

**PERFORMANCE ANALYSIS OF DETECTION OF COVID 19
USING X-RAY IMAGES**

A Project Report Phase – II

Submitted in partial fulfillment of the requirements for the award of
Bachelor of Engineering Degree in Electronics and Communication Engineering

By

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SATHYABAMA

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BONAFIDE CERTIFICATE

This is to certify that this Final Year Project Report is the bonafide work of **JAYABHARATHI A (39130181)** and **SOWMIYA P (39130438)** who carried out the project entitled “**PERFORMANCE ANALYSIS OF DETECTION OF COVID 19 USING X-RAY IMAGES**” under our supervision from November 2022 to April 2023.

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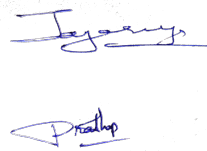
DECLARATION

We, **JAYABHARATHI A (39130181)** and **SOWMIYA P (39130438)**, hereby declare that the Project Report on “**PERFORMANCE ANALYSIS OF DETECTION OF COVID 19 USING X-RAY IMAGES**” done by us under the guidance of **Ms.R.SAKTHI PRABHA, M.E., (Ph.D)** at Sathyabama Institute of Science and technology is submitted in partial fulfilment of the requirements of the award of Bachelor of Engineering Degree in **Electronics and Communication Engineering**.

DATE: 26.04.2023

PLACE: Chennai

SIGNATURE OF THE CANDIDATES



The image shows two handwritten signatures in blue ink. The top signature is 'Jayabharathi A' and the bottom signature is 'Sowmiya P'. The signatures are written on a white background with some faint, illegible text visible in the background.

ACKNOWLEDGEMENT

We are pleased to acknowledge my sincere thanks to Board of Management of **SATHYABAMA** for their kind encouragement in doing this project and for completing it successfully. I am grateful to them.

We convey my thanks to **Dr. N.M. NANDHITHA M.E., Ph.D, Dean, School of Electrical and Electronics, Dr. T. RAVI M.E., Ph.D., Head of the Department of Electronics and Communication Engineering** for providing me necessary support and details at the right time during the progressive reviews.

We would like to express my sincere and deep sense of gratitude to my Project Guide **Ms. R. SAKTHI PRABHA, M.E., (Ph.D)**, Assistant professor, Department of Electronics and Communication Engineering for her valuable guidance, suggestions and constant encouragement paved way for the successful completion of my phase-2 project work.

We convey my thanks to Panel Members and Year Co-Ordinator, Department of Electronics and Communication Engineering for providing me necessary support and details at the right time during the progressive reviews.

We wish to express my thanks to all Teaching and Non-teaching staff members of the Department of Electronics and Communication Engineering who were helpful in many ways for the completion of the project.

ABSTRACT

Coronavirus disease 2019 (COVID-19) is an extremely contagious and quickly spreading Coronavirus infestation. Given the effects of COVID-19 on pulmonary tissues, chest radiographic imaging has become a necessity for screening and monitoring the disease. Recently, numerous studies have proposed Deep Learning approaches based on Convolutional Neural Networks (CNNs, or AIs) for the automatic diagnosis of COVID-19 from chest X-rays (CXR). Although these methods achieved astonishing performance in early detection and diagnosis, they have used limited CXR repositories for evaluation, usually with a few hundred COVID-19 CXR images only. Thus, such data scarcity prevents reliable evaluation with the potential of overfitting. In addition, manual annotation of X-rays (delineation of the lung, or infection regions) is another challenge due to the extensive time and manual labor required from the physicians. Therefore, most of the proposed studies showed no or limited performance in infection localization and severity grading of COVID-19 pneumonia. Moreover, the proposed system was able to discriminate between different COVID family members, which is an extremely challenging task for medical doctors without the aid of clinical data. Sensitivities of 96.94%, 79.68%, and 90.26% were achieved for classifying COVID-19, MERS, and SARS classes, respectively. Furthermore, a good performance was obtained for the second classification scheme with sensitivities of 91.52%, 93.21%, and 91.12 for COVID-19, non-COVID, and normal classes, respectively.

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LIST OF ABBREVIATIONS

ABBREVIATION	DESCRIPTION
AI	Artificial Intelligence
MERS	Middle East Respiratory Syndrome Coronavirus
SARS	Severe Acute Respiratory Syndrome Coronavirus
WHO	World Health Organization
ARDS	Acute Respiratory Distress Syndrome
RT-PCR	Reverse Transcription Polymerase Chain Reaction
CT SCAN	Computed Tomography Scan
CXR	Chest X Ray
MDS	Medical Doctors
ACGAN	Auxiliary Classifier Generative Adversarial Network
VGG	Visual Geometry Group
RNA	Ribonucleic Acid
PA	Posterior to Anterior
AP	Anterior to Posterior
SNR	Signal to Noise Ratio
HMC	Hamad Medical Corporation
ROC	Receiver Operating Characteristics Curve
PBT	Pixel Brightness Transformation
FBN	Feature Pyramid Architecture

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CHAPTER 1

INTRODUCTION

The World has experienced outbreaks of coronavirus infections during different points of time in the last two decades: (i) the severe acute respiratory syndrome (SARS)-CoV outbreak in 2002-2003 from Guangdong, China; (ii) the Middle East Respiratory Syndrome (MERS)-CoV outbreak in 2011 from Jeddah, Saudi Arabia; and (iii) Coronavirus Disease 2019 (COVID-19) or SARS-CoV-2 outbreak from Wuhan, China in December 2019. Even though all three diseases are from the same family of coronavirus [1], the genomic sequence of COVID-19 showed similar but distinct genome composition from its predecessors SARS and MERS [1, 2]. Despite a lower fatality rate of COVID-19, i.e., around 3% [3] when compared to SARS (10%) and MERS (35%), COVID-19 has resulted in many fold deaths (>3M already) than combined deaths of MERS and SARS (around 1700) [4]. The SARS-CoV epidemic has spread to 26 countries worldwide using person-to-person human contact [5]. In 2012, the infectious outbreak caused by MERS-CoV epidemic had spread to more than 1600 patients in 27 countries, resulting in over 600 deaths, 80% of which were reported in Saudi Arabia [6, 7]. The recent outbreak of COVID-19 was and still is an extremely infectious disease that has spread all over the world, forcing the World Health Organization (WHO) on 11th March 2020 to declare it as a pandemic [8].

The business, economic, and social dynamics of the whole world were affected. Governments have imposed flight restrictions, social distancing, and increasing awareness of hygiene. However, COVID-19 is still spreading at a very rapid rate. The common symptoms of coronavirus include fever, cough, shortness of breath, and pneumonia. Severe cases of the CoV diseases include acute respiratory distress syndrome (ARDS) or complete respiratory failure, which requires support from mechanical ventilation and intensive-care unit. People with a compromised immune system, elderly people, or people with other chronic diseases are more likely to develop serious illnesses, including organs failure, particularly kidneys or septic shocks [9].

Intuitively, reliable detection of COVID-19 disease has the utmost importance. However, the diagnosis procedures are not straightforward, as the common symptoms of COVID-19 are generally indistinguishable from the other viral infections [10, 11]. Currently, the primary diagnostic tool to detect COVID-19 is reverse-transcription

polymerase chain reaction (RT-PCR) arrays, where the presence of SARS-CoV-2 RNA is tested on collected respiratory specimens from the suspected case [12, 13]. However, RT-PCR arrays have a high false alarm rate caused by sample contamination, damage to the sample, or virus mutations in the COVID-19 genome [14, 15]. Therefore, several studies suggested using chest computed tomography (CT) imaging as a primary diagnostic tool since it shows higher sensitivity values compared to RT-PCR [16, 17]. In addition, several studies [16-18] suggest performing CT as a secondary test if the suspected patients with shortness of breath or other respiratory symptoms showed negative RT-PCR findings. Despite the superior performance, CT scans are challenged by several limitations. Their sensitivity is limited for early COVID-19 cases, slow in imaging acquisition, and costly. On the other hand, X-ray imaging is a cheaper and faster method, where the body gets exposed to less radiation compared to CT [19]. Chest X-ray imaging is widely used as an assistive diagnostic tool in COVID-19 screening, and it is reported to have high potential prognostic capabilities [20].

Lung segmentation is an important pre-classification step, which narrows the region of interest from the entire CXR down to the region of lungs to increase network reliability. Thus, avoiding irrelevant areas in the decision-making process, such as heart, bones, background, or text. However, the reported segmentation performance is limited for COVID-19 cases. In general, the proposed lung segmentation networks miss highly COVID-19 infected lung regions, such as peripheral infection or fluid accumulation in lower lung lobes. Such poor performance takes place, as so far, there are no lung segmentation masks datasets available for COVID-19 X-ray images.

Coronavirus infection is thought to be highly contagious. To combat the spread of infection, it should be detected early, and patients should be quarantined. The gold standard for detecting coronavirus infection is Reverse Transcription Polymerase Chain Reaction (RT-PCR). It comprises detecting viral RNA from a nasopharyngeal swab. The major limitation of the RT-PCR test is that it has less sensitivity, due to which it is not efficient to detect the rate of positive cases rapidly. This test requires more time to get the results; moreover, the availability of material required is limited in the health sector. To overcome this limitation, biomedical imaging-based methods such as chest X-ray images, radio images, or Computed Tomography (CT) scanners could be used for rapid screening. Detection of coronavirus infection at the initial stage through biomedical imaging can avoid the spread of this contagious disease. Automated COVID-19 classification techniques have been preferred over manual techniques,

which usually are followed by a preprocessing, segmentation, selection, and classification phase. As a consequence, there is a need to introduce an Artificial Intelligence (AI) based decision support system.

On the other hand, the majority of the proposed AI-based COVID-19 recognition approaches tries to distinguish COVID-19 from other viral/bacterial infections or normal X-rays. However, up to the author's knowledge, there is no work in the literature to recognize COVID-19 infection from the other two COVID-family members, MERS and SARS. Due to the overlapping patterns of lung infections, without the aid of clinical data, it is difficult for Medical Doctors (MDs) to distinguish between the images from different CoV family members using CXR only. Therefore, investigating the similarities of COVID family members in the eyes of AI can provide meaningful insights that can help in the medical diagnosis.

The standard COVID-19 test is known as the polymerase chain reaction (PCR) test and is used to detect the existence of infection antibodies. Unfortunately, these tests demand high precision and are time-consuming with a non-negligible possibility of false negatives [4]. It goes without saying that an erroneous conclusion of the absence of the virus can lead to drastic results and is counterintuitive to governments' efforts to restrict the spread of the virus. Moreover, many countries lack the adequate resources to implement COVID-19 tests and testing sites on a large scale. To bypass such issues, radiography chest image analysis is considered an alternative method to the PCR test. Artificial Intelligence (AI) models can be an apt solution.

Coronavirus disease 2019 (COVID-19), which is caused by the SARS-CoV-2 virus, has wreaked havoc on humanity, especially healthcare systems. For example, recently, the wave of infections in India has caused a great number of families to seek care at home due to a lack of intensive care units. Worldwide, millions have succumbed to this pandemic and many more have suffered long- and short-term health problems. The most common symptoms of this viral syndrome are fever, dry cough, fatigue, aches and pains, loss of taste/smell, and breathing problems [1]. Other less common symptoms are also possible (e.g., diarrhea, conjunctivitis) [2]. Infections are officially confirmed using real-time reverse transcription polymerase chain reaction (RT-PCR) [3]. However, chest radiographs using plain chest X-rays (CXRs) and computerized tomography (CT) play an important role confirming the infection and evaluating the extent of damage incurred to the lungs. CXR and CT scans are considered major evidence for clinical diagnosis of COVID-19 [4].

Chest X-ray images are one of the most common clinical diagnosis methods. However, reaching the correct judgement requires specialist knowledge and experience. The strain on medical staff worldwide incurred by the COVID-19 pandemic, in addition to the already inadequate number of radiologists per person worldwide [5], necessitates innovative accessible solutions. Advances in artificial intelligence have enabled the implementation of sophisticated applications that can meet clinical accuracy requirements and handle large volumes of data. Incorporating computer-aided diagnosis tools into the medical hierarchy has the potential to reduce errors, improve workload conditions, increase reliability, and replace by enhance the workflow and reduce diagnostic errors by providing radiologists with references for diagnostics.

