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Identification and Classification of COVID-19 using Radiological Images

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***Abstract*— The outbreak of the COVID-19 has put the whole world in an unpleasant situation. There is a surge in number of people affected by this disease day by day. Many people have lost their lives to this pandemic disease. At present, the detection of corona virus disease 2019 (COVID-19) is one of the main challenges in the world. This paper implements an artificial intelligence technique based on a deep Convolution Neural Network (CNN) models to detect COVID-19 automatically using real-world datasets. A qualitative analysis is performed to inspect the decisions made by CNN model using a technique known as Class Activation Mapping (CAM). Using CAM, the activations contributed most to the decision of CNN models can be mapped to visualize the most discriminating regions on the input image. Chest CT scan plays a very crucial role in determining the severity of the disease in the infected patients. An AI based image-assisted system is formulated to extract COVID-19 infected sections from lung CT scans (axial view).Threshold filter is applied to extract the lung region and eliminate possible artifacts. Then image segmentation is performed using graph-cut method to extract the region of interest (lung area and infected regions). The binary images of region of interest are then employed to identify the pixel ratio between the lung area and infection sections to calculate the severity level of infection. The classification of COVID-19 infected cases based on severity assist the pulmonologist not only to detect but also to help plan the treatment process efficiently.**

Index Terms: **COVID-19, Artificial Intelligence, Convolution Neural Network, CT scan, Class Activation Mapping, Graph-cut Method, Region of Interest.**

I.INTRODUCTION

Corona virus disease (COVID-19) is an infectious pandemic disease caused by a newly discovered corona virus. It is first identified in December 2019 at Wuhan, China. Then it has spread all over the world. Till now more than 44 crores of people are affected with COVID-19 and 60 lakhs people have lost their lives to this pandemic disease. At present, vaccines have been invented and made available for the people to combat Corona virus disease. Most people infected with the COVID-19 virus will experience mild to moderate respiratory illness and recover without requiring special treatment or hospitalization. From mild condition respiratory tract illness may progress to severe pneumonia, multi organ failure, and eventually death [8]. COVID-19 can provisionally be diagnosed on the basis of symptoms and confirmed using reverse transcription polymerase chain reaction (RT-PCR) testing of infected secretions. The diagnosis and severity assessment of COVID 19 can be done by using either x-ray or chest CT. The CT scan provides us more detailed diagnosis than x-ray [9]. The prominent clinical findings that differentiate COVID 19 from other illness are Peripheral and bilateral Ground Glass Opacity (GGO) with consolidation.

As the person presents to the hospital with COVID-19 symptoms, Initially the person has to undergo RT-PCR test then if he is tested as positive, the severity of infection is assessed by the physician using medical imaging modalities to plan the treatment accordingly. It is a time consuming process and it may delay the treatment planning. Now-a-days Artificial intelligence is gaining more attention as it is widely used in various aspects of life. In health care industry, it simplifies the work of doctors and hospital administrators by performing tasks that are typically done by humans, in less time, low cost with greatest accuracy [5]. Deep learning-based systems have been utilized to increase image classification accuracy. From the literature, the CNN based technique is adopted in this paper to classify covid and non covid x-ray and CT images. CNN models are image classification network that has already learned to extract powerful and informative features from natural images and it can be used as a starting point to learn a new task. CNN models used in this paper are Resnet 50, mobilenetv2 and squeezenet models. These CNN models are validated using real world datasets. The Class activation mapping technique shows the visual explanations of the predictions of convolutional neural networks.

The main motive of the work is to develop an AI based image assisted system to detect COVID-19 from radiological images and classify them as mild, moderate and severe based on severity of infection. In this paper CNN models were trained using image dataset and their performance were validated. Then the threshold based segmentation and graph cut method segmentation is performed on the COVID-19 CT images for extracting features from the images. Based on the extracted features the severity of COVID-19 infection is calculated and images are classified based on percentage of infection. The remaining part of this paper is presented as follows; section 2 discusses the literature works, section 3 outlines the methodology adopted in this research work, sections 4 portrays the implementation of the methodology and section 5 and 6 presents results discussion and the conclusion respectively.

II. LITERATURE REVIEW

COVID-19 has emerged as a global health issue and a significant number of research works are initiated to discover the solution to control the spread of the COVID-19 and assess the severity of infection. The necessity of assessing the severity of this infection is to take the decision regarding treatment procedure to be adopted, drug dosage to the patients and to track their recovery. The non-invasive image assisted COVID-19 detection procedures followed in the hospitals to detect the severity of the COVID-19 pneumonia and the imaging modalilities used in hospitals are briefly discussed [15, 19]. This section briefly presents the enormous literature available in this research domain.

