source COVID-CT data collection are employed. With a high sensitivity of 91.10%, specificity of 81.62%, correctness at 79.73%, and an F score of 80.65%, the performance passed the test with flying colours. [4]

Convolutional neural networks (CNNs), one type of deep learning network, need a lot of training data. In their research, they employ two separate data sets. The first is the data set, which was compiled from several available sources and includes 1518 COVID-19 and 1548 normal CT scans. The second data set is an internal data set with 3189 CT images that were utilised to train two distinct trials (with and without GAN). On this limited data set, the improvement in the generalisation capacity of CNN models was tested using synthetic data augmentation techniques, GAN. Both tests were run on a separate data set. For categorisation, this study used two classifications (COVID-19 and normal). Synthetic data augmentation with GAN broadens the data pool, increasing variability. An approach for increasing the accuracy of COVID-19 detection with a small data set was described, which involved creating synthetic images of CT scans. [5]

Using constant wavelet transform, CT scan images are divided into three levels, and COVID-2019 is then detected from these stages using transfer learning. To increase detection accuracy, a three-phase detection model has been developed. Initially, the images acquired are resized to meet the specifications. Phase 1 involves data augmentation in deconstructing Computed tomography layers using a stationary Fourier, Phase 2 involves the identification of COVID-19 using an exemplary pre-trained CNN, and Phase 3 involves pinpointing irregularities in Tomography images. This paper presents a three-phase method for separating COVID-19 and hardly COVID- 2019-class lung CT scan slices. This methodology would undoubtedly aid in finding COVID-19 signatures more quickly and precisely from lung CT scan slices. [6]

The objective was to create a classifier combining quantitative computed tomography and early clinical data to predict the overall severity of COVID-19 sickness. The ideal clinical-radiological traits were identified using minimum achievable contraction, shortlisting observer investigation of logistic regression, and a prognostic nanogram prototype built using five-fold merge estimation. Between January 25 and February 5, 2020, 189 individuals with COVID-19 were completely registered in their centres. Laboratory and clinical data were examined. For all patients, the pneumonia severity index (PSI) was determined. The seriousness of COVID-19 was reliably predicted by the PSI and CT parameters, and indeed the Deep learning-based quantification CT approach was shown to be much more systematic. [7]

CT images from the chest of 98 persons were additionally diagnosed with COVID-19 from hospitals in two Chinese provinces, 100 patients infected with bacteria pneumonia and 75 healthy persons were gathered for comparison and modelling. The patients were chosen only based on positive nucleic acid readings and high-resolution computed tomography scans of the chest with no missing images or significant artefacts. Furthermore, their model will be able to extract aspects of the major lesion, namely the GGO, namely ground-glass opacity, which will aid in the diagnosis by medical specialists. [8]

The objective of this work would have been to develop an Automation methodology to forecast disease severity and further quantify the probability of acquiring severity in COVID-2019 patients using computed tomography (CT) images. A total of 301 patients from 459 patients are added to the original final analysis. They received and reviewed all included patients' acute digitized health information, radiological reports, and staffing documents. the model achieved Coding sequences for 0.811 and 0.786 and accuracies of 80.59% and 74.68%, correspondingly. [9]

A layered array conceptual and a clustering method based on deep learning are used in the study to start large-scale learning for COVID-19 categorization. The CT data collection has 7546 images, whereas the CXR data set contains 8462 images. Using the split method of scipy learn, these data were arbitrarily divided between train and test branches. The results of the approach revealed that the best performance model had been misclassified for the samples of COVID-19 and Non-COVID-19 for both the CT and X-ray data sets. [10]

A small number of prospective consecutive patients (8) were recruited at Wuhan University's Renmin Hospital to compare radiologists' productivity against 2019-CoV pneumonia to that of the model generated. To create the model and detect COVID-19 pneumonia, 44,134 CT scan images from 48 COVID-19 pneumonia patients and 49 control patients from the same hospital were gathered. An external data set was obtained from 97 patients at Qianjiang Central Hospital in China to determine the system's robustness (11,543 from 48 COVID-19 patients and 16,326 images from 44 normal control patients). The radiologists' reading time was reduced by 57% under the direction of that model. [11]

