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AI-BASED MEDICAL IMAGE ANALYSIS FOR EARLY COVID-19 DETECTION

by
HUSSEIN AHMAD KAHEEL

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by

HUSSEIN AHMAD KAHEEL

Approved by:

Ali Chehab

Dr. Ali Chehab, Professor — Advisor
Electrical and Computer Engineering

Dr. Rouwaida Kanj, Associate Professor — Member of Committee
Electrical and Computer Engineering

Ibrahim Issa

Dr. Ibrahim Issa, Assistant Professor — Member of Committee
Electrical and Computer Engineering

Dr. Ali Hussein, Lecturer — Member of Committee
Electrical and Computer Engineering

Date of thesis defense: April 30, 2021

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Student Name: Kaheel Hussein Ahmad

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Kaheel	Hussein	Ahmad

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Recently, the healthcare system is facing strenuous challenges in terms of supporting the ever-increasing number of patients and associated costs due to the COVID-19 spread. Thus, the recent impact of COVID-19 mandates a shift in the healthcare sector mindset. As such, it becomes essential to benefit from modern technology, such as Machine Learning, in order to design and develop intelligent and autonomous healthcare solutions. In this context, researchers tried to fight COVID-19 by proposing Artificial Intelligence (AI)-based solutions. Several companies around the world provided a set of AI-based solutions during the last month to detect COVID-19, based on chest CT or X-ray scans. The main goal of this thesis is to design and develop a fast, efficient and reliable technique to detect COVID-19 based on Deep Learning, which is used to develop medical diagnosis in line with the initial objective.

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Chapter 1

Introduction

The range of topics that are associated with artificial intelligence (AI) is broad. Experts and amateur people alike have integrated different fields with the keyword AI. In fact, each company or research institute has different approach for AI that suits the targeted application. In general, AI is a branch of computer science that deals with the mapping of "intelligent" behavior through IT. AI has not made the leap from universities to companies for a long time. The technology could not meet many expectations of the early years, but now the media keep reporting about breakthroughs, new areas of application and new potential dangers. Three factors are responsible for the development of AI: more data, cheaper storage capacities and constantly increasing computing power (graphics processing unit). These factors enable companies to use AI processes in increasingly complex configurations. Specialists separate between "strong AI", the point of which is to emulate human knowledge, and "weak AI", which is utilized to make intelligent classifications for specific domains [1]. Strong AI is technically beyond the current prospects. Powerless AI, on contrary, is a methodology that assumed to be a big part in numerous applications today.

Artificial intelligence encompasses an extensive set of methods, processes and technologies. The core of an AI system is a model that is exhibited for a specific question - for example to support certain decisions or to make predictions. There are many different types of models as well as different techniques for creating them. Basically, AI can be divided into supervised and unsupervised systems based on the representation of knowledge. In a supervised system, rules and relationships are focused on the labeled data and less on the understandability of humans. The model can be read and recorded by people. Unsupervised systems, on the other hand, are largely black box systems for people, the contents of which are not easy to understand.

One of the big fields that AI has large influence in is the medical field. A great opportunity lies in medicine precision, where treatment is tailored to the patient's individual physiology and pathology. The development of medicine precision relies on the collection of large amounts of data and the ability to interpret it. In the final step, the expert believes that artificial intelligence can have a huge impact by giving radiologists tools to make faster, more accurate diagnoses and prognoses, resulting in more effective treatment. Big data and artificial intelligence will change the way radiologists work because computers will be able to use huge amounts of patient data to become experts on very specific tasks [2].

The first computer programs for evaluating radiological images were based on the principle of pattern recognition. The program is initially fed with many different images of the pattern being sought. At the end of this learning phase, the computer is able to recognize the pattern on its own. For more than ten years, this procedure has been used to detect skin cancer, for example. The most striking features of malignant melanomas (skin cancer) are their asymmetry and their composition of different colors and different structures [3]. Special diagnostic programs see these patterns, no matter how weak they are, and they can track changes in the suspicious areas over time because all recordings can be saved and compared with one another.

There is no doubt that the use of artificial intelligence has succeeded in overcoming some chronic diseases in the past. At the present time, some people are relying on an expected role for artificial intelligence, as scientists seek to find a treatment that helps eliminate the emerging corona virus, and reduce the rate of panic that people live in all countries of the world. Many companies, research and development laboratories, and government institutions around the world have used this technology to deal with the current epidemic through multiple smart technologies such as natural language processing, predictive analytics, automated chat systems, face recognition systems, recognition and tracking of people with fever, smart diagnostic systems, pattern recognition and identification from big data. There is no doubt that artificial intelligence is now helping to combat the COVID-19 epidemic and contributing to curbing its worst effects.

Computer programs for machine learning, often referred to as artificial intelligence, help with many questions concerning the pandemic starting from vaccine and drug research, where people move and how and whether they adhere to the social distancing guidelines, ending in evaluating CT-scans and X -rays of the lungs for faster diagnosis of severe progressions.

Progressive effort in diagnosing COVID-19 are in process using machine learning algorithms. Advanced types of neural networks aimed over a large-scale screening of the virus to classify patients based on their respiratory pattern [4]. Similarly, detection of the existence of COVID-19 was raised by analyzing chest CT [5]. The development of automated diagnostic systems contributes in the growth of the accuracy and speed of diagnosis, and protects workers in the health sector by notifying them of the severity condition of each infected patient [6].

In this thesis, we plan to perform a comprehensive analysis of COVID-19 diagnosis methods, focusing on the existing Machine Learning based solutions that unfortunately do not ensure high accuracy and reliability. We will propose a new Deep Learning based COVID-19 diagnosis solution based on pulmonary CT scan, ensuring a high-speed delivery of the test results.

The outline of this thesis is as follows: Chapter 2 presents a literature review covering AI applications in the field of medical imaging with a brief definition of each deep learning method used. The literature review also covers many techniques involving detection of COVID-19 and its severity. In Chapter 3, the methodology that will be followed in this thesis will be elaborated in details: tasks to be done, codes to be tested and developed, and working packages. Chapter 4 will discuss the architecture proposed in details with a full explanation for each module. The model simulations and results will be presented in chapter 5.

Chapter 2

Literature Review

In this chapter, an overview of the previous work presented within the scope of AI in medical imaging and COVID-19 applications. We first present an overview of artificial intelligence in medical imaging. Second, we present a review of the existing AI techniques in the field of COVID-19.

2.1 AI in Medical Imaging

Image classification can be described as the task of sorting images into one of numerous classes. It is a fundamental computer vision issue. It provides the basis for other computer vision functions such as detection, localization, and segmentation [7]. This type of problems have been solved in recent years by deep learning models that leverage several layers of non-linear acquired knowledge processing, for the extraction and transformation of functions as well as for pattern analysis and classification [8]

Computer-assisted image processing have been assisting in problems involving the area of medical imaging. Recent development in machine learning, particularly in deep learning, has made a huge breakthrough in the field of image interpretation to help recognize, classify and quantify patterns in medical images [9]. In particular, the usage of hierarchical function representations gained exclusively from data is the cornerstone of the innovations instead of handcrafted features often focused on domain-specific information. Deep learning thus easily appears to be the new building block and achieves increased efficiency in numerous medical applications [9].

The key force behind the advent of AI in medical imaging was the need for more quality and effectiveness of clinical treatment. Radiological imaging data tends to increase at a significant pace relative to the amount of qualified readers available, and the reduction in image payment has pressured healthcare professionals to compensate through-efficiency [10].

Remarkable developments to other machine learning methods in literature have been reported through the renaissance of deep learning. These achievements were compelling enough to draw researchers in the field of computational medical imaging to explore, for example, the ability of deep learning in medical images acquired with computed tomography (CT), magnetic resonance imaging (MRI), positron emission tomography PET, and X-ray. The following are functional implementations of deep learning for image localization, cell structure recognition, tissue segmentation, and computer-aided disease diagnosis [9].

Artificial neural networks in machine learning are a family of models that emulate the structural beauty of the neural system and learn hidden pattern from observations. The perceptron [11] is the first trainable, single-layer neural network consisting of an input and output layer. The modified perceptron, with several output units, is considered as a linear model that prevents applications to deal with complex data patterns, even with the use of non-linear functions present in the output layer. This constraint is effectively bypassed by adding a hidden layer between the input layer and the output layer.

Taking into consideration certain assumptions on the activation function, a two-layer neural network consisting of finite number of hidden layers can estimate any continuous function [12], and is therefore called a universal approximator. However, it is often possible to estimate functions at the same precision using a deep design, that is more than two layers, with fewer units in total [13]. Thus, the number of trainable parameters may be decreased, facilitating the process training with a comparatively limited dataset [14].

