LUNG INFECTION DETECTION OF COVID 19 PATIENTS

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Abstract— the corona virus disease (COVID-19) is rapidly spreading all over the world, and has infected more than 1,966,000 people in more than 200 countries and territories as of October, 2020. Detecting COVID-19 at early stage is essential to deliver proper healthcare to the patients and also to protect the uninfected population. To this end, we develop a framework to automatically diagnose COVID-19 from the community acquired pneumonia (CAP) in chest computed tomography (CT). In particular, we propose a Noise Robust Segmentation approach with a recurrent neural network (RNN) to focus on the infection regions in lungs when making decisions of diagnoses. Note that there exists imbalanced distribution of the sizes of the infection regions between COVID-19 and CAP, partially due to fast progress of COVID-19 after symptom onset. Our framework is evaluated upon the largest multi-center CT data for COVID-19 from hospitals.

Keywords – COVID-19, Deep Learning, Recurrent neural network, noisy label, segmentation, pneumonia.

I. INTRODUCTION

The coronavirus disease 2019 (COVID-19) has become a global pandemic since the beginning of 2020. The disease has been regarded as a Public Health Emergency of International Concern (PHEIC) by the World Health Organization (WHO) and the end of January 2020. Up to April 10, 2020, there have been more than 1.5 million cases of COVID19 reported globally, with more than 92 thousands deaths. The most common symptoms of COVID-19 patients include fever, cough and shortness of breath, and the patients typically suffer from pneumonia. Computed Tomography (CT) imaging plays a critical role for detection of manifestations in the lung associated with COVID-19, where segmentation of the infection lesions from CT scans is important for quantitative measurement of the disease progression in accurate diagnosis and follow-up assessment. As manual segmentation of the lesions from 3D volumes is labor-intensive, time-consuming and suffers from inter- and intra-observer variabilities, automatic segmentation of the lesions is highly desirable in clinic practice.

Despite its importance for diagnosis and treatment decisions, automatic segmentation of COVID-19 pneumonia lesions from CT scans is challenging due to several reasons. First, the infection lesions have a variety of complex appearances such as Ground-Glass Opacity (GGO), reticulation, consolidation and others. Second, the sizes and positions of the pneumonia lesions vary largely at different stages of the infection and among different patients. In addition, the lesions have irregular shapes and ambiguous boundaries, and some lesion patterns such as GGO have a low contrast with surrounding regions.

The goal of this work is three-fold. First, to deal with noisy annotations for training RNNs to segment COVID19 pneumonia lesions, we propose a novel noise-robust Dice loss function, which is a combination and generalization of MAE loss that is robust against noisy labels and Dice loss that is insensitive to foreground-background imbalance. Second, we propose a novel noise-robust learning framework based on self-ensembling of RNNs where an Exponential Moving Average (EMA, a.k.a. teacher) of a model is used to guide a standard model (a.k.a.

student) to improve the robustness. Differently from previous self ensembling methods for semi-supervised learning and domain adaptation, we propose two adaptive mechanisms to better deal with noisy labels: adaptive teacher that suppresses the contribution of the student to EMA when the latter has a large training loss, and adaptive student that learns from the teacher only when the teacher outperforms the student. Thirdly, to better deal with the complex lesions, we propose a novel COVID-19 Pneumonia Lesion segmentation network (COPLE-Net) that uses a combination of max-pooling and average pooling to reduce information loss during downsampling, and employs bridge layers to alleviate the semantic gap between features in the encoder and decoder.

1.1. Problem Statement/Objective

COVID19 is contagious disease and in some cases it affects lungs fatally. This paper proposed lungs infection detection technique which is able to tell whether a person is infected or not and calculate % of infection so that early detection may save person's life.

1.2. Scope

Although system will be accurate but may not predict % infection detection correctly when two similar CT scan or X-ray are compared.

I. RELATED WORK

In December 2019[1], a cluster of patients with pneumonia of unknown cause was linked to a seafood wholesale market in Wuhan, China. A previously unknown betacoronavirus was discovered through the use of unbiased sequencing in samples from patients with pneumonia. Human airway epithelial cells were used to isolate a novel coronavirus, named 2019-nCoV, which formed another clade within the subgenus sarbecovirus,Orthocoronavirinae subfamily. Different from both MERS-CoV and SARS-CoV, 2019-nCoV is the seventh member of the family of coronaviruses that infect humans.

This study[2] describes the same population genetic dynamic underlying the SARS 2003 epidemic, and suggests the urgent need for the development of effective molecular surveillance strategies of Betacoronavirus among animals and Rhinolophus of the bat family.

This paper[3] discusses how AI provides safe, accurate and efficient imaging solutions in COVID-19 applications. The intelligent imaging platforms, clinical diagnosis, and pioneering research are reviewed in detail, which covers the entire pipeline of AI-empowered imaging applications in COVID-19. Two imaging modalities, i.e., X-ray and CT, are used to demonstrates the effectiveness of AI-empowered medical imaging for COVID-19.

The purpose of this study[4] was to assess a quantitative CT Image Parameter,defined as the percentage of lung opacification(QCT-PLO), calculated automatically using a deep learning tool. We evaluated QCT-PLO in covid -19 patients at baseline and on follow up scans,focusing on cross-sectional and longitudinal differences in patients with different degrees of clinical severity.

On the basis[5] of epidemiologic characteristics, clinical manifestations, chest images, and laboratory findings, the diagnosis of 2019-nCoV pneumonia was made. After receiving 3 days of treatment, combined with interferon inhalation, the patient was clinically worse with progressive pulmonary opacities found at repeat chest CT.