Artificial intelligence covers the wide area. The machine learning is a subset of artificial intelligence and deep learning is a subset of machine learning. The neural network comes under deep learning. In the papers [6-8] existing AI techniques in clinical data analysis, including neural systems, classical SVM, and edge significant learning were discussed and advantages of AI implementation in combating various similar viruses were emphasized. Ilker Ozsahin, Boran Sekeroglu, Musa Sani Musa have proposed a method to diagnose COVID 19 from chest CT images and performance of different pretrained CNN models like Resnet18, VGG 16 and shufflenet were compared to perform image classification task [3]. Tuan D. Pham A has presented an investigation on 16 pretrained CNNs for classification of COVID-19 using a large public database of CT scans collected from COVID-19 patients and non-COVID-19 subjects. Then accuracy, sensitivity and specificity, F1 score were calculated [11]. Taban Majeed et al, have used a simple CNN architecture with a small number of parameters that perform well on distinguishing COVID-19 from normal X-rays. Then, a qualitative investigation performed to inspect the decisions made by CNNs using a technique known as class activation maps (CAM). Using CAMs, activations that contributed most to the decision of CNNs is mapped back to the original image to visualize the most discriminating regions on the input image [16].

The various methods available for assessment of COVID-19 severity in chest CT images are briefly discussed in [1,12-15]. V. Rajinikanth et al, have formulated an image-assisted system to extract COVID-19 infected sections from lung CT scans (coronal view and axial view). They have used threshold filter to extract the lung region by eliminating possible artifacts, and image enhancement has been done using Harmony-Search-Optimization and Otsu thresholding, Image segmentation is performed using warershed segmentation method to extract infected region and Region-of-interest (ROI) extraction from binary image was done by ITK snap tool to compute level of severity. The features that are extracted from ROI are then employed to identify the pixel ratio between the lung and infection sections to identify infection level of severity [15]. Biswajoy Ghosh el al, have proposed a method to quantify severity by assessing chest CT image feature is demonstrated for COVID-19 patients. The severity determining feature Lnorm was quantified and established to be statistically distinct for the three mild, moderate, and severe classes (p-value<0.0001). The thresholds of Lnorm for a 3-class classification were determined based on the optimum sensitivity/specificity combination from Receiver Operating Characteristic (ROC) analyses. The feature Lnorm classified the cases in the three severity categories with 86.88% accuracy. Here segmentation of images was done using semi automatic graph cut method [14].

From the above literature, in this paper the CNN models such as Resnet50, Mobilenetv2 and squeezenet architectures were adopted for the classification of covid and non covid CT and x-ray images. Then their performance were compared in terms of accuracy, sensitivity and specificity. The comparison was also done for small and large image dataset. For classification of images based on severity the threshold filtering was used to extract the lung region from the artifacts. The segmentation of infected section and lung region is done using graph-cut method. Then the pixel ratio between the lung and infection sections is calculated to compute the severity of infection.

III. METHODOLOGY

The proposed research work can be classified into two parts. In the first part the classification of covid and non covid image dataset using Convolution Neural Network models like Resnet50, Mobilenetv2, Squeezenet and their performance analysis are carried out. The second part deals with classification of CT covid images into mild, moderate and severe based on severity of infection. The procedure followed is pictorially explained below in Fig. 1 and 2.

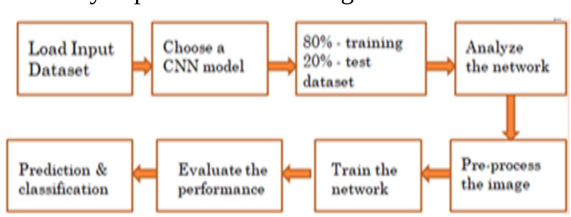


Fig. 1: Classification of Covid and Non Covid images

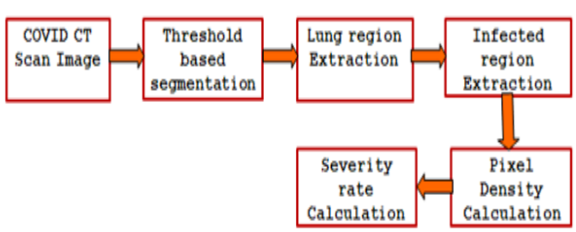


Fig. 2: Severity Computation of CT COVID-19 images

IV. IMPLEMENTATION

4.1 COVID AND NON COVID IMAGE CLASSIFICATION

A. Dataset

In this paper x-ray dataset and CT dataset are utilized for covid and non covid classification. The x-ray dataset consists of 25 normal images and 25 covid images. The CT dataset [20] consist of 349 covid images and 397 non covid images.

B. Convolution Neural Network

A convolution neural network (CNN) is a class of deep neural networks most commonly applied to analyzing visual imagery. A convolution neural network consists of an input layer, multiple hidden layers and output layers. The activation function used in CNN is commonly a ReLU layer. The architecture of CNN is shown in Fig. 3.