Upon this overview about deep neural network, here are the well-known deep learning algorithms in the field of medical imaging:

2.1.1 Convolutional Neural Networks:

Convolutional Neural Networks (CNN) is a one of the critical deep learning methods used to process large dataset. It is commonly applied to solve medical imaging problems [15,16]. What distinguish CNN from other artificial intelligence architectures can be demonstrated by two aspects: no need for handcrafted feature extraction, and segmentation is not big concern for its architecture [17]. CNN consists of multiple blocks: input layer, hidden layers - convolution with activation function layer and pooling layer-, output layer. The first stage is the loading stage where the dataset is fed in. The data passes through the hidden layers which is responsible of feature extraction. This done by filtering the data by different convolutional filters yielding a set of maps called feature maps. Then, the activation function discretize the values. Pooling layer takes these maps and perform a down-sampling operation, and the result is flattened and fed to another connected network to create a fully connected layer where relationship between the features is driven. The output layer is final result of the previous procedure.

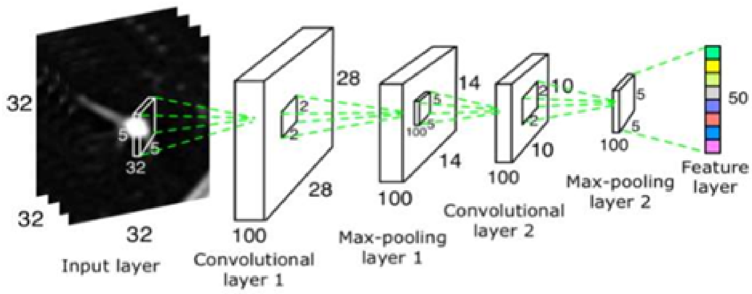

Figure 2.1: Illustration of CNN [18]

2.1.2 Regional Convolutional Neural Networks:

R-CNN mainly focused on localization aspect of CNN [19]. CNN's localization approach was established on a sliding window paradigm basis suffering from attaining an acceptable precision in the presence of higher convolutional layers. As a result, [20] proposed a three module design based on region to solve the problem of localization. The first one uses selective search [21], a combination of segmentation intuitions and exhaustive search to create category-independent regions. The second module consider Caffe implementation of CNN in the specific regions [22]. The final module tackle the problem of tightening the coordinates of these regions through linear regression. [23] introduces a faster version of R-CNN in order to enhance the performance of the algorithm by adding a layer called Region Proposal Network (RPN) and eliminating the past regions created by module one. This layer a fully convolutional one that can in parallel estimate the bounds and weights. [23] proposed that this layer takes the feature map derived by CNN as the input. The following diagram show the architecture of this algorithm.

2.1.3 Recurrent Neural Network:

RNN is quite popular class of network that is suitable for processing sequential data since it has an internal memory state and can retain information regarding previous pieces of data. One type of RNNs, long short-term memory (LSTM), [25] has enhanced memory recall relative to standard RNNs and showed considerable effectiveness over a variety of image captioning tasks [26,27].

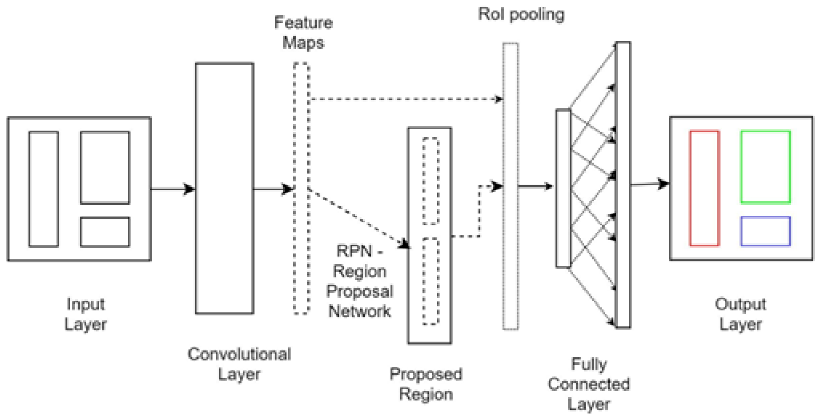

Figure 2.2: Illustration of CNN [24]

2.1.4 Generative adversarial networks:

GANs are another interesting DL architecture class consisting of two networks: a generator and discriminator. The generator network generates new data instances that aim to replicate data used in training whereas the discriminator network attempts to decide whether or not the candidates produced belong to the training samples [28]. GAN have displayed promising results through its engagement with medical imaging problems mainly in the reconstruction of compressed sensing images in MRI [29].

2.1.5 Convolutional Recurrent Neural Network

Inspired by the combination of CNN and RNN, [30] presented a remarkable fingerprint in medical imaging by the proposed architecture of the convolutional recurrent unit CRNN. This algorithm improved data fidelity and is able to inherit the ability of iterative reconstruction of MRI.

2.2 AI for COVID-19 Detection

The medical sector is seeking, in this global health problem, for innovative solutions to track and contain COVID-19 (Coronavirus) pandemic. Artificial intelligence is a technology that humanity can rely on, since it can quickly classify high-risk patients, monitor the progression of this virus, and effectively manage this outbreak in real-time. This technology has also the power of estimating the severity of the case through examining previous patient records, but still the rates of accuracy, true negative and false positive can be enhanced more to avoid misinterpretation in medical treatment [31-33]. The main application of AI in COVID-19 pandemic that this thesis rely on, is the early detection and diagnosis of the infection. Artificial intelligence could easily analyze abnormalities viewed by symptoms and the so called "red flags", warning through this process patients and health authorities [34, 35]. It creates a cost-effective quick decision-making algorithm. With the help of numerous algorithm in AI, modern COVID-19 cases can be detected and managed in a classified framework. Computed tomography (CT) and magnetic resonance imaging (MRI) were a great input to AI algorithms scanning human body sections for the sake of diagnosis.

The basic phase in image processing and interpretation to determine and measure COVID-19 is segmentation. It defines the key factor for AI algorithm which is regions of interest (ROIs) captured in chest X-ray or CT images. Self-learned features or even handcrafted ones can be derived using these segmented regions for the sake of diagnosis [36].

Computed tomography is one of the main contributors of high-quality 3D images in the field of COVID detection. Deep learning techniques shines in the domain of ROIs segmentation where the most popular ones used for coronavirus are U-Net [37-42], U-Net++ [43, 44], VB-Net [45]. Despite the dominance of X-ray over CT in the medical sector due to its accessibility, the segmentation process in X-ray images is more difficult. This is a result of the image contrast in the 2D projection of ribs onto soft tissue.

In the context of COVID-19, segmentation is demonstrated as an essential block in the interpretation of this virus. Here [46] proposed Attention-U-Net for the segmentation of lungs that can extract features related to pneumonia. Such a method can be associated with diagnosis of coronavirus [36].

Segmentation mechanisms are categorized into two groups: segmentation of lung according to regions, segmentation of according to damages. The first conduct the separation of the lung itself and its lobes from other regions in X-ray or CT, and this is the first step in every application targeting COVID-19 [37-41, 44, 45, 47]. The second conduct the separation of damages inside the lung from the regions of the lung [38-45, 47, 48]. These lesions are variable in shape and in texture thus identifying their regions is considered a complex task. However, [46] presented an attention mechanism that was regarded as an effective localization algorithm in screening lesions. This mechanism can be used to track damages caused by COVID. Back to the first group, [44] created a pipelined method consisted of two stages to capture COVID-19 in CT images where the first stage is to detect the lung region. This method was based on U-Net++.

Passing through literature, lung segmentation was tackled with several methods aiming toward different goals [49-53]. One of the popular techniques used in COVID apps is U-Net [37-40]. This method proved its capability in both groups mentioned before. Ronneberger [54], the father of U-Net, defined this algorithm to be a fully CNN that has a U-shape structure with the feature of symmetry in both encoding and decoding paths. In each level, a shortcut connection is introduced if the layers are connected in these paths. As a result, visual semantics can be efficiently learned likewise textures which is main concern of medical segmentation. Advanced version of U-Net have been developed in the COVID field. Higher dimension U-Net (3D) was presented by [49] where layer in this technique were exchanged by a 3D model. U-Net++ was more adaptive model [51] where nested convolutional architecture is inserted between the encoding and decoding paths. This algorithm also contributes in presenting solutions for the pandemic through localization of damages in COVID diagnosis [43]. A composite method that uses attention mechanism and U-Net [53] was able to extract exact feature in medical image which can be considered as an appropriate segmentation method to deal with COVID. Another technique that serve segmentation is V-Net. This technique [50] consider residual module to be the basic convolutional module and Dice loss as its optimizer. By adding bottle-neck to the convolutional module, VB-net has an effective segmentation [45]. Each type of these network achieves better segmentation performance. However, the main concern is how the training procedure would be done. Adequate labeled data is the principle constraint for training a segmentation. The availability of a sufficient data was a hard task in COVID image segmentation since handcrafted portraying of lesions exhaust labor and time. Researchers and radiologists cooperate to solve this problem. Initial seed was fed into U-Net algorithm was shown in [40] to converge toward acceptable threshold. [37] restructured the problem in an unsupervised method in order to create a pseudo segmentation mask for CT images. COVID literature proved that unsupervised and weakly-supervised learning mechanisms are desired techniques due to the shortage of labelled medical images.