II. EXISTING SYSTEM

Due to the challenges of this novel disease, healthcare providers, patients, and their families have been required to rapidly make crucial and difficult decisions with limited information. The phenotypes of COVID-19 range from no or relatively mild symptoms and uneventful recovery to rapid deterioration,

acute respiratory distress syndrome (ARDS), multi-organ system failure, and death. The trajectory for patients most likely to decompensate is being investigated but remains elusive at present; lack of standardized care is forcing unprecedented workflow for physicians and nurses. Given the gravity of these circumstances and increase in the number of cases, there is a pressing need for tools that can augment current healthcare resources. Machine learning (ML) and artificial intelligence (AI) methods can be applied to understand subgroups of patients, guide clinical decision-making, and improve both operation- and patient-centered outcomes. This perspective highlights the benefits of these

tools observed at various clinical settings and describes how the value of ML and AI algorithms, when conscientiously built, may be augmented during the COVID-19 pandemic.

III. PROPOSED SYSTEM

1. Input image is image from database (for training) and real time image (lungs infection detection).
2. Pre-processing is a common name for operations with images at the lowest level of abstraction both input and output are intensity images.
   - The aim of pre-processing is an improvement of the image data that suppresses unwanted distortions or enhances some image features important for further processing.
   - Before discussing the extraction of feature points it is necessary to have a measure to compare parts of images.
3. The extraction and matching of features is based on these measures.
   - Besides the simple point feature a more advanced type of feature is also presented.
   - Feature extraction technique is used to extract the features by keeping as much information as possible from large set of data of image.
4. Dataset is given to train CNN.
5. Classification is performed using CNN.

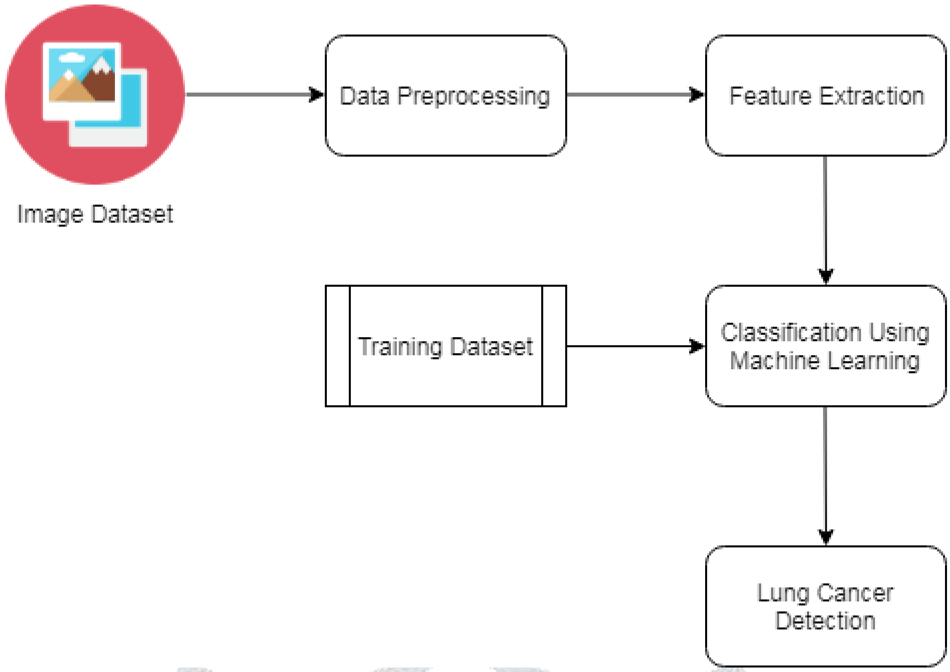


Fig 1: System Architecture

IV.ENVIROMENTAL SPECIFICATION

Hardware Requirements:

1. PROCESSOR	- INTEL I3/I5/I7
2. Speed	- 1.1 GHz
3. RAM	- 2 GB(min)
4. Hard Disk	- 40 GB
5. Key Board	- Standard Windows Keyboard
6. Mouse	- Two or Three Button Mouse
7. Monitor	- SVGA

Software Requirements:

1. Operating System	- Windows 7/8/10
2. Application Server	- Apache Tomcat 7/8/9
3. Front End	- HTML, JDK 1.8, JSP
4. Scripts	- JavaScript.
5. Server side Script	- Java Server Pages.
6. Database	- My SQL 5.0
7. IDE	- Eclipse Oxygen

V.ALGORITHAMS

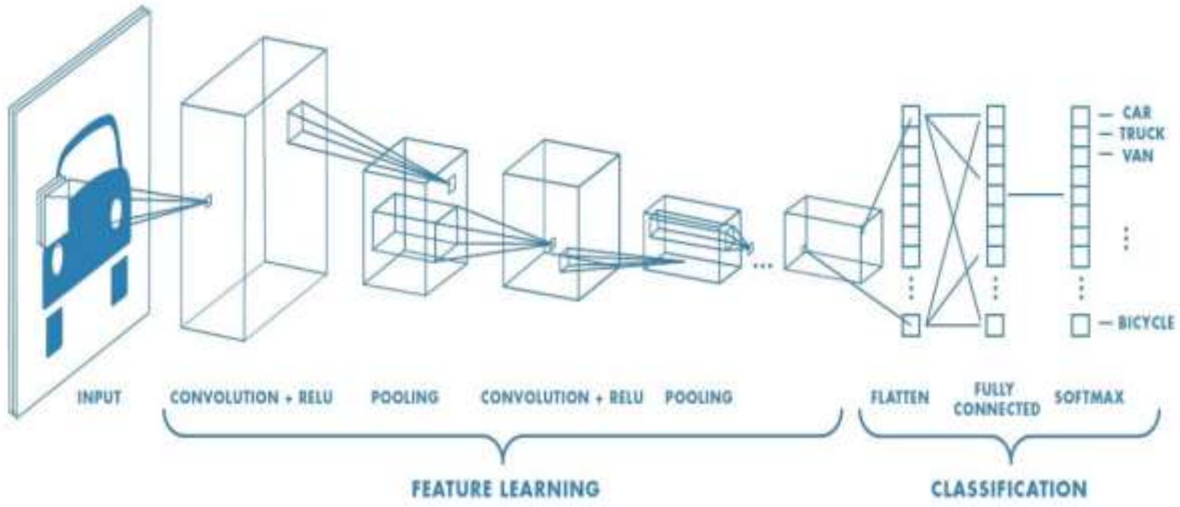


Fig 2: Fearture Extraction and Classification

Convolution Layer

Convolution is the first layer to extract features from an input image (image). Convolution preserves the relationship between pixels by learning image features using small squares of input data. Convolution of an image with different filters can perform operations such as edge detection, blur and sharpen by applying filters i.e. identity filter, edge detection, sharpen, box blur and Gaussian blur filter.

