

# **Implementation of Framework for Covid-19 Screening From Chest Ct Scan Images Using Machine Learning**

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Submitted: 01-08-2021

Revised: 07-08-2021 \_\_\_\_\_

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Accepted: 10-08-2021

# ABSTRACT

Coronavirus Disease (COVID19) is a fastspreading infectious disease that is currently causing a healthcare crisis around the world. Due to the current limitations of the reverse transcriptionpolymerase chain reaction (RT-PCR) based tests for detecting COVID19, recently radiology imaging based ideas have been proposed by various works. Recognition of COVID-19 in Chest CT Scan images is a challenging task. Identification of disease in a human organ demands expert's opinion and the patients medications are completely dependent on the results given by that expert. However, there might be situations where experts may not be available or too busy. To tackle the emergencies, which arise due to lack of experts. In this paper, we developed a framework that inputs an image of Chest CT to classify whether the chest CT scan image is COVID-19 infectious or noninfectious i.e. healthy. This research work implemented a Machine-Learning-System (MLS) to detect the COVID-19 infection using the CT scan Slices (CTS) with effective feature extraction using pre-trained deep learning model. The proposed system is implemented and analyzed using MATLAB software.

Keywords: COVID-19, Chest CT Scan, MATLAB, Medical Imaging, Machine Learning

# I. INTRODUCTION

In the recent years, medical CT Images have been applied in clinical diagnosis widely. It assists physicians to detect and locate pathological changes with more accuracy. Computed tomography images can be distinguished for different tissues according to their different gray levels. Lung diseases can be caused by infection, an exposure at the workplace, medications and various disorders. X-ray chest radiography and computer tomography (CT) are two common anatomic imaging modalities that are routinely used in the detection and diagnosis of a variety of lung diseases. Medical images play a vital role in patient diagnosis, therapy, surgical, medical reference, and training. The Digital Imaging and Communications in Medicine (DICOM) standard allows storing textual descriptions, known as metadata, along with the images. It was the most important breakthrough since the discovery of the X-rays, and CT has remained a cornerstone of diagnostic radiology throughout the years [1].

The COVID-19 pandemic, caused by severe acute respiratory syndrome coronavirus 2 (SARS- CoV-2), has lead to a global public health crisis, and continues to spread worldwide. Medical imaging, especially Computed Tomography (CT), has been playing an important role for clinical diagnosis and monitoring of patients with the disease infections [3]. However, the growth rate of COVID-19 suspicious cases has overloaded the public health service capacity and manifested shortage of trained radiologists. Therefore. developing effective computational methods for automated COVID-19 CT image analysis is highly demanded towards improving the diagnosis outcomes and patient management, as well as helping clinicians on tedious image interpretation workload for releasing their precious time which can otherwise be dedicated to more urgent things on the frontline. The respiratory tract infection due to the Coronavirus Disease (COVID-19) is emerged as one of the major threat globally due to its acuteness and the infection rate. It is one of the major communicable infectious diseases caused by Severe Acute Respiratory Syndrome-Corona Virus-2 (SARS-CoV-2) and according to a recent report [7] [8], it affected a larger human community, irrespective of their race and gender. The infection caused by COVID-19 severely affects the respiratory system by causing the severe pneumonia. Due to its harshness and the spreading rate, the World Health Organization (WHO) recently announced it as pandemic [9]. Even



though various controlling and treatment procedures are implemented from December 2019 to till date, the mortality due to COVID-19 infection is rapidly increasing.