Segmentation in COVID-19 apps is a rich topic in literature. [42] performed lung segmentation to differentiate between coronavirus existence and pneumonia using U-Net on chest CT. Early detection of COVID is the most important factor in protecting the community, so fast machine learning method be used in the process of diagnosis. [44] proposed such a method depending on CT slices as an input to the model where these slices were the result of a segmentation network. As a conclusion, segmentation process is one of the foundations in the world of COVID apps by making radiologists' lives easier. It provides them with accurate recognition of regions of interest and reliable diagnosis of the virus.

Before talking about classification of COVID from non-COVID and the severity of the virus infecting certain patient, a brief summary concerning the stages of radiological pattern in CT images must be conducted. [57] reported that these patterns are analyzed over four stages. First, early stage (day 0 to day 4), initial symptoms arises and lesions' regions extracted from chest CT can be observed in the lower lobes of the lung. Stage two (day 5 to day 8), lesions spread out and become thicker reaching multi-lobes. In the third stage (day 9 to day 14), lesions are widespread with a dense intensity which is considered the dangerous stage. An absorption stage defines the last stage where the virus is contained. The importance of these patterns lies mainly in the classification and severity analysis of the infectious virus.

Distinguishing between COVID-19 patient and non-COVID-19 is a top-notch task that recent studies are targeting. [43] deployed the segmentation model obtained using U-Net++ to label patients as COVID and non-COVID. Segmented lesions in this article was sufficient in order to predict the label and distinguish between COVID patients from patients with other diseases. The study used CT images of 106 patients and classified them. These contributions have saved reading time of radiologists. Other paper [37] used a combination of U-Net model for segmentation process and a 3D convolutional neural network that takes the output of the previous model as an input and generates the probability of labels. A dataset that consists of 540 chest CT images was tested yielding the following rates: sensitivity 0.907, specificity 0.911 and accuracy 0.959. Another method [44] combined U-Net++ for the sake of lesion localization and ResNet50 as a classification mechanism. This paper showed better results in specificity and sensitivity (0.922 and 0.974 respectively) based on 1136 chest CT images.

Another factor that play a principal role in medical treatment is the severity assessment. Vb-Net was used to identify this factor in [55]. The segmentation is done based on infection volumes in the regions of interest in order to train the RF architecture. Another RF-based architecture was introduced by [56] to classify COVID-19 level as severe or non-severe where 176 chest CT images were test to evaluate severity. This architecture showed an accuracy rate of 0.875. As a conclusion, researchers developed promising techniques with the use of artificial intelligence in COVID-19 diagnosis field. The results of these studies can be counted on in classifying patients. Also, severity estimation is a key factor in the treatment procedure because it determines the need of ICU for example.

Chapter 3

Methodology

Currently, a set of companies started selling their solutions at a high cost, and others are distributing free demo online versions (limited features). This project will manage and use a large crowd sourced medical image repository to develop an efficient and robust AI-powered chest scanning analysis solution. The potential of the proposed solution is to reduce the growing burden on radiologists that should examine and prioritize the required chest scans of patients every day. Additionally, the proposed solution will help in identifying and separating the patients who most likely will require a ventilator or medication, and the ones who could be sent home to increase hospital capacity.

Moreover, the proposed AI-based system will have an efficient design to enable it to process huge amounts of CT scans daily, and thus, diagnose a large population quickly.

This thesis will help less experienced medical staff to make preliminary diagnoses, expanding the overall diagnostic efforts.

The main idea is to develop a Deep Learning solution (CNN model) for COVID-19 diagnosis and prediction. It will be based on pulmonary CT-Scan images. In fact, this project aims to develop an innovative product with high added value, which combines Virology expertise, Machine Learning and Image Processing skills, to reduce the risk of medical accidents by accurately predicting COVID-19 emergencies. In addition, it is targeted to ensure better efficiency, reliability, safety and security compared to existing COVID-19 diagnosis solutions. Finally, the proposed AI-solution could contribute to the defeat of COVID-19 by identifying, monitoring, and predicting patients' status. The solution will augment the limited hospital resources, especially in terms of the available number of radiologists. Furthermore, we hope that the proposed system will be able to identify the patients who will soon require a ventilator, and those who no longer need one.

We will enable our AI system to detect COVID-19 and follow the progress of a specific patient, such that future chest scans of diagnosed patients are analyzed to detect any recovery. This is possible through tracking a patient's progress by providing a numerical "Corona score", (a measurement of disease severity), which can be used to quantify the disease over time.

Thus, the objectives of this project can be summarized as follows:

- Image preprocessing and Segmentation.
- Developing a CNN model for COVID-19 diagnosis based on pulmonary CT scan.
- Studying the evolution and severity of the COVID-19 infection by examining the CT scan at different infection stages and cases.
- Analyzing the similarity between COVID-19 and other viral or non-viral pneumonia for possible treatments.

3.1 Project Tasks:

The target of the project is to contribute to the fight against COVID-19. Its corresponding research methodology focuses on building AI systems to help healthcare specialists in gaining important insights, leveraging techniques based on Artificial Intelligence (AI), especially Deep Learning.

Deep Learning is a Machine Learning method that it is based on a deep architecture consisting of multiple linear as well as nonlinear processing units to model high-level abstraction existing in the input data [58]. Several Deep Learning variants are currently being employed in a variety of applications such as auto-encoders, stacked auto-encoders, restricted Boltzmann machines (RBMs), deep belief networks (DBNs), and deep convolution neural networks (CNNs). In addition, CNN-based methods have become popular in the field of vision systems as well as in the domain of medical image analysis [58,59]. The methodology to be adopted in this project consists of the following tasks:

- **Data collection and preprocessing:** after acquiring the data, images with labels are transformed into 3D vectors. Given that Deep Learning is a data-hungry method, data augmentation method using Generative Deep Learning architectures (e.g. GAN) will be used to augment the size of the data. GAN will be trained to generate images very similar to the real ones by extracting/learning the main features.

- **Model conception and evaluation:** different CNN architectures (ResNet, ConvNet, GoogleNet, etc.) will be compared in terms of accuracy and precision. An ensemble method will be proposed to enhance the accuracy and precision.
- **Hierarchical classification model for infection severity classification:** having data related to different levels of severity, a hierarchical classification model will be conceived to further classify the CT scan images based on the severity of the cases.
- **Evaluating the similarity between pneumonia using unsupervised Machine Learning methods:** unsupervised based methods are used to evaluate the similarity between recent pneumonia diseases (SARS, MERS, etc.) in addition to other pneumonia infections to find common patterns (effects) towards finding possible treatments to COVID-19.

3.2 Deliverables:

The project is subdivided into four deliverable sets (DS):

- **The first DS** represents a preliminary study. In this study, we analyzed and compared the existing COVID-19 diagnosis techniques, which principally use Deep Learning variants. Each one of these variants has its advantages and limitations.
- **The second DS** mostly focused on designing an efficient and robust COVID-19 Deep Learning-based diagnosis solution that uses Convolution Neural Networks or another Deep Learning variant (various configurations). The activities of this step can be summarized by:
  - **Data collection:** collecting data from public repositories [60-68].
  - **Model conception and evaluation:** comparing existing CNN models on COVID-19 dataset, including ResNet, CNN, and attention models.
  - **Analysis of disease evolution** and similarity to other pneumonia infections with different patients' histories (smoking, other disease (cancer, diabetes, etc.))
- **The third DS** combines a set of possible Deep Learning solutions and apply an ensemble learning towards increasing the accuracy level.

Finally, in **the fourth DS**, we prepared a prototype tested of the proposed solution that can, not only be used to assess the proposed technique, but also as a platform for future research and enhancements in coordination with interested end-users in the government and industry.

3.3 Impact:

The main impact of the proposed solution is assisting doctors in preserving the lives of millions of patients who can suffer from COVID-19 since it provides: higher level of efficiency and accuracy detection and reporting during emergency, reliability as compared to the existing solutions. More importantly, the proposed solution would increase the trust in AI medical diagnostic systems and hence, would encourage their deployments.
The expected project outputs include:

- A theoretical and experimental framework for fundamentally characterizing and optimizing the proposed diagnosis solution of COVID-19.
- Enhancement of existing COVID-19 diagnosis techniques by designing an innovative lightweight Machine Learning based diagnosis solution that focuses on accuracy, delay, and practical limitations of CT-scan devices.
- Setting up and performing simulations to assess the performance of the proposed method and the different tasks using appropriate simulation software. Different methods and techniques will be compared under different simulation scenarios and their performance will be studied and analyzed in depth.