Pooling Layer

Pooling layers would reduce the number of parameters when the images are too large. Spatial pooling also called subsampling or down sampling which reduces the dimensionality of each map but retains important information.

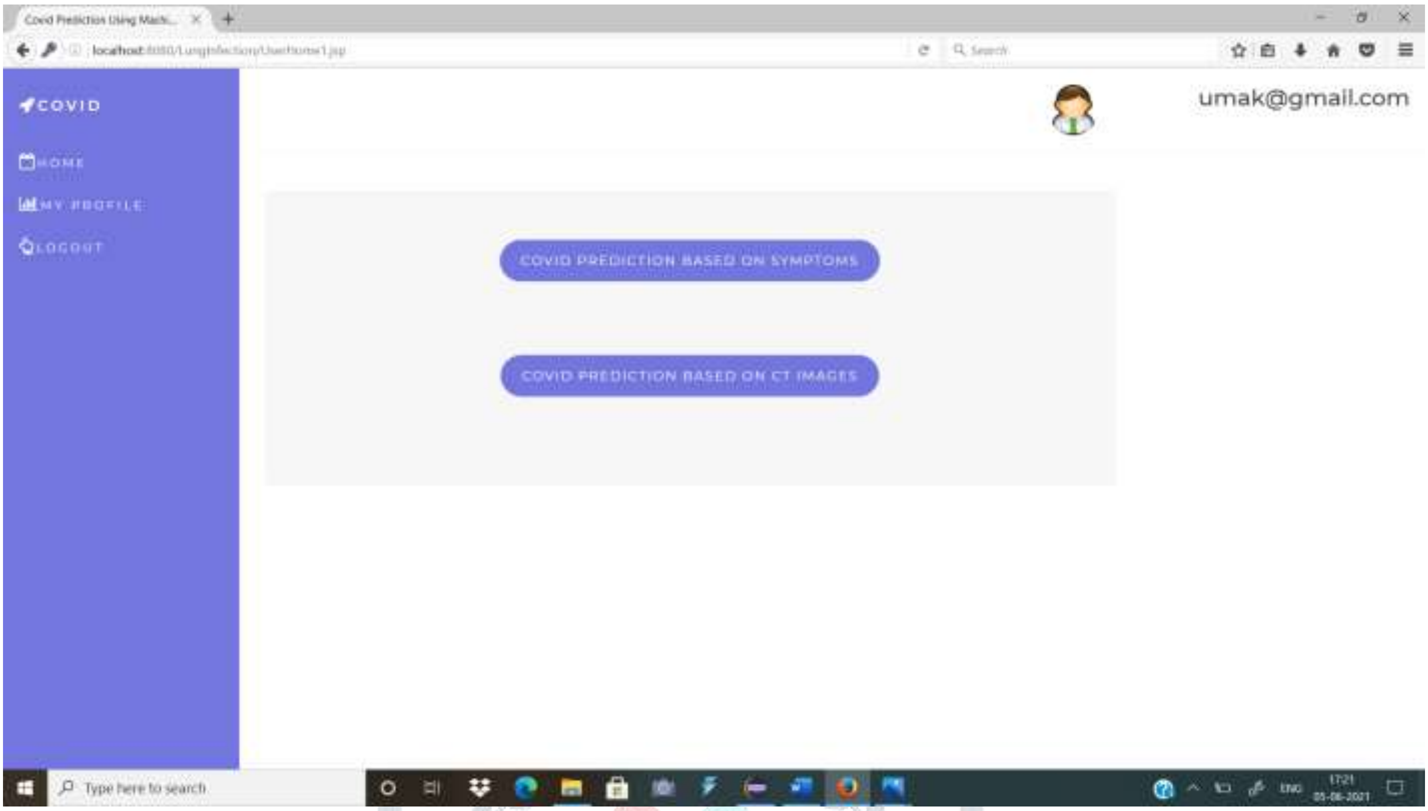
Fully Connected Layer

In this layer Feature map matrix will be converted as vector (x1, x2, x3, …). With the fully connected layers, we combined these features together to create a model.

Softmax Classifier

Finally, we have an activation function such as softmax or sigmoid to classify the outputs.

VI. RESULT


COVID
HOME
MY PROFILE
LOGOUT
umak@gmail.com
COVID PREDICTION BASED ON SYMPTOMS
COVID PREDICTION BASED ON CT IMAGES
Type here to search


