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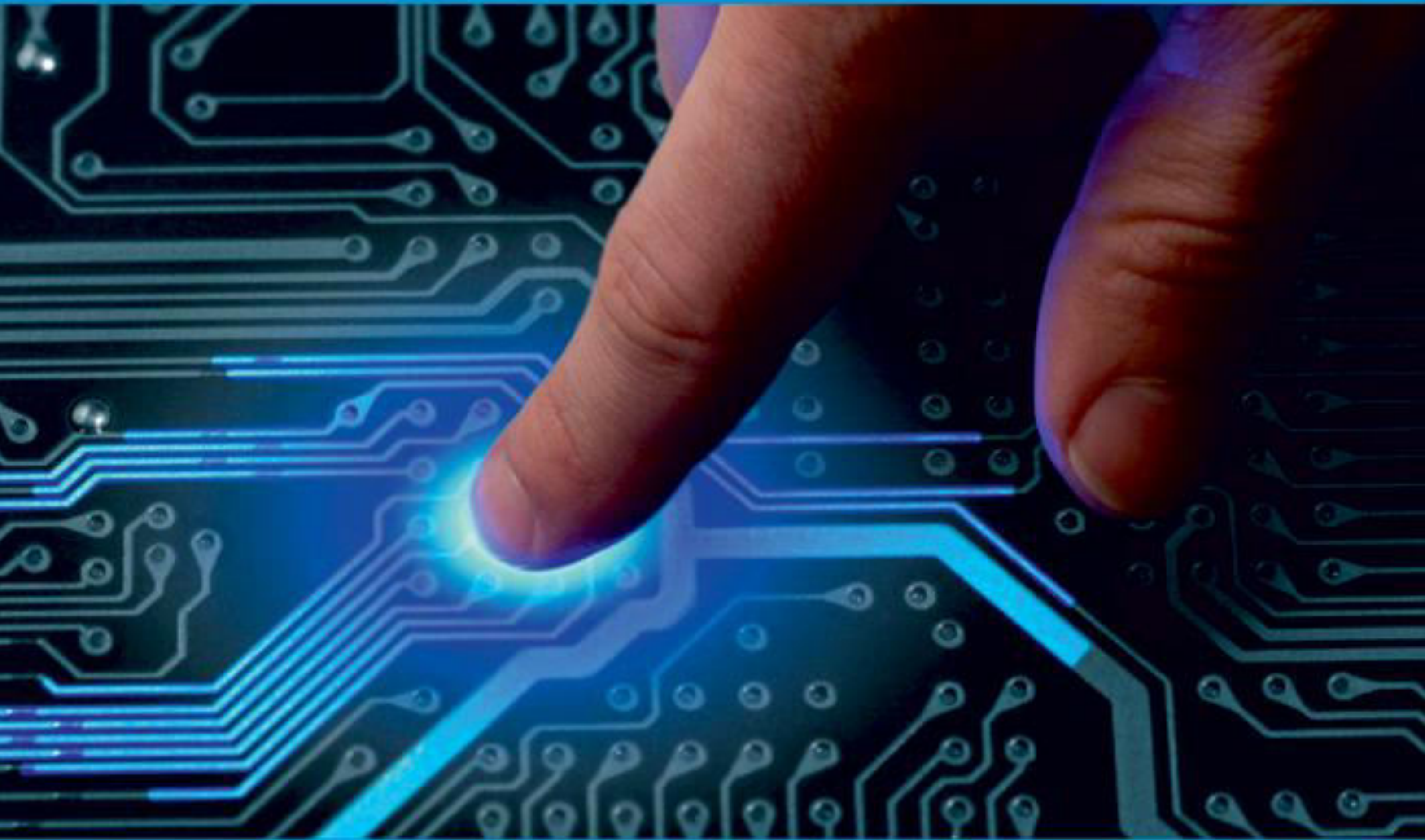

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Covid-19 Recognition from X-Ray Image Using Deep Learning