Moreover, the project is expected to lead to several outcomes and to have an important impact in the area of COVID-19 diagnosis.

Chapter 4

The Medical Hub Architecture

4.1 Architecture Overview and Challenges

One of the main challenges in every healthcare system is the limited resources. The availability and quality of data determine the reliability of the study and quality of the architecture. Using CT images requires a large dataset to ensure the aforementioned influences of data availability. Therefore, a large dataset was deployed in this study consisting 1219 CT scans (see section 5.1).

We are proposing an AI-based medical hub platform that integrates AI and image processing for early detection of different problematic medical conditions. This platform targets medical problems that involve medical imaging. It provides the detection of abnormalities and classifies them accordingly. For the purpose of this work, we are targeting COVID-19 as a priority medical condition. The chest images, in the dataset, go through several blocks in this architecture, as shown in the figure below.

First, the data is augmented to enrich the latter blocks with more images and to highlight special features to be recognized. This is done by rotating, shearing, zooming and blurring images. Then, augmented data is preprocessed in two stages: standardization and normalization. These stages are essential to unify the data fed to the network. In order to identify abnormalities in images, the preprocessed images are fed into the lesion segmentation block that uses InfNet to treat abnormal aspects and features. In addition to early detection using this block, we are enabling it to detect the condition severity through further image analysis. Finally, the abnormal images are loaded into a deep network using transfer learning method in order to distinguish between COVID-19 and other viral pneumonia conditions. Detailed information on each block will be elaborated in the following sections.

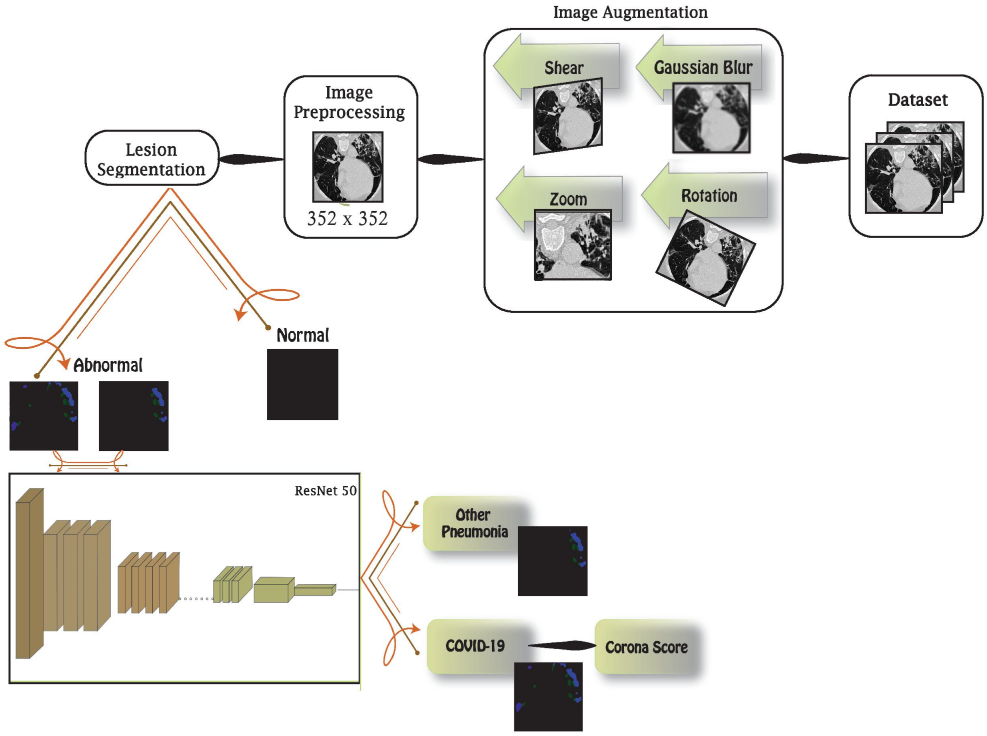

Figure 4.1: Block Diagram of the Whole Architecture

4.2 Image Augmentation

Data augmentation is a method used to yield extra data from the current dataset. It creates perturbed copies of the existing images, in this case. The main goal is to reinforce the neural network with various diversities which leads to a network that distinguishes relevant from irrelevant characteristics in the dataset. Image augmentation can be done using several techniques. Augmentation techniques are used efficiently when necessary according to data availability and quality. Our thesis integrates multiple techniques, to support a large number of datasets for different conditions, as follows:

- Rotation: the image is rotated within an interval between -10and 10.
- Zoom: scaling the image by zooming in or out would also increase the set.
- Shear: image shearing can be performed using rotation with the third dimension imitation factor.
- Gaussian Blur: using a Gaussian filter, high frequency factors can be eliminated causing a blurred version of an image.

Using these methods, the dataset was enlarged and used in the training phase. Nevertheless, during the testing phase, the testing set will not be augmented. This would assert the robustness of the architecture and avoid over-fitting.

4.3 Image Preprocessing

Since the data typically comes from various origins, a strategy to guide the complexity and accuracy is essential. Image preprocessing ensure the complexity reduction and a better accuracy yielded from certain data. This method standardizes the data through several stages in order to feed the network with a clean dataset. In this architecture, data preprocessing is performed through the following stages:

- Image Standardization: neural networks that deal with images need unified aspect ratio images. Therefore, the first step is to resize the images into unique dimensions and a square shape, which is the typical shape used in neural networks.

- Normalization: input pixels to any machine learning algorithm must have normalized data distribution to enhance the convergence of the training phase. Normalization is the action of subtracting the mean of the distribution from each pixel and dividing by standard deviation. To achieve positive values, scaling normalized data is considered at the end of this step.

4.4 Lesions Segmentation

Ground glass opacities (GGO) and consolidation are the main extracted features in the case of COVID-19 patients where 97.86% of patients have such infections within 21 days of COVID-19 presence [69]. Therefore, we used lesions' segmentation to identify the existence of these infections and the infected volume. These infections are also caused by other viral pneumonia, so this block will classify an input image as normal or abnormal. Normal ones are released as output while abnormal ones will enter the ResNet block in order to identify COVID-19 patients. The segmentation method uses the architecture of InfNet.

The preprocessed data consisting of CT images will undergo the famous split ratio mentioned by the Pareto principle. 80% of the images will be considered in the training process while 20% of the dataset will be used in testing the network.

The preprocessed CT images are fed into two convolutional layers where low resolution features are extracted. Then, these features are inserted into three convolutional layers to extract the high-level ones. In the context of segmentation, it was shown that edge information can be beneficial and thus, an edge attention unit is placed to enhance the demonstration of regions of interest.

Global map is produced by accumulating the high-level features using a parallel partial decoder to segment the lung lesions. The output and high-level features are joined with low-level features to be inserted in a cascaded reverse attention units based on the global map. Finally, the output is inserted into an activation function (Sigmoid) to estimate the regions of infections [70].

This block segments the infected sections in a CT-scan image to create a colored representation of the GGO and consolidation segment. The absence of such sections will result in a blank black image. Blank images are classified as normal. The rest of the abnormal images are fed to the ResNet50 deep network model. These representations are also quantified to be used later in calculating the corona score.

4.5 ResNet50 Deep Network

Transferring learning is a well-known method that can be used to train convolutional neural networks as it occupies a huge space within the literature. Using this method, the network is pre-trained based on a vast database known as ImageNet. This step leads to the initialization of the layers' weights where loading such weights before deploying the network in the current architecture diminishes the vanishing gradient problem. This is a key advantage for transfer learning that enhances the convergence of the objective. Another advantage using this type of learning is acquiring relevant features of images such as realizing shape and edges. As a result, the computational time is reduced by limiting the computations to the final layers in the training procedure.
The Residual Network ResNet is one of the advanced deep learning algorithms that surpasses many other dense networks in various metrics, especially accuracy and computational complexity [71,72]. This is why we used this algorithm for detecting the coronavirus and distinguishing it from other viral pneumonia infections using transfer learning.

In order to identify the dataset through numerous classes, the pre-trained model characterizes the last layers as classification layers and thus, the extracted features will be saved in the last convolutional layer to be transformed into prediction values for each class. The initialized weights (the fundamental factor of transfer learning methods) do not change except for the last layer, which will be trained to produce estimates, which leads the classification process for our new set of images. Other layers are inserted into this model like the pooling layer, dropout layer, flattening layer and the activation functions (Rectified Linear Unit).

The residual network used in this architecture consists of 50 layers ResNet50 [71], which is a deep network that considers the learning rate as an assessment in the stage to adapt the weights of the layers. In each iteration, the weights are updated based on the loss derived from the input and expected values. The formula of the updated weights is as follows:

$$w_{i+1} = w_i - \alpha \frac{\partial L(w)}{\partial w_i} \tag{4.1}$$

where w represents the weight, i is the iteration in process, L is the loss function, and α is the learning rate.