COVID
HOME
ADMIN
USER
Lung infection detection for Covid 19 using machine learning
MEDICAL
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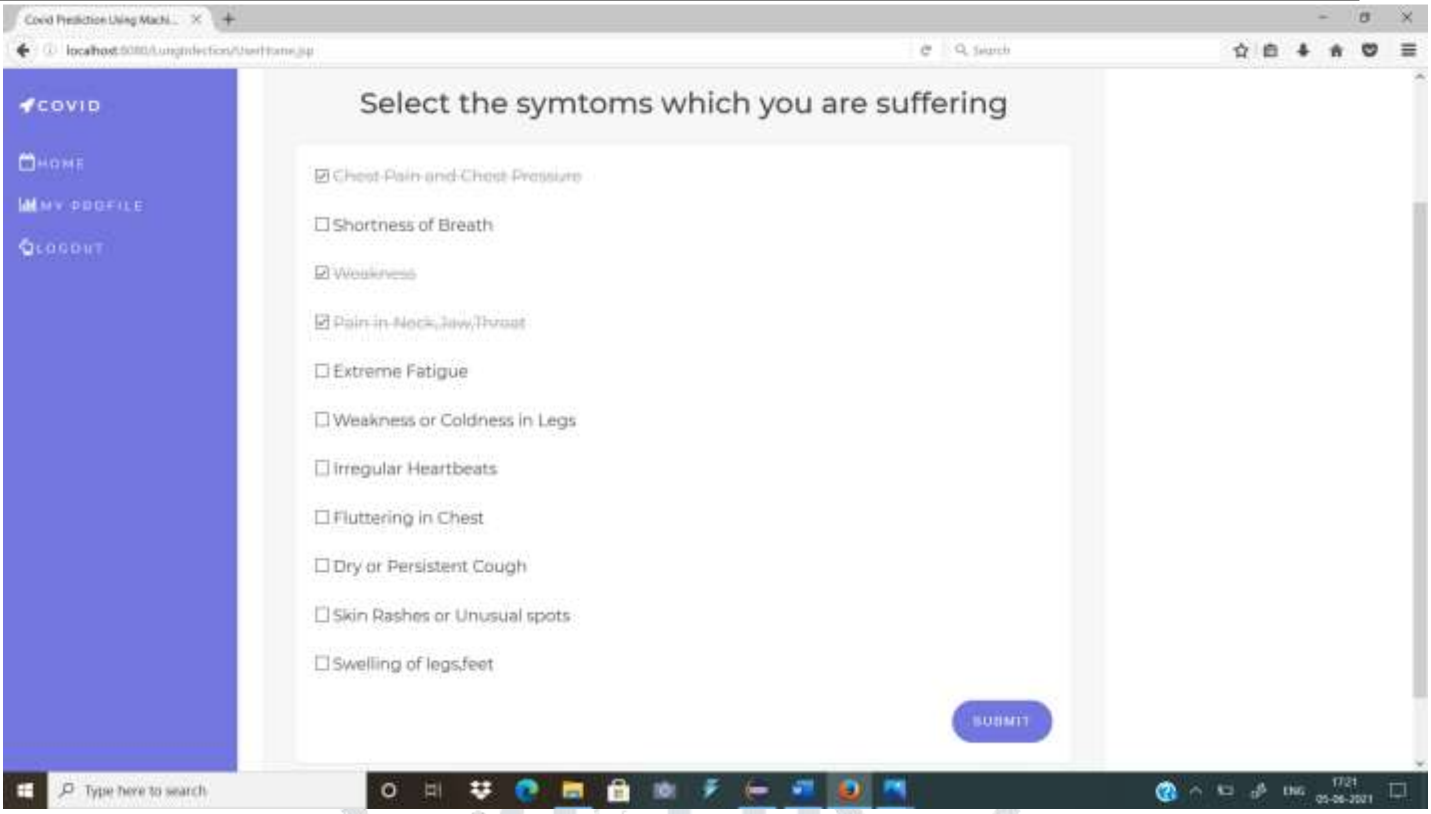
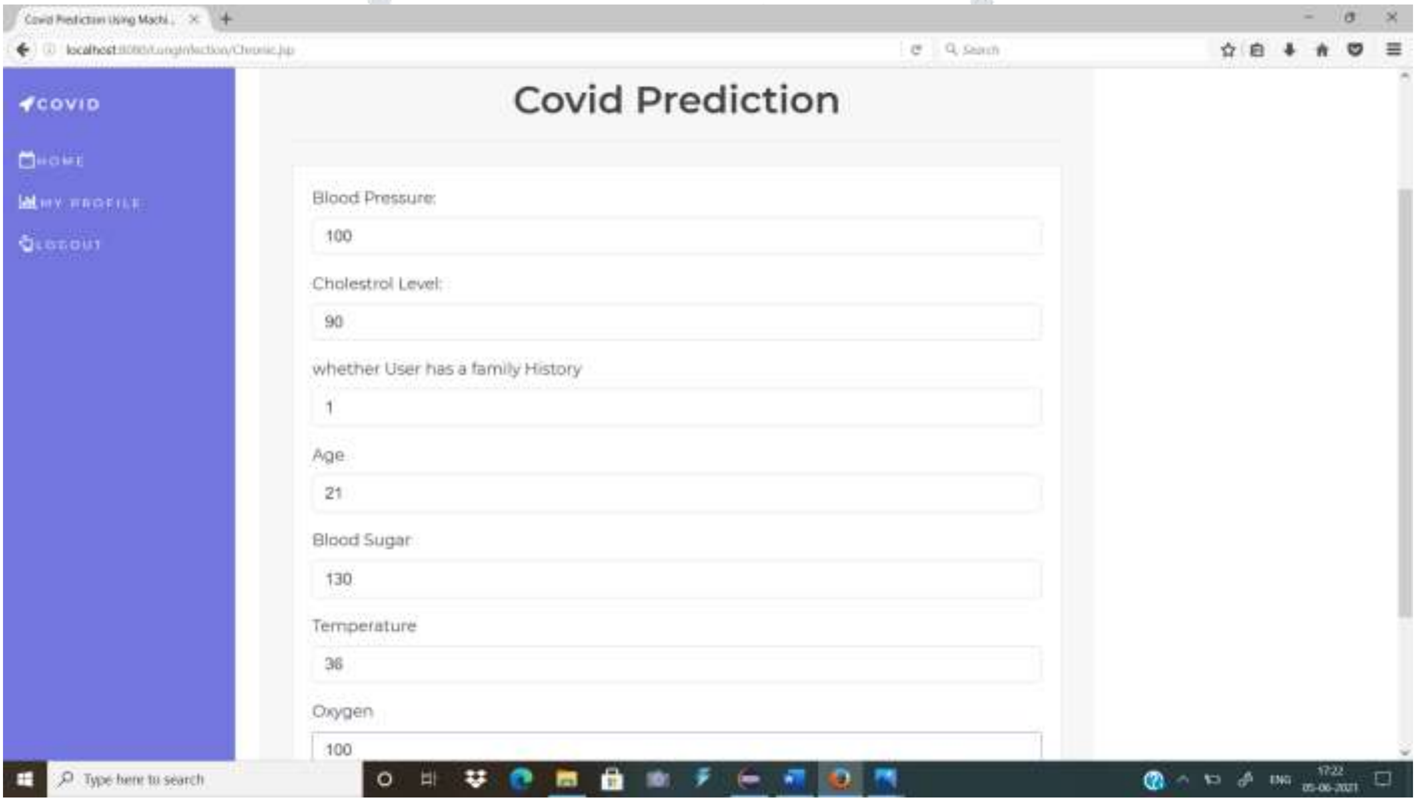

