Heriot-Watt University

FINAL YEAR DISSERTATION

Automated Diagnosis of COVID-19 using Medical Imagery

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Declaration of Authorship

I, **Alister George Luiz**, confirm that this work submitted for assessment is my own and is expressed in my own words. Any uses made within it of the works of other authors in any form (e.g., ideas, equations, figures, text, tables, programs) are properly acknowledged at any point of their use. A list of the references employed is included.

Signed: **Alister George Luiz**

Date: **November 26, 2020**

"The only limit to our realization of tomorrow will be our doubts of today."

Franklin D. Roosevelt

Abstract

The Coronavirus Disease (COVID-19) since its inception in late 2019 has spread all across the world and have led to an increased burden on healthcare professionals due to the urgent need for rapid disease diagnosis and effectuating quarantine protocols.

Currently, the Real-Time Reverse Transcription Polymerase Chain Reaction (RT-PCR) test recommended by the World Health Organization (WHO) remains the front runner in terms of COVID-19 diagnosis when compared to other testing mechanisms. But using this test as a primary diagnosis tool involves serious downsides, a few of them include the shortage in RT-PCR test kits, delays in receiving test results (up to 2 days), but most importantly the low accuracy of COVID-19 detection.

The primary objective of this project is to develop a fully automated framework that rapidly diagnoses patients with COVID-19. We aim to utilize medical imagery such as Chest X-rays and CT scans, apply deep learning techniques and achieve much higher accuracy compared to the traditional RT-PCR test. This ultimately decreases the workload on medical professionals and minimizes human to human interaction thus reducing virus exposure.

Keywords: COVID-19, SARS-CoV-2, Chest X-ray, Chest CT, Medical Image Classification, Deep Learning, Convolutional Neural Networks, Transfer Learning

Acknowledgements

I would like to thank Dr. Hani Ragab for his constant guidance and support throughout the tenure of this project. I would also like to thank my parents whose prayers and encouragement made me who I am today ...

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COVID-19	**C**oronavirus **D**isease 20**19**
SARS-CoV-2	**S**evere **A**cute **R**espiratory **S**yndrome **C**oronavirus **2**
RT-PCR	**R**everse **T**ranscription **P**olymerase **C**hain **R**eaction
CT	**C**omputed **T**omography
AI	**A**rtificial **I**ntelligence
CNN	**C**onvolutional **N**eural **N**etwork
WHO	**W**orld **H**ealth **O**rganization
RNA	**R**ibo**n**ucleic **A**cid
DNA	**D**eoxyribo**n**ucleic **A**cid
GGO	**G**round **G**lass **O**pacity
ROI	**R**egions **o**f **I**nterest
CAP	**C**ommunity **A**cquired **P**neumonia

Chapter 1

Introduction

COVID-19, which was declared a global pandemic by the World Health Organization on March 11, 2020, has affected millions of lives worldwide in terms of both health and finances and have also had a severe global economic impact.

With over a million tests carried out on average daily across the world for diagnosing patients with COVID-19 [1], it is therefore the need of the hour to alleviate the burden on healthcare professionals who conducts these diagnoses on a day-to-day basis, and more importantly, minimize the exposure rate between patients and healthcare professionals.

1.1 Aim

This project aims to **automate the diagnoses of COVID-19 with medical imagery using Deep Learning**. The main focus being to achieve the highest diagnostic accuracy possible, minimizing the false-negative rate, which, if not accounted for may have adverse real-world implications. We also intend to compare the usage of X-rays vs CT scans in this project considering the limitations in terms of the equipment available on medical facilities, radiation exposure, and the results obtained in both cases.

The overall goal of this project is to develop a framework that enables highly accurate rapid diagnoses of COVID-19. This would lead to a safer environment for healthcare professionals by minimizing the rate of exposure and following quarantine protocols therefore curbing the spread of COVID-19.

1.2 Objectives

The objective of this project is to develop a framework that rapidly diagnoses patients with COVID-19 with medical imagery and thereby provide assistance to healthcare professionals.

These are the primary objectives for this thesis:

1. Analyse X-ray and CT imaging features of COVID-19.
2. Build a deep learning model that diagnoses patients with COVID-19 using chest X-rays.
3. Test the accuracy of the proposed COVID-19 diagnoses model by comparing with other similar models implemented previously.
4. Develop a deep learning API that can be used by healthcare professionals and medical facilities to diagnose COVID-19.
5. Optionally, build a deep learning model that diagnoses patients with COVID-19 using chest CT scans and compare the accuracy and results obtained from both models respectively.

1.3 Manuscript Organization

This manuscript contains 4 chapters, starting with a comprehensive **Introduction** of the main objectives of this project. This is followed by the **Literature Review** chapter which aims to synthesize and sum up relevant research and implementations previously conducted in this same field. The next chapter **Requirements Analysis** conducts a detailed study on the use cases of this project and identifies user requirements and labels their priority. An additional section **Design** has also been included, which demonstrates the pipeline and the workflow of the proposed model. Following this, is a section for **Evaluation Strategy** which specifies the analysis and assessment that needs to be administered for this project. The last chapter is dedicated to **Project Management** which provides a detailed schedule that must be strictly adhered to, in order to ensure the success of this project, as well as examining the risks involved and the ethical, legal and, social issues pertaining to this project.

Chapter 2

Literature Review

A comprehensive analysis of the existing research and methodologies pertaining to COVID-19 detection using medical imagery and deep learning have been provided in this section.

2.1 The COVID-19 Pandemic Era

Coronavirus disease (COVID-19) is a highly contagious respiratory disease caused by the newly discovered coronavirus. The virus mainly spreads through the discharge of saliva droplets when an infected person coughs or sneezes [2].

Most people affected by COVID-19 often show mild symptoms but those who have a compromised immune system such as older adults or those with underlying medical conditions are at a much higher risk of developing severe illness [3].

Therefore, one must follow the advice of medical professionals and adhere to social distancing protocols. This must be combined with other preventive measures such as maintaining personal hygiene and wearing masks to reduce the spread of the virus [4].

Further information about the novel coronavirus, the timeline demonstrating its spread across the world, and decisive events are discussed in Appendix A.

2.2 Diagnosing COVID-19

The following section discusses in detail the traditional procedure used in detecting COVID-19 using the real-time RT-PCR test but more importantly gives an insight on how medical imagery could be used to achieve the same. The specific patterns and lesions observed from the lung scans of patients diagnosed with COVID-19 are also showcased in this section.

2.2.1 The RT-PCR Test

The real-time RT-PCR test is a nuclear-derived method that detects the presence of specific genetic material in any pathogen which includes a virus. Scientists would be able to see the results even when the process is ongoing using the real-time RT-PCR test whereas the conventional RT-PCR provides the result only after the process is complete.

The real-time RT-PCR test has been widely used to detect viruses such as Ebola and Zika, and therefore is extensively used to detect COVID-19 in laboratories across the world [5]. The real-time RT-PCR test has been recommended by the WHO for COVID-19 diagnosis.

'Reverse Transcription' involves converting Ribonucleic Acid (RNA) to Deoxyribonucleic Acid (DNA), the reason for this being the ability to amplify specific parts of DNA which allows the scientists to spot strands of the virus among genetic information. Samples are collected from the patient's throat or nose, typically where the COVID-19 virus tend to gather.

Scientists add short DNA fragments, which complements the viral DNA. Therefore the virus, if present, leads to these added fragments to be attached to the target sections of the viral DNA. When marker labels attach to these DNA strands, a fluorescent dye is released, which is measured by the RT-PCR machine. When a certain threshold of fluorescence have passed the scientists could then diagnose the patient with COVID-19 [5].

Despite the high sensitivity and reliable diagnosis by the real-time RT-PCR test, there exist certain limitations which have led researchers to identify alternate methods of COVID-19 diagnoses, such as using medical imagery which includes X-Ray and CT scans.

During these trying times where the numbers keep rising rapidly, medical facilities are running short of RT-PCR test kits and therefore, are in dire need of alternate sources of diagnosis. Furthermore, the high false-negative rate of the real-time RT-PCR, which is as high as 100% before the time of symptom onset and decreases only up to 64% on the day of symptom onset [6] could lead to severe consequences in the real world where the infected person could spread the virus as they are not under quarantine.

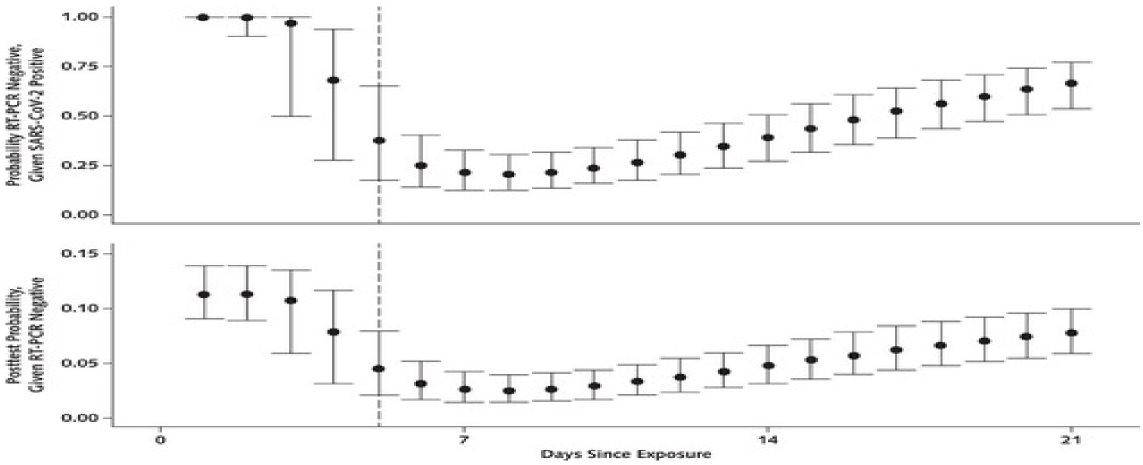

FIGURE 2.1: Probability of having a negative RT-PCR test result given SARS-CoV-2 infection (top) and of being infected with SARS-CoV-2 after a negative RT-PCR test result (bottom), by days since exposure [6]

Another important factor considering the daily rising numbers are the delays in receiving the results for the RT-PCR test. This places extra strain on the medical professionals in terms of workload and makes it difficult for them to apply safety protocols on suspected patients.

Therefore, due to these aforementioned limitations of the real-time RT-PCR test, finding a safer, more accurate, and faster diagnosis mechanism is essential. Thus, making COVID-19 diagnosis using medical imagery an ideal alternative candidate.

2.2.2 Medical Imagery

Medical Imagery such as X-rays and CT scans have proven to be a viable alternative to the RT-PCR test for COVID-19 detection due to the limitations mentioned above. The reduced exposure risks, and faster diagnosis time are also added benefits.