Convolutional neural networks were used in the COVID-19 training and testing. The performance of several pre-trained models on CT image testing was examined, and it was discovered that bigger, out-of-field data sets improved the model's testing power. Those significant CT images of the visible qualities that the model employed were also evaluated and built so that they might aid clinical specialists in manual screening. [12]

The article aims to see how effectively deep learning models trained on chest CT scans can diagnose COVID-19-infected people quickly and automatically. Extensive studies were conducted on two CT image data sets, the COVID-19-CT and the SARS-CoV-2 CT scan. Compared to prior investigations, the results showed that these models performed better.[13]

To construct a composite poor attribute supervised learning algorithm, the patient's illness results of clinical reports were combined with hand-labelled bronchial halftones from COVID-19 pneumonia. A U-Net was initially trained using semantic labels to segregate the infected areas. This deep learning technique for illness and aggregation discrimination using Computed tomography was presented and is based on hybrid weak labels.[14]

Yago et al. produced the open-source data set known as COVID-CT. These data sets contain 342 non-COVID-19 CT scans and 258 COVID-19 CT images from 119 patients. An AI-based assessment framework that can identify COVID-19 from CT images was developed using the data collection. A total of 69 images were used to evaluate the pre-trained PLG-21 network, and the precision among COVID-2019-infected and never-inflammatory CT scans was 79%. A PLG-21 pre-training network was used for transfer learning, producing results with an accuracy of 78.89%.[15]

The study investigates the ability of transfer learning-based models to autonomously detect illnesses like COVID-19, which can help the medical community, especially during outbreaks. The results acquired on the various data sets illustrate the supremacy and dependability of the work begun. For radiological data, a pre-processing approach was also proposed. The study also correlates classification models, and pre-trained CNN architectures launched against the approach. [16]

3. MATERIALS AND METHODS

Infections found on lung CT in most patients who developed COVID-19 symptoms at least four days later showed the presence of a new coronavirus. Medical imaging could be used for preliminary COVID-19 diagnosis even though it is not recommended for final diagnosis due to the shortcomings of other methods. Despite having negative RT-PCR test results, some people with acute COVID-2019 indications had recent coronavirus infections. The results of both tests were then repeated a few weeks later, and their result supported the interpretive conclusions of the CT scan. Imaging can be utilised as a primary diagnostic strategy to help contain a suspected person and stop the infection from spreading to those in the preliminary phases of infection, even though it is not recommended for a firm diagnosis of COVID-19.

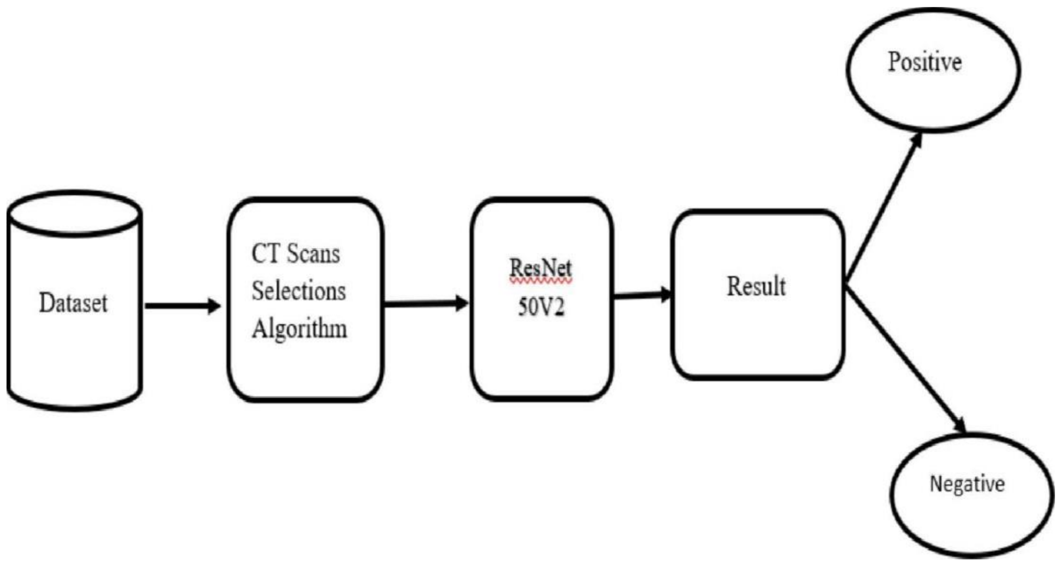
The ability of machine learning to detect viral infections using medical images. Deep learning is one of the most effective approaches to machine vision [13]. Numerous supervised learning uses exist in medicine, agriculture, business, and other fields.[4]. This has resulted in the elimination of human mistakes and the creation of automation in a variety of disciplines. Combining machine learning and transfer learning is one of the most efficient methods for locating malignancies and pathogens brought on by human illnesses. This method is applied in many medical imaging applications, such as the segmentation of skin and brain lesions, the treatment of malignant tumours and lung lumps, and the identification and cutting-edge marrow attenuation in X-ray images. It has been found that machine vision and deep learning were far more competent than radiologists at spotting infections. For instance, in [15], the approach used has an accuracy of about 90%, compared to the specialists' assessment reliability of about 70%.