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ABSTRACT: Coronavirus Disease 2019 (COVID-19) has become a major health problem causing severe acute respiratory illness in humans. It has spread rapidly around the globe since its first identification in Wuhan, China, in December 2019. The causative virus is called severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2), and the World Health Organization (WHO) named the new epidemic disease Coronavirus Disease (COVID-19). The incidence of COVID-19 continues to increase with more than three million confirmed cases and over 244,000 deaths worldwide. There is currently no specific treatment or vaccine against COVID-19. Therefore, in the absence of pharmaceutical interventions, the implementation of precautions and hygienic measures will be essential to control and to minimize human transmission of the virus. In this review, we highlight the epidemiology, transmission, symptoms, and treatment of this disease, as well as future strategies to manage the spread of this fatal coronavirus. These Techniques have been used for related features selection from data set and then selected features have been used for training and testing of classifier for accurate and on time detection of covid-19.

KEYWORDS: Image Processing, Covid detection.

I. INTRODUCTION

CORONAVIRUS disease 2019 (COVID-19) has been declared as a pandemic by the World Health Organization (WHO) a few months after its first appearance. It has infected more than 70 million people, caused a few million causalities, and has so far paralyzed mobility all around the world. The spreading rate of COVID-19 is so high that the number of cases is expected to be doubled every three days if the social distancing is not strictly observed to slow this accretion Roughly around half of the COVID-19 positive patients also exhibit a comorbidity ,making it difficult to differentiate COVID-19 from other lung diseases. Automated and accurate COVID-19 diagnosis is critical for both saving lives and preventing its rapid spread in the community. Currently, reverse transcription-polymerase chain reaction (RT-PCR) and computed tomography (CT) are the common diagnostic techniques used today. RT-PCR results are ready at the earliest 24 h for critical cases and generally take several days to conclude a decision. CT may be an alternative at initial presentation; however, it is expensive and not easily accessible . The most common tool that medical experts use for both diagnostic and monitoring the course of the disease is X-ray imaging. Compared to RT-PCR or CT test, having an X-ray image is an extremely low cost and a fast process, usually taking only a few seconds. Recently, WHO reported that even RT-PCR may give false results in COVID-19 cases due to several reasons such as poor quality specimen from the patient, inappropriate processing of the specimen, taking the specimen at an early or late stage of the disease. For this reason, X-ray imaging has a great potential to be an alternative technological tool to be used along with the other tests for an accurate diagnosis. In this study, we aim to differentiate X-ray images of COVID-19 patients among other classes; bacterial pneumonia, viral pneumonia, and normal. For this work, a benchmark COVID-19 X-ray data set, Qata-Cov19 (Qatar University and Tampere University COVID-19 Data set) that contains 462 X-ray images from COVID-19 patients was collected. The images in the data set are different in quality, resolution, and SNR levels. QaTa-Cov19 also contains many X-ray images from the COVID-19 patients who are in the early stages; therefore, their X-ray images show mild or nosign of COVID-19 infestation by the naked eye. Another fact that makes the diagnosis far more challenging is that interclass similarity can be very high for many X-ray images. Against such high interclass similarities and intraclass variations, in this study, we aim for a high robustness level.

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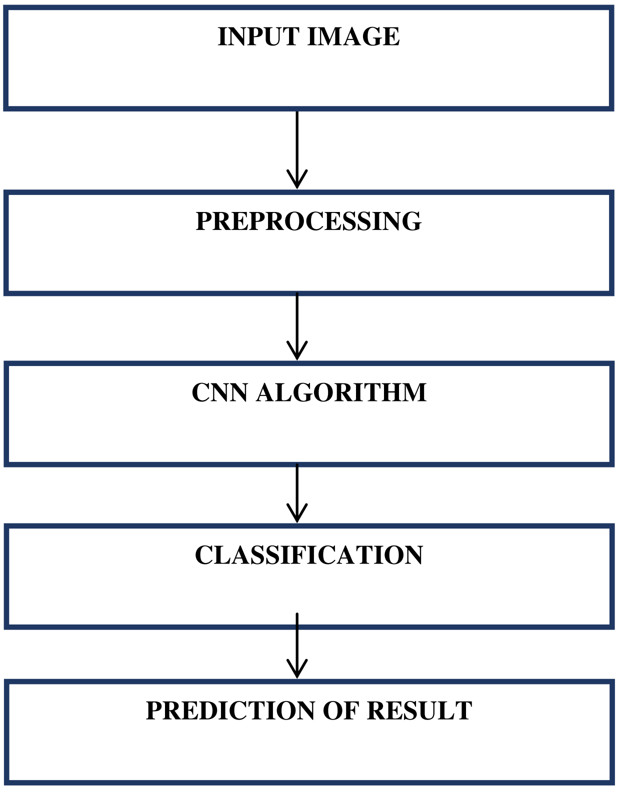
II. SYSTEM ARCHITECTURE

