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Efficient Detection of Corona Virus (COVID-19) In Chest CT scans Using Deep Learning

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ABSTRACT

In recent month, coronavirus disease 2019 (COVID-19) has infected millions of people worldwide. The Coronavirus disease (COVID-19) is an infectious disease that primarily affects lungs. This virus has spread in almost every continents. Countries are racing to slow down the spread by testing and treating patients. Detecting COVID19 is a significant task for medical professionals today because of its rapid spread. To overcome this problem ,medical professionals have used various techniques and methods to detect to inhibit the proliferation of COVID19.CT(Computed Tomography) scan is currently the best method for detecting COVID19. This diagnostic method is very accurate because it can see organs in three dimension .However , this method requires a radiologist to detect the disease and requires a long time , which means it will cut valuable time for medical practitioners if a patient is sick. Therefore it is necessary to implement a system to detect the COVID19 virus automatically as an alternative quickly. This study intends to help medical practitioners to detect computer tomography (CT) scans of lungs infected with COVID19. Our system helps to find COVID affected CT scans using image processing and deep learning techniques. Our system helps to reduce the number of medical personnel needed for disease detection to minimum. If our system is developed in such a way that it can detect any time of diseases if is trained in such a way.

I. INTRODUCTION

A. Background

Coronavirus Disease 2019(COVID 19) is ahighly contagious disease that spreads from one person to another with appearance of respiratory distress. It has been spread all over the world since December 2019 and so far ,it more than millions of people. The clinical tests like reverse transcription –polymerase chain reaction(RT-PCR) are usually used for classifying the suspected patients but medical imaging techniques such as computed tomography (CT) has also been used to detect and evaluate COVID-19. The chest CT-based COVID19 classification of the suspected patients requires radiologists and considerable amounts of their times as the number of COVID19 suspects increases at a rapid rate. Moreover it hjas been found that the COVID-19 infected patients show some patterns on chest CT images that are not easily detectable by the human eye.

Therefore ,an automatic detection tool is much needed to assist in screening COVID-19 pneumonia using chest CT imaging [3,4].Like many other methodological innovations ,image processing has been applied to the timely , rapid ,and effective diagnosis of COVID-19 using chest CT images.AI-Driven tools may provide automated and fast approaches for the detection and classification of COVID -19 on chest CT .

In this study, we developed deep learning based Convolutional Neural Network (CNN) model to classify COVID-19 cases from healthy cases .we collected 10979 chest CT images of 131 COVID-19 positive patients , with the infections masks segmented by a radiologist , and 150 healthy subjects . for network training 1936 CT slices from healthy subjects, with slice locations similar to slices of the COVID-19 positive group were used, to eliminate non –infection differences between the groups and make the model more generalized , reliable, and focused on the infected regions .The main processes of our system can be divided to two parts- Training and Detection. Training is used to teach the system to find covid affected lungs from C.T images. For this we have to give the system images of both covid affected and healthy lung images.Wecant directly train the system with Lung C.T images, pre-processing has to be done on them so that we can extract the covid affected area of the lung and train.The preprocessing stage consists of many processes such as slicing, binarization, edge detection, classification, Histogtram of orientied gradients(H.O.G) generation etc. After preprocessing the system is trained with the resultant image. Detection phase is mainly aimed to find whether the lung image provided has covid or not. For classification of the test data we have to do some preprocessing steps and after that we compare the image with the images that we have trained earlier. If there is any similarity with the trained images we will confirm that lung has covid or not.

B. Realted works

Recently, several deep learning methods have been applied on chest x-ray images and CT scans for COVID-19 diagnosis as well as segmentation of lung infections.In a scientists constructed a support vector machine(SVM) model for the classification of patients with COVID-19 and other type of pneumonia using CT chest images this was done by extracting textual and histogram features of the infection and obtaining a radionics features vector from each sample. The method achieved a classification accuracy of 88.33%. This study showed that the SVM model using radionics features of chest CT images could effectively identify patients with COVID-19 compared with other type of pneumonia.

Besides, in a SVM model has been used for the classification of patients with COVID-19 using the features extracted by gray level images

In another study ,S.Hu et al. proposed a weakly supervised deep learning method of classification of COVID -19 and non- COVID-19 cases from chest CT images . in thsstudy , for 450 chest CT images of COVID-19, community acquired pneumonia(CAP) and non pneumonia (NP) patients , acquired from two participating hospitals between September 2016 and March 2020 , were used for analysis . classification of COVID-19 from NP cases achieved a mean accuracy of 96.2%,precision .