The effectiveness of machine vision and deep learning in diagnostic imaging, particularly CT scans and X-ray images, have been used to identify COVID-19.[4] Convolutional layers have allowed it to develop models like EfficientNet, which have generated reliable results. The idea of residual layers was performed by ResNet models [3], which helped models lessen the effects of data extraction while feeding through layers. Convolutional architecture called Xecption has distinct layers. A complex CNN model and a flow trap layer of convolution were deployed one after the other to construct these layers. Convolutional separable layers promoted the idea that the product of a convolution doesn't have to be applied to every input channel and can instead be divided by temporal and spatial operations.

3.1. SYSTEM DESCRIPTION

Figure 1 shows the workflow of the proposed approach. In this work,there are two modules. The firstis a CT selection algorithm, which removes unwanted images from the dataset, and the second is a deep learning model, ResNet50V2, where the selected images are used for training and validation. The export data (images) of the pulmonary high-resolution and computed tomography scan devices are used in this methodology to introduce an entirely computerised method for finding COVID-19 cases. The process of analysing all CT images of an individual to detect whether that individual is affected with COVID-2019 without the need for any medical professionals for system configuration

Figure 1 Workflow for the proposed approach.



The COVID CT collection has been introduced, consisting of 47,144 typical images from 292 healthy individuals and 14,346 COVID-19 images from 92 cases. During the first part of our research, an image processing method was used to handpick CT scan images inside the lung and those that showed probable inflammations. As a result, the procedure runs faster since the network does not have to check every image. In addition, the detection accuracywasincreased by feeding the model to just relevant images. In the end, our model was estimated using a different technique, and the following step analyses the automation of the complete diagnosing system, which was tried on a maximum of 292 patients and 47,144 images

3.2. CT SELECTION ALGORITHM

The high-resolution computed tomography scan of the lung collects progressively several images (we'll call it a series of video frames) from the patient's chest to determine whether they are infected with COVID-19. The point of infection may appear in some of the images but not in others throughout the sequence of consecutive frames. The medical specialists reviewed the sequence of images and if they detected an infection in one of the patients who had been diagnosed to be infected. To address this, we divided the data set into three categories: infection-visible, no-infection, and closed lung. Even though this avoids the problem by splitting the data set into three groups, it has other consequences also, such as spending a significant amount of time creating new labels and changing the model's evaluation method.

Numerous ways of selecting an image from each patient's lung high-resolution computed tomography images and then utilising them for training and validation had been used previously. Assume we have a neural network trained to classify COVID-19 cases based on their existence and the lung's visibility inside them. When such models were tested on each image in a patient-specific sequence of images, they may fail. Because each CT scan image set began and ended with the lung closed. As a result, the model may have missed certain samples during training, resulting in erroneous identification and inferior performance. The model should have already seen all the patient's CT scan images, which prolongs processing time. Regardless, we launched a few different procedures to reject the images inside the lungs and would not be seen inside them. By doing so, the processing time will be reduced since, in a prior way, the networks should have seen all the images. However, now only a subset of the images will be viewed.

Figure 2. This figure presents some of the first, middle, and final images of a patient's CT scan sequence.