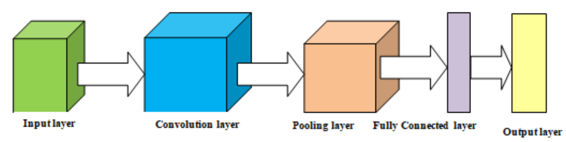


Fig. 3: Convolution Neural Network Architecture

CNN models are image classification network that has already learned to extract powerful and informative features from natural images and it can be used as a starting point to learn a new task

1) Resnet50

Resnet50 is one of the popular CNN model which has 50 layers. It contains 49 convolution layers and 1 fully connected layer. It is a model that makes use of the residual module involving shortcut connections. The image input size of resnet50 is 224 by 224.

2) MobilenetV2

MobileNetV2 provides a very efficient mobile-oriented model that can be used as a base for many visual recognition tasks. It is a very effective feature extractor for object detection and segmentation. It is a neural network which is 53 layers deep. It consists of inverted residuals and linear bottlenecks. The image input size of Mobilenetv2 model is 224 by 224. Mobilenetv2 networks are small, low-latency, low-power models designed to maximize the accuracy.

3) Squeezenet

Squeezenet is a convolution neural network which is 18 layers deep that employs design strategies to reduce the number of parameters, notably with the use of fire modules that "squeeze" parameters using 1x1 convolutions. It aims in decreasing the quantity of parameters in a CNN while attempting to preserve accuracy.

These three CNN models are adopted in this paper for the classification of Covid and Non Covid images. For training the network input image dataset is randomly split into training dataset and test dataset. Here the image dataset is split into 80% training dataset and 20% test dataset.

C. Training the Network

For training the network for image classification, the network has to be analyzed. In the analysis result the type of layers, activation functions used in the networks and learnable parameters i.e., weights and biases used in networks are shown in detail. The images in the dataset are pre-processed to fit to the new input dataset. The three methods of data augmentation are scaling, random reflection and random translation. The network is trained using stochastic gradient descent algorithm. It estimates the error gradient for the current state of model using samples from training dataset and update weights of model using backpropogation. Learning rate plays a major role in training process. Choosing the learning rate is challenging as too small may result in long training process and large value may result in fast unstable training process. Usually the learning rate lies between 0.0 – 1. Here the learning rate is chosen as 0.01 as a result of trial and error method.

D. Evaluation of the Networks

The performance of the trained network is evaluated using confusion matrix. The confusion matrix displays the observation based on accuracy, sensitivity and specificity. It shows the number and percentage of correct and incorrect classifications by the trained network. In this work covid and non covid images are the two main classes considered. The first row of the confusion matrix consist of observation of covid images output obtained through the trained network. The second row of the confusion matrix consist of observation of non covid images output obtained through the trained network. The column of the confusion matrix consist of observation of covid images target to be obtained through the trained network. The second column of the confusion matrix consist of observation of non covid images target to be obtained through the trained network. The first row third column indicates percentage of sensitivity, The second row third column indicates percentage of specificity, The third row third column indicates percentage of accuracy. Calculating a confusion matrix can give us a better idea of what our classification model is getting right and identify what kind of wrong interpretations are made. The rows of a confusion matrix indicate output class and column indicates target class. The Sensitivity, specificity and accuracy of a network can be obtained through confusion matrix. Sensitivity is the ability of the network to predict covid images correctly. Specificity is the ability of the network to predict non covid images correctly

Fig. 4(a): Confusion matrix of Resnet50 network (x-ray dataset)

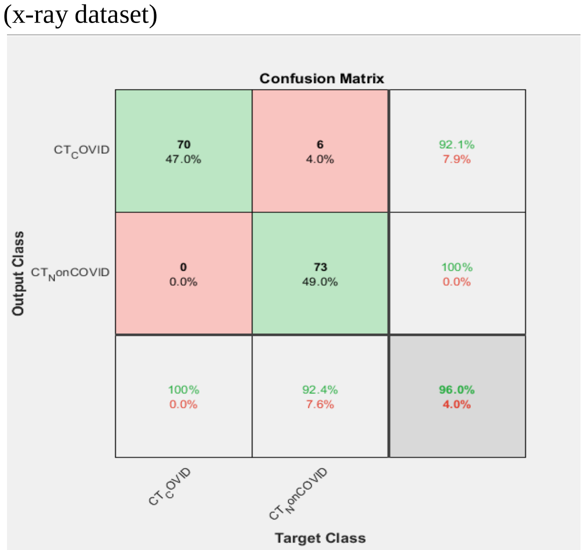


Fig. 4(b): Confusion matrix of Resnet50 network

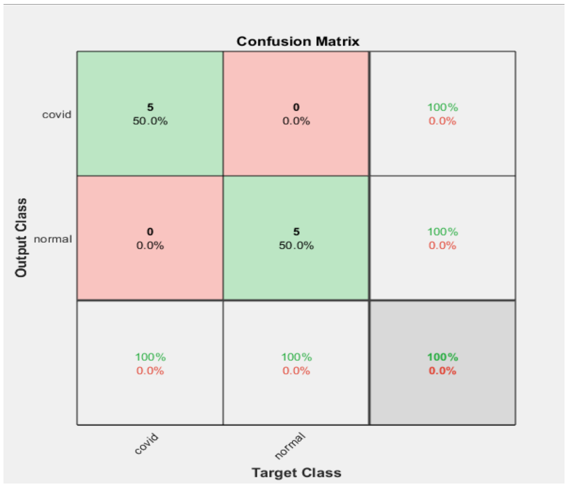


Fig. 5(a): Confusion matrix of MobilenetV2 network (x-ray dataset)