The fight against COVID-19 has taken several forms and fronts. Computerized solutions offer contactless alternatives to many aspects of dealing with the pandemic [6]. Some examples include robotic solutions for physical sampling, vital sign monitoring, and disinfection. Moreover, image recognition and AI are being actively used to identify confirmed cases not adhering to quarantine protocols. In this work, we propose an automatic diagnosis artificial intelligence (AI) system that is able to identify COVID-19-related pneumonia from chest X-ray images with high accuracy. One customized convolutional neural networks model and two pre-trained models (i.e., MobileNets [7] and VGG16 [8]) were incorporated. Moreover, CXR images of confirmed COVID-19 subjects were collected from a large local hospital and inspected by board-accredited specialists over a period of 6 months. These images were used to enrich the limited number of existing public datasets and form a larger training/testing group of images in comparison to the related literature. Importantly, the reported results come from testing the models with this completely foreign set of images in addition to evaluating the models using the fused aggregate set. This approach exposed any overfitting of the model to a specific set of CXR images, especially as some datasets contain multiple images per subject.

CHAPTER 2

LITERATURE SURVEY

Tahr. A, Ridhi Arora et al., [2020] With the availability of deep AI, deep learning methods on chest X-ray images are gaining popularity with promising results in several applications. Several deep learning and compact classifier approaches were evaluated over Early-QaTa-COV19 datasets with 1,065 early-stage COVID-19, and 12,544 Normal CXR images. [34]

Vikash, Rahul Kumar et al., [2020] applied the principle of transfer learning to distinguish pneumonia infection from conventional CXR by introducing an ensemble method that combines the output of five deep models that have been trained, obtaining a sensitivity value of >98% for pneumonia class. [37].

Rajpurkar, Nikhil Singh et al., [2018] The CheXNet network, one of the best-performing CXR architectures, was constructed using DenseNet121 on the ChestX-ray14 dataset, the largest available CXR dataset with over 100,000 X-ray pictures for 14 different diseases. The network produced satisfactory results with 98% COVID-19 sensitivity over the benchmark QaTa-COV19 dataset that contains 462 COVID-19 CXR images. [35].

Lakhani, Eki Satria et al., [2017] demonstrated an AUC of 0.99 on a database of 1007 CXR images by classifying CXR images as symptomatic of pulmonary tuberculosis (TB) or healthy. They do this by combining GoogleNet and AlexNet. Therefore, the segmentation performance degrades in unseen scenarios such as severe COVID-19 cases or low-quality images with poor SNR levels. [38].

Ozturk, Suwanto Sanjaya et al., [2020] adapted DarkNet to provide reliable detection for binary classification (COVID-19 vs. normal) and multiclass classification (COVID-19 vs. COVID-19 pneumonia and normal).¹¹⁴ The data was used to test the proposed arrangement of CXR COVID-19. basically. However, the binary and multi-class schemes showed poor performance with 90.65% and 85.35% of the sensitivity level of COVID-19, respectively. [21].

Apostolopoulos, Benny Sukma Negara et al., [2020] consisted of 504 plain X-rays, 714 confirmed cases of viral or bacterial pneumonia, and 224 confirmed cases of COVID-19. High COVID-19 sensitivity (98.7%) and discrimination accuracy (96.7%) were achieved by the MobileNetV2 model. [22].

Wang, Dimas Reynaldi D.S et al., [2020] presented a novel AI architecture (COVID-Net) designed to recognize COVID-19. When tested on a database containing 358 CXRs of COVID-19, the COVID-Net yielded 91%, 94%, and 95% for the COVID19, non-COVID-19 pneumonia, and normal classes, respectively. [23].

Waheed, Rishie Nandhan Babu et al., [2020] presented a synthetic data augmentation technique to address the lack of publicly available X-ray COVI-19 data. An Auxiliary Classifier Generative Adversarial Network (ACGAN) model was presented and applied to 403 COVID-19 and 721 normal CXR images. The accuracy and sensitivity of the ACGAN model of COVID19 with synthetic data augmentation were 95% and 90%, respectively. [24].

Apostolopoulos, Mohamed Medhat Gaber et al., [2020] used a 7-class dataset of 358 COVID-19, 1,342 normal images, and 1,199 radiographs for five common chest abnormalities to train MobileNetV2. The subsequent method yielded results in the following categories: 87.66% 7-class accuracy, 99.18% 2-class accuracy (COVID-19 vs. remaining classes), and 97.36% COVID-19 sensitivity. [25].

Chowdhury, Rohan Pandey et al., [2020] generated a dataset that included 423 COVID-19, 1485 viral pneumonia, and 1579 normal radiographs. using a range of deep AI. Both 2-class (COVID-19 vs. Normal) and 3-class strategies were used to train these AIs. The best classifier performance was shown by DenseNet201, which had a sensitivity to COVID-19 of 99.7% for 2-class and 97.9% for 3-class schemes. However, most studies that have been completed have used only small amounts of data; for example, the largest dataset contains only a small number of CXR samples. As a result, it is difficult to generalize their findings to the real world. [26].

Rajaraman, Rajeev Kumar et al., [2020] proposed a two-stage recognition methodology using COVID-19. The lung regions were segmented in the first stage using the U-Net segmentation network. The second step was to iteratively prune a number of pre-trained deep models (VGG16, VGG19, InceptionV3, etc.) to reduce the complexity of the network while maintaining acceptable classification performance. The collected findings demonstrated that the performance is significantly enhanced by the weighted average of the top three trimmed models, yielding 99% COVID-19 sensitivity and 99.72% AUC. [29].

Oh, Park, Mohammed M. Abdelsamea et al., [2020] proposed a patch-based deep artificial intelligence architecture for recognizing COVID19. Lung regions were first extracted using a Fully Connected (FC) network called DenseNet103, and then

patch-based categorization was performed using ResNet50. The final choice was then made using the majority approach. The overall classification accuracy and sensitivity for the proposed approach were 85.9% and 88.9%, respectively. [28].

Worth, Asmaa Abbas et al., [2020] In the generated database, many encoder-decoder AIs were trained and evaluated, and the best system achieved an infection localization score of 85.81%. [44]. Montgomery [41] and Shenzhen [42] CXR lung mask dataset, which combinedly creates 704 X-ray images for normal and tuberculosis (TB) cases. Hence, lung areas can be partially or incompletely segmented for severe infections such as bilateral consolidation or fluid accumulation at lower-lung lobes. Consequently, the classification performance degrades. Therefore, creating a large benchmark CXR dataset with ground-truth lung segmentation masks is of high importance, and will help the research community to provide more reliable detection system for COVID-19 and other thorax pathologies.

Yamac, Hou Jin and Si Jinhai et al., [2020] developed a compact architecture that uses the cutting-edge CheXNet pneumonia detection network as a feature extractor to categorize the target CXR as COVID-19, bacterial pneumonia, viral pneumonia, or normal using the suggested Convolution Support Estimation Network (CSEN) classifier. [39]. Satisfactory results were obtained with >97% and 95% COVID-19 sensitivity for the best deep learning (CheXNet) and compact (CSEN) approaches, respectively. Lung Segmentation as a First Stage in the COVID-19 Recognition System Moreover, several studies [27-29] considered lung segmentation as the first stage in their recognition system. This ensures reliable decision-making in the classification phase and guards the network against irrelevant features from non-lung areas.

M. Ahishali, Yi Wenhui et al., [2020] compared to [39], developed a robust early warning system to distinguish early-stage COVID-19 cases from normal cases. Various deep learning and mobile classification methods were studied on the initial QaTa-COV19 database consisting of early-stage COVID-19 images and 12,544 normal CXR images. Satisfactory results were achieved for the most efficient deep learning (CheXNet) and mobile learning (CSEN) approaches with sensitivity >97% and 95% of COVID-19 respectively [40].

Degerli, Sohaib Asif et al., [2019] proposed a novel approach for COVID-19 infection map generation by compiling the largest COVID-19 dataset consisting of 2,951 CX images with annotated ground-truth infection segmentation masks. Several

encode-decoder (E-D) AIs were trained and evaluated on the generated dataset, where the best performing network achieved an 85.81% f1-score for infection localization. Classification of Coronavirus Family Members: COVID-19, MERS and SARS On the other hand, worldwide researchers have presented numerous clinical and experimental information regarding the SARS and MERS, which could be useful in the fight against COVID-19 [54]. There have been studies in the literature investigating the similarities between the genome structure of SARS, MERS, and COVID-19 [55]. However, up to the author's knowledge, COVID-19 recognition from the other two family members, MERS and SARs, using CXR has never been investigated.[44].

Tianxing Ji , Zhenwei Liu , GuoQiang Wang et. al., [2020] presented a work on Detection of COVID-19. The rapid spread of severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) has led to the coronavirus disease 2019 (COVID-19) worldwide pandemic. Finally, provide a review of the biosensors which hold promising potential for point-of-care detection of COVID-19 patients. This review thereby provides general guidelines for both scientists in the biosensing research community and for those in the biosensor industry to develop a highly sensitive and accurate point-of-care COVID-19 detection system, which would be of enormous benefit for controlling the current COVID-19 pandemic.[19].

Lizhou Xu , Danyang Li, Yanbin Li et. al., [2021] presented a work on Facile biosensors for rapid detection of COVID-19. Currently the world is being challenged by a public health emergency caused by the coronavirus pandemic (COVID-19). This review summaries recent advances in strategies reported by international researchers and engineers concerning how to tackle COVID-19 via rapid testing, mainly through nucleic acid- and antibody- testing. The roles of biosensors as powerful analytical tools are emphasized for the detection of viral RNAs, surface antigens, whole viral particles, antibodies and other potential biomarkers in human specimen. It helps researchers working on novel sensor technologies to tailor their technologies in a way to address the challenge for effective detection of COVID-19.[16].

Degerli, Candemir. S et al., [44] proposed a novel approach for COVID-19 infection map generation by compiling the largest COVID-19 dataset consisting of 2,951 CX images with annotated ground-truth infection segmentation masks. Several encode-decoder (E-D) AIs were trained and evaluated on the generated dataset,

where the best performing network achieved an 85.81% f1-score for infection localization. However, their proposed approach is limited to infection localization. Therefore, there is room to revisit the problem with both lung and infection segmentation models to localize and quantify infection regions by computing the overall percentage of infected lungs. This can help medical doctors to better assess the severity and progress of COVID-19 pneumonia.

Anuraag Shankar, Yash Sonar and Dr. Kavita A et. al., [2020] presented a work on Detection of COVID-19 using Chest X-Ray Scans. COVID-19 has proven to be the unseen and unforeseen pandemic nobody was prepared to face. Healthcare professionals and radiologists have been under a lot of pressure ever since the outbreak to treat and develop faster ways to detect the disease. The proposed research involves the classification of chest X-ray scans to identify whether a patient has been infected with COVID-19 or not using the concept of Transfer Learning. By comparing the two methods of classification, it can be concluded that the two-way classification model performs better and shows metrics which are unmatched by any other model. Of all the models tested, the VGG-19 yielded the best results. This model can act as a crucial and fast method to detect COVID-19 in patients thus resulting in quicker and more appropriate treatment.[29].

2.1 INFERENCES FROM LITERATURE SURVEY

The tremendous development in Machine Learning and Deep Learning techniques in recent years led to state-of-the-art performance in several Computer Vision tasks, such as image classification, object detection, and image segmentation. This breakthrough in performance led to increased utilization of AI-based solutions in various fields, including biomedical health problems and complications. Specifically, AI has been proven extremely beneficial in several biomedical imaging applications, such as skin lesion classification [30], brain tumor detection [31], and breast cancer detection [32], and lung pathology screening [33, 34]. Deep Learning techniques on chest X-ray images are gaining popularity with the availability of deep AIs, showing promising results in various applications.

2.2 PROBLEM DEFINITION IN EXISTING SYSTEM

Readily available radiological imaging techniques such as chest CT and X-ray are crucial tools for COVID-19 detection. The majority of early COVID-19 cases show

similar features on radiographic images, including bilateral, multi-focal, ground-glass opacities with posterior or peripheral distribution, mainly in the lower lung lobes, while it develops to pulmonary consolidation in the late stage. Even though chest radiographs can help in the early screening of the suspected case, the images of several viral pneumonia are similar. They show a high overlap with other inflammatory lung diseases. Therefore, it is difficult for medical doctors to distinguish COVID-19 infection from other viral pneumonia. Hence, this symptom similarity can lead to wrong diagnosis in the current situation. Such an incorrect result can lead to non-COVID-19 viral pneumonia being falsely diagnosed as a highly suspicious COVID-19 case, thus delaying the treatment with consequent effort, costs, and risk of exposure to positive COVID-19 patients.