4.6 Evaluation Metrics

The performance of the proposed architecture is evaluated based on several statistical measures in addition to our new metric, defined as the corona score.

4.6.1 Accuracy

Accuracy is a metric that quantifies the competency of the method in defining the correct predicted cases:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{4.2}$$

- TP: true positive is equal to the number of correct predicted positive cases
- FP: false positive is equal to the number of incorrect predicted positive cases
- TN: true negative is equal to the number of correct predicted negative cases
- FN: false negative is equal to the number of incorrect predicted negative cases

4.6.2 Recall

Recall is the sensitivity of the method:

$$Recall = \frac{TP}{TP + FN} \tag{4.3}$$

4.6.3 Precision

Precision is the ratio of the unnecessary positive case to the total number of positives:

$$Precision = \frac{TP}{TP + FP} \tag{4.4}$$

4.6.4 Specificity

Specificity is the ratio of correct predicted negatives over negative observations:

$$Specificity = \frac{TN}{TN + FP} \tag{4.5}$$

4.6.5 F1-Score

F1-Score is the measure of the quality of detection:

$$F1 - Score = 2 * \frac{Precision * Recall}{Precision + Recall} \tag{4.6}$$

4.7 Corona Score

The Corona score is a new measure introduced to evaluate the severity of the virus inside the lungs. It depends on the volume of the lungs and the volume of the infected part evaluated by the segmentation block. This measure is calculated as follows:

- Given a lung CT image, the volume of lung is first observed
- The alveolar region, known as parenchyma, represents 90% of the total volume of the lung[73].
- Radiologists categorize the severity of coronavirus based on the degree of GGO and consolidation present in lung CT images: minimal (10% less than of lung parenchyma), moderate (10% – 25%), intermediate (25% – 50%), severe (50% – 75%), critical (more than 75% of lung parenchyma) [74].

$$CoronaScore = \frac{InfectedVolume}{0.9 * (LungVolume)} \tag{4.7}$$

4.8 Calibration Metrics

This architecture integrates different calibration techniques according to the test results and task at hand. In this section, we highlight the different techniques accounted for in our platform.

4.8.1 Learning Rate

This rate is a critical value when updating the weights' formula. Its optimal value is unreachable sometimes. Low and high values of learning rates lead to several problems. Low values decrease the speed of the training process causing a delay in the whole procedure. In contrast, high values increase the speed of convergence and reduce the set weights and hence, no sub-optimal weight is achieved. In this model, we used the optimal choice of this rate proposed by [75]. The authors varied the learning rates cyclically in a practical interval to achieve better classification accuracy. Another technique for defining this rate is through initializing it and updating it using the SGD optimizer.

$$LearningRate = \frac{InitialLearningRate}{1 + decay * iterations} \tag{4.8}$$

where iterations represent the steps within an epoch, and decay is a decaying parameter proposed by the optimizer.

4.8.2 Loss Function

The loss function is a way of calculating the performance of the algorithm upon training it with the used dataset. It estimates how far the predictions are from reality. This factor is used later in optimizing the algorithm by minimizing the incurred loss. In fact, the loss function is an indicator whether tuning the algorithm in a certain way is beneficial. There are different categories of loss functions: regression, binary classification, and multi-class classification. In the current study, binary classification loss functions are more likely to be used, since the output of both blocks, segmentation and ResNet50, are producing binary classification (normal, abnormal) and (COVID, Non-COVID), respectively. Under this category, there exists several loss functions: binary cross entropy, hinge loss, and squared hinge loss.

4.8.3 Regularization

One of the main problems in machine learning algorithms to be avoided is over-fitting, which could be interpreted by subjecting the architecture of the algorithm explicitly to the training set. The output of the network is restricted only to the specific output obtained previously by the training set irrespective of the input. Regularization is a mechanism that adjusts the mapping and mitigates over-fitting. Data augmentation is known to be used for increasing the training dataset thus, reducing over-fitting, but large memory cost could be a big concern in this method. Regularization methods can be used irrespective of the training dataset size. Dropout and drop-connect are the most famous regularization techniques. Fully connected networks are usually subjected to dropout mechanisms based on the probability distributions of connections in each layer. In this process, connections are dropped and nodes would be dropped as a result. Dropout has many versions that are utilized according to the given problem like: fast dropout, adaptive dropout, evolution dropout, spatial dropout, nested dropout, and max pooling dropout.

Chapter 5

Model Simulation and Results

The proposed architecture was implemented in Python v3.6 using PyCharm in Windows 10 environment with the aid of different AI and image processing libraries that increase training efficiency to achieve a better performance. Our testing environment employed fastai, numpy, scipy and openCV libraries and was accelerated by NVIDIA GeForce RTX 2070 super GPU with 8 GB dedicated memory. The simulation is based on Linux and Python coding that is compatible with most hardware, and we are testing our models using real datasets used in the literature.

In this section, we will discuss the testing procedure of both blocks, lesion segmentation and ResNet50 deep network, separately. Each block will have its own evaluation metrics based on the predicted output. Next, the entire system will be subjected to a full test to evaluate the system's performance. The platform test results are shown in the following tables and figures.

5.1 Dataset

The CT chest image dataset used in our study was presented by the China National Center for Bio-information. These images are labeled into three categories: coronavirus pneumonia, common pneumonia and normal. The China National Center released these datasets publicly to assist researchers in their fight with the pandemic. The dataset consists of 1219 CT scans distributed over 416 COVID-19 patients, 396 normal and 407 common pneumonia patients. Figure 5.1 shows the different classes conducted in this study: (a) Normal, (b) COVID-19 Pneumonia, (c) Common Pneumonia. In our study, all images in the dataset are used. The dataset was also augmented to produced 300 additional images (approximately 25% of each class). Image augmentation showed significant improvement in accuracy and precision of deep learning algorithms and increasing the number of images by 25% is the best that can be achieved [78].

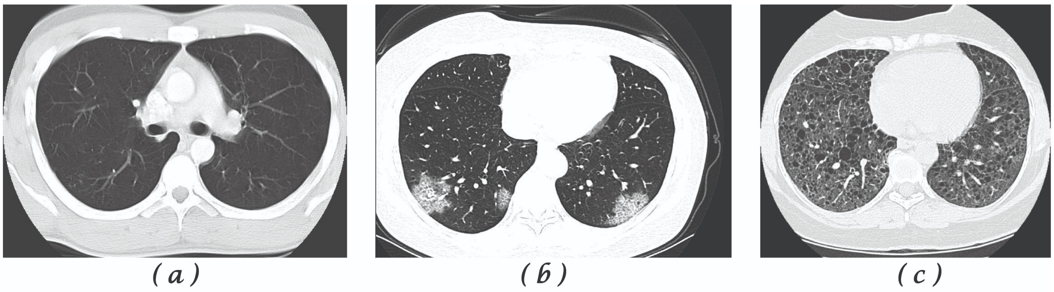

Figure 5.1: CT Chest Images: (a) Normal ,(b) COVID-19 Pneumonia, (c) Common Pneumonia.

5.2 Lesion Segmentation Block

Our proposed model was trained to analyze CT-scan chest images aiming to separate abnormal (infected lungs) from normal (healthy lungs).

The segmentation block was fed with a large dataset including augmentation to analyze and detect the existence of GGO and consolidation, and to measure their size and position in patients' lungs. The existence of one or both of these infections was the criterion in classifying normal and abnormal cases. The result of augmented data and real data was approximately 1500 CT chest images: 500 normal, 500 COVID-19, and 500 other pneumonia diseases. As mentioned earlier, 80% of these images (1200 images) were used as a training set. The output representation of this block is either blank that refers to the absence of infection or segmented version of the image showing GGO and consolidation in blue and green as shown in figure 5.3. After abnormality is detected, the corona score is calculated and passed as an output alongside the positive COVID-19 prediction in the latter block.

The size of the CT image fed to the system is 352x352. Images are re-sampled in order to generalize the module.

The learning rate in this module is set through Adam optimizer to be 0.0001. The training part considers pseudo values that gain convergence in about 8 hours based on 200 epochs. The loss function used is BCE, as mentioned in the calibration metrics section. This function considers the ground truth map and the edge map generated by the convolutional layer. The trained data is then regularized using a fast dropout.