The most common test technique currently used for COVID-19 diagnosis is a real-time reverse transcription-polymerase chain reaction (RT-PCR). Chest radiological imaging such as computed tomography (CT) and X-ray have vital roles in early diagnosis and treatment of this disease [8]. Due to the low RT-PCR sensitivity of 60%-70%, even if negative results are obtained, symptoms can be detected by examining radiological images of patients [9] [10]. It is stated that CT is a sensitive method to detect COVID-19 pneumonia, and can be considered as a screening tool with RT-PRC [11]. CT findings are observed over a long interval after the onset of symptoms, and patients usually have a normal CT in the first 0-2 days [12]. In a study on lung CT of patients who survived COVID-19 pneumonia, the most significant lung disease is observed ten days after the onset of symptoms [13]. The use of medical imaging tools is the second approach of COVID-19 virus detection. These tools are playing an important role in the management of patients that are confirmed or suspected to be infected with the virus. It is worthy of note that without clinical suspicion, findings from X-ray, or CT images are nonspecific as many other diseases could have a similar pattern. Thoracic CT scan is the imaging modality of choice that plays a vital role in the management of COVID-19. Thoracic CT has a high sensitivity for diagnosis of COVID-19

which makes it a primary tool for COVID-19 detection. CT scan involves transmitting X-rays through the patient's chest, which are then detected by radiation detectors and reconstructed into highresolution medical images. There are certain patterns to look out for in a chest CT scans which present themselves in different characteristic manifestations. The potential findings with 100% confidence for COVID-19 in thoracic CT images are ground - glass opacity - paving and consolidation, air bronchograms, reverse halo, and perilobular pattern. The abovementioned findings are reports presented by a radiologist who specializes in interpreting medical images. Interpretation of these findings by expert radiologists does not have a very high sensitivity. Artificial intelligence (AI) has been employed as it plays a key role in every aspect of COVID-19 crisis management. AI has proven to be useful in medical applications since its inception, and it became widely accepted due to its high prediction and accuracy rates. In the diagnosis stage of COVID-

19, AI can be used to recognize patterns on medical images taken by CT. Other applications of AI include, but not limited to, virus detection, diagnosis and prediction, prevention, response, recovery, and to accelerate research [7]. AI can be used to segment regions of interest and capture fine structures in chest CT images, self-learned features can easily be extracted for diagnosis and other applications as well. A recent study showed that AI accurately detected COVID-19 and was also able to differentiate it from other lung diseases and community acquired pneumonia. In this paper, we implemented the diagnosis of COVID-19 by using chest CT toward Machine Learning approach [14].

# **II. LITERATURE REVIEW**

Research work presented by various authors related to COVID-19 diagnosis described is as given below.

Zhao Wang et.al. [1] proposes a novel joint learning framework to perform accurate COVID- 19 identification by effectively learning with heterogeneous datasets with distribution discrepancy. Extensive experiments show that our approach consistently improves the performances on both datasets, outperforming the original COVID-Net trained on each dataset by 12.16% and 14.23% in AUC respectively. Muskan Lawania et.al. [2] proposes a productive strategy to identify the lung malignancy and its stages effectively and furthermore means to have progressively precise outcomes by utilizing KNN and Image Processing systems.

Seifedine Kadry et.al. [3] propose a Machine-Learning-System (MLS) to detect the COVID-19 infection using the CT scan Slices (CTS). In this work, the classifiers, such as Naive Bayes (NB), k-Nearest Neighbors (KNN), Decision Tree (DT), Random Forest (RF) and Support Vector Machine with linear kernel (SVM) are implemented and the classification task is performed using various feature vectors. The experimental investigation of this study confirms that, the classification accuracy of SVM is 89.80% when 2 FFV is considered to train, test and validate the classifier. Arnab Kumar Mishra et.al. [4] explored various Deep CNN based approaches are explored for detecting the presence of COVID19 from chest CT images. An experimental evaluation of existing Deep CNN based image classification approaches is presented in order to identify COVID19 positive cases from chest CT scan images. Experimental results show that the proposed decision fusion based approach is able to achieve above 86% results across all the performance metrics under consideration, with



average AUROC and F1-Score being 0.883 and 0.867, respectively. From the extensive experimentations, it is observed that the proposed approach can achieve very impressive results, with above 86% in terms of every performance metric under consideration, while having a good reduction of the number of False Positives.