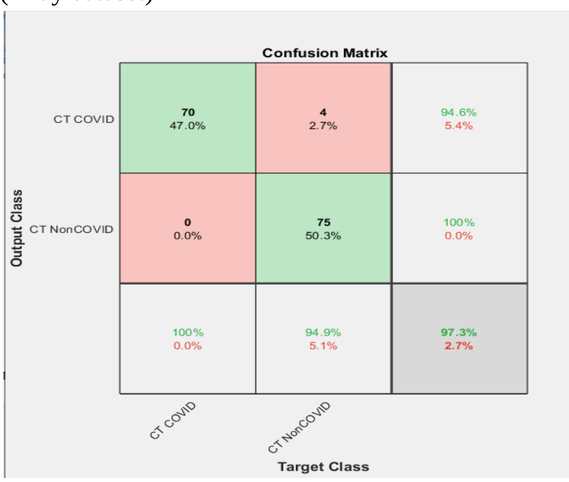


Fig. 5(b): Confusion matrix of MobilenetV2 network (CT dataset)

Fig. 6(a): Confusion matrix of Squeezenet network (x-ray dataset)

Fig. 6(b): Confusion matrix of Squeezenet network (CT dataset)

Fig.4(a) represents the confusion matrix of Resnet50 network for the x-ray dataset. Fig.5(a) represents the confusion matrix of MobilenetV2 network for the x-ray dataset. Fig.6(a) represents the confusion matrix of Squeezenet network for the x-ray dataset. They have classified the covid and non covid x-ray images correctly. Hence the accuracy, sensitivity and specificity are 100%. The fig.4(b) shows that Resnet50 network trained using CT dataset has classified 6 covid images wrongly as non covid CT images. Hence, the sensitivity of the network is 92.1%. The non covid images are correctly classified. So, the specificity is 100%. As a result the ac curacy is 96%. The fig. 5(b) shows that mobilenetv2 network trained using CT dataset has classified 4 covid images wrongly as non covid CT images. Hence, the sensitivity of the network is 94.6%. The non covid images are correctly classified. So, the specificity is 100%. As a result the ac curacy is 97.3%. The fig. 6(b) shows that squeezenet network trained using CT dataset has classified 8 covid images wrongly as non covid CT images. Hence, the sensitivity of the network is 88.4%. Then 9 non covid images are wrongly classified as covid images. So, the specificity is 88.8%. As a result the accuracy is 88.6%.

E. Validation of the Networks

The validation is a process of checking or proving the validity or accuracy of the networks. Earlier we have split the x-ray and CT dataset into training and test dataset. The test dataset is used to validate the performance of the CNN models. The validation results of resnet50, mobilenetv2 and squeezenet networks using x-ray and CT dataset are shown below in Fig. 7(a) – 9(b). The percentage present nearer to the category label represents the probability of the classification to be a covid or non covid image category.

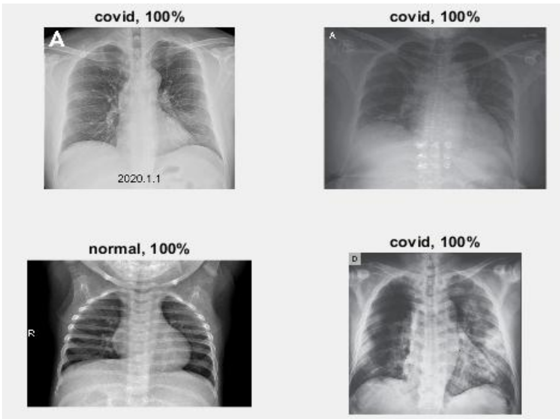


Fig. 7(a): Validation of Resnet50 network (x-ray dataset)

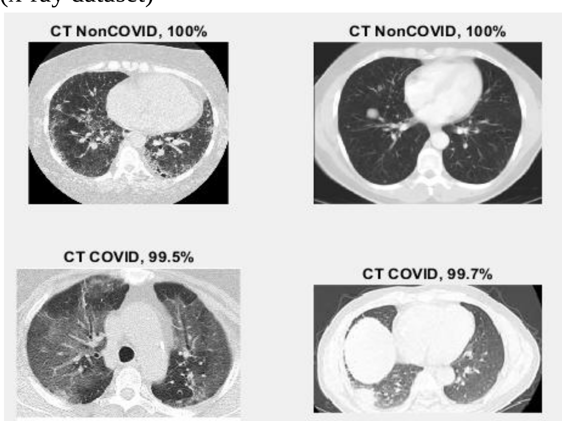


Fig. 7(b): Validation of Resnet50 network (CT dataset)