In this section, CT imaging features of the novel coronavirus shall be presented to lay a foundation for future sections where we illustrate how deep learning could learn these features and use it for automated real-time COVID-19 diagnosis.

A study conducted by Chung et al. on 21 symptomatic patients infected with coronavirus admitted to three hospitals in three provinces Guangdong, Jiangxi and Shandong respectively in China from January 18^{th} 2020 to until January 27^{th} 2020 aimed to identify potential imaging features of COVID-19 from CT scans reviewed and verified by two fellowship-trained cardiothoracic radiologists with approximately 5 years of experience each.

The degree of lobe involvement was assessed and a "Total Severity Score" was assigned by summing up the each of the individual lob scores. Patients were also re-evaluated in order to study the progression of features by the same two radiologists [7].

After evaluation, the following common characteristics tabulated in Table 2.1 were observed. Other abnormalities such as Cavitation, Reticulation, Interlobular Septal Thickening, Calcification, and Bronchiectasis were also assessed.

Finding	**Value**
Ground-glass opacities and consolidation	
Absence of both ground-glass opacities and consolidation	3 (14%)
Presence of either ground-glass opacities or consolidation	18 (86%)
Presence of ground-glass opacities without consolidation	12 (57%)
Presence of ground-glass opacities with consolidation	6 (29%)
Presence of consolidation without ground-glass opacities	0 (0%)
More than two lobes affected	15 (71%)
Bilateral lung disease	16 (76%)
Frequency of lobe involvement	
Right Upper Lobe	3 (14%)
Right Middle Lobe	1 (5%)
Right Lower Lobe	2 (10%)
Left Upper Lobe	3 (14%)
Left Lower Lobe	4 (19%)
Total lung severity score	
Mean	9.9
Range	0-19
Opacification distribution and pattern	
Rounded Morphology	7 (33%)
Linear Opacities	3 (14%)
Crazy-Paving Pattern	4 (19%)
Peripheral Distribution	7 (33%)

TABLE 2.1: Findings at Initial Chest CT Examination in 21 Patients [7].

A follow-up chest CT scan was conducted on 8 of the initial 21 patients, within a range of 1 to 4 days. Only 1 patient out of the 8 had normal initial and follow-up CT scan results. 5 out of eight experienced mild progression in the lung characteristics, the remaining 2 displayed moderate progression. Fortunately, none of the patients experienced severe progression.

The primary observations from this study on 21 patients include GGO's found in 12 patients and consolidation in 6 patients. There is also a high possibility the virus affects more than two lobes with bilateral involvement. Other observations include rounded morphology detected in 7 patients, reticulation in 3 patients, and crazy-paving in 4 patients [7].

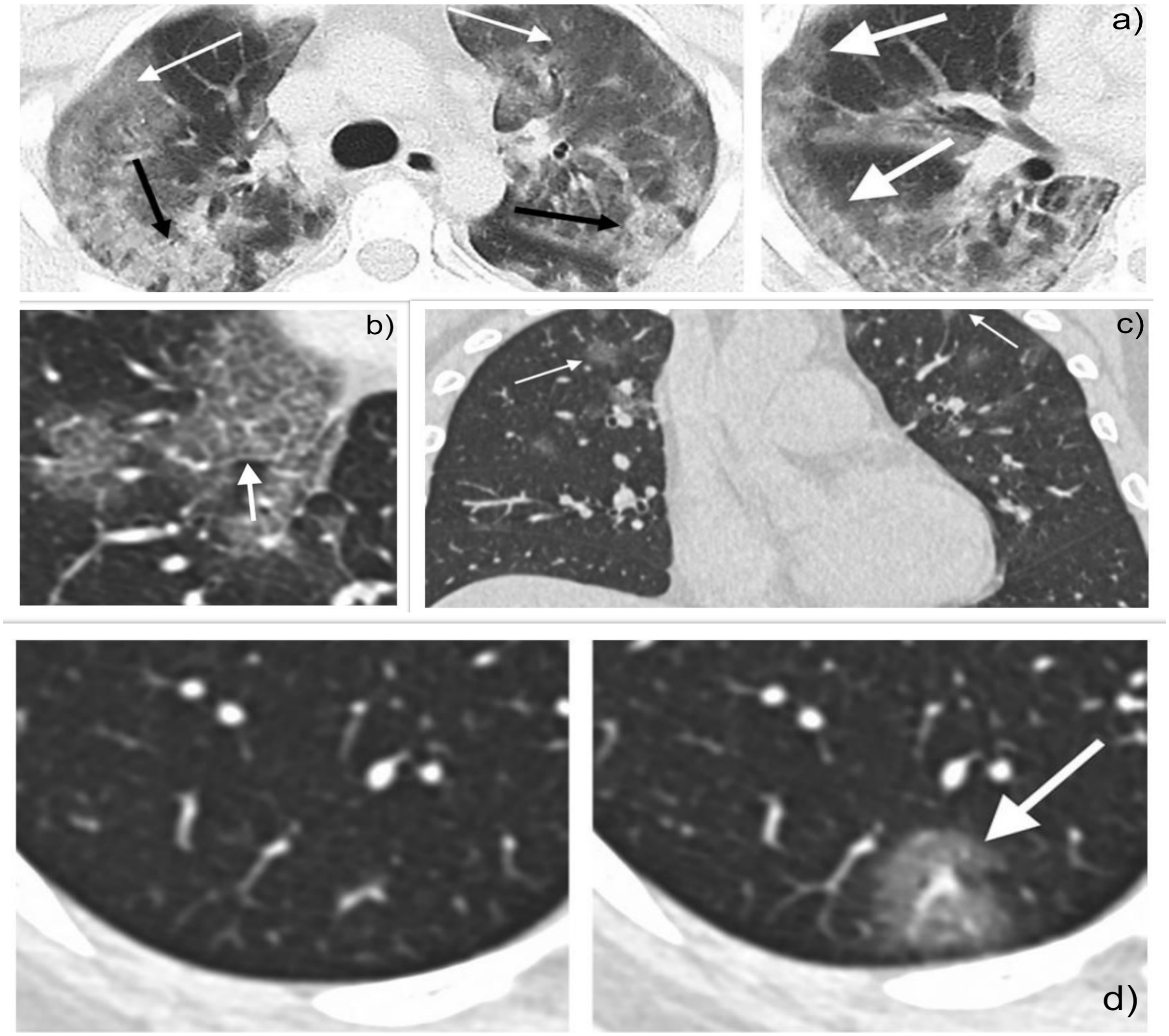

FIGURE 2.2: Observed lung CT Scan characteristics. a) White arrow indicates patchy GGO, and black arrow indicates consolidative pulmonary opacities. b) White arrow indicates GGO's with a rounded morphology. c) White arrow indicates crazy-paving pattern, GGO and interlobular sepal thickening with intralobular lines. d) Follow-up CT scan progression. White arrow indicates new solitary, rounded, peripheral ground-glass lesion [7].

One obvious limitation of this study is the relatively low number of patients, with only 8 out of 21 carrying out a follow-up CT scan. As this study was conducted during the dawn of coronavirus, this number is certainly a very respective amount.

Another study by Morales et al. whose results are summarized in Appendix B, also observe similar lung characteristics. As we have now seen the prominent imaging characteristics of COVID-19, we shall now discuss how deep learning could learn these features and accurately diagnose patients with COVID-19 in real-time.

2.3 Deep Learning for COVID-19 Diagnosis

The coronavirus global pandemic spreading rapidly all across the world have forced scientists and researchers to identify alternative diagnosis mechanisms in addition to the RT-PCR test to overcome its limitations. As we have seen in previous sections, medical imagery such as X-rays and CT scans have played a vital role in combating the rising numbers by saving valuable time in diagnosis and reducing virus exposure.

Deep learning techniques have further enhanced COVID-19 diagnosis using medical imagery due to its rapid detection capabilities, fully automated and efficient diagnosis workflow, and assisting medical practitioners by highlighting observed COVID-19 lung characteristics similar to the features discussed in the section 2.2.2. A detailed overview of the modern CT and X-ray systems enabling automated diagnosis workflow ensuring minimal virus exposure can be found in Appendix C.

To identify the regions of interest (ROIs), segmentation of the lung CT or X-ray scans are a vital pre-requisite. The former produces high-quality 3D images for detecting COVID-19 whereas the latter involves the ribs being projected onto soft-tissues in 2D.

As a result, segmentation in X-ray scans is more challenging as compared to CT scans. But on the other hand, X-ray scans are more widely accessible in medical facilities all across the world and are usually the first imaging modality used on patients suspected of COVID-19.

Keeping in mind these limitations, the next two subsections review the segmentation techniques using deep learning for both CT and X-rays respectively and discuss the results obtained.

2.3.1 CT Based Diagnosis of COVID-19

To identify the ROIs from a CT scan for diagnosis, deep learning techniques are extensively used. These techniques could be narrowed down to the three most prominent segmentation methods which are **U-Net** [8]–[13], **UNet++** [14], [15], and **VB-Net** [16] respectively.

From section 2.2.2, we can infer that the main ROIs could be classified into two specific categories, which are lung-region and lung-lesion oriented methods. The latter is more of a challenge in terms of its detection as lesions could be in a variety of shapes and sizes, furthermore, locating its region also adds to the difficulty in identifying it.

The literature indicates the U-Net architecture as the most reliable in terms of segmenting both lung regions and lesions in COVID-19 diagnosis applications. Designed by Ronneberger, the U-Net as its name suggests has a U-shape architecture, such that it has a symmetric expansive and contracting path [17].