Tulin Ozturk et.al. [8] presented new model for automatic COVID-19 detection using raw chest X-ray images is presented. The proposed model is developed to provide accurate diagnostics for binary classification (COVID vs. No-Findings) and multi- class classification (COVID vs. No-Findings vs. Pneumonia). Our model produced a classification accuracy of 98.08% for binary classes and 87.02% for multi-class cases. Varalakshmi Perumal et.al. [9] applied the transfer learning technique to clinical images of different types of pulmonary diseases, including COVID-19. They propose a transfer learning model to quicken the prediction process and assist the medical professionals. The proposed model produces precision of 91%, recall of 90% and accuracy of 93% by VGG-16 using transfer learning, which outperforms other existing models for this pandemic period.

Lin Li et.al. [10] designed and evaluated a threedimensional deep learning model for detecting coronavirus disease 2019 (COVID-19) from chest CT scans. On an independent testing data set, we showed that this model achieved high sensitivity (90% [95% confidence interval [CI]: 83%, 94%])

and high specificity (96% [95% CI: 93%, 98%]) in the detection of COVID-19. Lal Hussain et.al. [12] employed an automated supervised learning AI classification of texture and morphological- based features on portable CXRs to distinguish COVID- 19 lung infections from normal, and other lung infections. The major finding was that the multi- class classification was able to accurately identify COVID-19 from amongst the four groups with a combined AUC of 0.87 and accuracy of 79.52%.

Stephanie A. Harmon et.al. [14] show that a series of deep learning algorithms, trained in a diverse multinational cohort of 1280 patients to localize parietal pleura/lung parenchyma followed by classification of COVID-19 pneumonia, can achieve up to 90.8% accuracy, with 84% sensitivity and 93% specificity, as evaluated in an independent test set (not included in training and validation) of 1337 patients.

# **III. PROPOSED WORK**

The entire working process of the presented method is shown in Fig. 1. As shown in figure, the presented model consists a series of processes which are discussed in the figure.



Fig 1: proposed methodology of system

# *1.* Chest CT-Scan Images Dataset

We are applied our methodology to standard benchmark image database, publicly available dataset LIDC and Radiopaedia database, is applied and observed under several aspects. The dataset has a collection of chest CT scan images that can be employed for the design.





Fig 2: sample test images (axial view)

For experimental evaluation, we used total 50 images. After that we have split the dataset into 70-30% ratio for training and testing set of images

# 2. Pre-processing

The input CT scan images are provided as input to the presented model. The input images are provided as input to the presented model. In the initial stage, the pre-processing takes place by the use of image resizing as per the size of trained model.

### *3.* Feature Extraction

At the next stage, a collection of important features gets extracted from the segmented image using pre- trained deep learning model. The pretrained deep learning model that will be used is Inception-v3 which is based on a convolutional neural network that is 48 layers deep. It has been developed by Google and has been trained for the ImageNet Competition using the data from 2012. We chose this model because of its high classification performance.



Fig 3: Inception V3 architecture

We have extracted from the segmented image using pre-trained deep learning model. The pre-trained deep learning model that will be used is Inception- v3. Feature extraction is the easiest and fastest way to use the representational power of pre-trained deep networks. Inception v3 mainly focuses on burning less computational power by modifying the previous Inception architectures.

#### 4. Classification

Then, the classification of images will be carried out using machine learning classification model which finally provides the output as classified image into 'normal' or 'abnormal'.

In our case, we use multi kernel support vector machine (SVM). Later if abnormal image is found then only it will show and detect the abnormal section. Training and testing of computer aided diagnosis models for detecting and diagnosing COVID-19 will be done in proposed approach. The process of extracting features takes place using image processing and classifier operation is carried out utilizing machine learning which helps to develop the trained prediction approaches from the filtered features in an easier way and rapid way.