The trained InfNet model showed 95.54% accuracy. Some abnormal images were miss classified due to the initial or early stage of pneumonia where lungs are not slightly damaged thus, infections are not recognized yet. Table 5.1 summarizes

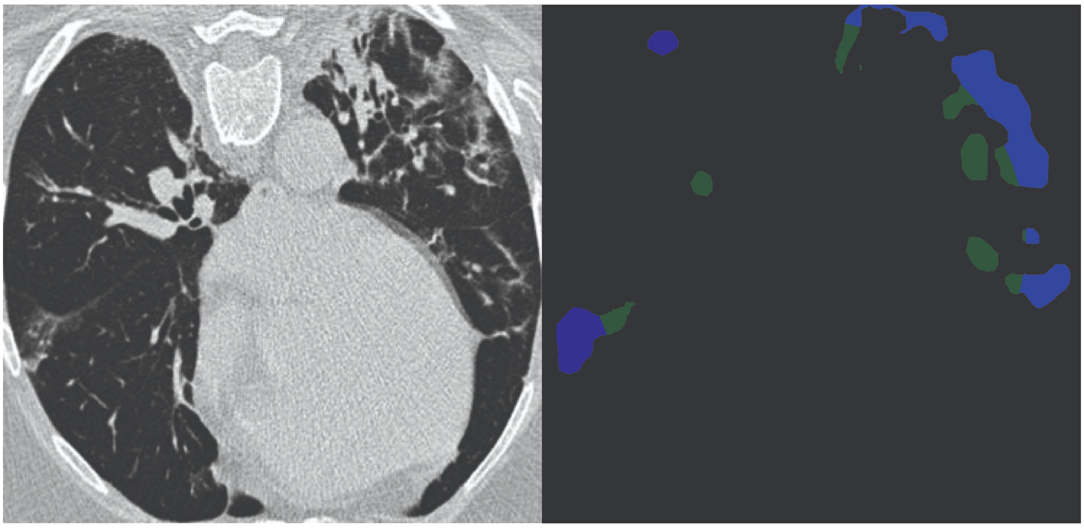

Figure 5.2: Segmentation of COVID-19 CT Image; GGO in Blue and Consolidation in Green

the results of the testing dataset. The proposed model showed that the prediction of abnormal images is 189 out of 200 (94.5%) and 97 out of 100 for normal images that are equal to sensitivity and specificity, respectively, with an f1–score equal to 0.964, and 98.44% for precision.

	True Normal	True Abnormal
Predicted Normal	97	11
Predicted Abnormal	3	189
Overall True	100	200
Accuracy	95.54%	
Precision	98.44%	
Sensitivity	94.5%	
Specificity	97%	
F1-Score	0.964	

Table 5.1: Testing Results of Lesions Segmentation Block

In order to make sure that Infnet is the best choice to be deployed in this architecture, different segmentation methods were tested and compared to these result.

Methods	Accuracy	Precision	Sensitivity	Specificity	F1-Score
InfNet	95.54%	98.44%	94.5%	97%	0.964
UNet	91.63%	90.15%	91.16%	92.53%	0.907
UNet++	94.71%	94.35%	92.3%	95.14%	0.933
Attention-UNet	93.42%	94.03%	91.67%	94.48%	0.928
Dense-UNet	94.26%	92.94%	91.75%	93.89%	0.923

Table 5.2: Evaluation Metrics of Different Methods Used in Segmentation

All the above methods in table 5.2 were tested to detect the infected regions (regions of interest). Accordingly, the classification is done and the evaluation metrics were derived.

5.3 ResNet50 Deep Network Block:

The deep network model ResNet50 is trained to classify the nature of pneumonia by distinguishing between COVID and non-COVID pneumonia presented in the images. This AI model depends on error back-propagation between layers. At the same time, weights are updated according to the learning derived to be sub-optimal 0.001 [75]. This algorithm has 23 million parameters that are tuned through several optimization techniques. One of these parameters is the loss function. In our current system, we used the binary cross entropy loss function. Similarly to the segmentation block, the augmented data set is fed to this block excluding normal cases. 700 images are considered to train the algorithm and 100 images for validation. The validation process is based on the value of the loss function, which depends on the difference between the predicted and true value and the probability of the class.

In the testing mode, the network focuses on the probability score of each class in order to make a prediction. Based on the minimum loss value, the class is predicted. Segmented images decreased the model convergence by minimizing the size of region of interest. Moreover, a better knowledge is acquired through the process of positioning of the infection where COVID-19 is known to infect the edges of the lungs bilaterally [77].

The trained deep network showed a 96.5% accuracy. Table 5.3 summarizes the results of the testing phase. The proposed model predicted the presence of COVID-19 in 97 out of 100 and its absence in 96 out of 100, where these values are equal to sensitivity and specificity of the model, respectively. It also showed f1–score of 0.965, and 96.04% for precision.

	True COVID	True Non-COVID
Predicted COVID	97	4
Predicted Non-COVID	3	96
Overall True	100	100
Accuracy	96.5%	
Precision	96.04%	
Sensitivity	97%	
Specificity	96%	
F1-Score	0.965	

Table 5.3: Testing Results of ResNet50 Block

Different techniques of regularisation were addressed in order to improve the accuracy of this module. The spatial dropout was clearly the best regularisation technique to implement reaching the best value mentioned before.

Model	Accuracy
ResNet50	95.2%
ResNet50 + dropout (kp = 0.7)	95.41%
ResNet50 + dropPath (kp = 0.9)	95.5%
ResNet50 + Cutout	95.21%
ResNet50 + Spatial dropout (kp = 0.9)	96.5%

Table 5.4: Accuracy of Different Regularisation Techniques Used ResNet50

In order to make sure that ResNet50 is the best choice to be deployed in this architecture, different classification methods were tested and compared to these result.

Methods	Accuracy	Precision	Sensitivity	Specificity	F1-Score
ResNet50	96.5%	96.04%	97%	96%	0.965
CoroNet	93.5%	93.63%	90%	92.53%	0.9177
DenseNet	96.4%	96%	96%	96%	0.96
CNN	91.21%	90.47%	90.52%	91.58%	0.905
VGG16	95%	95.5%	90%	97%	0.927

Table 5.5: Evaluation Metrics of Different Methods Used in Pneumonia Classification

The methods in table 5.5 were tested to distinguish between COVID infection and other pneumonia diseases. As a result, the classification is done and the evaluation metrics were derived.

5.4 Complete Model

Each block was tested separately to validate its effectiveness. The later block leverages the fact that it is tested with segmented images for convergence purposes. A full system test was performed by passing the dataset as input to evaluate the overall performance. Such a scenario undergoes a more realistic test environment were the ResNet block receives a sample of wrongly classified normal images from the previous block. The accuracy of the full system test was shown to be 95%. Table 5.6 illustrates all classifications and metrics where each classification has its own precision and sensitivity.

	Normal	COVID-19	Other Pneumonia	Precision
Predicted Normal	97	4	1	95.1%
Predicted COVID-19	2	93	4	93.94%
Other Pneumonia	1	3	95	95.96%
Overall True	100	100	100	
Sensitivity	97%	93%	95%	
Overall Accuracy	95%			

Table 5.6: Testing Results of the whole Architecture

5.5 Corona Score

At the output, a Corona score was derived for all positive COVID-19 scans, and the cases were categorized as discussed earlier into four categories. By referring to the ground truth segmentation figures, we verified the correctness of the severity classifications and discovered that the severity of all cases was correctly classified. Below is a list of four COVID-19 classified figures with the corresponding corona score.

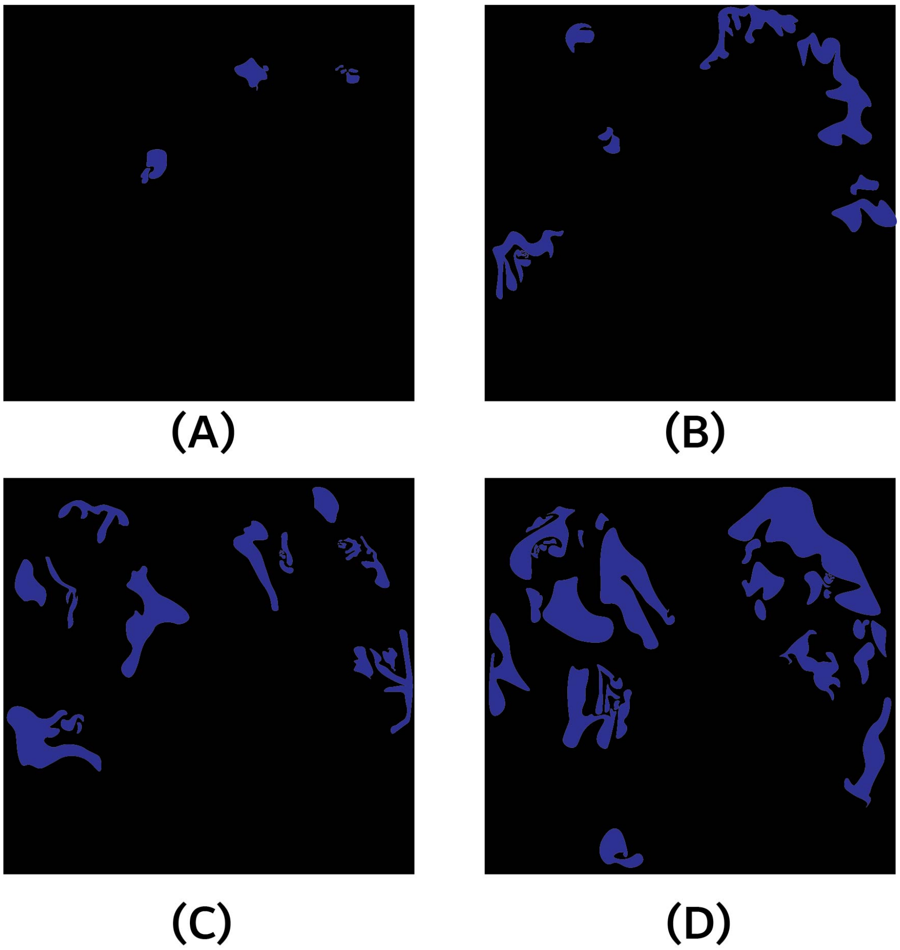

Figure 5.3: Segmented COVID-19 Classified CT Scans with corona score and severity respectively; (A) 0.012 minimal, (B) 0.1352 moderate, (C) 0.3621 intermediate, (D) 0.7356 severe