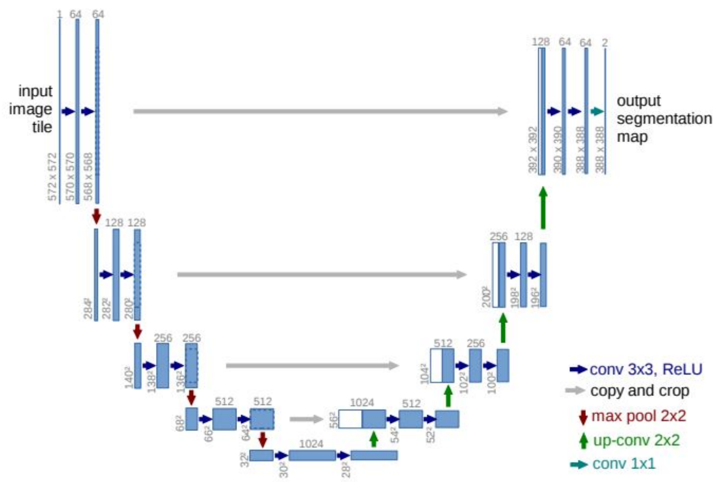

FIGURE 2.3: A representation of the U-Net architecture [17]

Various variants of the U-Net have been developed since its inception due to its high ability to learn visual semantics and therefore are suitable for many medical applications. They include the following:

- **3D U-Net** - Replaces the conventional U-Net layers with 3D layers. [18]
- **V-Net** - Utilizes residual blocks as the convolutional block, network optimization carried out through Dice Loss. [19]
- **VB-Net** - Combination of V-Net with a bottle-neck structure. [16]

- **UNet++** - A more complex version of U-Net, inserts a nested convolutional structure between the expansive and contracting path. [20]
- **Attention U-Net** - Integrates Attention Gates with U-Net architecture to focus on target structures of various shapes and sizes. [21]

Identifying and labeling the training data for the purpose of COVID-19 diagnosis is often time consuming and labour intensive, especially the manual detection of lesions. Shan et al. proposes a workaround which involves the "human-in-the-loop" strategy, where radiologists play an integral part in the training process [16]. Another similar suggestion from Yue et al. was to allow the radiologists to provide initial seeds for the U-Net model [11].

Zheng et al. suggests an alternative approach, where unsupervised methods are used to generate pseudo segmentation masks for images to overcome the labeling process and thus avoid its limitations. In addition to reviewing the results of the lung segmentation from the U-Net model, Zheng et al. also utilizes a 3D CNN to predict the probability of COVID-19 using the images obtained as an input [8]. With a dataset of 540 patients, 313 with COVID-19, and the remaining without COVID-19 are used for training and testing purposes. The model attains a sensitivity of 90.7% and specificity 91.1%.

The lung segmentation's obtained could be used for COVID-19 diagnosis and for the quantification of data. The literature mentioned in this section includes both of the objectives.

Li et al. conducted a multi-center study by distinguishing COVID-19 from community-acquired pneumonia [13]. A combination of U-Net and ResNet-50 was proposed with the former used to extract lung regions using pre-processed 2D slices. The latter along with shared weights between the 2D slices combined with max-pooling is used for COVID-19 diagnosis. This study utilizes a large dataset with 1296 COVID-19 patients, 1735 with community-acquired pneumonia, and 1325 non-pneumonia patients. The model achieves a specificity of 96% and sensitivity of 90%.

An AI system developed by Jin et al. for rapid COVID-19 diagnosis, involves the input to the classification model being the CT slices which have been segmented [15]. Instead of a 3D CNN, a ResNet-50 model was used for diagnosis and UNet++ for lung segmentation and lesion identification. The model is trained on 1136 images, 723 COVID-19 positives, and 413 negatives and achieves sensitivity and specificity of 97.4% and 92.2% respectively.

As for the quantification of data, both Cao et al. [9] and Huang et al. [10] monitor the longitudinal progression of COVID-19 using the CT segmentation of pulmonary opacities using the segmentation of the lung region and GGO. Therefore, the image segmentation obtained aids radiologists in infection identification, analysis, and diagnosis.

Most of the classification studies involve segregating COVID-19 patients from non-COVID-19 patients with most of the latter patients being segregated further into pneumonia and non-pneumonia subjects.

Chen et al. developed a UNet++ model which segments the lung lesions [14] using CT images of 51 COVID-19 patients and 55 patients with other diseases and diagnose patients with 95.2% accuracy thus reducing the reading time of radiologists by 65%. Given raw images to the model, prediction boxes displaying suspected regions were output, after further extraction and filtering a logic linking of predictions was added, which aimed to aid the radiologists in manual detection of the virus.

Jin et al. considers an alternative approach utilizing 2D Deeplab v1 and 2D ResNet-152 models for lung segmentation and lung-mask slice based classification of COVID-19 respectively [22]. The model achieves a respectable score of 94.1% sensitivity and 95.5% specificity using a dataset of 496 COVID-19 positive CT scan images.

The objective of the remaining studies besides COVID-19 diagnosis is its differentiation with common pneumonia which primarily includes viral pneumonia. The main reason for this objective being the very similar radiological appearances of both the diseases.

Wang et al. classifies between COVID-19 and viral pneumonia using a 2D CNN model on delineated region patches [23]. Experiments were conducted on chest CT scans from 44 COVID-19 and 55 pneumonia patients with external testing resulting in 79.3% accuracy.

Experiments carried out by Song et al. employs OpenCV to segment 2D slices which include lung regions [24]. The 3D chest CT images resulted in 15 2D slices of complete lungs and each slice were fed into the deep learning based CT diagnosis system also called DeepPneumonia. A combination of a pre-trained ResNet-50 along with Feature Pyramid Network (FPN) which can extract specific ranked details from the images, coupled with an attention module to learn these extracted details were used to develop this model.

The dataset includes 88 COVID-19 patients, 101 with bacterial pneumonia and 86 healthy patients. The proposed model achieves an accuracy of 86% for classification between COVID-19 and bacterial pneumonia.

Table 2.2 and 2.3 summarizes all the COVID-19 image segmentation applications mentioned in this section, and the results of diagnosis experiments conducted across various medical facilities. An extended version of Table 2.2 can be found in Appendix D.

Study	Method	Target ROI
Cao et al. [9]	U-Net	Lung
		Lesion
Huang et al. [10]	U-Net	Lung
		Lung Lobes
		Lesion
Yue et al. [11]	U-Net	Lung Lobes
		Lesion
Gozel et al. [12]	U-Net	Lung
		Lesion
Tang et al. [25]	Commercial Software	Lung
		Lesion
		Trachea
		Bronchus

TABLE 2.2: CT Image Segmentation Techniques in COVID-19 Quantification Applications [26]

Study	Subjects	Method	Result
Zheng et al. [8]	313 COVID-19	U-Net	90.7% (Sens.)
	229 Others	CNN	91.1% (Spec.)
Li et al. [13]	468 COVID-19	ResNet-50	90.0% (Sens.)
	1551 CAP		96.0% (Spec.)
	1445 Non-pneu.		0.95 (AUC.)
Chen et al. [14]	51 COVID-19	UNet++	100% (Sens.)
	55 Others		93.6% (Spec.)

Jin et al. [15]	723 COVID-19	UNet++	97.4% (Sens.)
	413 Others		92.2% (Spec.)
Jin et al. [22]	496 COVID-19	CNN	94.1% (Sens.)
	1385 Others		95.5% (Spec.)
Song et al. [24]	88 COVID-19	ResNet-50	86.0% (Acc.)
	100 Bac. Pneu.		
	86 Normal		
Wang et al. [23]	44 COVID-19	CNN	79.3% (Acc.)
	55 Vir. Pneu.		

TABLE 2.3: COVID-19 Diagnosis Applications and their results from CT Image Segmentation [26]

* Bac. - Bacterial, Vir. - Viral, Pneu. - Pneumonia

As we have seen, the above studies result in promising diagnosis outcomes. Therefore, COVID-19 diagnosis with CT images could facilitate early detection of the coronavirus and also reduce the high exposure rates between patients and medical professionals.

2.3.2 X-ray Based Diagnosis of COVID-19

X-rays are most often the first imaging modality used on suspected patients, due to its wide availability in most clinics and medical facilities. As seen in section 2.2.2, radiological signs include GGOs, consolidation, and opacification.

In order to detect these abnormalities in lung X-ray scans, three popular architecture's are used across various studies which are **ResNet** [27], **ResNet-50** [28], and **CNN** [29], [30].

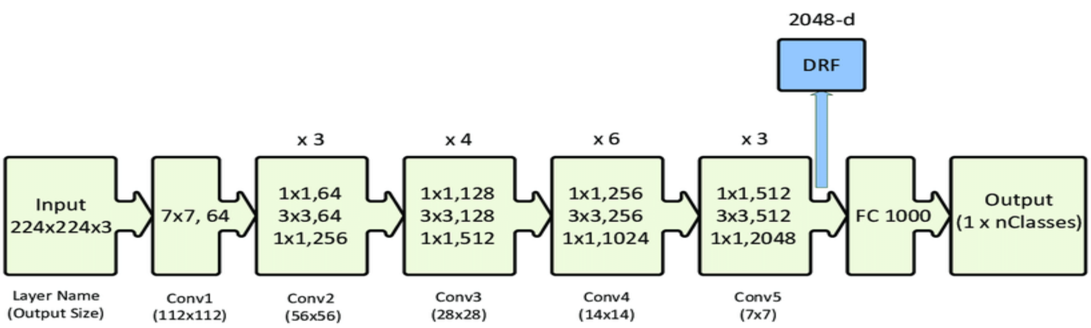

FIGURE 2.4: ResNet-50 architecture with residual units [31]

X-rays despite, as mentioned previously, being the first imaging modality for patients suspected with COVID-19 is less sensitive than 3D chest CT images. Anomalous chest radiographs are found in 69% of the patients initially during admission and this number increases to 80% after a certain period once hospitalized [32].

To estimate the uncertainty in COVID-19 prediction Ghoshal et al. [29] proposes a Bayesian CNN. X-rays of 70 COVID-19 patients are obtained from Cohen et al. [33] and others from Kaggle's chest X-ray images. Bayesian inference improves the detection accuracy of the model from 85.7% to 92.9% from the experiments conducted by the authors.

Narin et al. experiments with three deep learning models i.e., ResNet-50, InceptionV3 and Inception-ResNetV2 respectively, with the objective to detect COVID-19 from X-ray images [28]. The dataset includes X-rays from 50 COVID-19 patients and 50 normal scans. The results from the study indicate that the ResNet-50 achieves the highest accuracy with 98% followed by InceptionV3 which attains 97%.

Zhang et al. also suggest a ResNet based model for COVID-19 detection [27]. But the model aims to achieve two objectives, one for COVID-19 classification and another for anomaly detection. The experiment was conducted on a dataset containing X-rays from 70 COVID-19 patients and 1008 other X-rays. The anomaly detection score in-turn optimizes the COVID-19 classification score which reaches 96% from the experiments conducted by the authors.

Wang et al. proposes a deep CNN based model (COVID-Net) and achieves a testing accuracy of 83.5% [30]. The dataset used for the study include X-rays from patients diagnosed with both Bacterial and Viral Pneumonia. More specifically, 45 COVID-19 positive, 931 Bacterial Pneumonia, 660 Viral Pneumonia, and 1203 normal X-rays.

Table 2.4 summarizes the results obtained by the experiments discussed in this section.