Along with COVID-19 detection, infection localization is another crucial point that helps in evaluating the status of the patient and in the treatment process [43]. Therefore, several studies utilized class activation maps which are generated from Deep Learning models trained for COVID-19 classification tasks to localize infected lung regions. Even though those localized regions are potential biomarkers for COVID-19, more precise and reliable localization can be provided by ground-truth infection mask from expert radiologists. Classification of Coronavirus Family Members: COVID-19, MERS and SARS On the other hand, worldwide researchers have presented numerous clinical and experimental information regarding the SARS and MERS, which could be useful in the fight against COVID-19 [54].

There have been studies in the literature investigating the similarities between the genome structure of SARS, MERS, and COVID-19 [55]. However, up to the author's knowledge, COVID-19 recognition from the other two family members, MERS and SARs, using CXR has never been investigated. Owing to the overlapping pattern of lung infections, it is very challenging for MDs to diagnose the COVID type without the aid of clinical data, specifically RT-PCR. Although, SARS epidemic was contained in July 2003, and no case has been reported since May 2004 [45]. However, MERS still exists, where the most recent laboratory-confirmed cases were reported by Riyadh in March 2020 [46]. Therefore, investigating the similarities and uniqueness of COVID family members in the eyes of AI can bridge the knowledge gaps and provide MDs with meaningful insights that help in the diagnosis process.

CHAPTER 3

AIM AND SCOPE OF THE PROJECT

3.1 OBJECTIVES

In order to overcome the mentioned limitations and challenges, the key objectives of this work are: Review the different proposed approaches in the literature for automatic COVID-19 recognition from CXR and investigate their gaps and limitations.

- 1) Compile the largest COVID-19 benchmark dataset, referred to as COVID-QU, which consists of 11,956 COVID-19, 11,263 non-COVID, 10,701 normal, 134 SARS, and 144 MERS chest X-rays images. This will help to investigate deepAI on a comparatively larger dataset, which can provide a more reliable solution with better generalization capabilities.
- 2) Create ground-truth lung segmentation masks for the entire COVID-QU dataset using an elegant human-machine collaborative approach which can significantly reduce human labor and thus speed up the annotation process.
- 3) Propose a robust system to segment the lung, detect, localize, and quantify COVID-19 infections from chest X-ray images. This is a crucial task for accurate diagnosis and follow-up of COVID-19 patients.
- 4) Train and evaluate the proposed recognition system for lung segmentation, infection segmentation, and two classification schemes:
- 5) COVID-19 recognition from non-COVID-19 infections, and normal cases.
- 6) COVID-19 recognition from the predecessor COVID family members, SARS, and MERS.

3.2 ARTIFICIAL INTELLIGENCE

Artificial intelligence (AI) refers to the simulation of human intelligence in machines that are programmed to think like humans and mimic their actions. The term may also be applied to any machine that exhibits traits associated with a human mind such as learning and problem-solving. Image processing with artificial intelligence can power face recognition and authentication functionality for ensuring security in

public places, detecting and recognizing objects and patterns in images and videos, and so on.

Artificial intelligence has become an emergent field by using its various techniques, such as deep neural networks, to solve a variety of problems, which are image classification, object detection, drug interaction, medical imaging, and speech recognition. More precisely, convolutional neural networks (CNN) showed promising results in the field of image processing. Enormous research studies presented the robustness of these techniques for image segmentation. Explainable artificial intelligence (XAI) is basically the integration of multiple AI models into an ergonomic GUI to assist radiologists in decision-making in order to improve understanding of COVID-19. The recent studies faced several challenges for the accurate classification of COVID-19 with normal chest X-ray images.

AI is important for its potential to change how we live, work and play. It has been effectively used in business to automate tasks done by humans, including customer service work, lead generation, fraud detection and quality control. In several areas, AI can perform tasks much better than humans. Particularly when it comes to repetitive, detail-oriented tasks, such as analyzing large numbers of legal documents to ensure relevant fields are filled in properly, AI tools often complete jobs quickly and with relatively few errors. Because of the massive data sets it can process, AI can also give enterprises insights into their operations they might not have been aware of. The rapidly expanding population of generative AI tools will be important in fields ranging from education and marketing to product design.

The first challenge is multiclass classification such as COVID-19, viral pneumonia, lung opacity, and normal images. Visually, the images are observed that the similarity among each image is very high, and it is a chance of misleading the correct classification accuracy. The second challenge is redundant and irrelevant feature extraction that not only degrades the classification accuracy but also increase the computational time. AI is important because it can give enterprises insights into their operations that they may not have been aware of previously and because, in some cases, AI can perform tasks better than humans. Particularly when it comes to repetitive, detail-oriented tasks like analyzing large numbers of legal documents to ensure relevant fields are filled in properly, AI tools often complete jobs quickly and with relatively few errors.

3.3 TYPES OF ARTIFICIAL INTELLIGENCE

AI can be categorized into four types, beginning with the task-specific intelligent systems in wide use today and progressing to sentient systems, which do not yet exist. The categories are as follows:

3.3.1 *Reactive machines*

These AI systems have no memory and are task specific. An example is Deep Blue, the IBM chess program that beat Garry Kasparov in the 1990s. Deep Blue can identify pieces on the chessboard and make predictions, but because it has no memory, it cannot use past experiences to inform future ones.

3.3.2 *Limited memory*

These AI systems have memory, so they can use past experiences to inform future decisions. Some of the decision-making functions in self-driving cars are designed this way.

3.3.3 *Theory of mind*

Theory of mind is a psychology term. When applied to AI, it means that the system would have the social intelligence to understand emotions. This type of AI will be able to infer human intentions and predict behavior, a necessary skill for AI systems to become integral members of human teams.

3.3.4 *Self-awareness*

In this category, AI systems have a sense of self, which gives them consciousness. Machines with self-awareness understand their own current state. This type of AI does not yet exist.

3.4 X-RAY IMAGE PROCESSING

X-rays are high-energy electromagnetic waves with short wavelengths and high frequencies. They develop from the electrons of an atom and become photons when they are energized from a higher energy level to a lower level, releasing energy in the process. This happens when fast electrons decelerate suddenly, and their large amount of kinetic energy transforms them into photons of electromagnetic radiation. The electromagnetic spectrum is the entire range of electromagnetic waves, including light. It is composed of different types of waves with different wavelengths and energies.

X-rays are important medical tool for doctors. X-rays are ionized forms of radiation which capture the image using rays. Doctors found that they could not get a detailed view of patient's body. Thus, different technology like MRI or CT scans are used which are more expensive for viewing the detailed information. X-rays images do not give any medical data for organs or tissues, only an image of bones. MRI and CT scans can give more bone details than traditional X-rays. CT scan has ability of creating a 3-D image of bone structures while an X-ray creates a 2-D image bone structure. But MRI and CT scans are more costly which not affordable to the patients. So that digital x-ray technology is solution for the X-ray which shows 3D digital image structure. Digital x-ray is also called as digital radiography.

The X-ray is capture for many reasons to diagnosis the disease. Therefore, the accurate diagnosis of bone fracture is important aspects to the doctors in medical field. So digital x-ray images help to provide appropriate treatment. Normally X-ray images are used for bone fracture analysis. But sometime x-ray does not provide or diagnosis the disease because of noise in the image or blurring images. The aim of this paper is to develop a digital x-ray based on image processing system which gives a quick and accurate classification of disease based on the information gained from the digital x-ray images which are saved in computer image format like jpeg, png etc. Digital X-ray images are providing the accurate result. This image is recorded digitally and characterized by large size, wide dynamic range and high resolution. In this research paper, x-ray image can be subjected to various degrees of noise reduction, compression and quality has been measurable provides accurate result in medical field.

CHAPTER 4

MATERIALS AND METHODOLOGY

In order to overcome the mentioned limitations and drawbacks, first, a large benchmark dataset so-called COVID-QU, is compiled with over 33,000 CXR images from five different classes: SARS, MERS, COVID-19, non-COVID-19 infections, and normal. Besides, a novel human-machine collaborative approach is proposed to generate lung saliency maps for the entire COVID-QU dataset. A systematic approach is proposed to segment the lung, detect, localize, and quantify COVID-19 infections from chest X-ray images. Furthermore, two classification schemes are tackled: COVID-19 recognition from non-COVID-19 and normal CXR, and COVID-19 discrimination from the other COVID family members MERS and SARs.

4.1 THE BENCHMARK COVID-19 DATASET

Sharing COVID-19 data will help researchers, doctors, and engineers around the world to come up with innovative solutions for the early detection of COVID-19. In this section, first show the data compilation process; then, propose a novel approach for ground-truth lung saliency map generation.

4.1.1 Data Compilation

Due to the emerging nature of the pandemic, initially, little efforts have been made by highly infected countries on sharing clinical and radiography data publicly. Therefore, a group of researchers from Qatar University (QU) and Tampere University (TU), including the author of this thesis, have created two datasets, the so-called COVID-Family [47] and QaTa-Cov19 datasets [39]. The COVID-Family dataset consists of 462 COVID-19, 144 MERS, and 134 X-ray images. While QaTa-Cov19 dataset contains the same 462 COVID-19 samples included in the COVID-Family dataset, along with 2,760 bacterial pneumonia, 1,485 viral pneumonia, and 1,579 normal X-rays. The QaTa-Cov19 dataset was extended in a recent study [44] to include 2,951 COVID-19 CXR along with their ground-truth infection masks. Gradually, more X-rays become available publicly, and QU group managed to collect additional X-rays images. Hence, QU group compiled the largest COVID-19 CXR dataset with over 33 thousand samples, called COVID-QU. The dataset includes X-rays from five different classes:

- 1) 134 SARS X-rays
- 2) 144 MERS X-rays
- 3) 11,956 COVID-19 X-rays
- 4) 11,263 non-COVID-19 infections (viral or bacterial pneumonia) X-rays
- 5) 10,701 normal X-rays

In this proposed work, only Posterior-To-Anterior (PA) or Anterior-To-Posterior (AP) chest X-rays were considered as this view of radiography is widely used by the radiologist. This dataset was created by utilizing numerous publicly available, scattered, and different format datasets and repositories. Authors ensured the quality of the provided information; duplicates, extremely low-quality, and over-exposed images were identified and removed in the preprocessing stage. Consequently, the dataset encapsulates images of high intraclass dissimilarity with varying resolution, quality, and SNR levels. Details of different data sources are listed below: COVID-19 CXR dataset: The dataset contains 11,956 positive COVID-19 CXR images: 10,814 images are collected from BIMCV-COVID19+ dataset [48], 183 images from a Germany medical school [49], 559 X-ray image from SIRM, GitHub, Kaggle and Tweeter [50-53], and 400 X-ray images from another COVID-19 chest X-ray repository [54].

RSNA CXR dataset (Lung opacity and normal CXR): RSNA pneumonia detection challenge dataset [55] consists of 26,684 chest X-ray images, where 8,851 images are normal, 11,821 are abnormal, and 6,012 are lung opacity images. All images are in DICOM format. This work consists of 8,851 normal and 6,012 lung opacity X-ray, where lung opacity images are used as non-COVID-19 class. Chest-Xray-Pneumonia dataset: This is a Kaggle dataset [56] that encapsulates 1,300 viral pneumonia, 1,700 bacterial pneumonia, and 1,000 normal X-rays. In this study, the viral and bacterial pneumonia are considered as non-COVID-19 class.

PadChest dataset: PadChest [57] dataset comprises more than 160,000 X-ray images from 67,000 patients that were collected and reported by radiologists at Hospital San Juan (Spain) from 2009 to 2017. It contains 4,000 normal, and 4,000 pneumonia/infiltrate cases as non-COVID-19 class.

SARS and MERS CXR dataset: SARS and MERS X-ray images are even scarcer compared to COVID-19. Therefore, collected and indexed X-ray images from

different publicly available online resources and articles. SARS and MERS radiographic images were collected from 55 different articles (25-MARS, 30-SARS). A total of 260 images was collected from articles, and 18 images were from Joseph Paul Cohens' GitHub database [58]. Out of these, 70 MERS X-ray images were collected from [59], while 16 SARS X-ray images were collected from [60].