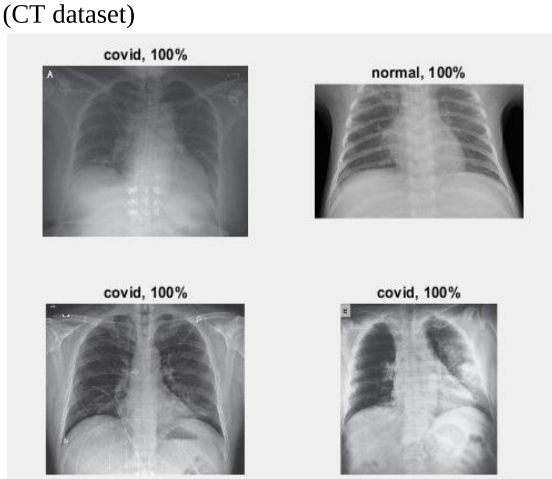


Fig. 8(a): Validation of MobilenetV2 network (x-ray dataset)

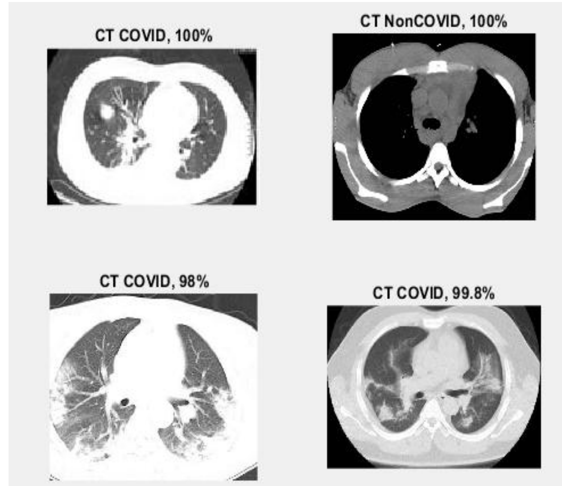


Fig. 8(b): Validation of MobilenetV2 network (CT dataset)

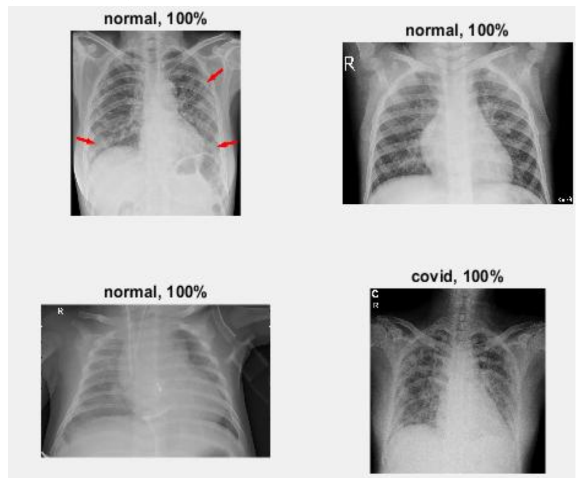


Fig. 9(a): Validation of Squeezenet network (x-ray dataset)

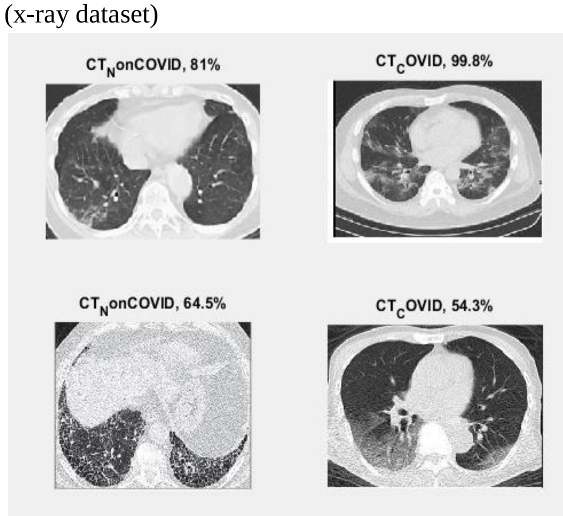


Fig. 9(b): Validation of Squeezenet network (CT dataset)

F. Class Activation Mapping

Class Activation Maps helps in the analysis of understanding as to which regions of an input image influence the Convolution Neural Network output prediction. CAM highlights the region in the image which contributes to the final output prediction. This can be achieved by means of colormap. The Class Activation Mapping is done by learning features of image dataset from activation layer of network used. The colormap “jet” is used in this work for class activation mapping. The colour of the jet map ranges from yellow to blue. The yellow colour indicates highest contribution region and the blue colour indicates lowest contribution region as shown in colorbar (yellow – 1, blue – 0)