<table>
<tr><th>Study</th><th>Subjects</th><th>Method</th><th>Result</th></tr>
<tr><td rowspan="2">Ghoshal et al. [29]</td><td>70 COVID-19</td><td rowspan="2">CNN</td><td rowspan="2">92.9% (Acc.)</td></tr>
<tr><td>Others</td></tr>
<tr><td rowspan="2">Zhang et al. [27]</td><td>70 COVID-19</td><td rowspan="2">ResNet</td><td>96.0% (Sens.)</td></tr>
<tr><td>1008 Others</td><td>70.7% (Spec.)</td></tr>
<tr><td rowspan="2">Narin et al. [28]</td><td>50 COVID-19</td><td rowspan="2">ResNet-50</td><td rowspan="2">98.0% (Acc.)</td></tr>
<tr><td>50 Normal</td></tr>
</table>

Wang et al. [30]	45 COVID-19	CNN	83.5% (Acc.)
	931 Bac. Pneu.		
	660 Viral Pneu.		
	1203 Normal		

TABLE 2.4: X-ray Image Segmentation Techniques in COVID-19 Diagnosis Applications [26]

* Acc. - Accuracy, Sens. - Sensitivity, Spec. - Specificity

As seen in the above studies on X-ray images, the classification of COVID-19 from other Pneumonia seems to be a repeating objective. The major limitation involves the lack of data available as currently there exist two online datasets with 70 images from COVID-19 patients, therefore the generalizability and stability of the model are yet to be evaluated.

2.3.3 Interpreting Deep Learning Results

Deep learning techniques are often regarded as "Black Boxes" concerning its training and classification mechanisms. In medical applications such as this topic where we aim to diagnose patients with COVID-19 in real-time, understanding the reasoning behind the model's prediction is of utmost importance.

More than just an additional insight, visualization of distinct features from the lung segmentation images would allow radiologists to cross-check their findings with that of the deep learning model and thus allow for an even better and reliable diagnosis.

Saliency methods are a set of popular and powerful tools which allow researchers to analyze and understand deep learning decisions [34]. Various interpretation methods exist in deep learning with a few of them mentioned below:

- **Saliency Map** - Estimates specific parts of the image which contributes to highest layer activation [35].
- **Class Activation Mapping (CAM)** - Averages and adds the activation's of each feature map (Global Average Pooling) and uses this to highlight important regions [36].
- **Gradient-Weighted CAM (Grad-CAM)** - Calculates the gradient of the classification score with respect to the convolutional features [37].

The saliency maps shown in Figure 2.5 and 2.6 highlight those regions in the lungs which as discussed in section 2.2.2, exhibit the most common characteristics in patients diagnosed with COVID-19. GGO's, consolidations, lesions, and crazy-paving patterns are some of the more contributing features for diagnosis purposes by the deep learning model as indicated by the saliency maps.

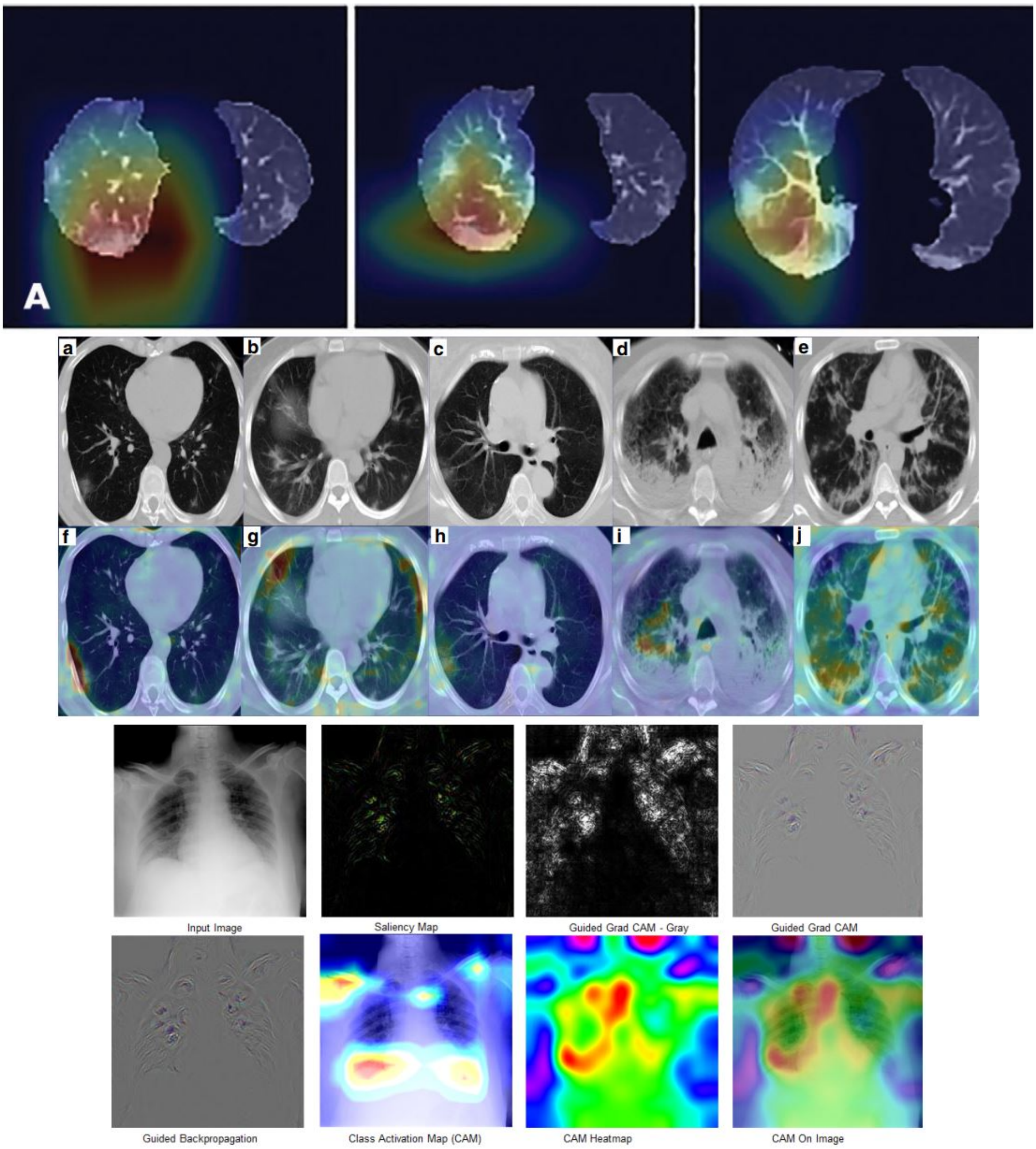

FIGURE 2.5: Saliency Maps displaying COVID-19 lung characteristics in CT and X-ray scans [13] [29] [38]

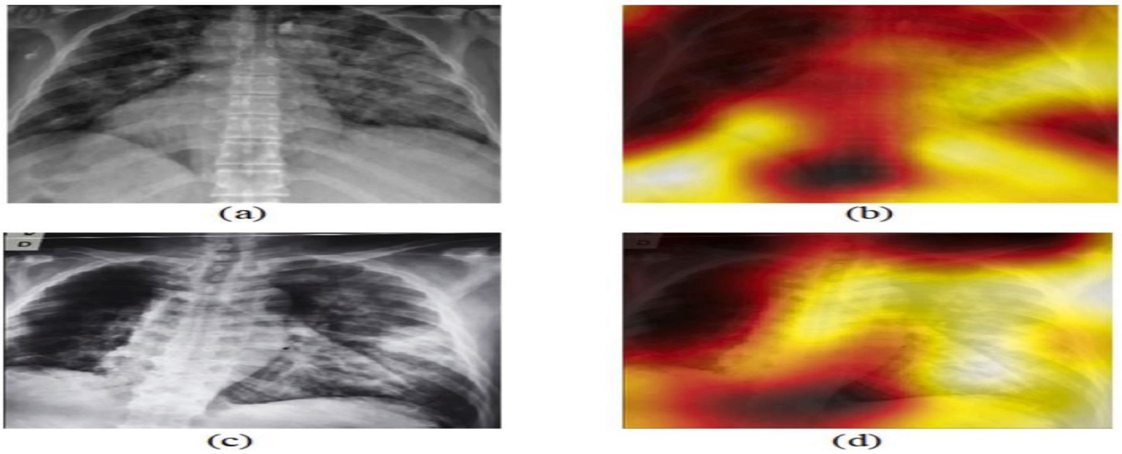

FIGURE 2.6: X-ray images and the corresponding heat maps [39]

The results of the saliency maps are therefore, in direct correlation with the studies shown above which displays the most repeating COVID-19 lung characteristics. This provides additional assistance and assurance to the radiologists who during diagnosis, look to identify the same lung characteristics.

2.4 Discussion

The integration of AI techniques in medical research has just scratched the surface. We have discussed many studies which have experimented on fully automated COVID-19 diagnosis employing deep learning methods and have yielded respectable results. But as mentioned, this is only the beginning and the medical industry is due for a breakthrough soon.

2.4.1 Overview of COVID-19 Applications

Among many medical applications, where AI could potentially optimize and improvise the standard procedures, automated imaging acquisition workflows as discussed previously, seem to be at the forefront. The overall efficiency of the scanning procedure whether it be CT or X-rays could be enhanced and as a direct result, exposure to transferable viruses such as the coronavirus could be decreased, thus protecting medical professionals.

Besides protecting the medical professionals, reducing patient exposure to X-rays is also important. Calculating the right amount of radiation to be used via the body region thickness of the patient, finding an optimal patient position without technician intervention by automated calculation of scan range and centering are promising AI-empowered solutions.

Section 2.3.3 discusses Class Activation Mapping (CAM) which is a conventional technique to focus on the prominent pixels or regions which lead to a resultant classification. Studies which have utilized this technique for COVID-19 diagnosis have seen a close correlation between the patterns identified by radiologists and the regions highlighted by the model therefore ensuring the reliability of the predictions given by the model.

Explainable Artificial Intelligence (XAI) methods [40], [41] are a recent addition to deep learning interpretability techniques which provides a finer localization map and exhibits more intricate details when compared to Class Activation Mapping (CAM) techniques.

2.4.2 Critical Review

Using medical imagery for disease diagnosis have variety of applications, for example, diagnosing COVID-19 as we have seen through experiments conducted by multiple studies. But one noticeable caveat is the observed negative radiological signs during the preliminary stages of the disease. This could have critical consequences in real-life circumstances especially amid a global pandemic.

Many studies mentioned above use U-Net architecture for lung segmentation and variants of CNN's such as ResNet and ResNet-50 for COVID-19 diagnosis. One of the limiting factors of AI-based experiments is the difficulty in extracting the reasons as to why the deep learning model resulted in a certain classification.

COVID-19 applications employing deep learning often require accurate labeling of data, but this task often is very time-consuming and medical professionals due to the rising numbers often would not be able to carry out this procedure. This leads to incomplete and inaccurate labeling of data which proves to be an additional challenge to deep learning models who train on this dataset and therefore result in an incorrect diagnosis.