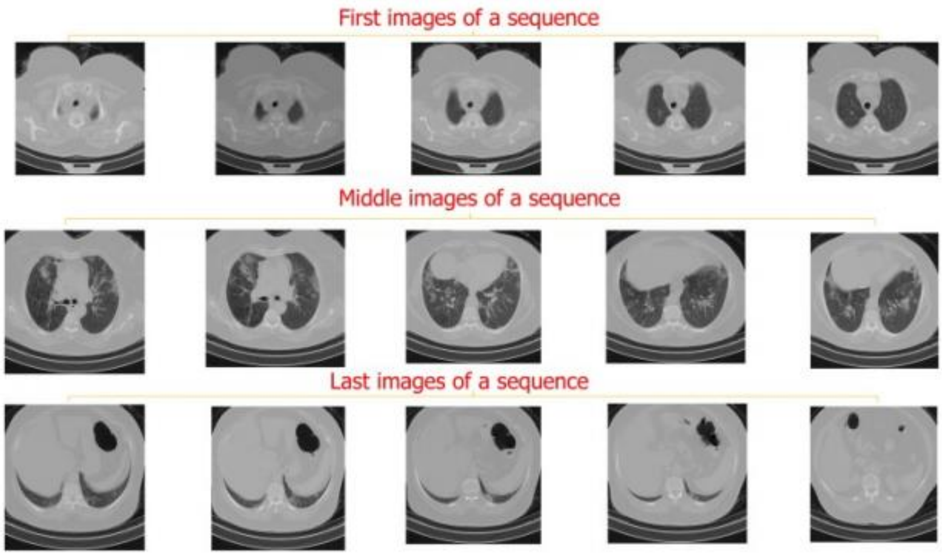
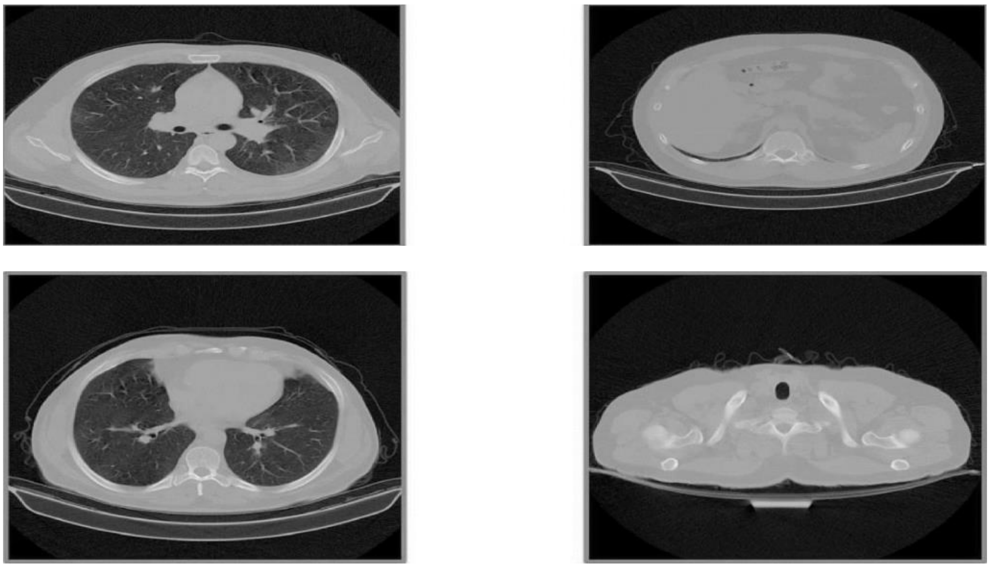


Figure 2 presents some of a patient's CT scan sequence's first, middle, and final images. The central region of the patient's lung in the open lung image exhibits lower pixel values, which is themain difference between it and the closed lung image (refer Figure 3). We first created a zone in the centre of the CT images to investigate the pixel values in the CT images. Those regions should be near the middle of the lung for all images, so the variations in those regions will be seen in both the open and closed lungs.

Unfortunately, those data set images were not on a single scale, and the location of the lungs varied across different patients. Thus, after studying and exploring, we lay down the region in the area on the x-axis of one hundred twenty to three hundred and seventy pixels and the y-axis of two hundred and forty to three hundred and forty pixels, such that the images have 512*512 resolution of the pixels ([120,240] to [370,340]). Those regions must be compelling, with the information about the lung in the centre of all images.