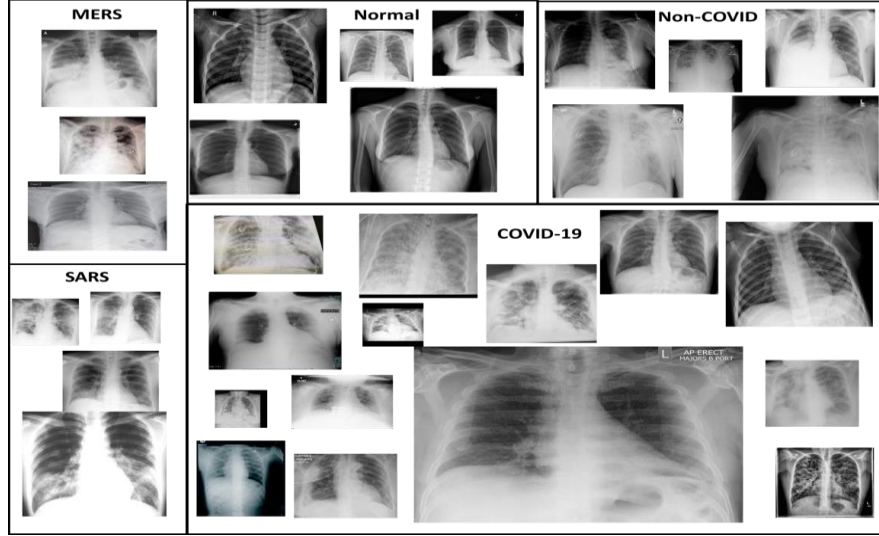


Fig 4.1: Chest X-Ray Images

The above figure 4.1 shows that the Sample X-ray images from the COVID-QU Dataset from five different classes: COVID-19, MERS, SARS, non-COVID-19 infections, and normal. The dataset encapsulates images from several countries around the world with different resolution, quality, and SNR levels. Montgomery and Shenzhen CXR lung mask dataset: This dataset consists of 704 CXR images with their corresponding lung segmentation masks. However, it was not included in the COVID-QU dataset. Still, it was used as initial ground truth masks to train the segmentation model in the first stage of the proposed human-machine collaborative approach.

The dataset was acquired by Shenzhen Hospital in China [42], and the tuberculosis control program of the Department of Health and Human Services of Montgomery County, MD, USA [41]. Montgomery dataset consists of 80 normal and 58 tuberculosis CXR with lung segmentation masks. While Shenzhen dataset comprises 326 normal and 336 tuberculosis CXR, where 566 out of 662 CXR are provided with their corresponding masks. QaTa-Cov19 CXR infection mask dataset [44]: This dataset was created by a research group from Qatar University and Tampere University. It consists of nearly 120K CXR images, including 2,913 COVID-19 images

with their corresponding ground-truth infection masks. In this study, the ground-truth infection masks were used to train and evaluate the infection segmentation models.

4.2 PROPOSED SYSTEM

The process of producing ground truth segmentation masks is an exhaustive task, where human experts need to delineate pixel-wise masks with high accuracy levels. Besides, with the emergent of the current pandemic, it is even more challenging to assign such a task to medical experts, as they are busy fighting the disease. In order to overcome this issue, a collaborative human-machine approach is proposed to produce ground-truth lung segmentation masks for CXR images accurately. The majority of the manual annotation process was assigned to biomedical engineering researcher assistants (RAs) from QU team to reduce the load on medical collaborators from Hamad Medical Corporation (HMC). Unlike infection segmentation, which needs precise delineation by medical experts, lung segmentation can be done by non-medical people with proper supervision by MDs. Therefore, before starting the annotation process, all RAs attended several training sessions conducted by MDs to grasp a general understanding of Chest X-ray imaging and get exposed to a variety of cases with mild, moderate, or severe infections. High attention was given to different types of abnormalities, such as lung opacity consolidation and fluid accumulation, which can make border detection more difficult.

The intended approach was performed in four main stages.

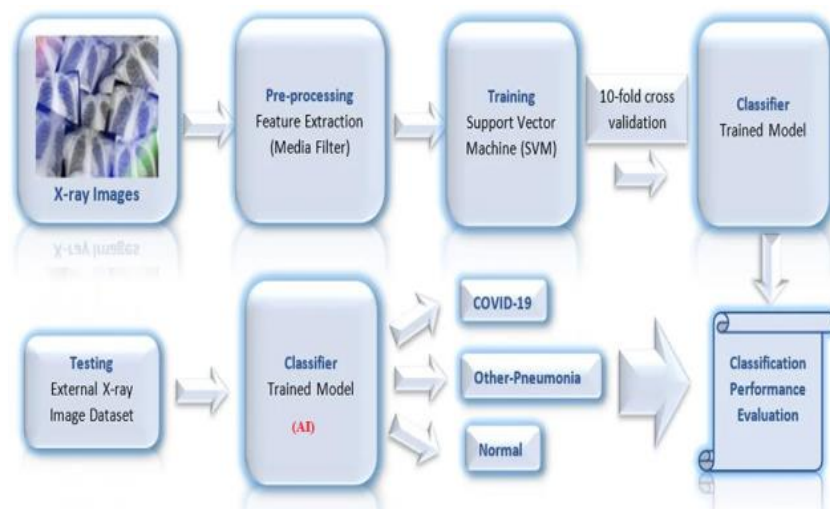


Fig 4.2: Block Diagram for Proposed System

The above proposed system in Figure 4.2 above can compare the features extracted from user input X-ray images with a database that has been prepared with

various features. Finally, the proposed approach compares the accuracy of deep learning models. The proposed approach, used a dataset of chest x-rays that include both positive and negative labels. The proposed system can accept human input. The proposed system can perform AI operations by separating training and testing data.

4.3 CATEGORIZATION PHASES

4.3.1 Initial Training

In the first stage, three variants of U-Net [61] segmentation model, are trained on 704 ground-truth CXR lung masks from Montgomery and Shenzhen dataset mentioned previously. The ground-truth CXR lung masks are referred to as CXR lung mask repository, and it is enlarged throughout the mask creation process. Next, the best performing network in terms of DSC is selected as the main network for evaluation, which is referred to as CXR-Segmentation network.

4.3.2 Collaborative Evaluation

In the second stage, an iterative training is utilized to create lung masks for a subset of 3,000 CXR samples (10% of the full dataset) that well present the diversity of COVID-QU dataset. Firstly, A subset of 500 samples is selected and inferred using CXR-Segmentation model. The predicated lung masks are then evaluated by researchers from QU group: as accept, reject, unsure, or exclude. Accepted masks that cover the lung areas are directly added to CXR-lung-mask-repository. Rejected mask are incomplete ones which miss parts of the lung areas or include extra areas. Those rejected masks are first modified by RAs then added to CXR-lung-mask-repository. Unsure masks are severe cases with highly infected areas; those are usually consolidations or fluid accumulation at lower lung lobes with a whitish color, which makes them indistinguishable from neighboring organs. The doubtful areas are first assessed by MDs; then, RAs adjust the masks based on their recommendations. While the generated masks and corresponding X-rays are excluded only if the quality is extremely bad, where the right lung is blurred and corrupted by extra lighting. Finally, the segmentation network is re-trained on the extended mask dataset. This process is repeated until ground-truth masks for all 3,000 CXR samples are generated.

4.3.3 Collaborative Selection

In the third stage, six deep segmentation networks, inspired by U-Net [61], U-Net++ [62], and FPN [63] architectures, are trained on the 3,000 collaborative masks

generated in evaluation. The trained networks are used to predict segmentation masks for the rest of COVID-QU dataset, which is around 30,900 unannotated samples (90% of the full dataset). Among the six predictions, RAs select the best one as a ground-truth or deny if none of the masks segments the lung properly. The latter case was a minority case that included less than 5% of unannotated data. The most selected network was considered as the main network and re-trained with the extended masks repository. The denied cases were then inferred by the main segmentation network and evaluated manually following the steps in evaluation. As a result, the ground-truth masks for 33,920 CXR images are gathered to construct the benchmark COVID-QU lung masks dataset. The proposed collaborative approach saves valuable human labor time. Also, it enhances the quality and reliability of the generated masks and reduces subjectivity.

4.3.4 Final Verification

In the final stage, a final verification is performed by MDs on 6,788 CXR samples (20% of the full dataset) that well presents the diversity of COVID-QU dataset. The samples are selected from COVID, non-COVID-19 and normal classes, with different resolution, quality, and SNR levels. Even though checking the entire dataset will result in higher quality masks. However, it is not a feasible solution with the large number of images that can have as it will add an extra burden for MDs. In this study, the verified subset (20%) was considered as a test set for all the experiments, while the remaining data (80%) was considered as train and validation sets.

4.4 COVID-19 RECOGNITION SYSTEM

First, a binary lung mask is generated from the input CXR image using the 1st encoder-decoder(E-D) AI. In parallel, the input CXR is fed to the 2nd E-D AI to generate COVID-19 infection masks. Next, generated lung and infection masks are superimposed with the CXR image to localize and quantify COVID-19 infected lung regions. The generated infection mask is then used to detect COVID-19 positive cases from COVID-19 negative cases, where the CXR is classified positive if at least one pixel of lung area is predicted as COVID-19 infection. Furthermore, a 3rd AI is trained and evaluated on two classification schemes:

1. COVID-19 recognition from non-COVID-19 infections and normal cases
2. COVID-19 recognition from the other coronaviruses SARS and MERS.

Additionally, Score-CAM visualization method is deployed to provide an interpretable

result and investigate the reasoning behind the specific decisions of the deep AI classifier.

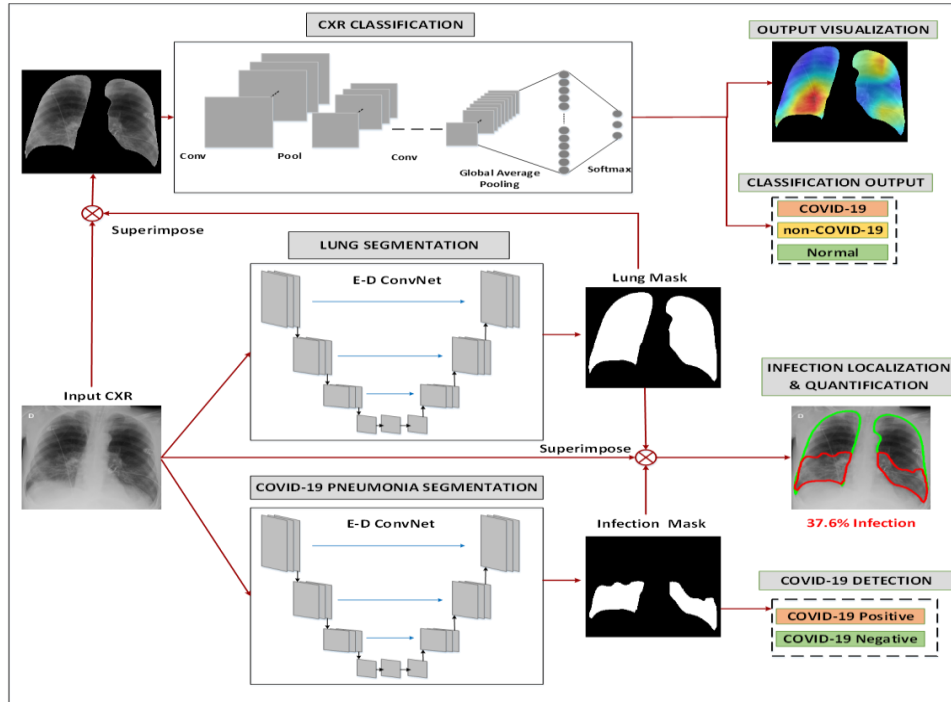


Fig 4.3: Schematic representation of the proposed COVID-19 recognition system

The above Fig 4.3 shows the classification network will be removed in future studies, once ground-truth infections masks are created for non-COVID-19 cases using the proposed collaborative human-machine approach. Therefore, the infection segmentation model can be used to generate a 3-channel infection mask, where the channels represent: background, non- COVID-19 lesion, and COVID-19 lesions. Thus, the 3-channel infection masks can be used to detect COVID-19 from non-COVID-19, or normal cases.