II. METHODOLOGY

A. Dataset

Dataset comprises of 349 CT scan images collected from 216 COVID patients and 396 images from non –COVID patients. Training data consists of 253 COVID images 291 non –COVID images , were as test set comprises of 98 COVID and 105 non COVID images . as the data set is limited, no separate validation-data set is used in the study instead , 5 fold cross- validation strategy is supplied such that test data is predicted each fold .After training ; test predictions of each fold are averaged and evaluvated against the ground truth.

As small data set for training may lead to over –fitting, so the data set is augmented to increase the number of images , along with transfer learning. Transfer learning can be domain specific such as training on other CT-image data set or domain generic such as training very large image data set containing millions of images and hundreds of classes such as image net data set . in this approach domain generic transfer learning is used , because to date; no other COVID CT scan data set is available publicly. We don't want to train on healthy CT –scans images to avoid pre learning on normal CT scans images which may leads to weight lifting towards the normal class . For data augmentation , different transformation techniques are used to synthesize data such as :

1. Flip: Images are flipped horizontally and vertically .
2. Rotate: Images are rotated by an angle
3. Shift: Images are shifted left, right, upward and downward

After transformation, these images are considered as separate images. Only flipping is performed in this study as it yields Much better results. Rotation mostly works better in circular images and shifting may result in loss of some information.

The image distribution in training and testing set. After horizontal and vertical flipping there are 1088 images for training ,among 544 are original images and 544 augmented . similarly flipping results in 203 more test images .

B. METHODOLOGY

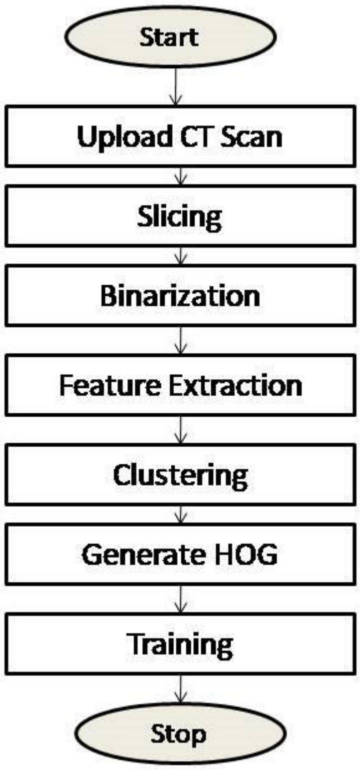
Our proposed system consists of mainly two phases

1. Training phase
2. Detection phase

1. Training phase

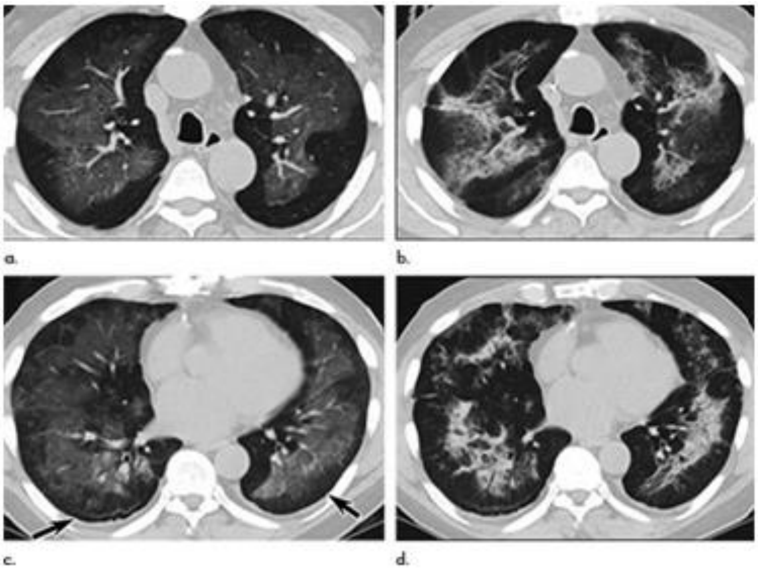
Training phase is intended to train the system so that it can identify the changes in lungs that was made by Covid-19 virus. Training makes our system more intelligent. More the training – chances of detection is more. Our training module consists of many sub modules , such as

1. Slicing
2. Binarization
3. Edge detection
4. Clustering
5. Generating Histogram of oriented gradients(H.O.G) pattern
6. Training



Block diagram of Training Module

Uploading C.T Scan :The C.T scan is uploaded for training.