Chapter 6

Conclusion

In this thesis, we proposed an advanced medical architecture with an AI system that consists of two phases: segmentation and ResNet deep network. The first phase is responsible of recognizing abnormalities in the CT images to separate normal from abnormal patients. The second one is responsible of distinguishing COVID-19 cases from other pneumonia conditions. Both phases showed promising performances. The accuracy of the segmentation was 95.54% and 96.5% for the ResNet50 block. The overall accuracy proved to be 95%. The whole model showed to be reliable and demanded much less computational time, since better convergence was achieved due to the presence of the segmentation block. Our study also introduced an evaluation score for the severity of COVID-19 cases (corona score). Even minimal severity can be detected which could initiate an instantaneous quarantine decision to avoid the spread of the virus. This platform concentrated on the detection COVID-19 in the current study, but it can be deployed and used for medical imaging analysis of other diseases.

Bibliography

[1] H. R. Tizhoosh, S. Kalra, S. Lifshitz and M. Babaie, "Subtractive Perceptrons for Learning Images: A Preliminary Report," 2019 Ninth International Conference on Image Processing Theory, Tools and Applications (IPTA), Istanbul, Turkey, 2019, pp. 1-6, doi: 10.1109/IPTA.2019.8936079.

[2] Shen, Dinggang et al. "Deep Learning in Medical Image Analysis." Annual review of biomedical engineering vol. 19 (2017): 221-248. doi:10.1146/annurev-bioeng-071516-044442

[3] Esteva, Andre, et al. "Dermatologist-level classification of skin cancer with deep neural networks." nature 542.7639 (2017): 115-118.

[4] Wang Y, Hu M, Li Q, Zhang X-P, Zhai G, Yao N. Abnormal respiratory patterns classifier may contribute to large-scale screening of people infected with COVID-19 in an accurate and unobtrusive manner. arXiv2002.05534. 2020.

[5] Gozes O, Frid-Adar M, Greenspan H, Browning PD, Zhang H, Ji W, Bernheim A, Siegel E. Rapid AI Development Cycle for the Coronavirus (COVID-19) Pandemic: Initial Results for Automated Detection & Patient Monitoring using Deep Learning CT Image Analysis. arXiv2003.05037. 2020.

[6] Alimadadi, Ahmad & Aryal, Sachin & Manandhar, Ishan & Munroe, Patricia & Joe, Bina & Cheng, Xi. (2020). Artificial Intelligence and Machine Learning to Fight COVID-19. Physiological Genomics. 52. 10.1152/physiolgenomics.00029.2020.

[7] Karpathy, Andrej. "Cs231n convolutional neural networks for visual recognition." Neural networks 1.1 (2016).

[8] Rawat, Waseem, and Zenghui Wang. "Deep convolutional neural networks for image classification: A comprehensive review." Neural computation 29.9 (2017): 2352-2449.

[9] Shen, Dinggang, Guorong Wu, and Heung-Il Suk. "Deep learning in medical image analysis." Annual review of biomedical engineering 19 (2017): 221-248.

[10] Wu G, Kim M, Wang Q, Munsell BC, Shen D. Scalable high-performance image registration framework by unsupervised deep feature representations learning. IEEE Transactions on Biomedical Engineering. 2016; 63:1505–1516. [PubMed: 26552069]

[11] Rosenblatt F. The perceptron: A probabilistic model for information storage and organization in the brain. Psychological Review. 1958:65–386. [PubMed: 13542702]

[12] Hornik K. Approximation capabilities of multilayer feedforward networks. Neural Networks. 1991; 4:251–257

[13] Bengio Y. Learning deep architectures for ai. Foundations and Trends in Machine Learning. 2009; 2:1–127.

[14] Schwarz G. Estimating the Dimension of a Model. The Annals of Statistics. 1978; 6:461–464

[15] Litjens, Geert, et al. "A survey on deep learning in medical image analysis." Medical image analysis 42 (2017): 60-88.

[16] Ker, Justin, et al. "Deep learning applications in medical image analysis." Ieee Access 6 (2017): 9375-9389.

[17] Yamashita, Rikiya, et al. "Convolutional neural networks: an overview and application in radiology." Insights into imaging 9.4 (2018): 611-629.

[18] El-Baz, Ayman, Georgy Gimel'farb, and Kenji Suzuki. "Machine learning applications in medical image analysis." (2017).

[19] Girshick, Ross, et al. "Rich feature hierarchies for accurate object detection and semantic segmentation." Proceedings of the IEEE conference on computer vision and pattern recognition. 2014.

[20] Gu, Chunhui, et al. "Recognition using regions." 2009 IEEE Conference on computer vision and pattern recognition. IEEE, 2009.

[21] Uijlings, Jasper RR, et al. "Selective search for object recognition." International journal of computer vision 104.2 (2013): 154-171.

[22] Krizhevsky, Alex, Ilya Sutskever, and Geoffrey E. Hinton. "Imagenet classification with deep convolutional neural networks." Advances in neural information processing systems. 2012.

[23] Ren, Shaoqing, et al. "Faster r-cnn: Towards real-time object detection with region proposal networks." Advances in neural information processing systems.

2015.

[24] Ismail, Azlan, Taufik Rahmat, and Sharifah Aliman. "CHEST X-RAY IMAGE CLASSIFICATION USING FASTER R-CNN." MALAYSIAN JOURNAL OF COMPUTING 4.1 (2019): 225-236.

[25] Hochreiter, Sepp, and Jürgen Schmidhuber. "Long short-term memory." Neural computation 9.8 (1997): 1735-1780.

[26] Vinyals, Oriol, et al. "Show and tell: A neural image caption generator." Proceedings of the IEEE conference on computer vision and pattern recognition. 2015.

[27] Shin, Hoo-Chang, et al. "Interleaved text/image deep mining on a large-scale radiology database for automated image interpretation." The Journal of Machine Learning Research 17.1 (2016): 3729-3759.

[28] Goodfellow, Ian, et al. "Generative adversarial nets." Advances in neural information processing systems. 2014.

[29] Mardani, Morteza, et al. "Deep generative adversarial networks for compressed sensing automates MRI." arXiv preprint arXiv:1706.00051 (2017).

[30] Qin, Chen, et al. "Convolutional recurrent neural networks for dynamic MR image reconstruction." IEEE transactions on medical imaging 38.1 (2018): 280-290.

[31] Haleem, Abid, Mohd Javaid, and Raju Vaishya. "Effects of COVID 19 pandemic in daily life." Current Medicine Research and Practice (2020).

[32] Bai, Harrison X., et al. "Performance of radiologists in differentiating COVID-19 from viral pneumonia on chest CT." Radiology (2020): 200823.

[33] Hu, Zixin, et al. "Artificial intelligence forecasting of covid-19 in china." arXiv preprint arXiv:2002.07112 (2020).

[34] Ai, Tao, et al. "Correlation of chest CT and RT-PCR testing in coronavirus disease 2019 (COVID-19) in China: a report of 1014 cases." Radiology (2020): 200642.

[35] Luo, Hui, et al. "Can Chinese medicine be used for prevention of corona virus disease 2019 (COVID-19)? A review of historical classics, research evidence and current prevention programs." Chinese journal of integrative medicine (2020): 1-

8.

[36] Shi, Feng, et al. "Review of artificial intelligence techniques in imaging data acquisition, segmentation and diagnosis for covid-19." IEEE reviews in biomedical engineering (2020).

[37] C. Zheng, X. Deng, Q. Fu, Q. Zhou, J. Feng, H. Ma, et al., "Deep learning-based detection for COVID-19 from chest CT using weak label," MedRxiv, 2020.