4.4.1 Channel Scheme

The 3-channel scheme was used as the input to the deep networks, where original, CLAHE, and complement images were used altogether. The pixel values for each image are concatenated into a single matrix in order to create a new image. This 3-channel approach is expected to enhance the network performance compared to grayscale X-ray images as the utilized deep AI classifiers were initially pre-trained on RGB images from the ImageNet dataset.

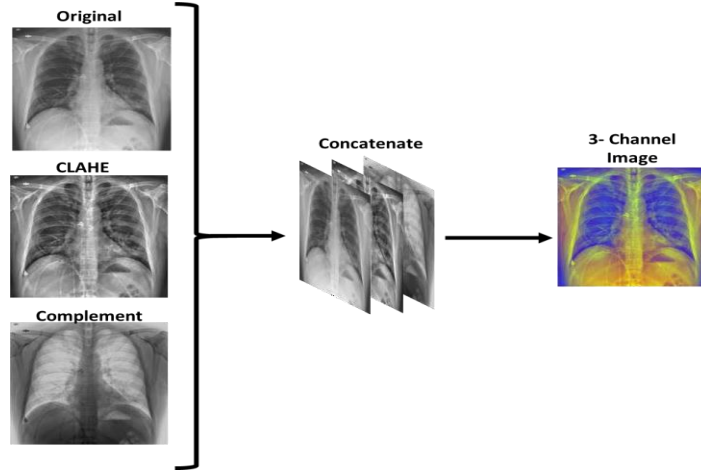


Fig 4.4: Illustration of 3-channel scheme

The above fig 4.4 shows the Lung parenchyma and COVID-19 infections segmentation were performed on CXR images using three state-of-the-art deep E-D AIs: U-Net [61], U-Net++ [62], and FPN [63] with different backbone (encoder) models using the variants of ResNet, DenseNet, and InceptionV4 networks. Five variants of the backbone models were considered starting from shallow to deep structures: ResNet18, ResNet50, DenseNet121, DenseNet161, and InceptionV4.

The deployed encoder-decoder structures provide a firm segmentation model that captures the context in the contracting path and empowers precise localization by the expanding path. U-Net architecture has a classical decoder part that is symmetric to the encoder part, where max-pooling operations are replaced with up-sampling operations. In addition, high-resolution features from the encoder path are merged with the up-sampled output from the corresponding decoder path through skip connection. Moreover, U-Net++ is a recent implementation that has further developed the decoder structure.

The encoder and decoder blocks are connected through a series of nested dense convolutional blocks. This ensures a firm bridge between the encoder and decoder parts of the network, where information can be transferred to the final layers more intensively compared to conventional U-Net. Both U-Net and U-Net++ architectures utilize 1×1 convolution to map the output from the last decoding block to two-channel feature maps, where a pixel-wise SoftMax activation function is applied to map each pixel into a binary class of background or lung for Lung segmentation task, and background or lesion for infection segmentation task. In contrast, FPN employs the

encoder-decoder as a pyramidal hierarchy by generating prediction masks at each spatial level of the decoder path. All predicted feature maps are unsampled to the same size, concatenated, convolved with 3x3 convolutional filter, and then SoftMax activation is applied to generate the final prediction mask. The main objective is to evaluate many approaches proposed the detection of COVID-19. An overview of CXR and its shortcomings and limitations to overcome the indicated limitations and obstacles. This will allow researchers to test deep AI on larger databases, offering more robust solutions with stronger generalization capabilities. For the segmentation network cost function, loss of entropy (CE) is used:

$$CE = -1 \sum_K \sum_k y_{k,c} \log(p(x_k)) \quad (1)$$

where x_k denotes the k th pixel in the predicted segmentation mask, $p(x_k)$ denotes its SoftMax probability, $y_{k,c}$ is a binary random variable getting 1 if $y_k = c$, otherwise 0, and c denotes the class category, i.e., $c \in \{background, lung\}$ for the lung segmentation task, and $c \in \{background, lesion\}$ for the infection segmentation. Two classification methods, a recognition system that proposes lung segmentation and infection segmentation, have recognized SARS, MERS, and other members of the COVID family.

4.4.2 Post-processing for Segmentation Masks

The predicted segmentation masks, $\hat{Y}$, by the segmentation models are defined as $\hat{Y}_{h,w} \in [0,1]$, where h and w represent the size of the image. In the post-processing step, binary segmentation masks are first generated by thresholding with a fixed value of 0.5. The predicted pixels are classified as lung if $\hat{y} > 0.5$ for the lung segmentation task, while classified as COVID-19 infection if $\hat{y} > 0.5$ for the infection segmentation task. The binary lung masks are further processed by hole filling and removal of small regions, <5% of the total positive predicted pixels. As a result, it increases the true-positives while minimizing the false-positives, non-lung regions that are falsely predicted as lung. In contrast, infection masks are and operated with post-processed lung masks to ensure that the infection region falls within the lung area and remove the false positives outside the lung region.

4.4.3 COVID-19 Detection and Quantification

The detection of COVID-19 is performed based on the prediction maps

generated by the infection segmentation network. Accordingly, a CXR image is classified as COVID-19 positive if at least one pixel of lung areas is predicted as COVID-19 infection, i.e., $p(x_k) > 0.5$. Otherwise, the image is considered as COVID-19 negative, healthy people or patients with non-COVID-19 pneumonia. Furthermore, COVID-19 infection is quantified by computing the overall percentage of infected lungs. Equivalently, the sum of predicted infection pixels over the sum of predicted lung pixels. In addition, the infection percentage of each lung is computed, enabling doctors to assess the progress of COVID-19 for each lung individually.

4.4.4 AI Models for Chest X-ray Classification

Choosing the best AI for a specific problem is usually a tradeoff between the following two criteria: computational complexity and classification accuracy.

Therefore, the model investigated several Deep Learnings, starting from shallow to deep models with sequential, residual, and dense connections. In this study, two classification schemes were considered: (i) COVID-19 recognition from SARS and MERS coronaviruses, (ii) COVID-19 recognition from non-COVID-19 infections and normal cases. For the first classification scheme, four pretrained models were investigated: SqueezeNet, ResNet18, DenseNet201, and InceptionV3. While for the second classification scheme, five pretrained models were investigated: ResNet18, ResNet50, DenseNet121, Densenet161, and InceptionV4. The output layer of each network was replaced by a SoftMax layer with three neurons to classify the X-ray images into one of the two 3-class schemes. Details of the employed models are given below:

SqueezeNet [68]: is the smallest network considered in this study, with 18 layers only. Introducing fire modules, where a squeeze convolutional layer with 1x1 kernels is fed to an expand layer that has a mix of 3x3 and 1x1 kernels. The network begins with a standalone convolutional layer, followed by eight fire block and end with a convolutional layer followed by a SoftMax layer. The network performs max-pooling after the first convolutional layer, 4th fire module, and 8th fire module. The compact architecture of SqueezeNet makes it favorable over other networks for such problems that it can achieve a comparable performance level.

ResNet [69]: Overfitting is a well-known paradigm for training deep AI that can drastically degrade the network performance when trained with scarce data. The overfitting problem becomes worse when higher number of training epochs are performed and eventually, the network saturates due to the vanishing gradients

problem. ResNet introduces the concept of residual blocks, where the input and output of stacked layers are merged by simply add-up, providing an extra path for the backward gradient flow. This prevents the vanishing gradients problem and enhances the generalization capabilities of the network. In this study three variants of ResNet model were considered: ResNet18, ResNet50, and ResNet152.

DenseNet [70]: aggregates all feature maps instead of summing residuals. All layers in a dense block are densely connected to their subsequent layers, receiving extrasupervision from previous layers. The dense structure creates a compact layer with littleredundancy in the learned feature, where different network parts can share pieces of collective knowledge. In this study three variants of DenseNet model were considered: DeneNet121, DenseNet161, and DenseNet201.

InceptionV3 [71]: showed improved performance compared to its deeper competitors in classifying different types of problems. Typically, larger kernels are favored for global features that are distributed over a large area of images. In contrast, smaller kernels are preferred for an area-specific feature that is distributed over image frame. This inspired the idea of inception layers, where kernels of different sizes (1x1, 3x3, and 5x5) are concatenated within the same layer instead of going deeper into the network. The Inception architecture increases the network space, where the best features can be selected by training.

InceptionV4 [72]: further factorized the convolutions and pruned the dimensions of the InceptionV3 network. Despite the lower complexity, it preserves a higher performance.

4.5 CLASSIFICATION LOSS FUNCTION

The cross-entropy loss is used as the cost function for the classification networks.

4.5.1 Transfer Learning

Transfer learning is a well-established Deep Learning approach, where gained knowledge from one problem is applied to a different but a related problem. To ensure an efficient training and faster convergence, transfer learning was utilized for the classification networks and on the encoder side of the segmentation networks by initializing the convolutional layers with ImageNet [73] weights.

4.5.2 AI Output Visualization

Artificial intelligence development is quite a bit different from typical software development: the first step writing software is the same, but instead of someone

using the software you wrote, like in normal software development, the AI software you write then takes some data as input and creates the software that ends up being used. This is referred to as the AI system training or learning, and the end result is usually called a model. This two-step process is key to the success of AI systems in certain domains like computer vision: AI software can create computer vision models better than humans can. On the other hand, the output of the AI development process is often spoken of as a “black box” because it wasn’t created by a human, and can’t easily be explained by or to humans. Data visualization has turned out to be critical to AI development because it can help both AI developers and people concerned about the adoption of AI systems explain and understand these systems.

The structure of AI software is usually that of a pipeline of steps that feed into each other in complex ways. AI developers find it helpful to be able see and edit visual representations of the pipelines they work with, and specialized visual tools have been developed to help them visualize them, such as the TensorFlow Graph Visualizer system in the popular TensorFlow library, or the Studio. Once the AI software has learned a model from a dataset, AI developers need to be able to evaluate how well it performs at its designated task. Often this results in disappointment, leading to a need to explain and understand what the system has learned in order to improve it. In evaluation, receiver operating characteristic (ROC) curves are used to evaluate the results of classification algorithms, and silhouette plots are used to do the same thing for clustering. Data visualization is especially helpful in evaluation because models often exhibit a range of behaviors whose outcome can’t be evaluated at a single point, but rather as a trade-off curve or surface or hyper-surface, which are often understandable only qualitatively via visualization rather than numerically as a score.

Visualization techniques help in understanding the internal mechanisms of AI and the reasoning behind the network making a specific decision. In addition, it interprets the results in a way that is easily understandable to human, thereby increasing the confidence of AI outcomes. The main visualization technique employed in literature is Gradient-weighted class Activation Map (Grad-CAM) [74], where activation maps are generated by backward passing the gradients of the target class back to the final convolutional layer in the network to produce the localization map. The localization map $\text{Grad-CAM } L^c \in \mathbb{R}^{h \times w}$ of height h and width w for class c is obtained by first computing the gradients of the score of target class

with respect to the feature map A^k as ∂y^c where y^c is the network output before SoftMax.

$$\partial A^k$$

Next, the gradients are backward passed through global average pooling to compute the α weights, which highlights the importance of feature map k for the decision making of target class c:

Recently, Score-CAM [75] was proposed as a promising alternative to GRD-CAM. Score-CAM gets rid of the dependencies on gradients by obtaining the weight of each activation map through forward passing scores of the target class. Given an AI model $y^c = f(CXR)$ that takes an input CXR image and outputs a scalar y^c . The contribution of a specific feature map A^k toward output y^c is defined as follows:

$$\alpha_k^c = f(CXR \circ H_l^k) - f(CXR) \quad (2)$$

$$H_l^k = n(Up(A_l^k)) \quad (3)$$

Where $Up(.)$ denotes the up-sampling operation of A into the input (CXR) size, $n(.)$ is a normalization function that maps elements of input matrix into $[0,1]$, and $\circ$ is the element-wise multiplication. Finally, the Score-CAM saliency map is computed using the same equation as Grad-CAM, Equation (2).

In this work, Score-CAM method is deployed to visualize the classification outputs of the proposed COVID-19 recognition system.