Support Vector Machine or SVM is one of the most popular Supervised Learning algorithms, which is used for Classification as well as Regression problems. However, primarily, it is used for Classification problems in Machine Learning. The goal of the SVM algorithm is to create the best line or decision boundary that can segregate n- dimensional space into classes so that we can easily put the new data point in the correct category in the future. This best decision boundary is called a hyperplane. SVM chooses the extreme points/vectors that help in creating the hyperplane.



These extreme cases are called as support vectors, and hence algorithm is termed as Support Vector Machine. Consider the below diagram in which there are two different categories that are classified using a decision boundary or hyperplane.



Fig 4: hyperplane structure of SVM

# IV. RESULT AND DISCUSSION

The proposed work is implemented on Intel CORE processor i5, 8GB RAM Laptop configuration and operating system is Windows 10. MATLAB R2018b software was used to write the programming code in this we used Image processing, Statistics and Machine Learning toolbox and Deep Learning toolbox. The input images is taken from LIDC and Radiopedia Dataset for experimentation. We have executed project in three phase, training, testing and evaluation phase.

# 1. Training Phase

In this experimentation, as per proposed block diagram, we have two implementation phase, first training and then testing.



Fig 5: Sample Images of Chest CT Scan Dataset

In training, train set of images need to be preprocessed as per dimension of deep network used. And then for feature extraction process of train images, we used automated feature extraction based on Inception V3 pre-trained deep convolutional neural network in which it consists of total 316 layers including input, feature, classification and output layer. We have used 'avg\_pool' feature layer to extract the features from images. Then after extraction features, we need to train the model using multi kernel SVM based on input and output data, where input is train image

DOI: 10.35629/5252-0308399408 Impact Factor value 7.429 | ISO 9001: 2008 Certified Journal Page 403



feature dataset and output is labels. After successful validation of training model, we saved the trained model. The samples images of dataset with total 2048 features of whole dataset images having dimension of 34\*2048.

# 2. Testing Phase

In testing phase, we need apply same procedure as for train images to predict the output whether its COVID-19 or normal chest CT scan image



Fig 6: a) Input Test Image - Covid-19



Fig. 6 b) Pre-process Input Image



Fig 7: a) Predicted Output b) Evaluation time required for testing of image





Fig 8: a) Pre-process



Fig.8 b) Input Image



Fig 9: a) Predicted Output b) Evaluation time required for testing of image



# *3.* System Evaluation Phase

In this phase, we have evaluated all test images from dataset to get the system performance parameters to show the system efficiency



Fig. 10: Confusion matrix of testing phase



Fig. 11: Evaluation time to execute all Test Images



Results True Positive:8 False Negative:1 True Negative:5 False Positive:1 Accuracy :86.6667 Error Rate :13.3333 Sensitivity (Recall/Hit Rate):88.8889 Specificity :83.3333 F- Score :88.8889 Positive Predictive Rate (Precision):88.8889 Negative Predictive Rate :83.3333 Matthews Correlation Coefficient :72.2222 Kappa Score :72.2222				×
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Matthews Correlation Coefficient :72.2222 Kappa Score :72.2222	Negative Predic	tive Rate :8	3.3333	
Kappa Score :72.2222	Matthews Corre	lation Coeff	icient :72.	2222
	Kappa Score :72	2.2222		
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Fig. 12: Result performance parameters of project in %



Fig. 13: ROC plot of testing phase

# V. CONCLUSION AND FUTURE SCOPE

A computerized system to distinguish the normal and COVID-19 CTS images from a considered standard benchmark image database. This work proposed a machine learning system using a sequence of procedures ranging from image pre-processing to the classification to implement a scheme with better detection accuracy with effective feature extraction using pre-trained deep neural network model. The overall class recognition accuracy of 86.7% is obtained. The simplicity, the high recognition rate, and the speed of the classification model, make it appropriate for implementing a productive and profitable computer vision machine for the healthcare system.

Further implementation in this project can include various disease category of lung infections. Also by using GPU, we can reduce the time of training of dataset features. Same model can be applied for any kind of dataset regarding to other disease classification.

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