[38] Y. Cao, Z. Xu, J. Feng, C. Jin, X. Han, H. Wu, et al., "Longitudinal assessment of COVID-19 using a deep learning–based quantitative CT pipeline: Illustration of two cases," Radiology: Cardiothoracic Imaging, vol. 2, p. e200082, 2020.

[39] L. Huang, R. Han, T. Ai, P. Yu, H. Kang, Q. Tao, et al., "Serial quantitative chest CT assessment of COVID-19: Deep-Learning Approach," Radiology: Cardiothoracic Imaging, vol. 2, p. e200075, 2020.

[40] X. Qi, Z. Jiang, Q. Yu, C. Shao, H. Zhang, H. Yue, et al., "Machine learning-based CT radiomics model for predicting hospital stay in patients with pneumonia associated with SARS-CoV-2 infection: A multicenter study," MedRxiv, 2020.

[41] O. Gozes, M. Frid-Adar, H. Greenspan, P. D. Browning, H. Zhang, W. Ji, et al., "Rapid AI development cycle for the coronavirus (covid-19) pandemic: Initial results for automated detection & patient monitoring using deep learning ct image analysis," arXiv:2003.05037, 2020.

[42] L. Li, L. Qin, Z. Xu, Y. Yin, X. Wang, B. Kong, et al., "Artificial intelligence distinguishes COVID-19 from community acquired pneumonia on chest CT," Radiology, p. 200905, 2020.

[43] J. Chen, L. Wu, J. Zhang, L. Zhang, D. Gong, Y. Zhao, et al., "Deep learning-based model for detecting 2019 novel coronavirus pneumonia on high-resolution computed tomography: a prospective study," MedRxiv, 2020.

[44] S. Jin, B. Wang, H. Xu, C. Luo, L. Wei, W. Zhao, et al., "AI-assisted CT imaging analysis for COVID-19 screening: Building and deploying a medical AI system in four weeks," MedRxiv, 2020.

[45] F. Shan, Y. Gao, J. Wang, W. Shi, N. Shi, M. Han, et al., "Lung infection quantification of COVID-19 in CT images with deep learning," arXiv:2003.04655, 2020.

[46] G. Gaál, B. Maga, and A. Lukács, "Attention U-Net based adversarial architectures for chest X-ray lung segmentation," arXiv:2003.10304, 2020.

[47] L. Tang, X. Zhang, Y. Wang, and X. Zeng, "Severe COVID-19 Pneumonia: Assessing inflammation burden with Volume-rendered Chest CT," Radiology: Cardiothoracic Imaging, vol. 2, p. e200044, 2020.

[48] C. Shen, N. Yu, S. Cai, J. Zhou, J. Sheng, K. Liu, et al., "Quantitative computed tomography analysis for stratifying the severity of Coronavirus Disease 2019," Journal of Pharmaceutical Analysis, 2020.

[49] Ö. Çiçek, A. Abdulkadir, S. S. Lienkamp, T. Brox, and O. Ronneberger, "3D U-Net: learning dense volumetric segmentation from sparse annotation," in International Conference on Medical Image Computing and Computer-Assisted Intervention, 2016, pp. 424-432.

[50] F. Milletari, N. Navab, and S.-A. Ahmadi, "V-net: Fully convolutional neural networks for volumetric medical image segmentation," in 2016 Fourth International Conference on 3D Vision (3DV), 2016, pp. 565-571.

[51] Z. Zhou, M. M. R. Siddiquee, N. Tajbakhsh, and J. Liang, "UNet++: A nested U-Net architecture for medical image segmentation," in Deep Learning in Medical Image Analysis and Multimodal Learning for Clinical Decision Support, ed: Springer, 2018, pp. 3-11.

[52] F. Isensee, J. Petersen, A. Klein, D. Zimmerer, P. F. Jaeger, S. Kohl, et al., "nnU-Net: Self-adapting framework for U-Net-based medical image segmentation," arXiv:1809. 10486, 2018.

[53] O. Oktay, J. Schlemper, L. L. Folgoc, M. Lee, M. Heinrich, K. Misawa, et al., "Attention U-Net: Learning where to look for the pancreas," arXiv:1804.03999, 2018.

[54] O. Ronneberger, P. Fischer, and T. Brox, "U-Net: Convolutional networks for biomedical image segmentation," in International Conference on Medical Image Computing and Computer-Assisted Intervention, 2015, pp. 234-241.

[55] F. Shi, L. Xia, F. Shan, D. Wu, Y. Wei, H. Yuan, et al., "Large-scale screening of COVID-19 from community acquired pneumonia using infection size-aware classification," arXiv:2003.09860, 2020.

[56] Z. Tang, W. Zhao, X. Xie, Z. Zhong, F. Shi, J. Liu, et al., "Severity assessment of coronavirus disease 2019 (COVID-19) using quantitative features from

chest CT images," arXiv:2003.11988, 2020.

[57] F. Pan, T. Ye, P. Sun, S. Gui, B. Liang, L. Li, et al., "Time course of lung changes on chest CT during recovery from 2019 novel coronavirus (COVID-19) pneumonia," Radiology, p. 200370, 2020.

[58] Anwar, S.M., Majid, M., Qayyum, A., Awais, M., Alnowami, M. and Khan, M.K., 2018. Medical image analysis using convolutional neural networks: a review. Journal of medical systems, 42(11), p.226.

[59] Razzak, M.I., Naz, S. and Zaib, A., 2018. Deep learning for medical image processing: Overview, challenges and the future. In Classification in BioApps (pp. 323-350). Springer, Cham.

[60] https://github.com/JordanMicahBennett/SMART-CT-SCAN_BASED-COVID19_VIRUS_DETECTOR/

[61] Johannes Hofmanninger, Forian Prayer, Jeanny Pan, Sebastian Röhrich, Helmut Prosch and Georg Langs. "Automatic lung segmentation in routine imaging is a data diversity problem, not a methodology problem". 1 2020, https://arxiv.org/abs/2001.11767

[62] https://radiopaedia.org/articles/covid-19-3

[63] https://towardsdatascience.com/covid-19-imaging-dataset-chest-xray-ct-for-annotation-collaboration-5f6e076f5f22

[64] https://www.kaggle.com/khoongweihao/covid19-xray-dataset-train-test-sets

[65] Zhao J, Zhang Y, He X, Xie P. COVID-CT-Dataset: A CT Scan Dataset about COVID-19. arXiv preprint arXiv:2003.13865. 2020 Mar 30.

[66] https://github.com/ieee8023/covid-chestxray-dataset

[67] https://github.com/UCSD-AI4H/COVID-CT

[68] https://venturebeat.com/2020/04/01/researchers-release-data-set-of-ct-scans-from-coronavirus-patients/

[69] Liang, T., Liu, Z., Wu, C.C. et al. Evolution of CT findings in patients with mild COVID-19 pneumonia. Eur Radiol 30, 4865–4873 (2020). https://doi.org/10.1007/s00330-020-06823-8

[70] Fan DP, Zhou T, Ji GP, Zhou Y, Chen G, Fu H, Shen J, Shao L. Inf-Net: Automatic COVID-19 Lung Infection Segmentation From CT Images. IEEE Trans Med Imaging. 2020 Aug;39(8):2626-2637. doi: 10.1109/TMI.2020.2996645. PMID: 32730213.

[71] Vatathanavaro, Supawit & Tungjitnob, Suchat & Pasupa, Kitsuchart. (2018). White Blood Cell Classification: A Comparison between VGG-16 and ResNet-50 Models.

[72] He, Kaiming, et al. "Deep residual learning for image recognition." Proceedings of the IEEE conference on computer vision and pattern recognition. 2016.

[73] Knudsen, Lars, and Matthias Ochs. "The micromechanics of lung alveoli: structure and function of surfactant and tissue components." Histochemistry and cell biology 150.6 (2018): 661-676.

[74] Guillo, Enora, et al. "COVID-19 pneumonia: Diagnostic and prognostic role of CT based on a retrospective analysis of 214 consecutive patients from Paris, France." European journal of radiology 131 (2020): 109209.

[75] Smith, Leslie N. "Cyclical learning rates for training neural networks." 2017 IEEE winter conference on applications of computer vision (WACV). IEEE, 2017.

[76] Zhang, Kang, et al. "Clinically applicable AI system for accurate diagnosis, quantitative measurements, and prognosis of COVID-19 pneumonia using computed tomography." Cell 181.6 (2020): 1423-1433.

[77] Ding, Xun, et al. "Chest CT findings of COVID-19 pneumonia by duration of symptoms." European journal of radiology 127 (2020): 109009.

[78] Shorten, Connor, and Taghi M. Khoshgoftaar. "A survey on image data augmentation for deep learning." Journal of Big Data 6.1 (2019): 1-48.