The use of advanced data-processing software, such as AI software, coupled with data visualization is sometimes referred to as Visual Analytics. In the visual analytics paradigm, a human enters into a discourse with a software system about some data, querying it and receiving results back in visual form, so as to accomplish a goal, be it answering a specific question or just getting a feel for what a dataset might contain. Current, slightly clunky examples of natural language approaches to this include Wolfram Alpha and Microsoft PowerBI Natural Language Querying. To the extent that modern AI systems are getting better and better at interpreting human speech however, for example with Apple's Siri and Amazon's Alexa might expect that this type of conversational visual analytic discourse will become more natural and powerful over time. The findings of this work released a unique dataset, COVID-family,

consisting of 701 CXR images with their corresponding ground-truth lung masks targeting a challenging classification task to distinguish among different COVID family members: SARS, MERS, COVID-19. A robust 2-stage system was employed, where first lung regions are segmented and then classified.

4.5.3 Preprocessing System

Data pre-processing or data cleansing is a crucial step and most of the ML engineers spend a good amount of time in data pre-processing before building the model. Some examples for data pre-processing includes outlier detection, missing value treatments and remove the unwanted or noisy data. Similarly, Image pre-processing is the term for operations on images at the lowest level of abstraction. These operations do not increase image information content but they decrease it if entropy is an information measure. The aim of pre-processing is an improvement of the image data that suppresses undesired distortions or enhances some image features relevant for further processing and analysis task. There are 4 different types of Image Pre-Processing techniques and they are listed below.

1. Pixel brightness transformations/ Brightness corrections
2. Geometric Transformations
3. Image Filtering and Segmentation
4. Fourier transform and Image restoration

It has use Pixel Brightness Transformations (PBT) Technique: Brightness transformations modify pixel brightness and the transformation depends on the properties of a pixel itself. In PBT, output pixel's value depends only on the corresponding input pixel value. Examples of such operators include brightness and contrast adjustments as well as color correction and transformations. Contrast enhancement is an important area in image processing for both human and computer vision. It is widely used for medical image processing and as a pre-processing step in speech recognition, texture synthesis, and many other image/video processing applications. There are two types of Brightness transformations and they are below.

1. Brightness corrections
2. Gray scale transformation

The most common Pixel brightness transforms operations are

1. Gamma correction or Power Law Transform
2. Sigmoid stretching
3. Histogram equalization

Two commonly used point processes are multiplication and addition with a constant.

$$g(x)=\alpha f(x)+\beta \quad (4)$$

Where the parameters $\alpha > 0$ and β are called the gain and bias parameters.

Sometimes these parameters are said to control contrast and brightness respectively. Convert Scale Abs (image, alpha=alpha, beta=beta) for different values of alpha and beta, the image brightness and contrast vary. A specific pre-processing technique is both problem and network dependent. Additionally, for future studies, it is worth investigating the effect of the ensemble technique on the X-ray classification scheme. The ensemble approach combines the output from several networks trained with different pre-processing techniques to generate the final classification output, rather than the 3-channel scheme used in this study, where the variants of the pre-processed input X-ray are combined and fed to a single network to make the final decision.

4.6 PERFORMANCE DESCRIPTION

An image recognition system was proposed using the concatenation of lung segmentation and classification networks. The U-Net segmentation network was pre-trained and validated on the Montgomery [41] and Shenzhen [42] lungmasks dataset. The pre-trained U-Net model was used to create lung masks for COVID-19, MERS, and SARS chest X-ray images. Next, the lung masks were fine-tuned by the MDs to develop ground truth masks for the COVID-family dataset. The deep classification networks were evaluated on the compiled COVID-family dataset and their corresponding lung masks. Two classification schemes were considered: plain CXR classification and segmented CXR classification. Both networks were trained using 5-fold cross-validation (CV), with 80% train and 20% test (unseen folds), where 20% of training data is used as a validation set to avoid overfitting. The CXR images were resized to have a fixed dimension of 256x256 pixels to be used as the input for deep networks. The imbalance class distribution ratio of the dataset has a major impact on the performance of deep models. Therefore, the size of each class was balanced in the train set using

data augmentation. Performed data augmentation by applying rotations of 5, 10, 20, and 25 degrees. In addition, horizontal and vertical image translations were used within the interval [-0.1, +0.1].

Both CXR classification and lung segmentation task were conducted over the constructed benchmark COVID-QU lung masks dataset. In contrast, the infection segmentation and COVID-19 detection tasks were conducted over a subset of 2,913 CXR samples from COVID-QU dataset with corresponding infection masks from QaTa-Cov19 dataset [44]. All tasks were performed with 20% test set, and 80% train set, where 20% of training data was used as a validation set

The performance of different AI models was assessed using different evaluation metrics with 95% confidence intervals (CIs). Accordingly, CI for each evaluation metric was computed as follows:

$$r = z \sqrt{\text{metric} (1 - \text{metric}) / N} \quad (5)$$

where, N is the number of test samples, and z is the level of significance that is 1.96 for 95% CI.

4.6.1 Segmentation Evaluation Metrics

The performance of the segmentation models is evaluated on a pixel-level, where the foreground (lung or infected region) was considered as the positive class and background as the negative class. Three evaluation metrics were computed to evaluate the segmentation performance:

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (6)$$

where *accuracy* is the ratio of the correctly classified pixels among the image pixels. *TP*, *TN*, *FP*, *FN* represent the true positive, true negative, false positive, and false negative, respectively.

$$\text{Intersection over Union (IoU)} = \frac{TP}{TP+FP+FN} \quad (7)$$

$$\text{Dice Similarity Coefficient (DSC)} = \frac{2*TP}{2*TP+FP+FN} \quad (8)$$

where, both *IoU* and *DSC* are statistical measures of spatial overlap between the binary ground-truth segmentation mask and the predicted segmentation mask, while the main difference is that *DSC* considers double weight for *TP* pixels (true lung/lesion predictions) compared to *IoU*.

4.6.2 Classification Evaluation Metrics

The performance of different classification networks is assessed using five evaluation metrics: Accuracy, Precision, Sensitivity, F1-score, and Specificity. Per-class values were computed over the overall confusion matrix that accumulates all test fold results of the 5-fold cross-validation.

$$Accuracy_{class_i} = \frac{TP_{class_i} + TN_{class_i}}{TP_{class_i} + TN_{class_i} + FP_{class_i} + FN_{class_i}} \quad (9)$$

where accuracy is the ratio of correctly classified CXR samples among all the data.

$$Precision_{class_i} = \frac{TP_{class_i}}{TP_{class_i} + FP_{class_i}} \quad (10)$$

Where class *i* is the classification of each class. where precision is the rate of correctly classified positive class CXR samples among all the samples classified as positive samples.

$$Sensitivity_{class_i} = \frac{TP_{class_i}}{TP_{class_i} + FN_{class_i}} \quad (11)$$

where sensitivity is the rate of correctly predicted positive samples in the positive class samples. where specificity is the sensitivity of the negative class.

CHAPTER 5

SIMULATION RESULTS AND DISCUSSION

Proposed a more practical diagnosis solution for the current pandemic, recognizing COVID-19 positive cases from non-COVID-19 infections or normal cases. Released the largest CXR lung mask dataset, COVID- QU, with over 33k CXR images. A reliable end-to-end solution was provided not for CXR classification only but to localize and quantify COVID-19 infections as well using a robust 3-stage system.

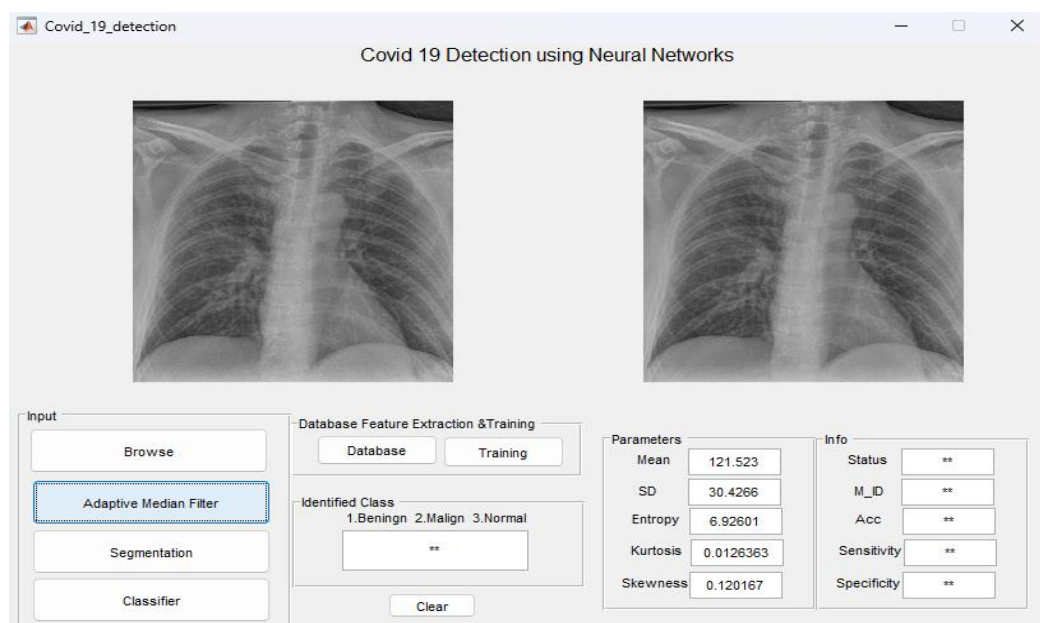


Fig 5.1: Preprocessed output

The adaptive median filter in Fig 5.1 above provides extensive processing to reduce noise in the image. Each pixel in the image is compared to its surrounding pixels by a filter. A pixel is considered noise if it differs significantly from most of the surrounding pixels. The neighboring pixel values are used to replace the noise pixels using the average filter method. This process is repeated until all the noise pixels in the image are removed.

Medical images are sometimes poor in contrast and often corrupted by noise due to different sources of interference, such as the imaging process and data acquisition. As a result, it may become harder to evaluate them visually. Contrast enhancement methods can play an important role in improving the image quality to provide a better

interpretable image to the medical doctors. Besides, it can boost the performance of deep recognition systems. In order to investigate potential enhancement on the classification performance, four pre-processing schemes were evaluated in this study: original chest X-ray image, which did not undergo any form of pre-processing, contrast limited adaptive histogram equalization (CLAHE), image complementation, and finally, the combination of the three (original, CLAHE, complemented) schemes applied altogether to form a 3-channel approach.

The performance of the lung segmentation models over the test. Each model was evaluated with five different encoder structures. For all models, it was observed that DenseNet encoders give the top-segmentation performance as they can share pieces of collective knowledge by densely connecting convolutional layers to their subsequent layers, therefore, preserving the information coming from the earlier layer through the output layer. The FPN model with DenseNet121 encoder holds the leading performance with 96.11% IoU, and 97.99% DSC.

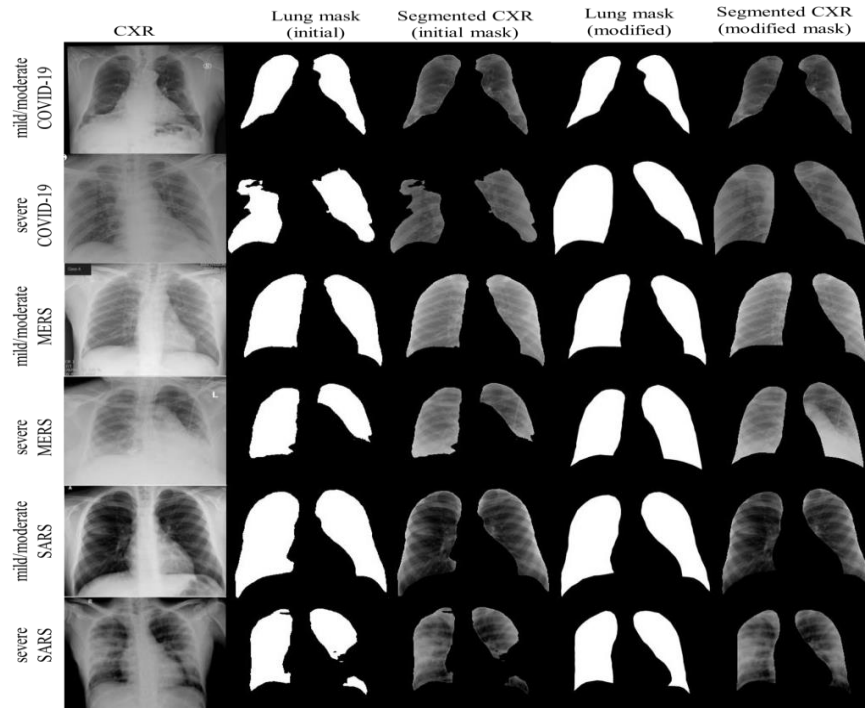


Fig 5.2: Segmented chest X-ray

The above figure 5.2 shows that Qualitative evaluation of the U-Net model. Original X-ray images (left), lungmask generated by the trained U-Net model and corresponding segmented lung, fine- tuned mask by the radiologist, and their corresponding lung segment. The qualitative evaluation of the trained U-Net model

on the compiled COVID-family dataset images is presented in above fig. The model can reliably segment the lung images if the lung areas are distinguishable; however, the segmentation network suffers from severely infected lungs due to the whitened infection area in the lungs. Predicted lung masks by the U-Net model were revised by medical doctors to ensure that the segmentation masks encapsulate the entire lung region. The U-Net segmentation model was trained and evaluated on 704 CXR samples with ground-truth lung masks of the Montgomery and Shenzhen dataset, as shown in Table 3. The model showed promising segmentation performance with IoU and DSC of 93.11% and 96.35%, respectively, on the two publicly available datasets.