Fig. 10(a): Activation Mapping of Covid X-ray image using CNN

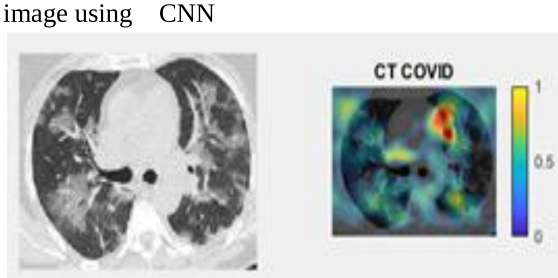


Fig. 10(b): Activation Mapping of Covid CT image using CNN

In this research work, the x-ray dataset consists of 25 normal images and 25 covid images. The CT dataset consist of 349 covid images and 397 non covid images. When covid and non covid x-ray and CT images are given as input, the image is resized to the size of image dataset and input and output classes are obtained from the network, then the labels of specified classes are identified correctly. Fig. 10(a) and 10(b) shows activation mapping of Covid x-ray and CT image using CNN. Then random COVID-19 x-ray image and COVID-19 CT image other than images in the dataset is given as input for CAM. The Class Activation Mapping is done by learning features of image dataset from activation layer of network. The activated regions in the image which contributes to the final prediction is indicated using heat map in red to yellow colour. The color bar shows than colour indication range. Here The yellow colour indicates highest contribution region and the blue colour indicates lowest contribution region.

4.2 COVID-19 Severity level classification

G. Image Segmentation

Medical image segmentation has an vital role in computer-aided diagnosis system in different applications. Image segmentation is considered the most essential medical imaging process as it extracts the region of interest (ROI) through a semiautomatic or automatic process. It divides an image into areas based on a specified description, such as segmenting body organs/tissues in the medical applications for edge detection, tumor detection/segmentation, and recently emerging and most essential application of image segmentation is COVID-19 detection from radiographic images [24].

Thresholding is the simplest method of image segmentation. From a gray scale image, thresholding can be used to create binary images. The advantage of obtaining first a binary image is that it reduces the complexity of the data interpretation and simplifies the process of recognition and classification. The CT covid image is taken as image input. The image is segmented into lungs region and artifacts based on the threshold value. An image histogram is a gray-scale value distribution showing the frequency of occurrence of each gray-level value. The range of threshold value for image segmentation is selected based on histogram of an image. Then appropriate value is selected using trial and error method.

H. Extraction of Region of Interest

The major requirement for computation of severity level of infection is pixel density of lung region and infected region in the lungs. To calculate severity rate the region of interest such as lung region and infected region in the lungs should be extracted from the input CT image. In this work, the region of interest is extracted using semi-automatic segmentation technique called Graph cut method using image segmenter app in Matlab software.

Graph cut method

Graph cut is a semiautomatic segmentation technique that you can use to segment an image into foreground and background elements.

I. Severity Rate Calculation

The examination of the COVID-19 in hospital is initiated with a laboratory test: RT-PCR to confirm the disease. After admitting the patient, the imaging procedures, such as CT/X-ray data are considered to identify infected section and its level of severity. Severity level calculation is most important for the process of effective treatment planning. COVID-19 infection severity rate calculation can be done by computing the pixel density of lung region and its infected section. Then formula to calculate percentage of severity of infection is as follows.

*Percentage of Infection = [(Pixel density of infected region) / (Pixel density of lung region)] *100*

In this work. covid CT images of the Radiopaedia database are considered to analyze the severity of the infection in the patients for the evaluation. This proposed work used the images of case studies, such as case 1 [25], 2 [26], 3 [27], 3 [28], 5 [29] for the experimental investigation.

CASE 1

The CT image is given as a input for segmentation of lung region from the artifacts using thresholding technique. The histogram is plotted for the input image. The x-axis of histogram is threshold level and y-axis indicates pixel value. The first peak region in histogram indicates the lung region and the second peak in the histogram indicates the artifacts. The threshold value for segmenting the image is selected as 180 manually by trial and error method. Then the segmentation is performed accordingly and results are displayed in Fig. 11(a). Then the lung region and infected section are segmented using graph-cut method as a binary image by marking foreground and background of the image. Then the results are displayed in Fig. 11(b).