COVID
HOME
MY PROFILE
LOGOUT
Select the symtoms which you are suffering
Chest Pain and Chest Pressure
Shortness of Breath
Weakness
Pain in Neck,Jaw,Throat
Extreme Fatigue
Weakness or Coldness in Legs
Irregular Heartbeats
Fluttering in Chest
Dry or Persistent Cough
Skin Rashes or Unusual spots
Swelling of legs,feet
SUBMIT
Type here to search


COVID
HOME
MY PROFILE
LOGOUT
Covid Prediction
Blood Pressure:
100
Cholestrol Level:
90
whether User has a family History
1
Age
21
Blood Sugar
130
Temperature
36
Oxygen
100
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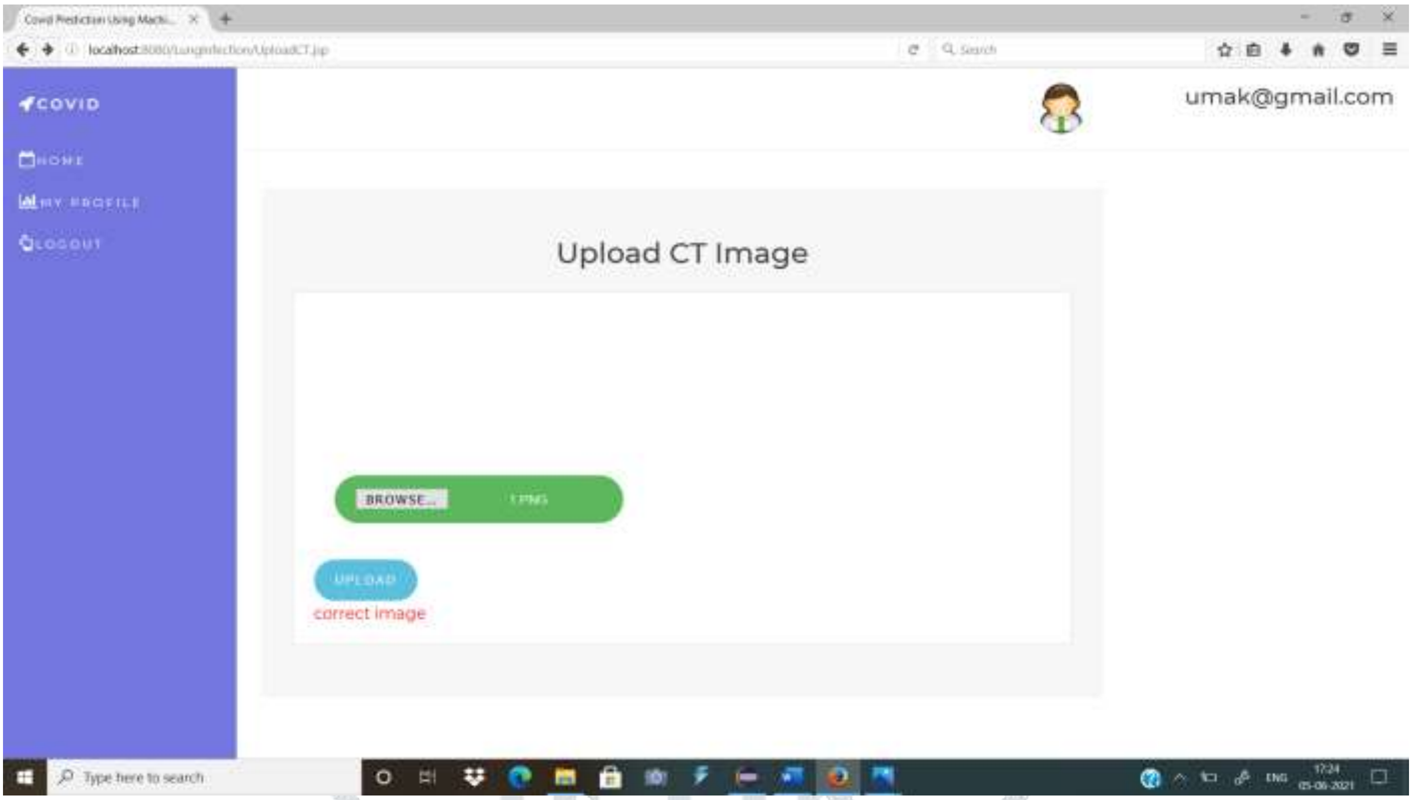
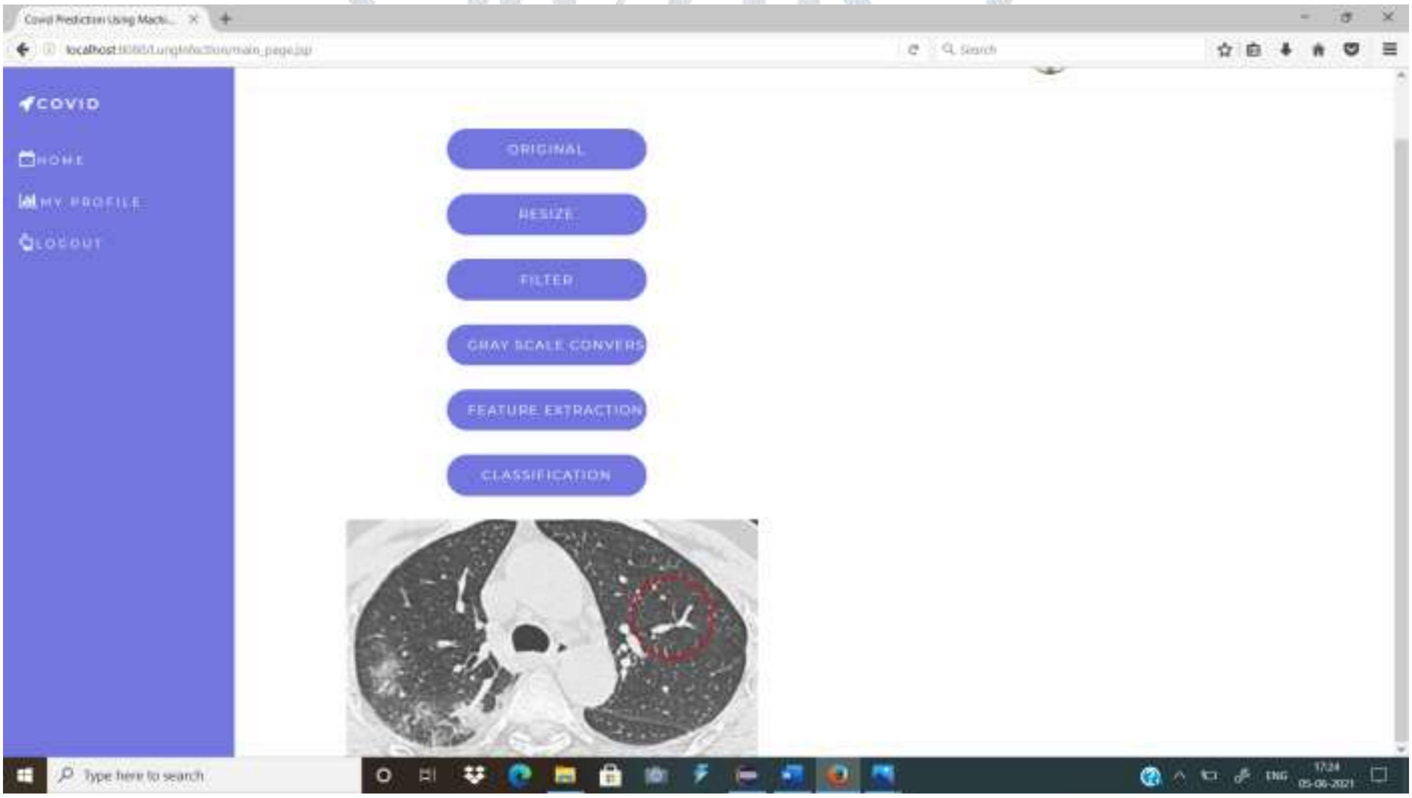