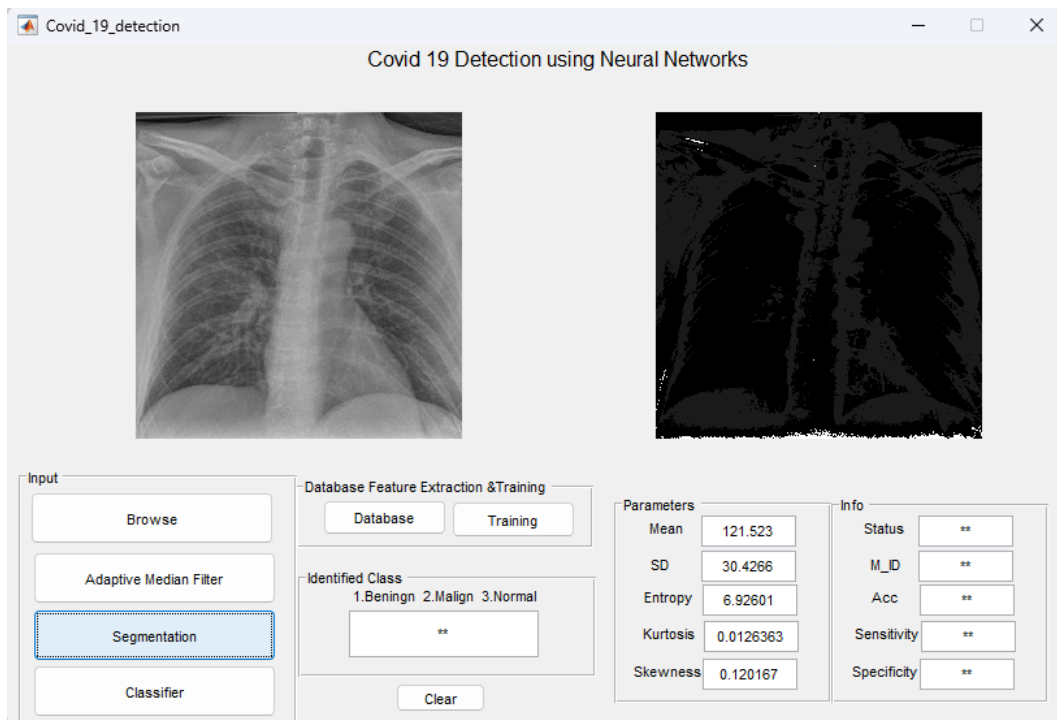


Fig 5.3: Segmented output

In above fig 5.3, image segmentation describes dividing the image into segments or regions. Image pixel characteristics are often the basis for this segmentation. For example, looking for sharp discontinuities in pixel values that often represent edges is one way to find areas in an image. Areas can be defined using these edges. Other methods divide the image into regions based on texture or color values. From a binary mask to a three-channel infection mask, the infection segmentation model can be expanded, non-COVID-19 lesions, COVID-19 lesions, and noise channels. Between Categories that are COVID-19, non-COVID-19, and typical, the multichannel infection conceal is able to recognize these individuals all. However,

segmented CXR provides more reliable results because the tissue is studied from the main area of interest, the lung part.

The performance of infection segmentation networks for COVID-19 detection from the CXR images is presented in Table 8. The sensitivity was considered as the primary metric for the detection task, as missing any COVID-19 positive case is critical. All the networks achieved high sensitivity values ($>97\%$), where U-Net with DenseNet121 backbone and FPN with ResNet18 backbone achieved the best performance with 99.66% sensitivity. Similarly, all models showed elegant specificity values ($>97\%$), where U-Net++ with ResNet18 backbone achieved the top performance with 100% specificity, indicating the absence of false alarm rate.

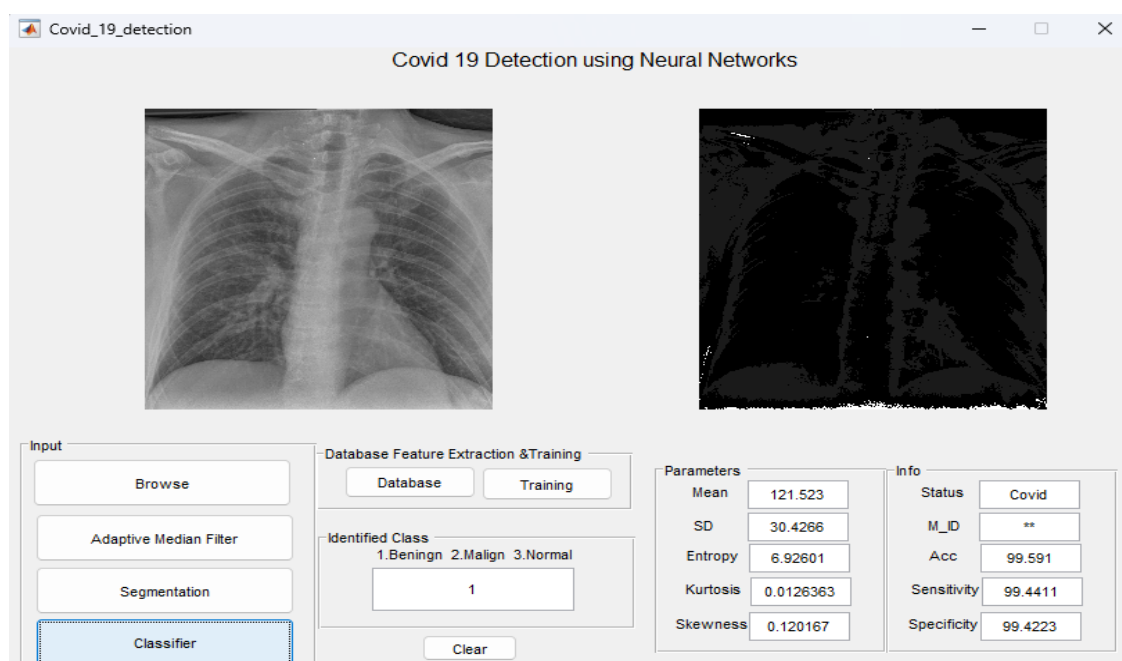


Fig 5.4: Classifier output for the initial phase

The above figure 5.4 above describes how a classification network is used in a Classifying CXR pictures as COVID-19, COVID-19, or standard uses a three-class recognition approach. Finally, the classification scheme uses a cascade design with lung segmentation and a classification model. A three-step wave treatment is used in the first step to improve the characteristics of the Xray image specifically for COVID-19. The proposed approach is then used to classify these enhanced images.

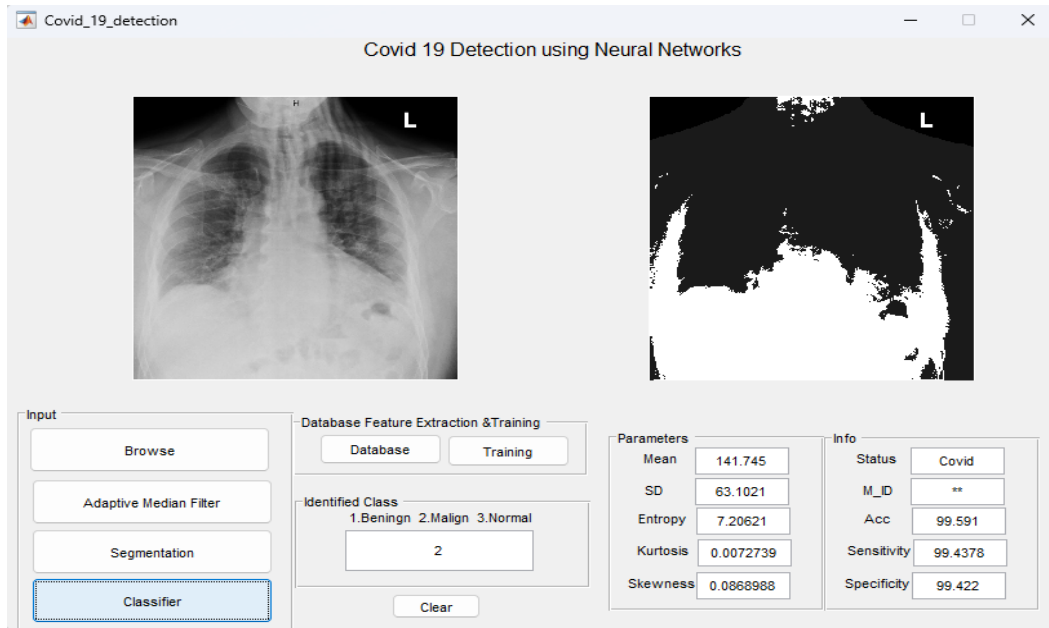


Fig 5.5: Classifier output for the malign phase

The above figure 5.5 above describes the purpose of identifying and analyzing areas affected by COVID-19, and the segmentation model is given images identified as infected images in the second step. In this context, a new paradigm for semantic segmentation is proposed, where the encoder and decoder block often use averaging and maximum weighting techniques.

Table 5.1. COVID-19 Detection Performance Results (%) Computed Over Test (Unseen)Set with Three Network Models and Five Encoder Architectures.

Model	Encoder	Accuracy	Precision	Sensitivity	F1-score	Specificity
	ResNet18	98.89 ± 0.6	99.14 ± 0.53	98.63 ± 0.67	98.88 ± 0.6	99.14 ± 0.53
	ResNet50	98.89 ± 0.6	98.47 ± 0.7	99.31 ± 0.48	98.89 ± 0.6	98.46 ± 0.71
U-Net	DenseNet121	98.8 ± 0.62	97.98 ± 0.81	99.66 ± 0.33	98.81 ± 0.62	97.94 ± 0.82
	DenseNet161	98.71 ± 0.65	97.97 ± 0.81	99.49 ± 0.41	98.72 ± 0.65	97.94 ± 0.82
	InceptionV4	98.03 ± 0.8	98.28 ± 0.75	97.77 ± 0.85	98.02 ± 0.8	98.28 ± 0.75
	ResNet18	99.23 ± 0.5	100 ± 0	98.46 ± 0.71	99.22 ± 0.5	100 ± 0
	ResNet50	99.14 ± 0.53	99.83 ± 0.24	98.46 ± 0.71	99.14 ± 0.53	99.83 ± 0.24

U-Net ++	DenseNet1 21	99.23 ± 0.5	99.14 ± 0.53	99.31 ± 0.48	99.22 ± 0.5	99.14 ± 0.53
	DenseNet1 61	98.2 ± 0.76	97.95 ± 0.81	98.46 ± 0.71	98.2 ± 0.76	97.94 ± 0.82
	InceptionV4	98.2 ± 0.76	98.45 ± 0.71	97.94 ± 0.82	98.19 ± 0.77	98.46 ± 0.71
	ResNet18	98.54 ± 0.69	97.48 ± 0.9	99.66 ± 0.33	98.56 ± 0.68	97.43 ± 0.91
	ResNet50	98.46 ± 0.71	98.46 ± 0.71	98.46 ± 0.71	98.46 ± 0.71	98.46 ± 0.71

The above table 5.1 shows the classification network was used for a 3-class recognition scheme to classify CXR images as COVID-19, non-COVID-19, or normal. However, this network will be removed in future studies once ground-truth infection masks are created for non- COVID-19 cases. Therefore, the binary masks generated by infection segmentation models can be extended to a 3-channel infection mask, where the channels denote: background, non-COVID-19 lesion, and COVID-19 lesions. Thus, the multi-channel infection mask can be used to distinguish between COVID-19, non-COVID-19, or normal images.