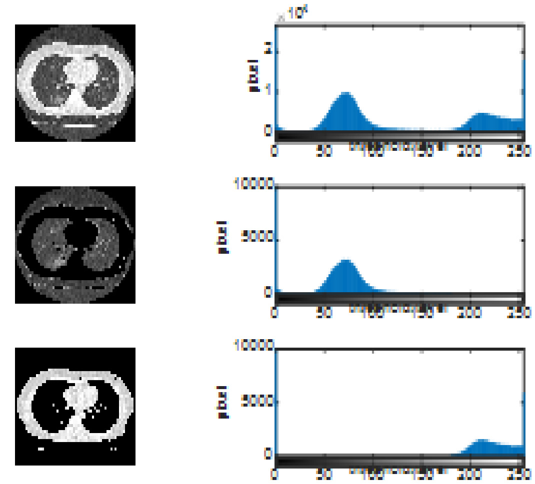
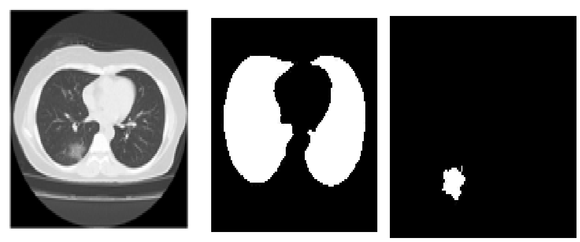


Fig. 11(a): Threshold based segmentation of Case 1



Input CT image, Segmented Lung Area, Segmented Infected section

Fig. 11(b): Graph-cut segmentation of case 1

Pixel density of infected region:	1602741
Pixel density of lung area	: 54075024
Percentage of infection	: 2%

Similarly the threshold value for image segmentation is selected using trial and error method . Then lung area and infected lung section s segmented using graph cut segmentation method. Subsequently, percentage of infection is calculated using the above mentioned formula for the cases 2,3,4 and 5.

Figure 12(a) – (d) shows the results of threshold based segmentation of covid CT images. Figure 12(e) – (h) represents input covid CT images considered from case study images of radiopaedia images considered for severity computation. Figure 12(i) – (l) shows the segmented lung area and Figure 12(m) – (p) shows the infected section of case 2,3,4 and 5 respectively.

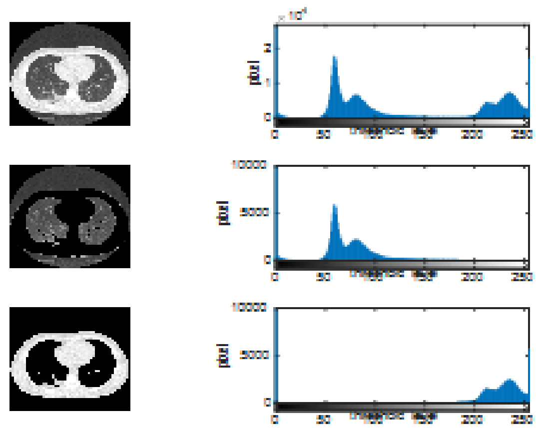


Fig 12(a)

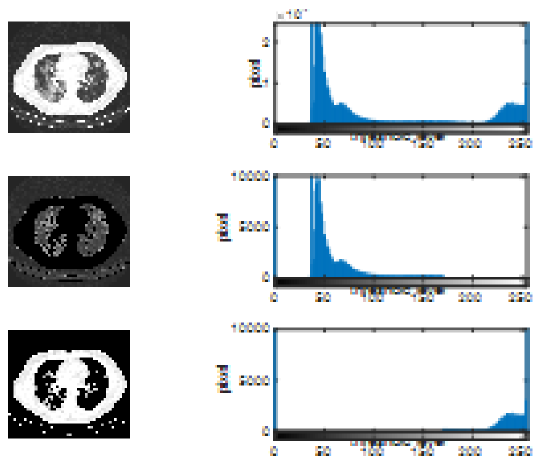


Fig 12(b)

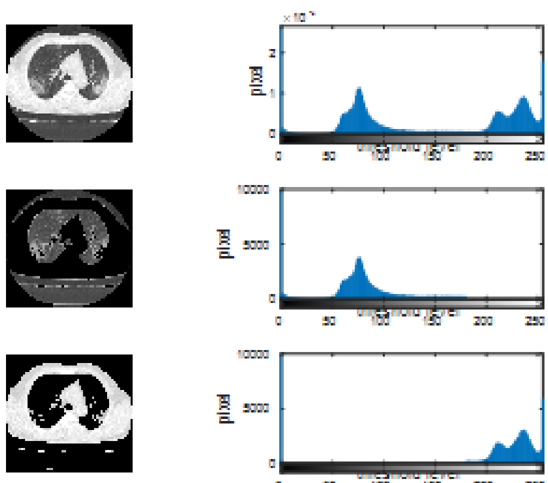


Fig 12(c)

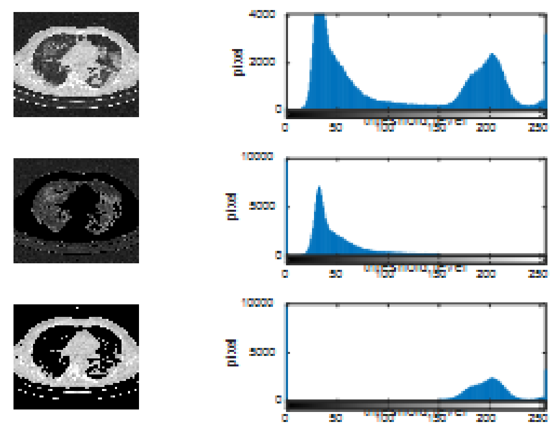


Fig 12(d)