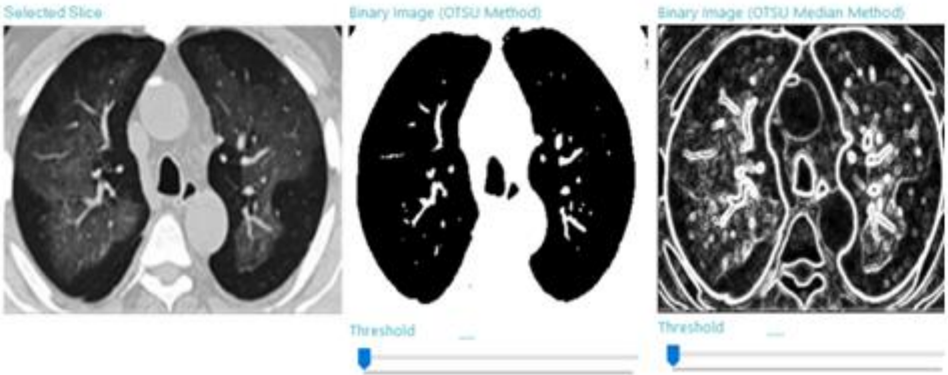
Sample Lung C.T Scan Image

Slicing : We know that Lung C.T Scan image is a collection of many images of the lung. These individual pictures are known as Slices. Before proceeding to other processes we have to select an individual slide for processing. For that we have to crop a slice image from the orginal CT Scan image. This processing is called Slicing

C.T Scan Image after Slicing

Binarization: Image Binarization is the conversion of document image into bi-level document image. Image pixels are separated into dual collection of pixels, i.e. black and white. The main goal of image binarization is the segmentation of document into foreground text and background. Binarization is needed in our project so that we can remove unwanted disturbances in our image. As we can observe the CT image will look like a binary image, but it is not. The image is made up of different colors such as grey etc. before processing we have to make the image into bi-colourimage : Black and White.

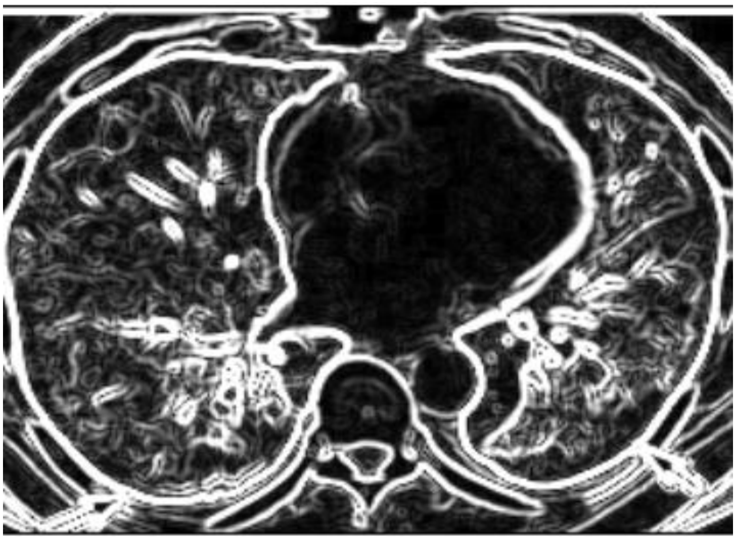
In our project we use two methodologies for Image binarization : Threshold technique and O.T.S.U binarization method



Lung C.T image after Binarization

Edge Detection: Edge detection is an image processing technique for finding the boundaries of objects within images. It works by detecting discontinuities in brightness. Edge detection is used for image segmentation and data extraction in areas such as image processing, computer vision, and machine vision.

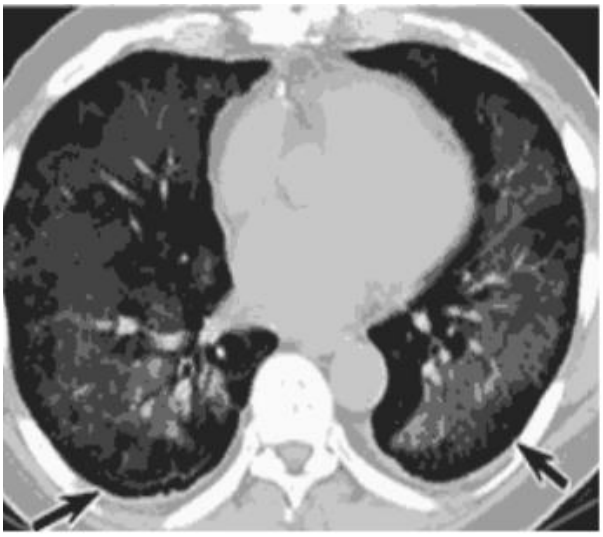
In our project we used Canny edge detection algorithm for performing Edge detection