Exploiting unsupervised training techniques [42], [43] or exploring transfer learning methods [44] where filters applied on a completely different dataset could be reused for COVID-19 applications are viable options to mitigate the above labeling complication.

As the coronavirus was declared a global pandemic fairly recently in early 2020, limited follow-up studies exist to identify treatment mechanisms and evaluating diagnosis tools. Few studies such as from Chung et al. [7], mentioned earlier did in fact carry out follow-up

CT scans to recognize progression patterns from segmented lung images, but due to the lack of participants when compared to the the initial version, the results obtained could not be reliably applied in the real world.

Tracking of COVID-19 patients is essential for containing the spread of the virus. Therefore medical facilities should enforce strict patient follow-up protocols carrying out long-term monitoring and capturing progression data which could be used by studies to further develop their models and deploy them in the real world.

2.5 Conclusion and Research Questions

The coronavirus has affected millions of lives throughout the world. Front-line workers combat the virus tirelessly to counter the rapidly rising numbers daily. In this chapter, we have discussed how deep learning could provide a safe, efficient and accurate workflow for COVID-19 diagnosis and be a suitable alternative to the RT-PCR test.

It is important to couple the results obtained using the same imaging workflow discussed in this chapter, with clinical observations and laboratory results to provide reliable COVID-19 diagnosis. From the experiments and studies discussed, it is safe to conclude that AI if utilized effectively could play a vital role in accurate diagnosis and analysis of COVID-19, and therefore potentially save precious lives and ultimately lead to our victory against the coronavirus global pandemic.

Research Questions

Based on the gaps we identified in this chapter, we plan to answer the following research questions:

1. Is there a correlation between the ROIs detected by the deep learning model and the lung characteristics observed on COVID-19 patients?
2. Are the results obtained by the deep learning approach better when compared to the standard RT-PCR test?
3. Is it feasible to deploy and utilize the deep learning model in medical facilities and laboratories for rapid real-time COVID-19 diagnosis?

Chapter 3

Requirements Analysis and Evaluation Strategy

This chapter provides an insight into the project requirements followed by demonstrating the project implementation workflow, UI wireframe, data collection, and processing methodology, and concludes with an evaluation strategy.

3.1 Requirements Analysis

This section identifies and outlines the functional and non-functional requirements pertaining to this project. The priority of each of these requirements are ranked according to the MSCW prioritization technique. The following color-scheme indicates the respective ranking order:

- **Must Have (M)** - These requirements are fundamental to achieve the aim of this project.
- **Should Have (S)** - These requirements are important to the project but not vital and could be achieved in the long run.
- **Could Have (C)** - These requirements are not fundamental to achieve the aim of this project but would be an added benefit if accomplished.
- **Want To Have (W)** - These requirements would be prioritized in later releases of the project.

3.1.1 Functional and Non-Functional Requirements

The Functional Requirements (FR's) describes the essential components, purpose, and objectives of this project. Table 3.1 tabulates the FR's along with a brief description for the same and its priority according to MSCW prioritization technique. An evaluation for each of these functional requirements is specified in section 3.3.

Non-Functional Requirements (NFR's) emphasizes the system's operation which includes its performance, usability, portability, and so on. Table 3.2 tabulates each of these NFR's and applies the MSCW prioritization technique.

Functional Requirements		
ID	**Description**	**Priority**
FR-1	**X-ray Segmentation** The system shall be able to accept and segment X-ray scans.	**M**
FR-2	**CT Segmentation** The system shall be able to accept and segment CT scans.	**S**
FR-3	**COVID-19 Diagnosis using X-ray Scans** The system shall be able to classify positive COVID-19 patients from others given test X-ray scans	**M**
FR-4	**COVID-19 Diagnosis using CT Scans** The system shall be able to classify positive COVID-19 patients from others given test CT scans.	**S**
FR-5	**Visualize Lung Region of Interest's** The system shall be able to interpret and visualize classification results by highlighting lung ROIs.	**M**
FR-6	**Multi-class Diagnosis** The system shall be able to differentiate COVID-19 and Pneumonia (Viral and Bacterial) patients.	**W**
FR-7	**Web Interface** The system shall have an interface which presents diagnosis results after segmentation for visualization and analysis purposes.	**S**

TABLE 3.1: Functional Requirements

Non-Functional Requirements		
ID	**Description**	**Priority**
NFR-1	**Environment** The system shall be deployed on a cloud platform such as IBM Cloud.	**C**
NFR-2	**User Interface** The system shall have an intuitive and user-friendly interface where the user can input scans and receive diagnosis results.	**S**
NFR-3	**Extensibility** The system shall be flexible to extensions, this includes bug fixes, updated features and performance improvement.	**S**
NFR-4	**Version Control** All versions of the code shall be published on a version control system such as GitHub and be open source.	**M**
NFR-5	**Documentation** The code shall include relevant comments and contain an instructions guide to setup the environment and run the code.	**M**
NFR-6	**Modular Programming** The program functionality shall be separated into independent components to emphasize the scalability of software.	**S**
NFR-7	**Reusability** The code developed shall be reusable by other researches and developers.	**C**

TABLE 3.2: Non-Functional Requirements

3.2 Implementation Workflow

The activity diagram displayed below provides a blueprint of the workflow that would be followed for the development phase commencing next semester. The wireframe illustrated in Appendix E displays the expected general layout of the COVID-19 diagnosis portal.

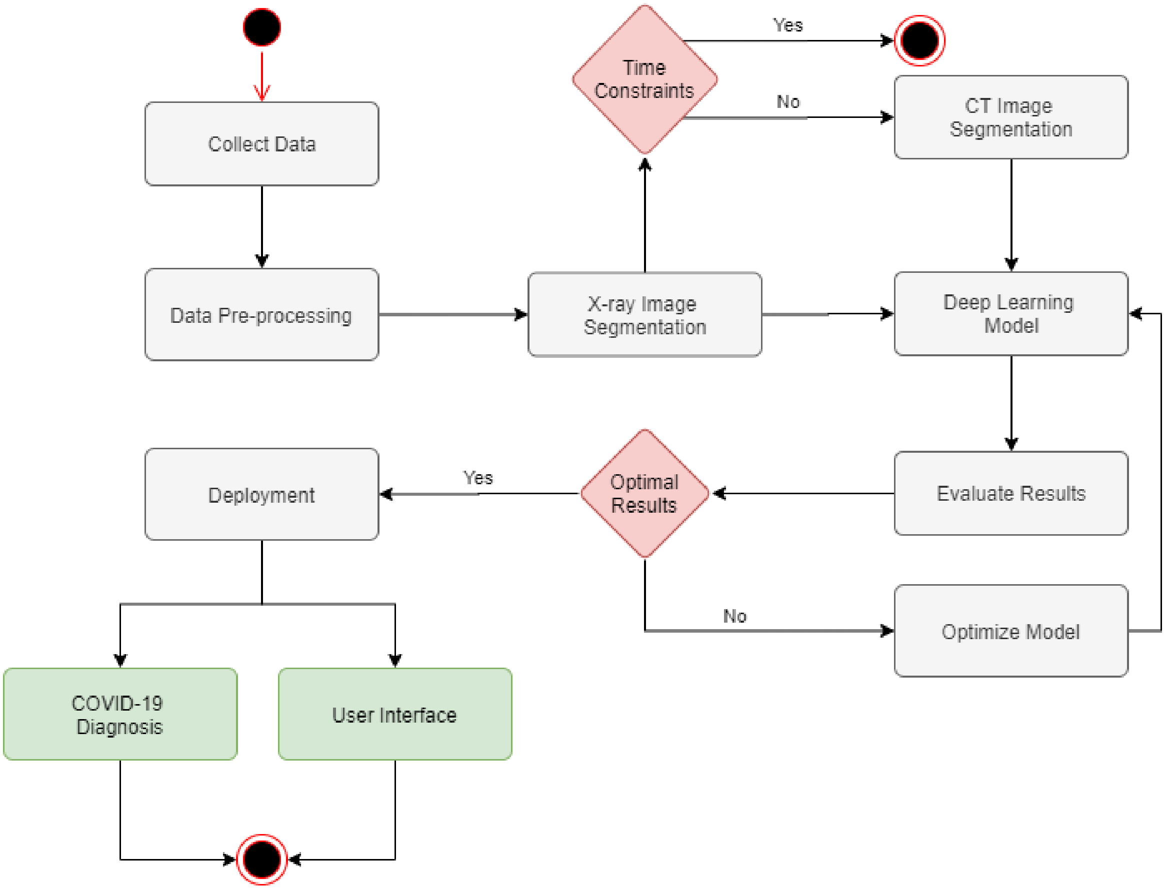

FIGURE 3.1: Activity Diagram displaying the implementation workflow.

3.3 Evaluation Strategy

Table 3.3 summarizes the methods and strategies used to evaluate each of the Functional Requirements described in Chapter 3.

Evaluation Strategy	
ID	**Description**
FR-1	**X-ray Segmentation** The lung segments produced from X-ray scans shall be evaluated based on its capability to identify possible ROIs.
FR-2	**CT Segmentation** The lung segments produced from CT scans shall be evaluated based on its capability to identify possible ROIs.

FR-3	**COVID-19 Diagnosis using X-ray Scans** The diagnosis results obtained after achieving FR-1 shall be evaluated against various statistical metrics such as Accuracy, Precision and Recall.
FR-4	**COVID-19 Diagnosis using CT Scans** The diagnosis results obtained after achieving FR-2 shall be evaluated against various statistical metrics such as Accuracy, Precision and Recall.
FR-5	**Visualize Lung Region of Interest's** The ROIs visualized correlates to the observed lung characteristics in COVID-19 patients.
FR-6	**Multi-class Diagnosis** The diagnosis results obtained shall be evaluated against various statistical metrics such as Accuracy, Precision and Recall.
FR-7	**Web Interface** The user interface developed shall evaluated based on the following metrics, that is, user-friendliness, consistency, familiarity, responsiveness, and intuitiveness

TABLE 3.3: Evaluation Strategy

3.4 Implementation Methodology

A brief summary of the methodology that would be carried out in semester 2 as well as their evaluation is described in this section.

3.4.1 Data Collection

The two primary sources for collecting open-source anonymized data would be the COVID-19 Kaggle datasets and the scans provided by Cohen et al. [33] as seen from the literature review. The images obtained shall be separated into X-ray and CT scans separately and furthermore, on the basis of their labels.

- **Testing** - Datasets which correspond to other lung diseases would also be used to analyze the generalizability of the model.
- **Evaluation** - Training would be conducted using 10-fold cross-validation, followed by rigorous verification to prevent the model from either overfitting or underfitting.