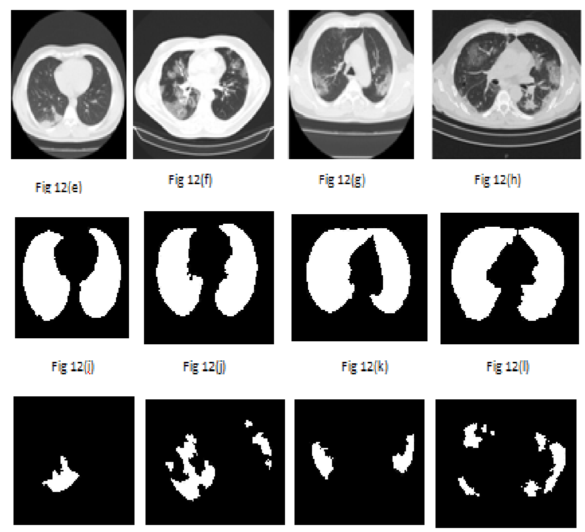


Fig 12(e) Fig 12(f) Fig 12(g) Fig 12(h)

Fig 12(i) Fig 12(j) Fig 12(k) Fig 12(l)

Fig 12(m) Fig 12(n) Fig 12(o) Fig 12(p)

Fig 12: Results obtained for severity computation

V. RESULTS DISCUSSION

This section summarizes the experimental results obtained from classification of covid and non covid images using Convolutional Neural Networks and severity classification of COVID-19 cases. The presented work is implemented using MATLAB software.

Table 1: Performance of trained CNN models using x-ray dataset

CNN Model	Accuracy	Sensitivity	Specificity	Duration
RESNET-50	100%	100%	100%	11 min
MOBILENETV2	100%	100%	100%	9 min
SQUEEZENET	100%	100%	100%	3 min

Table 2: Performance of trained CNN models using CT dataset

CNN Model	Accuracy	Sensitivity	Specificity	Duration
RESNET-50	95.97%	92.1%	100%	142 min
MOBILENETV2	97.32%	94.6%	100%	115 min
SQUEEZENET	88.59%	88.4%	88.8%	29 min

In this paper, the chest x-ray and CT image datasets are collected. Then Resnet50, Mobilenetv2 and squeezenet CNN models are trained to classify the covid and non covid images correctly. The trained network is evaluated using confusion matrix. The increase of epochs in training the network may lead to exact classification of images. The accuracy, sensitivity and specificity obtained at the end of training implies the network provides greatest accuracy for small image dataset. While comparing the performance of these CNN models Resnet50 and mobilenetv2 CNN models gives similar results. Whereas in squeezenet CNN model the performance is comparatively fast but less accurate. Then these CNN models are validated for the classification of covid and non covid images. Thus the CNN models are quantitatively compared and the accuracy, sensitivity and specificity of Resnet50, Mobilenetv2 and Squeezenet networks for x-ray and CT dataset obtained are summarized and tabulated in Table 1 and 2 respectively.

Table 3: Classification of COVID-19 cases based on percentage of infection

Cases	Severity	Observation	Category
Case 1	2%	GGO in the left lower lobe	Mild
Case 2	6%	GGO in the left lower lobe	Mild
Case 3	31.8%	Multiple GGO with consolidation	Severe
Case 4	13.5%	GGO in the right and left lower lobe	Moderate
Case 5	22.4%	Multiple GGO with consolidation	Severe

According to prior literature [12], severe patients had multiple ground-glass opacities with consolidation, which can lead to ventilatory dysfunction and even respiratory failure. In this work the COVID-19 CT image of case 1 with percentage of infection 2% is categorized as mild, case 2 with 6% severity is categorized as moderate, case 3 with 31.8% severity and multiple ground-glass opacities with consolidation is categorized as severe, case 4 with 13.5% severity is classified as moderate and case 5 with 22.4% severity and multiple ground glass opacity is categorized as severe. The classification is summarized in Table 3. This DIAGNOSIS OBTAINED WILL HELP THE PHYSICIAN IN EFFICIENT TREATMENT PLANNING AND TRACKING THE RECOVERY.

VI. CONCLUSION

The main motive of the work is to develop an AI based image assisted system to detect COVID-19 from radiological images and classify them based on severity of infection. As a conclusion, in this work work Convolution Neural network is used to detect and classify covid and non covid images in the x-ray and CT dataset. Then the COVID-19 infected CT images are classified into mild moderate and severe based on the severity of infection. However categorization based on severity is not done in x-ray images. Hence in future the classification based on severity of infection can be done in COVID-19 infected x-ray images. The limitation in this research work is that the obtained results are not correlated with clinical results.

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