COVID
HOME
MY PROFILE
LOGOUT
umak@gmail.com
Upload CT Image
BROWSE...
UPLOAD
correct image
Type here to search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CLASSIFICATION
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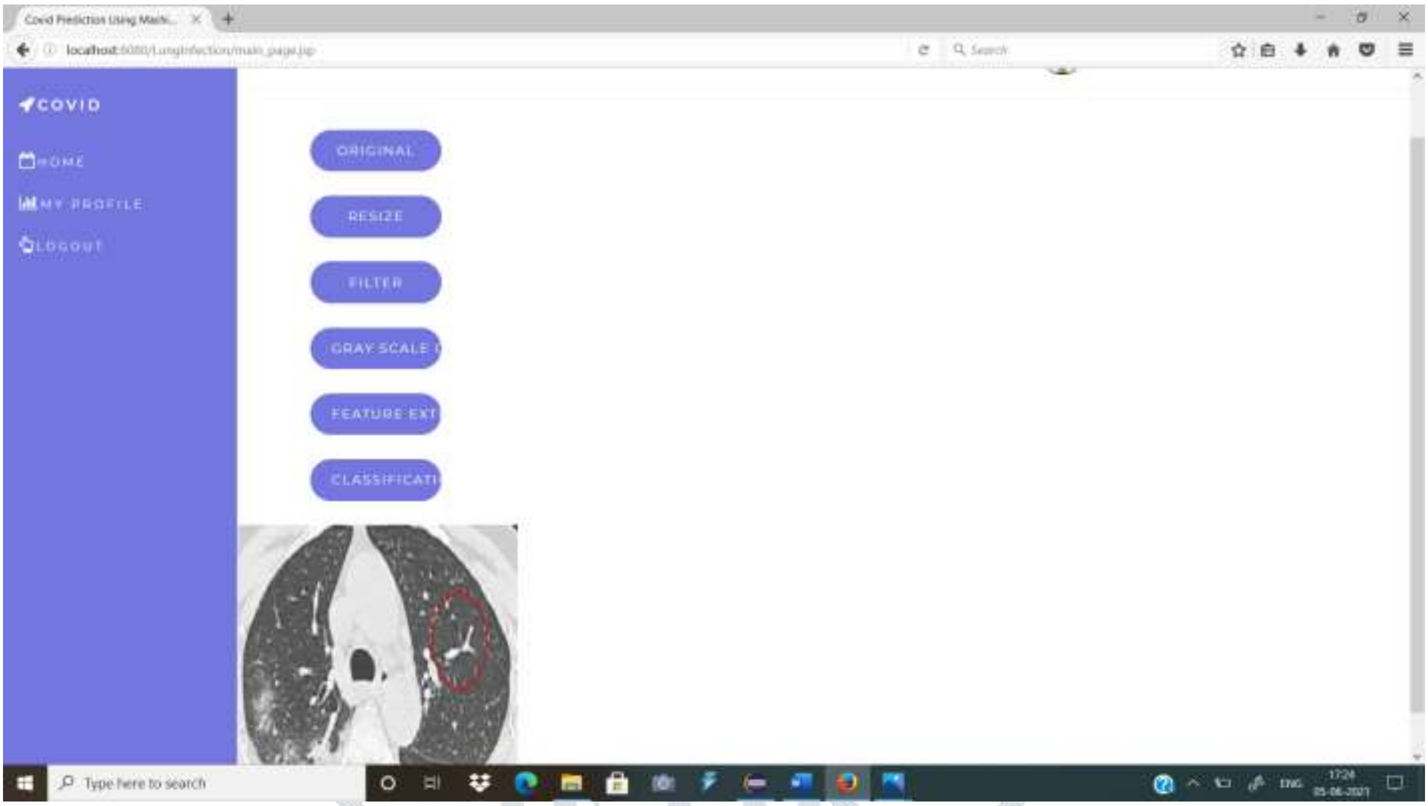
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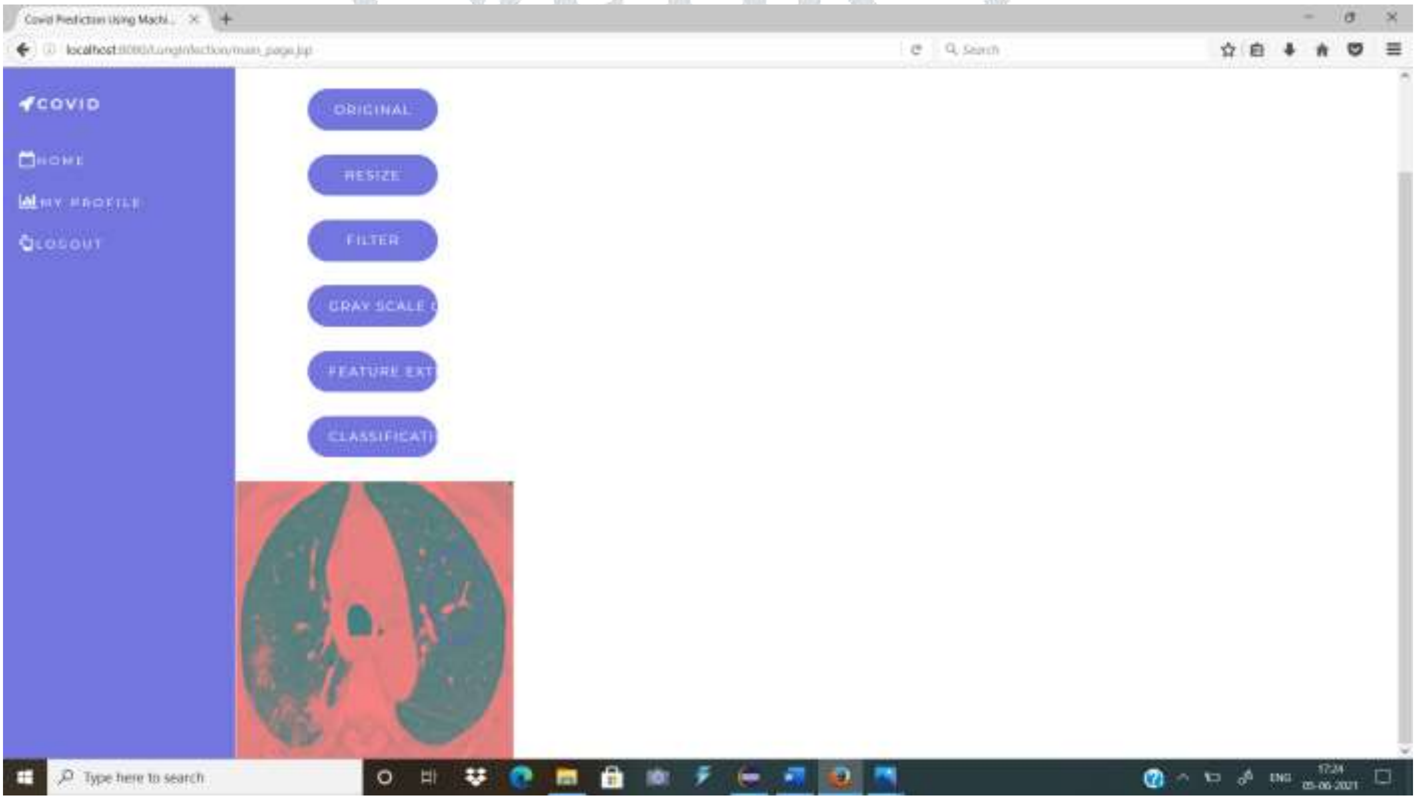
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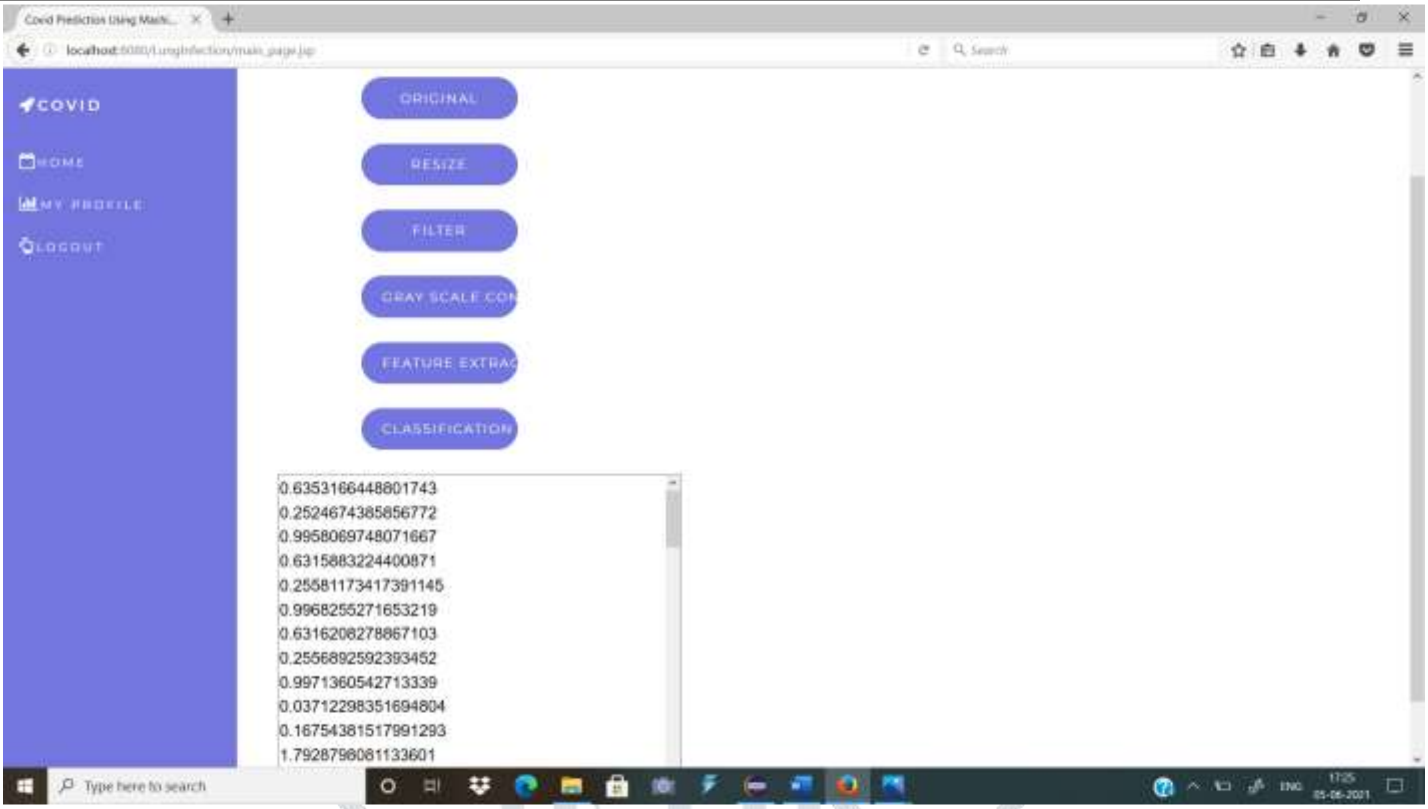