Figure 3 Images of Open lung and Closed lung

Open-lung mode Closed-lung mode



Algorithm 1: CT Selection Algorithm

Patient A CT scans

Set the Analysis Region(AR)-[120:370,240:340]

Count the dark pixels(dp)(pixels value < 300) in AR

Find images with max dark pixels(mx) and min dark pixels(mm)

Set tr=(mx-mm)/1.5

If(dp>tr) :

Select the CT Scan image for the next stage of analysis

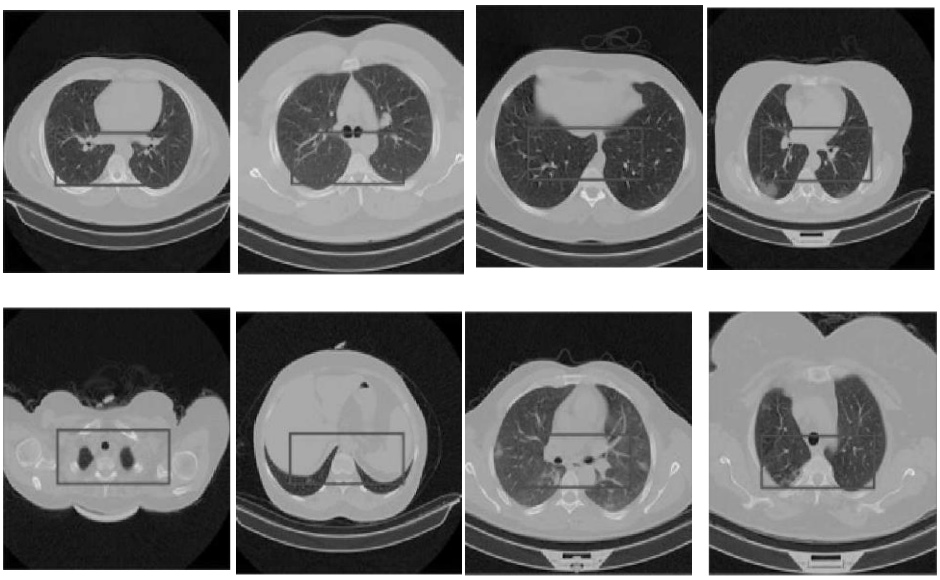
Else :

Discard that CT scan image

Our data collection of images consisted of sixteen-bit grayscale images. The highest value of the pixel in all the images is nearly equal to five thousand. The images with the highest values have a significant mismatch. we want to compute the pixel of each image in the suggested area with a value of less than three hundred, referring to them as dark pixels, at the next phase for discarding a few of the patient's CT scan images and handpicking the remaining for additional inspection. Those images were picked for our study. For each image series, we count the number of black pixels or pixels in the provided region with a frequency of just under 300 (refer Algorithm 1). The difference between the maximum and minimum numbers counted would then be divided by 1.5. The result of the calculation is our threshold. The threshold, for instance, would be two thousand in a CT scan image series where one image had many pixels intensities equivalent to three thousand and other images had a limited handful of dark pixels equal to thirty pixels. Images with fewer black pixels than the threshold in the region showed that the lung was virtually closed. Still, images with more pixel intensities than the threshold were shown inside the lung. We compute those thresholds so that those sequences of images (patient's CT scan) are studied together since the scaling of images does not change in one sequence. Until now, it may change across various CT scans of different patients. Following that, images with fewer detected pixel intensities than the computed threshold were removed.

As a result, images with far more black pixels than the computed threshold would be identified and sent to the model for classification of the image sequence of one patient, one indicating where it may be detected. The other images the system rejects would be selected. The medical facility employs a SOMOTON scope model and Synego VC30 CT simple IQ version of the software for comprehending and visualising the patients' lung high-resolution computed tomography images. The image file output was 512*512 image quality, 16-bit grayscale digital imaging, and communications in medicine format. Though the patient's data was available in medical files via digital imaging and communications, we converted them to TIFF format, including similar 16-bit grayscale data but not the patient’s private data. As a result, those formats were more easily compatible with standard programming libraries. The Digital Imaging and Communications in Medicine files were converted to 8-bit information, which may result in less data loss, especially when certain illnesses persist in the image, which is difficult to anticipate even for medical specialists. As a result, the initial data of the 16-bit image of CT scans may include knowledge that human eyes cannot distinguish, but systems can detect it during processing. The pixel values of images range from zero to five thousand, and the maximum pixel values were distinct. As a result, scaling them by a suitable amount or resizing each image depending on its maximum pixel value may create difficulties and impair the model's accuracy (refer Figure4). As an outcome, all COVID-CT image collection was in TIFF format, containing 16-bit grayscale images.