3.4.2 Data Pre-processing

Before carrying out image segmentation for both X-ray and CT scans, all images in the training dataset shall undergo the same data pre-processing pipeline as per the model's input parameters.

- **Testing** - The model would be tested on images with different dimensions to ensure no input errors are caused.
- **Evaluation** - An input verification technique shall be applied to validate the provided training images before the deep learning workflow commences.

3.4.3 Image Segmentation

The provided training images, both X-ray and CT scans shall undergo segmentation such that the ROIs would be highlighted and lead to effective COVID-19 diagnosis

- **Testing** - Multiple image segmentation techniques as suggested by the literature shall be used during the development phase to identify the one that yields the best results.
- **Evaluation** - All models used for experimentation purposes would be documented and the best would be utilized for final demonstration purposes.

3.4.4 Model Optimization

As observed in the literature review, multiple studies [8]–[16] indicate variants of the U-Net architecture to be the best suited for CT scan segmentation whereas, for X-rays, variants of ResNet and CNN seem to be ideal as per the research conducted [27]–[30].

- **Testing** - Each of the proposed model variations shall be experimented with for testing purposes, and the results obtained shall be compared to existing literature.
- **Evaluation** - The results obtained after tweaking the various hyper-parameters for each of the proposed models shall be tracked, thus being able to identify the most optimal set of values.

Chapter 4

Project Management

This chapter highlights the possible ethical issues and risks that could affect the development phase of this project. Furthermore, the proposed development methodology and project plan are also included in this section.

4.1 Risk Management

To plan out a balanced and well-thought project development schedule, it is essential to take into account the inevitable risks that would occur during the phase and therefore, draw out efficient risk mitigation strategies to reduce the impact of the risk on the completion of this project. Risk Management comprises of four steps:

- **Risk Identification** - Recognizing various risks and labeling their type as follows.

Tools	People	Estimation	Requirements	Organization	Technology

- **Risk Analysis** - Analyzing the probability of risk occurance and their impact if it does infact occur. The following color scheme maps the likelihood and impact of a risk.

Color	**Likelihood**	**Impact**
	High	Catastrophic
	Medium	Serious
	Low	Tolerable

- **Risk Planning** - Devising risk mitigating strategies and thus reduce its impact on the development phase. These strategies could belong to either **Avoidance**, **Minimization**, and **Contingency** categories respectively.

- **Risk Monitoring** - Regularly assessing each of the possible risks according to its probability of occurrence.

Table 4.3 summarizes the identified risks and describes possible mitigating strategies.

Risk Management		
	Planning and Monitoring	
Risk, Type Likelihood, Impact	**Monitoring and Avoidance**	**Contingency and Minimization**
Insufficient Data Type: Requirements **Likelihood** **Impact**	**Monitoring:** Review if the learning model underfits on the training data. **Avoidance:** Explore and store all possible open source COVID-19 data sources such as Kaggle.	**Contingency:** Use datasets for other lung diseases and experiment with Transfer Learning. **Minimization:** Ensure sufficient data from open source COVID-19 repositories are utilized.
Inadequate Computation Power Type: Technology **Likelihood** **Impact**	**Monitoring:** Track and ensure reasonable time taken for model training. **Avoidance:** Set up GPU powered deep learning libraries such as Tensorflow-GPU before development phase commences, and ensure sufficient storage on local machine.	**Contingency:** Utilize GPU powered cloud computing services such as IBM Cloud or MACS computers. **Minimization:** Ensure GPU powered deep learning libraries are installed and configured on local machine.

Difficulty in Implementation Type: Requirements **Likelihood** **Impact**	**Monitoring:** Rank the proposed models based on ease of implementation, model performance and documentation. **Avoidance:** Thorough literature review and research into the proposed models.	**Contingency:** Utilize alternative models which are well documented and are easily usable. **Minimization:** Allow sufficient time for project development phase after thorough research into existing studies.
Loss of Data Type: Tools **Likelihood** **Impact**	**Monitoring:** Perform regular checks on backup sources and processes. **Avoidance:** Set up version control and frequently commit changes to the project repository on GitHub.	**Contingency:** Restart project development phase from scratch. **Minimization:** Ensure that all phases in development are well documented, and utilize it in an unfortunate scenario of data loss.
Slow Project Progression Type: Estimation **Likelihood** **Impact**	**Monitoring:** Ensure that the devised project development schedule is followed precisely. **Avoidance:** Ensure all tools and datasets are set up before commencing development phase and start as early as possible.	**Contingency:** Aim to complete the tasks with the highest priority given limited development time. **Minimization:** Create a rank based priority list for each of the requirements as per project supervisor's recommendation.
Personal Health and Deadlines Type: People **Likelihood** **Impact**	**Monitoring:** Keep track of the deadlines announced and update the project plan accordingly. **Avoidance:** Achieve weekly targets and ensure that the project supervisor is aware of the announced deadlines.	**Contingency:** Complete tasks as per its importance after discussion with project supervisor. **Minimization:** Adhere to healthy living practices, follow social distancing protocols and keep flexible plans as per new deadlines.

TABLE 4.3: Risk Analysis

4.2 Project Plan

The various tasks involved in this project and their proposed completion dates for next semester has been illustrated using a Gantt Chart which is displayed in Figure 4.1. Team-Gantt was used for designing the Gantt Chart, Microsoft Planner would be used to keep track of the weekly requirements.

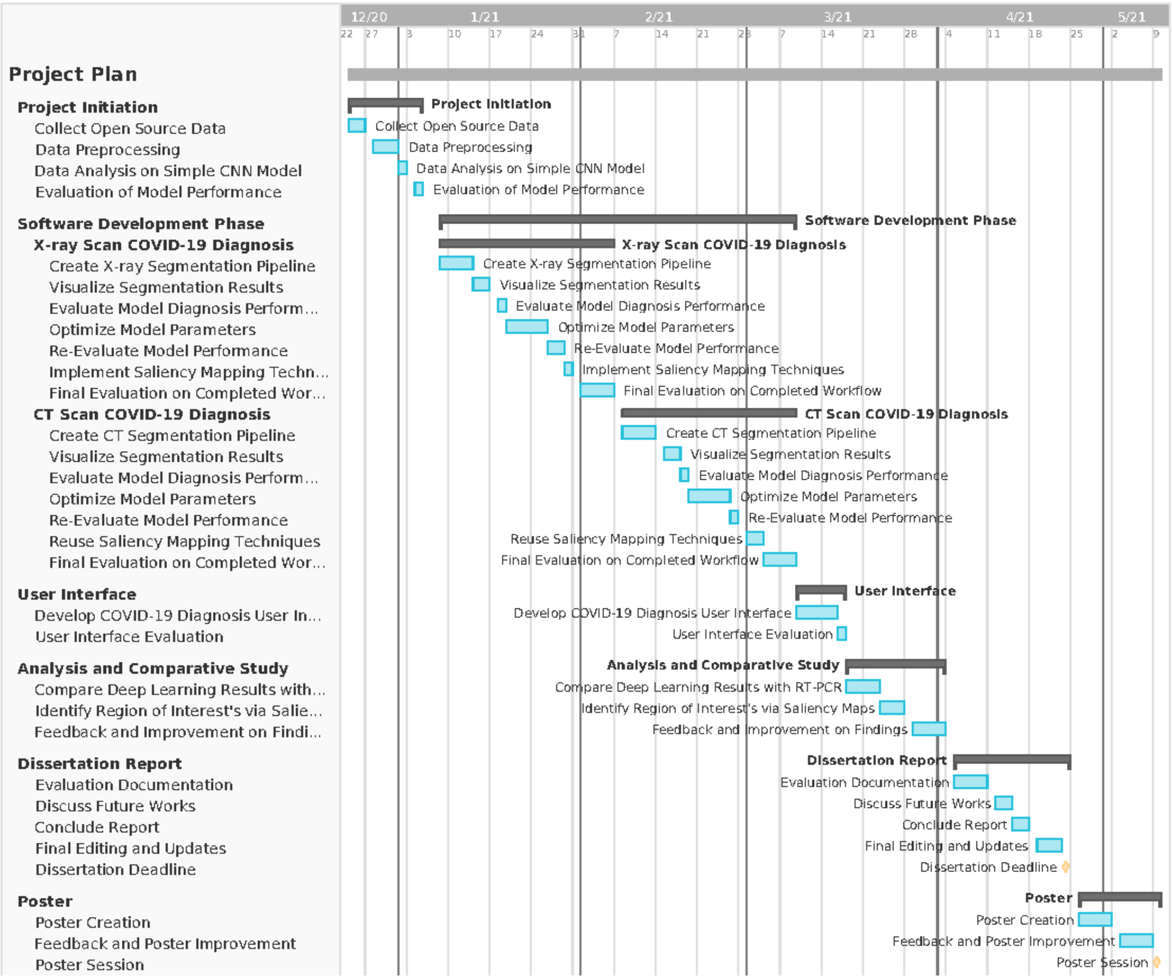

FIGURE 4.1: Gantt Chart Displaying the proposed Project Plan.

4.3 Development Methodology

For this project which involves building a deep learning model accompanied by a suitable interface for user interaction, an iterative development approach is ideal. **SCRUM** [45], a subset of Agile development methodology proves to be a viable approach.

Implementing each of the components involved in this project independently and adhering to the weekly plan and supervisor's suggestions would lead to the deadlines being met and therefore guarantee a successful project completion.

Further discussion into SCRUM development methodology can be found in Appendix F.

4.4 Professional, Legal, Ethical and Social Issues

4.4.1 Professional and Legal Issues

All research papers discussed in this document are referenced accordingly. Any code used from external sources in this project shall acknowledge the original authors and would be well documented. The research papers referenced in this project are either open source or have been granted access. The code used for this project shall be open source and would be published under the MIT License.

4.4.2 Ethical and Social Issues

No human subjects are involved in this dissertation project. The datasets used would be open source and will not contain any personal user information and therefore anonymized. Furthermore, all data utilized in this project shall be referenced. This project shall not cause any harm to the surrounding environment or to any observers.

This project aims to develop a fully automated and rapid COVID-19 diagnosis mechanism that reduces virus exposure between patients and medical professionals. Through this project, medical professionals would receive real-time COVID-19 diagnosis from the provided lung scans, and thus, would be able to rank them based on severity, and ultimately save lives.

Appendix A

The COVID-19 Pandemic Era

Rise of the Global Pandemic

COVID-19 which is now officially declared as a global pandemic by the WHO was initially discovered in late 2019 emerging from Wuhan, People's Republic of China. A media statement was released by the Wuhan Municipal Health Commission confirming multiple cases of "Viral Pneumonia from an unknown cause" on December 31st 2019 [46].