The classification performances of the deep AI models in-terms of the per-class performance metrics for plain and segmented X-ray image classifications. For each network, four different pre-processing schemes (original, CLAHE, complemented, and 3-channel) were compared, and the best performing scheme is presented in Table 5.1. For plain X-ray images, it was observed that SqueezeNet achieved the best classification performance on original images, while ResNet18 and Inceptionv3 outperformed on 3-channel images. For the segmented lung X-ray images, SqueezeNet and InceptionV3 showed the best performance with the original lung images without any pre-processing, and InceptionV3 outperformed all the networks.

On the other hand, ResNet18 and DenseNet201 performed better on 3- Channel images. In general, the investigated AI models showed high COVID-19 sensitivity values (>96%) for segmented data, while it showed varying results with plain X-rays. For instance, with plain X-ray, SqueezeNet showed 91.97% COVID-19 sensitivity, while InceptionV3 showed 99.53% COVID-19 sensitivity. For SARS and MERS, the InceptionV3 network achieved the highest sensitivities for a plain and segmented lung X-ray image. The sensitivity for MERS and SARS detection were 93.1%/79.68% and

97.04%/90.26% for plain/segmented lung CXRs, respectively. It is evident that the overall performance for MERS detection significantly degrades with segmentation. This is most likely due to a large number of lower-quality chest X-ray images in the MERS dataset. Even though the performance degrades with segmented lungs, as the network learns from the main region of interest (lung area), the results obtained from the segmented lungs are much more reliable.

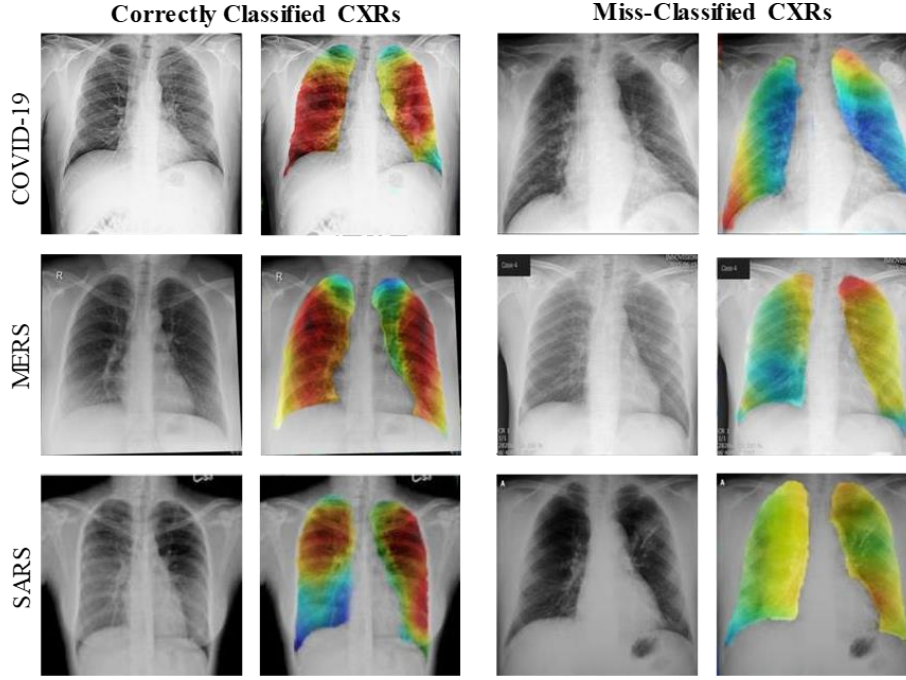


Fig 5.6: InceptionV3 compares Score-CAM for correctly classified and miss-classified CXR images.

The above fig 5.6 shows sample miss-classified X-ray images, corresponding lung image and Score-CAM visualization for COVID-19, MERS, and SARS images to identify the potential reasons of the network failure. It can be seen from above Figure that InceptionV3 failed to classify the lung images properly if the network did not learn from the lung areas exclusively whereas, for those images that are correctly classified by the network, Score-CAM is showing that the AI model is learning from the entire lung region by the network, Score-CAM is showing that the AI model is learning from the entire lung region. Therefore, it can be summarized that the reliable segmentation of lung from the X-ray images and the use of segmented X-ray images for the classification problem can significantly increase the reliability of AI-based computer-aided diagnosis applications.

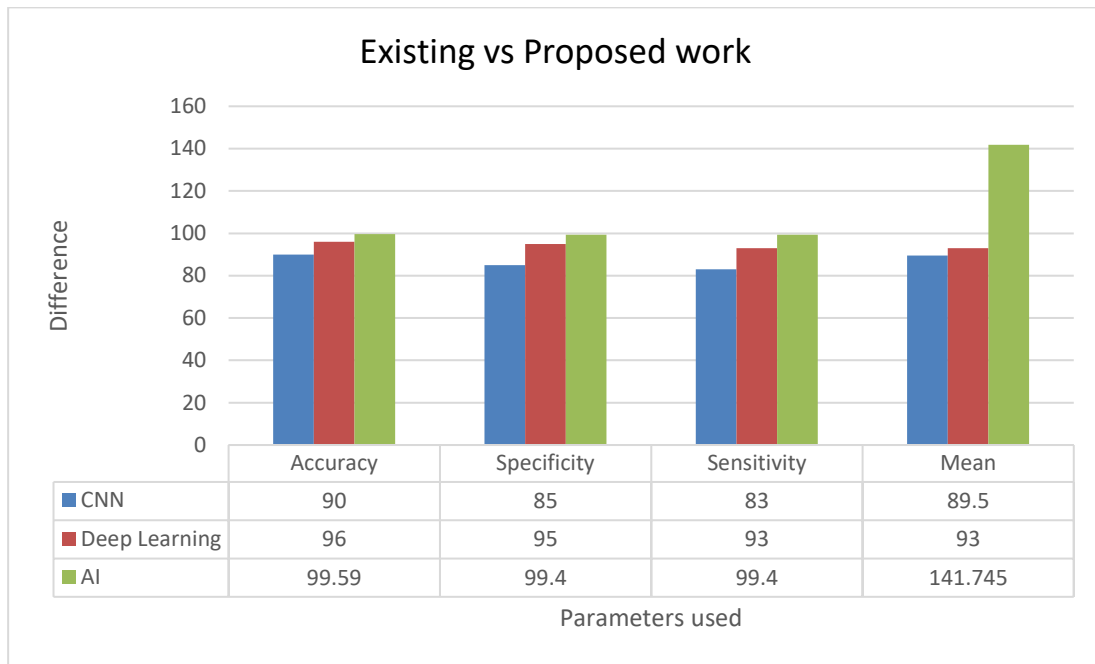


Fig 5.7: Comparison of Existing and Proposed Methodologies

The above fig 5:7 shows that difference between Existing and Proposed methodology, five evaluation criteria are used to compare the performance of various categorization networks: accuracy, precision, sensitivity, F1-score, and specificity. An adaptive learning rate that reduces the learning parameter by a factor of 5 if validation loss did not improve for 3 consecutive epochs; and a mini-batch size of 4 images with 40 back propagation epochs. The benchmark COVID-family dataset was used to assess the deep AI-based classification networks. With segmented data, the examined AI models generally displayed high COVID-19 sensitivity values (>96%), however it produced varied results for plain X-rays. The Coronavirus (COVID-19) Infection Survey data collection method change from study worker home visits to remote data collection is discussed in the current quality report.

CHAPTER 6

CONCLUSION AND FUTURE WORK

Early identification and isolation of highly infectious COVID-19 cases play a vital role in preventing the spread of the virus. X-ray imaging is a low-cost, easily accessible, and fast method that can be an excellent alternative for conventional diagnostic methods such as RT-PCR and CT. Therefore, numerous studies proposed AI-based solutions for automatic and real-time detection of COVID-19. In general, these methods showed outstanding performance for early detection and diagnosis. However, they have used limited CXR repositories for evaluation with a small number, a few hundreds, of COVID-19 samples. Thus, the generalization of the achieved results on large cohort dataset is not guaranteed. In addition, they showed limited performance in infection localization and severity grading of COVID-19 pneumonia. In it proposed a robust system to segment the lung, detect, localize, and quantify COVID-19 infections from CXR images. To accomplish this, it compiled the largest CXR dataset, COVID-QU, which consists of 11,956 COVID-19, 11,263 non-COVID-19 pneumonia, and 10,701 normal, 134 SARS-CoV, and 144 MERS-CoV images. An extensive set of experiments using state-of-the-art AIs over COVID-QU dataset showed superior lung segmentation performance with 96.11% IoU and 97.99% DSC. Moreover, the proposed system proved reliable in localizing COVID-19 infection of various sizes and shapes, achieving IoU and DSC values of 83.05% and 88.21%, respectively. Furthermore, two classification schemes were tackled: (i) COVID-19 recognition from non-COVID-19 infections, and normal cases, (ii) COVID-19 recognition from other coronaviruses, SARS, and MERS. For the first classification scheme, the best network achieved sensitivities of 96.94%, 79.68%, and 90.26% for classifying COVID-19, MERS, and SARS images, respectively. For the second classification scheme achieved sensitivities of 91.52%, 93.21%, and 91.12 for COVID-19, non-COVID, and normal classes, respectively.

6.1 FUTURE SCOPE

COVID-19 has been a hot research topic in recent years due to a large number of deaths worldwide. Many computer-based techniques have been introduced by researchers, but there is still much room for improvement in terms of accuracy and computational time. Proposed a deep learning and explainable AI-based framework for COVID 19 diagnosis and classification using chest X-ray images in this paper. The

proposed framework includes several steps, from contrast enhancement to ELM-based classification. The Grad-CAM-based visualization is used to highlight the image's hot spots. Tree datasets were used in the experiment, and the results were significantly better than the middle steps and a few other neural nets. Based on the findings, it is concluded that the contrast enhancement and feature optimization techniques improve the proposed framework's accuracy. In the future work to modify our system to localize non-COVID-19 infections as well by creating ground-truth infection masks for non-COVID-19 CXR images using the collaborative human-machine approach. In addition to explore robust quantization and model compression techniques to further reduce the model complexity and accelerate the inference process, using the new generation of heterogeneous network models, Self-Organized Operational Neural Networks.

IEEE STANDARDS AND CONSTRAINTS

IEEE STANDARDS FOR DETECTION OF COVID-19

IEEE realizes that many are directly or indirectly engaged in the fight against COVID-19 and its effects on global health and safety, research, infrastructure, communications, and more. IEEE has identified articles and standards from the IEEE Xplore digital library that may help researchers understand and manage different aspects of the COVID-19 pandemic and technologies that can be leveraged to combat it.

- 1 11073-10424-2016 – ISO/IEEE International Standard – Health informatics– Personal health device communication – Part 10424: Device Specialization– Sleep Apnoea Breathing Therapy Equipment (SABTE)
- 2 11073-10421-2010 – Health informatics–Personal health device communication Part 10421: Device specialization–Peak expiratory flow monitor (peak flow)
- 3 2010-2012 – IEEE Recommended Practice for Neurofeedback Systems
- 4 1708-2014 – IEEE Standard for Wearable Cuffless Blood Pressure Measuring Devices
- 5 1708a-2019 – IEEE Standard for Wearable, Cuffless Blood Pressure Measuring Devices – Amendment 1
- 6 1680.2-2012 – IEEE Standard for Environmental Assessment of Imaging Equipment
- 7 1680.2a-2017 – IEEE Standard for Environmental Assessment of Imaging Equipment – Amendment 1
- 8 C63.27-2017 – American National Standard for Evaluation of Wireless Coexistence 3D Printing Relevant Standards
- 9 3333.1.2-2017 – IEEE Standard for the Perceptual Quality Assessment of Three-Dimensional (3D) and Ultra-High-Definition (UHD) Contents
- 10 3333.2.1-2015 – IEEE Recommended Practice for Three-Dimensional (3D) Medical Modeling

IEEE has made these standards available at no cost to help speed developmental response to the current global health crisis.

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