Figure 4 The selected region in different images with different scales



We split the training, testing, and validation data sets to report more accurate and precise results. Each fold received approximately 20% of COVID-19 patients for testing. The remaining data were used for training, and a subset of the testing data was used to authenticate the system after each session during training. Because there were more normal images and patients left than the infected patients, we chose many normal images that were identical to the COVID-19 images to balance the data set. we included a few images of COVID-19 patients with apparent infections in each series of images for testing and training. As a result, fewer COVID-19 patient images will be left than normal patient images. We picked enough large number of normal patients such that the number of standard images develops in direct proportion to the amount of COVID-19 category images. Those numbers were adequate for the classification system to learn the images swiftly, and the outcomes were outstanding. Although many images of normal patients remained, we selected a large amount of normal data for validation to demonstrate the true achievement of the systems to be trained.

4. RESULTS FOR THE CT SELECTION ALGORITHM

The image with fewer dark pixels in the region than the threshold is the image that the lung is almost closed in that, and the image with more dark pixels than the threshold is the one that inside the lung is visible in it. We calculated the threshold in this manner that the images in a sequence (CT scans of a patient) be analysed together because, in one sequence, the imaging scale does not differ. Still, it may vary between different CT scans (of different patients). After that, we discard those images that have fewer counted dark pixels than the calculated threshold. So, the images with more dark pixels than the computed threshold will be selected to be given to the model for classification. The image sequence of one patient is depicted, where it can be observed, which of the images the algorithm discards, and which will be selected.

The highlighted images are the ones that the algorithm discards. It is observable that those images that clearly show inside the lung are selected to be classified at the next stage.

Table 1 Results of CT Selection Algorithm

	Total Number of Patients	Total Number of Patient Images	Rejected Images	Selected Images
Number	152	48,260	41,698	6562

The CT Selection Algorithm was done for 152 patients, and the total number of patient images was 48,260. The Rejected images in the CT Selection Algorithm were 41,698, and the selected images for the next stage of classification were 6562 (refer Table 1).We have also used Morphological operations here to enhance the clarity of an image. Morphological Operations are a broad set of image processing operations that process digital images based on their shapes. In a morphological operation, each image pixel corresponds to the value of other pixels in its neighbourhood. The objective of using morphological operations is to remove the imperfections in the structure of an image. Most of the operations used here combine two processes, dilation and erosion. The operation uses a small matrix structure called a structuring element.

5. DISCUSSION

In our investigation, ResNet50V2 were employed early in our tasks to categorise the selected image as normal or COVID-19. We used the Keras library on the Tensorflow backend for developing and running the deep networks. We introduced ResNet50V2 to execute the classification. Though we investigate image classification, to accomplish so, the model should have learned about the point of infection and categorised based on the images existing in it.

We divided the data collection into two parts. The first section was the unprocessed data for each subject. The second portion discusses data testing, data training, and data authentication. We made use of these data to train and evaluate trained models. We separated the data set into five layers for training, verification, and evaluation to describe more precise and authentic results. Although this was the case, only about 20% of COVID-19 patients were assigned to each fold for testing. The remaining were considered for training, and after each epoch, a subset of the training data was used to validate the model. We chose approximately the same number of images as COVID-19 images to remain balanced within the data set, even though the number of normal images and normal patients was higher than the number of infected patients. As a result, more normal images were left than the training images that needed to be analysed for testing in the model (refer to Figure 5).

Figure 5. Model Evaluation in ResNet50V2

```
models/ResNet50V2-FPN-foldl-03- 0.7800.hdf5 tp: 0 fp: 0
models/ResNet50V2-FPN-foldl-10- 0.8498.hdf5 tp: 0 fp: 0
models/ResNet50V2-FPN-foldl-01- 0.7599.hdf5 tp: 0 fp: 0
models/ResNet50V2-FPN-foldl-05- 0.8155.hdf5 tp: 0 fp: 0
models/ResNet50V2-FPN-foldl-09- 0.8344.hdf5 tp: 0 fp: 0
models/ResNet50V2-FPN-foldl-06- 0.8238.hdf5 tp: O fp: 0
```

We selected an expected number of normal patients to ensure that most regular images equally captured the number in the COVID-19 category. These numbers were enough for the network to learn how to recognise images correctly, and the investigation results were highly positive. While we still had plenty of normal images, we set aside a suitable amount of data for evaluation to understand better how the trained model functions.