On January 7th 2020, this unknown disease was identified as the novel coronavirus by the WHO. Three days later, the first known death caused by the coronavirus was reported [47]. The spread of the virus continued rapidly within China and on January 20th 2020, WHO reports the first confirmed cases outside China in Thailand, Japan, and South Korea. The very next day The United States reports its first confirmed coronavirus case [48].

Following these set of events saw the introduction of quarantine protocols via lockdowns. Starting with Wuhan, many other cities across the world also adopted the same orders to suspend the spread of the coronavirus. This prompted the WHO to declare the outbreak a global public health emergency [49].

Within the span of a month, the death toll from COVID-19 surpassed that of SARS and the WHO gives the official name for the disease caused by the coronavirus "COVID-19" [50]. The adverse effects of COVID-19 on various industries and the stock market began to show.

Travel bans, high-profile event cancellations and activation of emergency funds were implemented across different countries as the number of positive cases rose above 100,000 [52].

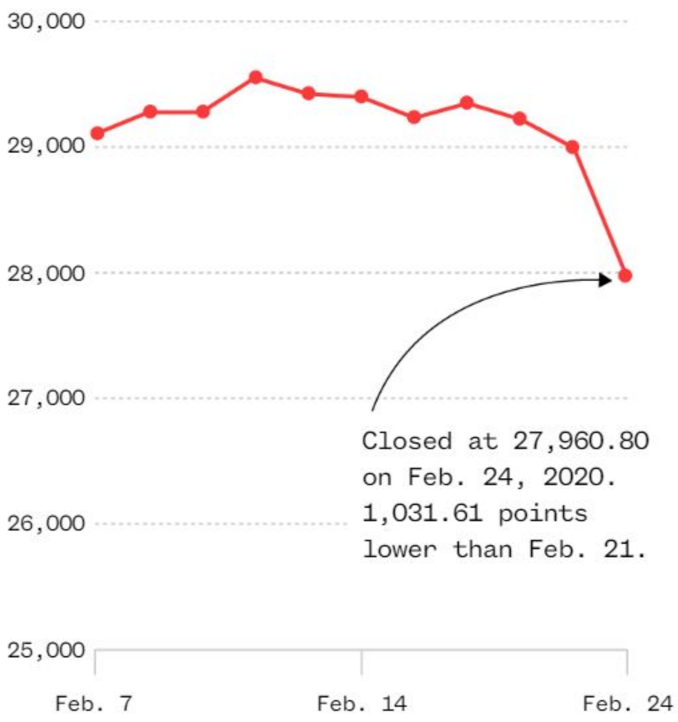

FIGURE A.1: Dow Jones Industrial Average experienced the worst day in two years. [51]

Due to the rapid spread of the virus worldwide, on March 11^{th} 2020, the WHO declares the coronavirus outbreak as a global pandemic [53]. Over the next few months, nationwide lockdowns were enforced in countries such as The United Kingdom, India, South Africa, Italy, Belgium, and so on.

At the end of March 2020, The United States coronavirus cases officially surpassed China, with the former reporting 82,474 cases and the latter 81,961 cases.

On April 2^{nd} 2020, the number of coronavirus cases worldwide surpassed 1 million with the number of deaths exceeding 51,000 [55]. The number of positive cases doubled in April and this trend continued to follow for the next few months were as of October 2^{nd} 2020, the total number of worldwide COVID-19 cases stand at 34,312,510, and the death toll surpassing over a million, to be precise 1,023,243 [56].

Among the countries affected by COVID-19, The United States, India and Brazil share the highest percentages of positive cases.

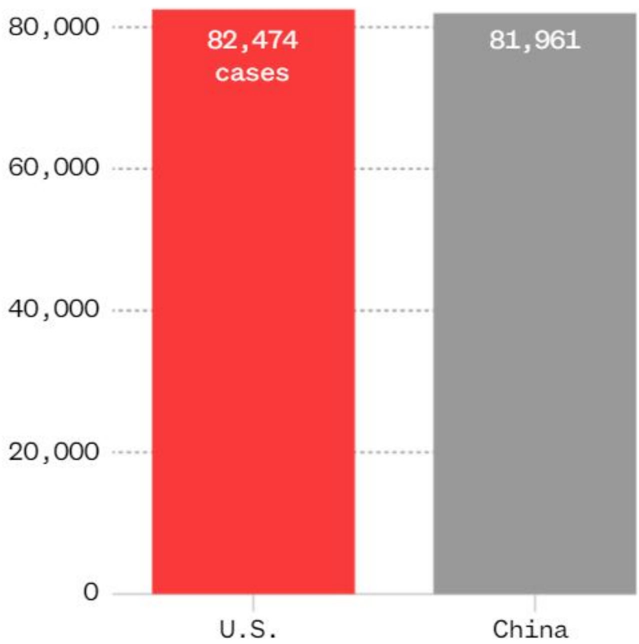

FIGURE A.2: COVID-19 cases comparison between The United States and China [54]

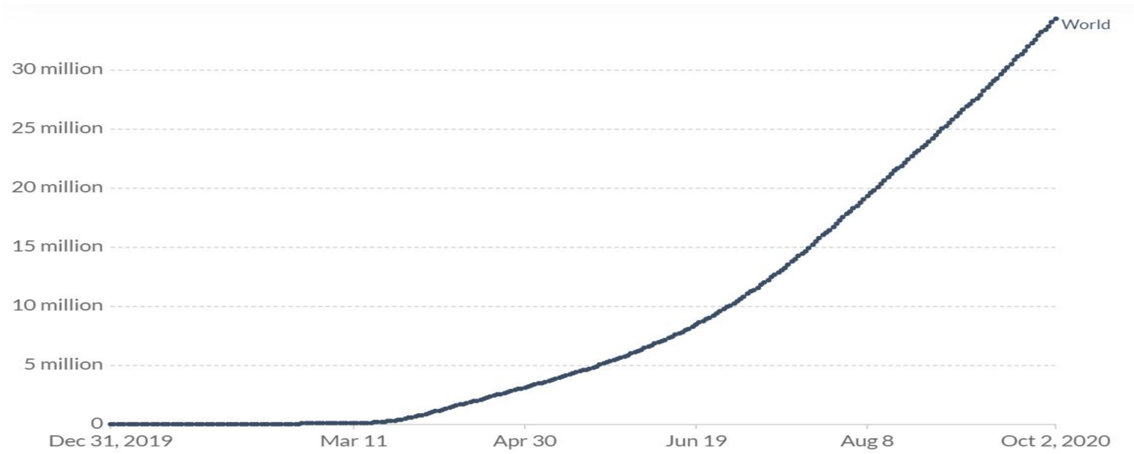

FIGURE A.3: Cumulative confirmed COVID-19 cases [57]

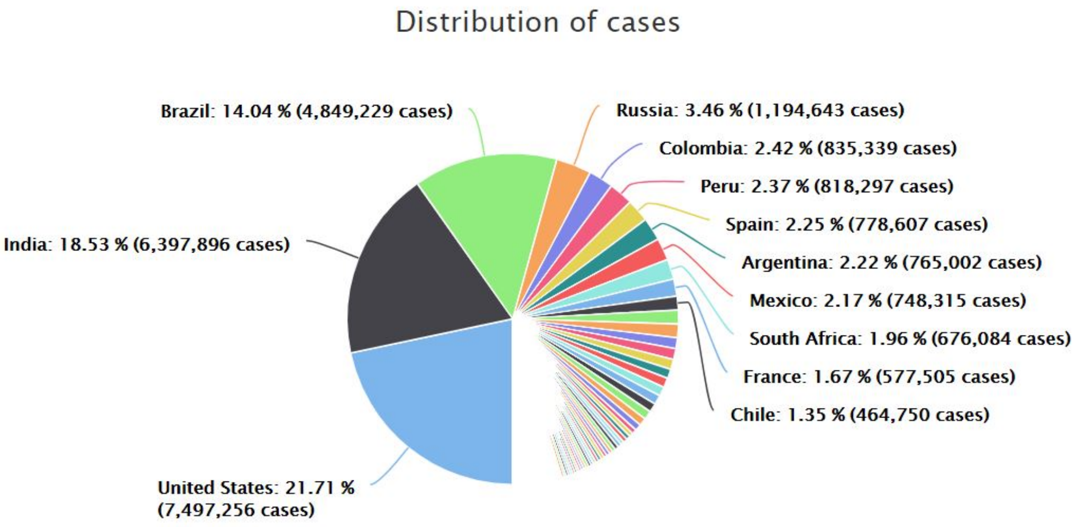

FIGURE A.4: Country wise distribution of COVID-19 cases [58]

As we have now seen the major trends and events that took place in the rapid spread of COVID-19, it is upon us to work together as a community, follow the recommendations suggested by national and international healthcare agencies through which we would be able to overcome this pandemic and successfully curb the spread of the virus.

Appendix B

COVID-19 Lung Characteristics

Additional Study on COVID-19 Patients

Morales et al. conducted a systematic literature review with meta-analysis of the imaging features of COVID-19 also observed similar lung characteristics such as GGO's from X-ray scans from patients diagnosed with COVID-19 from multiple studies [59], the results are tabulated in Table B.1.

Study	**Unilateral Pneumonia**	**Bilateral Pneumonia**	**Ground-glass Opacity**
Huang et al. [60]	-	40 (97.6%)	12 (29.3%)
Chen et al. [61]	25 (25.3%)	74 (74.7%)	14 (14.1%)
Wang et al. [62]	0 (0%)	138 (100.0%)	138 (100.0%)
Liu et al. [63]	-	36 (26.3%)	55 (40.1%)
Chang et al. [64]	1 (7.7%)	-	6 (46.2%)
Pan et al. [65]	-	38 (60.3%)	14 (22.2%)
Zhang et al. [66]	2 (22.2%)	5 (55.6%)	7 (77.8%)

TABLE B.1: Chest X-ray imaging characteristics from multiple studies

Appendix C

Automated Diagnosis Workflow

AI Powered Medical Scanning

Chest X-ray and CT scans are the primary screening mechanisms for diagnosing COVID-19. The limitation to these being the viral exposure between the technician and the patient, as assistance is required to perfect patient positioning for these scans to yield satisfactory results. Therefore, an automated and contact-less workflow is the need of the hour.

Modern CT and X-ray systems include cameras to allow technicians to remotely monitor the patient. But especially since the outbreak of the pandemic, this would not be sufficient as technicians would not be able to determine scanning parameters such as scan range [26].

Fortunately, a fully automated scanning workflow is indeed possible through AI. Patient pose and shape could be acquired via visual sensors such as RGB, Time-of-Flight (TOF) pressure imaging or thermal (FIR) cameras. Therefore, optimal scanning parameters could be determined [67]–[74].