A deep CNN architecture has been proposed in this paper for the diagnosis of COVID-19 based on the chest X-ray image classification.

2.1 FLOW CHART:



2.2 IMAGE PROCESSING:

Image processing is a method to perform some operations on an image, in order to get an enhanced image or to extract some useful information from it. It is a type of signal processing in which input is an image and output may be image or characteristics/features associated with that image. Nowadays, image processing is among rapidly growing technologies. It forms core research area within engineering and computer science disciplines too.

Image processing basically includes the following three steps:

- Importing the image via image acquisition tools;
- Analysing and manipulating the image;
- Output in which result can be altered image or report that is based on image analysis.

There are two types of methods used for image processing namely, analogue and digital image processing. Analogue image processing can be used for the hard copies like printouts and photographs. Image analysts use various fundamentals of interpretation while using these visual techniques. Digital image processing techniques help in manipulation of the digital images by using computers. The three general phases that all types of data have to undergo while using digital technique are pre-processing, enhancement, and display, information extraction. In this lecture we will talk about a few fundamental definitions such as image, digital image, and digital image processing. Different sources of digital images will be discussed and examples for each source will be provided. The continuum from image processing to computer vision will be covered in this lecture. Finally we will talk about image acquisition and different types of image sensors.

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III. SOFTWARE DESCRIPTION

3.1 DEEP LEARNING:

Deep learning is a branch of machine learning that teaches computers to do what comes naturally to humans: learn from experience. Machine learning algorithms use computational methods to "learn" information directly from data without relying on a predetermined equation as a model. Deep learning is especially suited for image recognition, which is important for solving problems such as facial recognition, motion detection, and many advanced driver assistance technologies such as autonomous driving, lane detection, pedestrian detection, and autonomous parking. Deep learning uses neural networks to learn useful representations of features directly from data. Neural networks combine multiple nonlinear processing layers, using simple elements operating in parallel and inspired by biological nervous systems. Deep learning models can achieve state-of-the-art accuracy in object classification, sometimes exceeding human-level performance.

You train models using a large set of labeled data and neural network architectures that contain many layers, usually including some convolutional layers. Training these models is computationally intensive and you can usually accelerate training by using a high performance GPU.