Figure 6. Implementation of COVID Training and Validation in ResNet50V2

```
Downloading data from 32 https://storage.googleapis.com/tensorflow/keras-applications/resnet/
resnet50v2_weights_tf_dim_ordering_tf_kernels_notop.h5 94674944/94668760
[==============================] - 0s 0us/step 94683136/94668760 [==============================]
- 0s 0us/step WARNING:tensorflow:Skipping loading weights for layer #2 (named convl_conv) due to mismatch in
shape for weight convl_conv/kernel:0. Weight expects shape (7, 7, 1, 64). Received saved
/usr/local/lib/python3.7/dist-packages/keras/optimizer_v2/adam.py:105: UserWarning: The 'lr' argument is
deprecated, use * learning rate' instead. super(Adam, self). init_ (name, **kwargs) /usr/local/ lib/python3.7/dist-
packages/ipykernel_launcher.py:75: UserWaming: "Model.fit generato Epoch 1/20 348/348
[==============================] - 291S 770ms/step - loss: 0.3070 - accuracy: 0.8717 - va Epoch 2/20
348/348 [========================= Epoch 3/20 348/348 [========================= Epoch 4/20
348/348 [========================= Epoch 5/20 348/348 [========================= Epoch 6/20
348/348 [========================= Epoch 7/20 348/348 [========================= Epoch 8/20
348/348 [========================= is deprecated and will be removed in a future version. Please use
"Model.fit", whic 1.2118 - val_accuracy: 0.7061 1.0547 - val_accuracy: 0.7883 1.0789 - val_accuracy: 0.7475 0.8530 -
val_accuracy: 0.8522 1.3278 - valaccuracy: 0.8498 0.8417 - val_accuracy: 0.8380 1.9336 - val_accuracy: 0.7156
1.7662 - val_accuracy: 0.6884 Figure 4.2 Implementation of COVID Training and Validation in ResNet50V2
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:75: UserWaming: 'Model.fit generator' is deprecated and
will be removed in a future version. Please use "Model.fit', which Epoch 1/20 348/348
[==============================] - 291s 770ms/step - loss: 0.3070 - accuracy: 0.8717 - val_loss: 1.2118 -
val_accuracy: 0.7061 Epoch 2/20 348/348 [==============================] - 259s 745ms/step - loss: 0.1128
- accuracy: 0.9589 - val_loss: 1.0547 - val_accuracy: 0.7883 Epoch 3/20 348/348
[==============================] - 258s 742ms/step - loss: 0.0523 - accuracy: 0.9832 - val_loss: 1.0789 -
val_accuracy: 0.7475 Epoch 4/20 348/348 [==============================] - 259s 744ms/step - loss: 0.0320
- accuracy: 0.9906 - val_loss: 0.8530 - val_accuracy: 0.8522 Epoch 5/20 348/348
[==============================] - 258s 741ms/step - loss: 0.0198 - accuracy: 0.9940 - val_loss: 1.3278 -
val_accuracy: 0.8498 Epoch 6/20 348/348 [==============================] - 258s 741ms/step - loss: 0.0302
- accuracy: 0.9895 - val_loss: 0.8417 - val_accuracy: 0.8380 Epoch 7/20 348/348
[==============================] - 258s 741ms/step - loss: 0.0264 - accuracy: 0.9918 - val_loss: 1.9336 -
val_accuracy: 0.7156 Epoch 8/20 348/348 [==============================] - 258s 741ms/step - loss: 0.0240
- accuracy: 0.9910 - val_loss: 1.7662 - val_accuracy: 0.6884 Epoch 9/20 348/348
[==============================] - 258s 741ms/step - loss: 0.0329 - accuracy: 0.9887 - val_loss: 0.9795 -
val_accuracy: 0.8072 Epoch 10/20 348/348 [==============================] - 258s 741ms/step - loss:
0.0112 - accuracy: 0.9961 - val_loss: 1.2550 - val_accuracy: 0.8415 Epoch 11/20 348/348
[==============================] - 258S 741ms/step - loss: 0.0064 - accuracy: 0.9982 - val_loss: 1.6723 -
val_accuracy: 0.7575 Epoch 12/20 348/348 [==============================] - 258s 742ms/step - loss:
0.0010 - accuracy: 0.9998 - val_loss: 1.7350 - val_accuracy: 0.8297 Epoch 13/20 348/348
[==============================] - 258s 741ms/step - loss: 6.7993e-05 - accuracy: 1.0000 - val_loss: 1.8167
- val_accuracy: 0.8255 Epoch 14/20 348/348 [==============================] - 258s 741ms/step - loss:
5.0730e-05 - accuracy: 1.0000 - val_loss: 1.8537 - val_accuracy: 0.8267 Epoch 15/20 348/348
[==============================] - 258s 741ms/step - loss: 1.8415e-05 - accuracy: 1.0000 - val_loss: 1.9080
- val_accuracy: 0.8267 Epoch 16/20 348/348 [==============================] - 258s 741ms/step - loss:
1.9587e-05 - accuracy: 1.0000 - val_loss: 1.8610 - val_accuracy: 0.8321
```