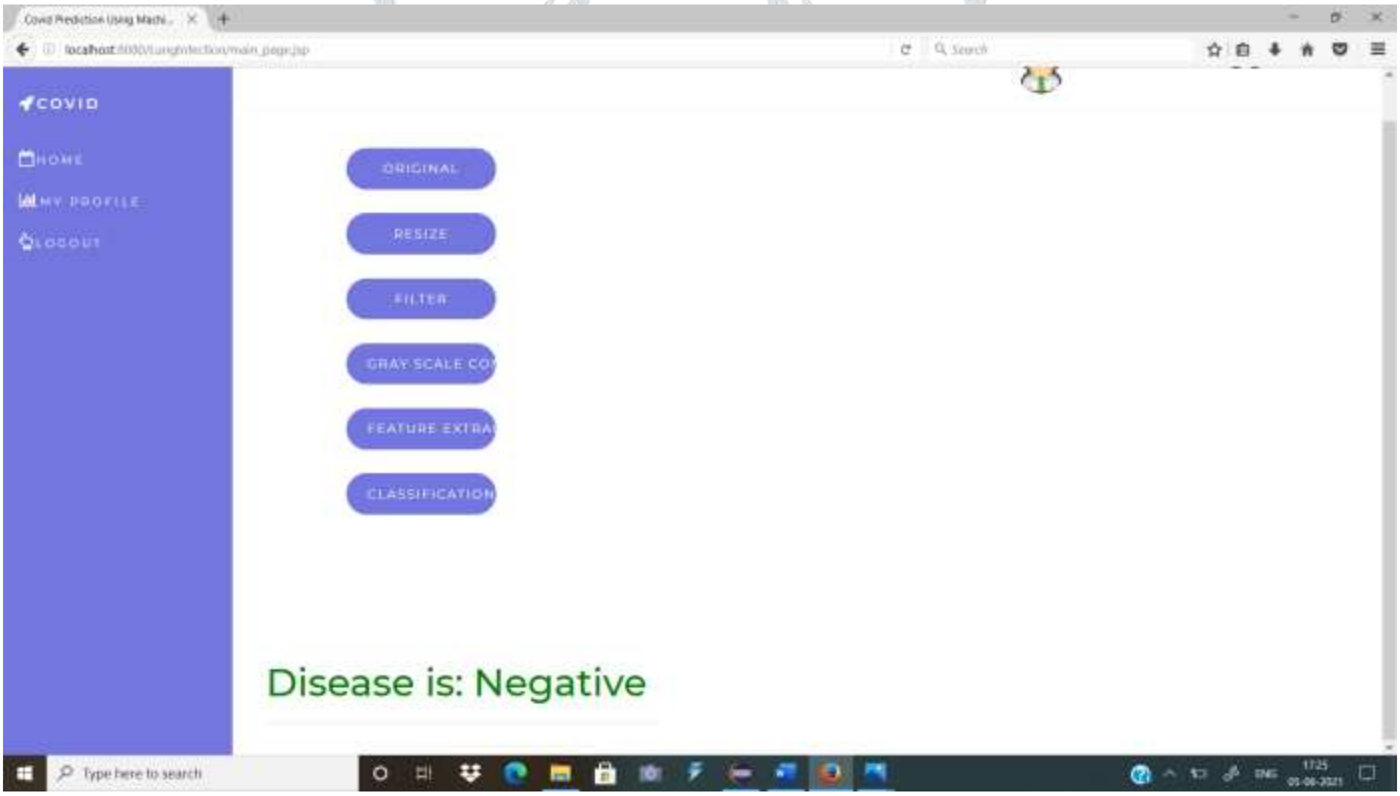

VII. CONCLUSION

COVID-19, it is important to get the diagnosis result at soon as possible. CT is shown as a powerful tool and could provide the chest scan results in several minutes. It is beneficial to develop an automatic diagnosis method based on chest CT to assist the COVID19 screening. In this study, we explore a deep-learning based method to perform automatic COVID-19 diagnosis from CAP in chest CT images. We evaluate our method by the largest multi-center CT data in the world.

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