Through this automated scanning workflow, radiation exposure can be reduced significantly as well as increasing the overall efficiency of the diagnosis procedure [75]. Especially during this period of the pandemic, using the same workflow would prevent virus exposure between technicians or medical practitioners and patients.

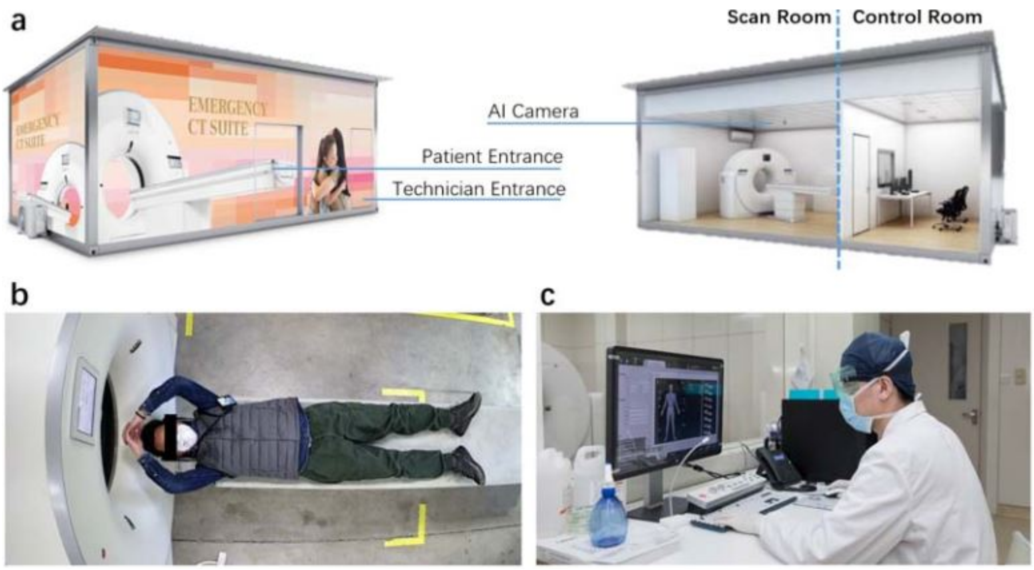

FIGURE C.1: AI-empowered automated image acquisition workflow [26].

Utilizing this workflow we can procure high-quality X-ray and CT scans suitable for segmentation, but more importantly, we can ensure the safety of both patients and technicians by reducing the radiation and virus exposure respectively.

Appendix D

CT Image Segmentation Techniques

Extended CT Scan COVID-19 Applications

Table D.1 below is an extended version of Table 2.2 which summarizes existing studies and research, both quantification and diagnosis COVID-19 applications conducted on CT scans.

<table>
<tr><th>Study</th><th>Method</th><th>Application</th><th>Target ROI</th></tr>
<tr><td>Zheng et al. [8]</td><td>U-Net</td><td>Diagnosis</td><td>Lung</td></tr>
<tr><td rowspan="2">Cao et al. [9]</td><td rowspan="2">U-Net</td><td rowspan="2">Quantification</td><td>Lung</td></tr>
<tr><td>Lesion</td></tr>
<tr><td rowspan="3">Huang et al. [10]</td><td rowspan="3">U-Net</td><td rowspan="3">Quantification</td><td>Lung</td></tr>
<tr><td>Lung Lobes</td></tr>
<tr><td>Lesion</td></tr>
<tr><td rowspan="2">Yue et al. [11]</td><td rowspan="2">U-Net</td><td rowspan="2">Quantification</td><td>Lung Lobes</td></tr>
<tr><td>Lesion</td></tr>
<tr><td rowspan="2">Gozel et al. [12]</td><td rowspan="2">U-Net</td><td rowspan="2">Diagnosis</td><td>Lung</td></tr>
<tr><td>Lesion</td></tr>
<tr><td rowspan="4">Shan et al. [16]</td><td rowspan="4">VB-Net</td><td rowspan="4">Diagnosis</td><td>Lung</td></tr>
<tr><td>Lung Lobes</td></tr>
<tr><td>Lung Segments</td></tr>
<tr><td>Lesion</td></tr>
<tr><td>Li et al. [13]</td><td>U-Net</td><td>Diagnosis</td><td>Lesion</td></tr>
<tr><td>Chen et al. [14]</td><td>UNet++</td><td>Diagnosis</td><td>Lesion</td></tr>
</table>

Jin et al. [15]	UNet++	Diagnosis	Lung
			Lesion
Tang et al. [25]	Commercial Software	Quantification	Lung
			Lesion
			Trachea
			Bronchus

TABLE D.1: CT Image Segmentation Techniques in COVID-19 Applications [26]

Appendix E

Wireframe

UI Interface Wireframe

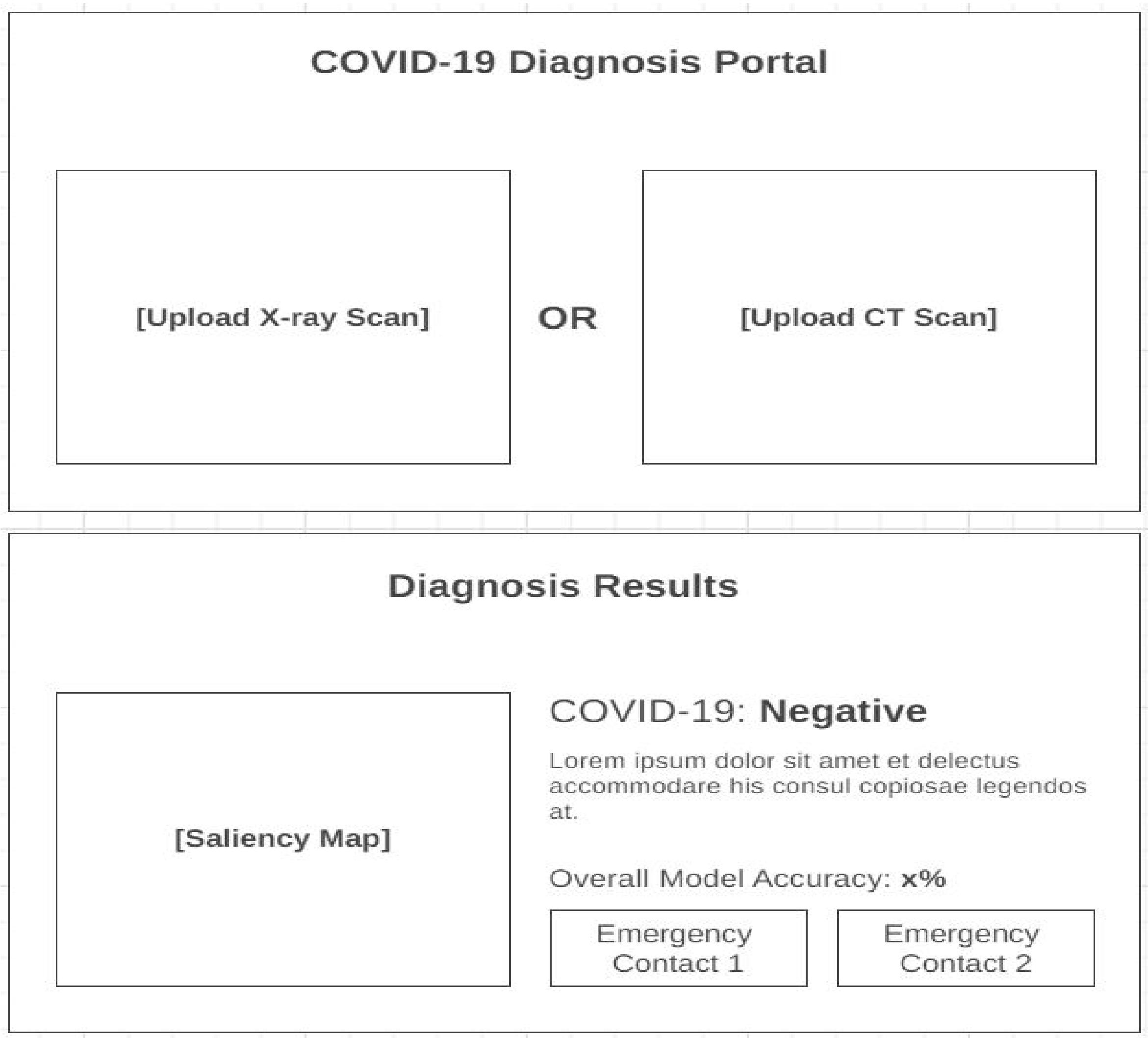

FIGURE E.1: General Layout of the proposed User Interface.

Appendix F

SCRUM

SCRUM Development Methodology

SCRUM involves building software iteratively coupled with a continuous integration and development pipeline if set up, this enables frequent feedback from the project supervisor. This development methodology allows us to perform weekly increments where a reasonable part of the functionality is developed or modified and these updates could be reviewed by the project supervisor. Therefore, it would be easier to detect and mitigate risks involved such as slow progression in model development or misinterpretation of the project requirements.

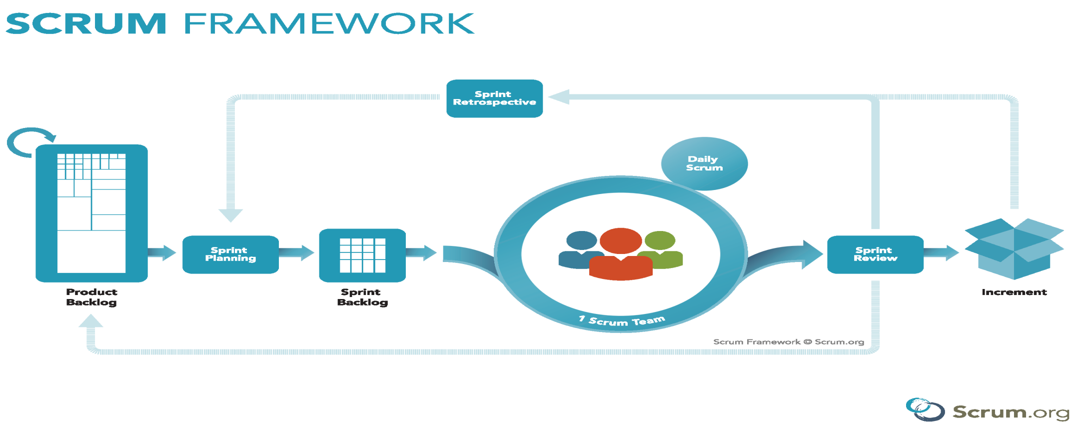

FIGURE F.1: SCRUM Development Methodology [76]

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