Lung C.T image after Edge detection using Canny edge detection algorithm

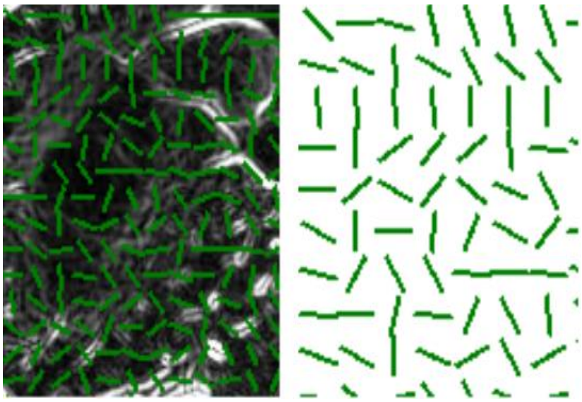
Clustering :Clustering is a powerful technique that has been reached in image segmentation. The cluster analysis is **to partition an image data set into a number of disjoint groups or clusters**. The clustering methods such as k means, improved k mean, fuzzy c mean (FCM) and improved fuzzy c mean algorithm (IFCM) have been proposed.

In our project we use K-means clustering method for clustering



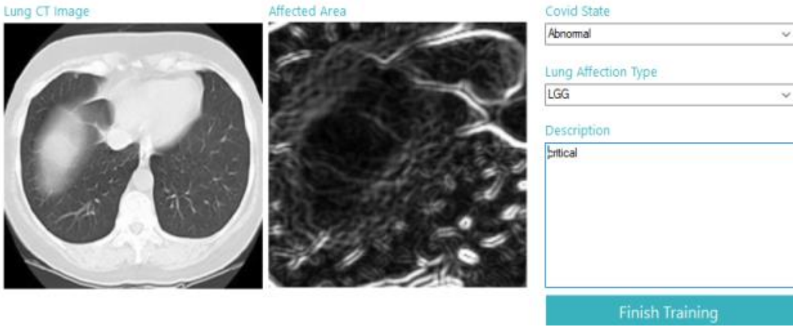
Lung C.T image after K-means Clustering

Generating Histogram of oriented gradients pattern: HOG, or **Histogram of Oriented Gradients**, is a feature descriptor that is often used to extract features from image data. It is widely used in computer vision tasks for object detection. The HOG features are widely use of object detection. HOG decomposes an image into small squared cells, computes an histogram of oriented gradients in each cell, normalizes the result using a block – wise pattern and return a descriptor for each cell.



Generating Histogram of oriented gradients pattern

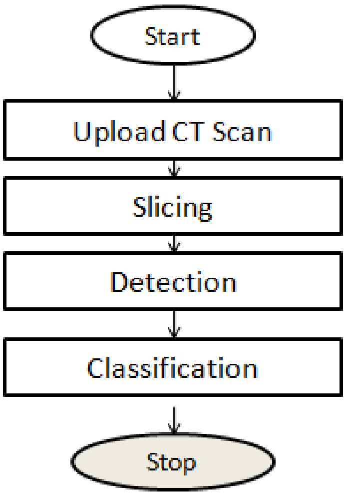
Training: Training consists **in learning a relation between data and attributes from a fraction of the training dataset**, and testing consists in testing predictions of this relation on another part of the dataset. Training is done we supplied many covid affected lung CT scan images and non covid affected. more the training for better performance of the system.



2. Detection phase

Detection phase is detect whether a CT scan image is of covid patient or a healthy person. The detection phase consists of four steps they are

1. Upload CT scan
2. Slicing
3. Detection
4. Classification



III. RESULT

IV. FUTURE ENHANCEMENT

Future work will include comparing our findings with traditional and non–AI-based segmentation techniques. Our overall objective is to develop a comprehensive medical hub that will support detection and analysis of several medical conditions. This medical hub would not be limited to COVID- 19, but it shall include the detection of other conditions and their diagnosis severity. Moreover, our team prioritizes keeping the system up-to-date, benefiting from new techniques and published work in the literature. Finally, we are currently working on reducing the false positives and errors by introducing and testing a new layer of validation and enhancing our calibration techniques.

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