3.2 INPUT LAYER:

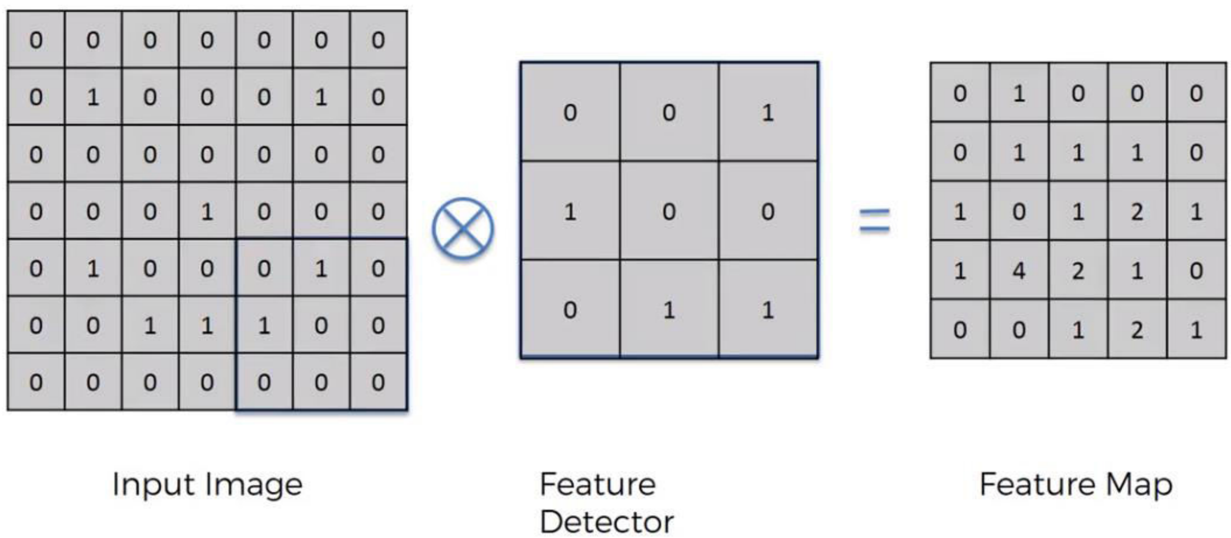
The input layer of a neural network is composed of artificial input neurons, and brings the initial data into the system for further processing by subsequent layers of artificial neurons. The input layer is the very beginning of the workflow for the artificial neural network.

3.3 CONVOLUTIONAL LAYER:

Convolution is an orderly procedure where two sources of information are intertwined; it's an operation that changes a function into something else. Convolutions have been used for a long time typically in image processing to blur and sharpen images, but also to perform other operations. (e.g. enhance edges and emboss) CNNs enforce a local connectivity pattern between neurons adjacent layers. CNNs make use of filters (also known as kernels), to detect what features, such as edges, are present throughout an image. There are four main operations in a CNN:

- Convolution
- Non Linearity (ReLU)
- Pooling or Sub Sampling
- Classification (Fully Connected Layer)

The first layer of a Convolutional Neural Network is always a Convolutional Layer. Convolutional layers apply a convolution operation to the input, passing the result to the next layer. A convolution converts all the pixels in its receptive field into a single value. For example, if you would apply a convolution to an image, you will be decreasing the image size as well as bringing all the information in the field together into a single pixel. The final output of the convolutional layer is a vector. Based on the type of problem we need to solve and on the kind of features we are looking to learn, we can use different kinds of convolutions.



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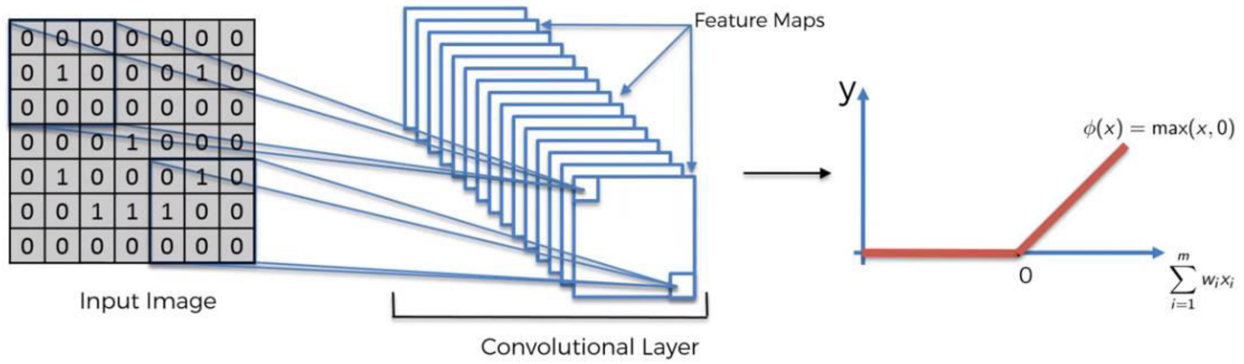
3.4 MAX POOLING LAYER:

Max Pooling is a convolution process where the Kernel extracts the maximum value of the area it convolves. Max Pooling simply says to the Convolutional Neural Network that we will carry forward only that information, if that is the largest information available amplitude wise. Max-pooling on a 4*4 channel using 2*2 kernel and a stride of 2: As we are convolving with a 2*2 Kernel. If we observe the first 2*2 set on which the kernel is focusing the channel have four values 8,3,4,7. Max-Pooling picks the maximum value from that set which is “8”. Here in our context, we will make a kernel that amplifies the image of the cat’s eye to such an extent that even after Max Pooling the predominant information is not lost. When Max Pooling now clips my pixels, the 25% pixels which are left are enough to get the information about the cat. So, there is going to be one channel or feature map which contains the information of the cat’s eye no matter what happens at the benefit of reducing 75% pixels. In another way, we can say that we are filtering information that we don’t want by building Kernels which can allow getting required information out through Max Pooling.

3.5 RELU LAYER:

In the context of artificial neural networks, the **rectifier** or **ReLU (Rectified Linear Unit) activation function**[1][2] is an activation function defined as the positive part of its argument:

where *x* is the input to a neuron. This is also known as a ramp function and is analogous to half-wave rectification in electrical engineering. This activation function started showing up in the context of visual feature extraction in hierarchical neural networks starting in the late 1960s. It was later argued that it has strong biological motivations and mathematical justifications. In 2011 it was found to enable better training of deeper networks, compared to the widely used activation functions prior to 2011, e.g., the logistic sigmoid (which is inspired by probability theory; see logistic regression) and its more practical counterpart, the hyperbolic tangent. The rectifier is, as of 2017, the most popular activation function for deep neural networks. Rectified linear units find applications in computer vision and speech recognition using deep neural nets and computational neuroscience.



3.6 BATCH NORMALIZATION LAYER:

Training deep neural networks with tens of layers is challenging as they can be sensitive to the initial random weights and configuration of the learning algorithm. One possible reason for this difficulty is the distribution of the inputs to layers deep in the network may change after each mini-batch when the weights are updated. This can cause the learning algorithm to forever chase a moving target. This change in the distribution of inputs to layers in the network is referred to the technical name “*internal covariate shift.”* Batch normalization is a technique for training very deep neural networks that standardizes the inputs to a layer for each mini-batch. This has the effect of stabilizing the learning process and dramatically reducing the number of training epochs required to train deep networks. In this post, you will discover the batch normalization method used to accelerate the training of deep learning neural networks.

- Deep neural networks are challenging to train, not least because the input from prior layers can change after weight updates.
- Batch normalization is a technique to standardize the inputs to a network, applied to ether the activations of a prior layer or inputs directly.
- Batch normalization accelerates training, in some cases by halving the epochs or better, and provides some regularization, reducing generalization error.

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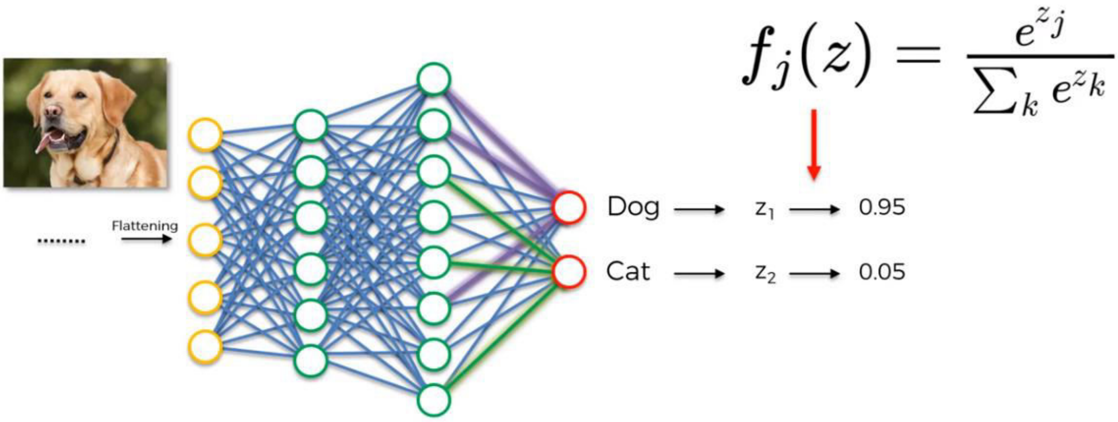
3.7 SOFT MAX LAYER:

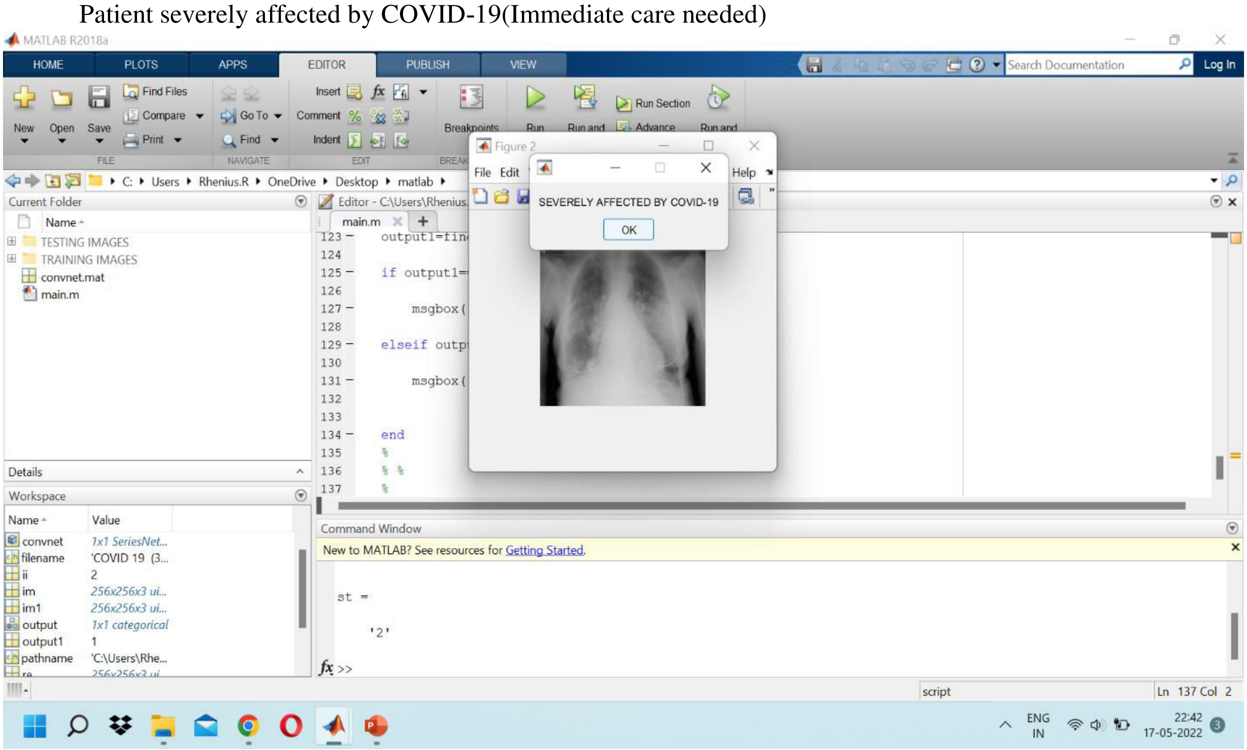
- From the figure about the detection of the dog, we found 0.95 Dog, and 0.05 Cat. The question is how these two values add up to 1. That is possible only introducing the Softmax Function, the formula is the following:



- As described by the formula in the figure above, the Softmax Function is a generalization of the Logistic Function, and it makes sure that our prediction add up to 1. Most of the time the Soft max Function is related to the Cross Entropy Function. In CNN, after the application of the Soft max Function, is to test the reliability of the model using as Loss Function the Cross Entropy Function, in order to maximize the performance of our neural network. There are several advantages to using the Cross Entropy Function. One of the best is that if for instance at the start of back propagation the output value is much smaller than the actual value, the gradient descent will be very slow. Because Cross Entropy uses the logarithm, it helps the network to assess even large errors.