Figure 7. Validated Image Filenames belonging to classes

```
Found 4871 validated image filenames belonging to 2 classes.
Found 1691 validated image filenames belonging to 2 classes.
Found 2190 validated image filenames belonging to 2 classes.
```

Our data set was created to be trained using Resnet50V2 until 20 epochs (refer Figure 5 & 6). To train the networks and speed up network convergence, we used transfer learning with pre-trained weights from

ImageNet.We choose the Nadam optimiser and the Categorical Cross-entropy loss function for training. We also used methodologies like data augmentation to structure learning and stop the network from overfitting. To preserve the information on any potential minor illnesses seen in the images, we did not use image scaling for either the training or the testing example.

Many of these data, such as X-ray images, are not like CT scan data, which may be calculated by studying a single image. CT scans are like films in that they are sequential sequences of images; therefore, the technique or clinical specialists should review several images in the series for medical diagnosis. For an automatic diagnostic system based on the conditions, the researchers should estimate their system differently than the classification of single images. If the estimated automated technique wished to cross-check if a person's illness is COVID-19, it would use each patient's CT scan images as input. Then it uses the estimated scan of CT to choose a method to select the scans of CT in which the lung is visible within those images. That set of images is made to sustain the neural network, which is deep enough to be classified as normal or COVID-19.

Figure 8. Output of COVID-19 Testing using ResNet50V2

File Name Class
Patient 100 COVID
Patient 101 COVID
Patient 103 COVID
Patient 115 COVID
Patient 117 COVID
Patient 120 COVID
Patient 193 NORMAL
Patient 270 NORMAL
Patient 405 NORMAL
Patient 406 NORMAL
Patient 407 NORMAL
Patient 408 NORMAL

The standard for determining a patient's status should be established. For each patient, even if the threshold for the number of scans of CT images to be characterised as stating COVID-19 is exceeded, that person would be regarded as infected; otherwise, his position would return to normal. The threshold value depends on how accurate the model is. Such criteria may be adjusted to zero in models with trained networks that have great accuracy, suggesting that the patient is affected by COVID-19 unless, at minimum, one Computed tomography image of such a patient is predicted (refer Figure 8). Apart from 152 patients,47 patients have been detected with COVID-19, and 105 patients have been detected as Normal. The average of five-fold shows that the model obtained 97.89% correctness overall and 95.45% along with class with COVID-2019 sensitivity.

6. CONCLUSION

We used a data set with 47,144 CT scan images from 292 healthy people and 14,346 CT images from 92 persons affected by COVID-19 infections. In the initial phase, the system is made to run our recommended image processing algorithm that examines the view of the lung to select those CT scan images inside the lung that will not be accurately observable in them. This can improve accuracy in many classification problems, especially for images containing important objects on small scales. These steps assist in reducing filtering interval and erroneous detection. Though COVID-19 infections were found on various scales, the majority of which were tiny, the use of the method significantly improved the classification's performance. Apart from 152 patients,47 patients have been detected with COVID-19, and 105 patients have been detected as Normal. The average of five-fold shows that the model obtained 97.89% correctness overall and 95.45% along with class with COVID-2019 sensitivity. According to the study, the model locates infection spots extremely well, while

ResNet50V2 regulates any identical points like infections and correctly classifies CT images as COVID-19 or Normal.

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