IV. RESULTS

- Patient severely affected by COVID-19(Immediate care needed)



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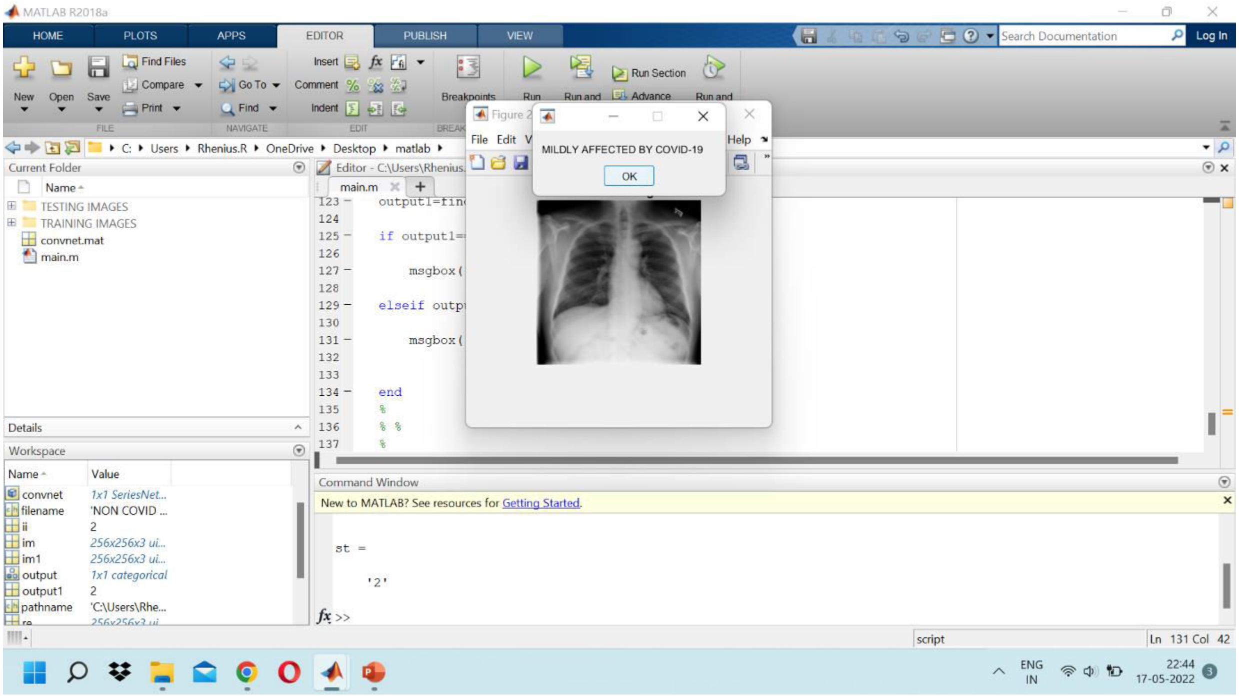
- Patient with mild danger of COVID-19 (Can be admitted in general ward)



V. CONCLUSIONS

The commonly used methods in COVID-19 diagnosis, namely RT-PCR and CT have certain limitations and drawbacks such as long processing times and unacceptably high misdiagnosis rates. These drawbacks are also shared by most of the recent works in the literature based on deep learning due to data scarcity from the COVID-19 cases. Although deep learning-based recognition techniques are dominant in computer vision where they achieved state-of-the-art performance, their performance degrades fast due to data scarcity, which is the reality in this problem at hand. This study aims to address such limitations by proposing a robust and highly accurate COVID-19 recognition approach directly from X-ray images. The proposed approach is based on the CSEN that can be seen as a bridge between deep learning models and representation based methods. CSEN uses both a dictionary and a set of training samples to learn a direct mapping from the query samples to the sparse support set of representation coefficients. With this unique ability and having the advantage of a compact network, the proposed CSEN-based COVID-19 recognition systems surpass the competing methods and achieve over 98% sensitivity and over 95% specificity. Furthermore, they yield the most computationally efficient scheme in terms of speed and memory.

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