NEAR EAST UNIVERSITY

INSTITUTE OF GRADUATE STUDIES

DEPARTMENT OF ELECTRICAL AND ELECTRONIC ENGINEERING

EFFECTS OF MULTIMODAL IMAGING ON SARS-COV-2 AND LUNG CARCINOMA CLASSIFICATION USING DEEP LEARNING

In Partial Fulfillment of the Requirements for The Masters of Science.

By

FALANA OLUROTIMI WILLIAM

Nicosia

JULY, 2022

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Declaration

I hereby declare that all information, documents, analysis and results in this thesis have been collected and presented according to the academic rules and ethical guidelines of Institute of Graduate Studies, Near East University. I also declare that as required by these rules and conduct, I have fully cited and referenced information and data that are not original to this study.

FALANA OLUROTIMI WILLIAM

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Falana Olurotimi William

Abstract

Effect of multimodal imaging on SARS-COV-2 and lung carcinoma classification using deep learning.

Falana Olurotimi William MSC, Department of Electrical And Electronic Engineering July, 2022, 50 pages

SARS-COV-2 and lung carcinoma are major lung disease with high risk factor. SARS-COV-2 originated from a Chinese city called Wuhan in late 2019 which has led to the major cause of mortality rate especially in 2020 across the globe. Lung carcinoma also is a lead cause of death among all types of cancer.

There has been different type of diagnosis methods and procedure for this two-lung related diseases. For SARS-COV-2 the RT-PCR test method are used and for lungs cancer chest X-rays are majorly used for testing.

Medical imaging can be used for detection and diagnosis of several medical diseases through medical imaging equipment's like chest radiograph and computerized tomography scans. Due to the similarities in medical imaging of both diseases we decided to investigate how well deep learning algorithms like AlexNet could be able to tell the difference between lung carcinoma and SARS-COV-2 and also to see if multimodal classification can significantly influence the classification results. To investigate this, we carried out three different classifications of lung carcinoma and SARS-COV-2 which were CT classification of lung carcinoma and SARS-COV-2, X-ray classification of lung carcinoma and SARS-COV-2 and then the combination of CT and Xray classification of lung carcinoma and SARS-COV-2.

The result obtained for this experiment shows that deep learning could tell difference between SARS-COV-2 and lung carcinoma disease with relatively high accuracies however no substantial improvement was observed as a result of multimodal imaging.

***Keywords**:* lung cancer, SARS-COV-2, Computed tomography, Radiography, Deep learning, AlexNet

özet

Effect of multimodal imaging on SARS-COV-2 and lung carcinoma classification using deep learning.

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SARS-COV-2 ve akciğer karsinomu, yüksek risk faktörü olan başlıca akciğer hastalıklarıdır. SARS-COV-2, 2019'un sonlarında Wuhan adlı bir Çin şehrinden kaynaklandı ve özellikle 2020'de dünya genelinde ölüm oranının ana nedenine yol açtı. Akciğer kanseri ayrıca tüm kanser türleri arasında önde gelen ölüm nedenidir.

Bu iki akciğer ile ilgili hastalıklar için farklı tipte teşhis yöntemleri ve prosedürleri olmuştur. SARS-COV-2 için RT-PCR test yöntemi kullanılır ve akciğer kanseri için göğüs röntgeni test için büyük ölçüde kullanılır.

Tıbbi görüntüleme, göğüs radyografisi ve bilgisayarlı tomografi taramaları gibi tıbbi görüntüleme cihazları aracılığıyla çeşitli tıbbi hastalıkların tespiti ve teşhisi için kullanılabilir. Her iki hastalığın tıbbi görüntülemesindeki benzerlikler nedeniyle, AlexNet gibi derin öğrenme algoritmalarının akciğer karsinomu ile SARS-COV-2 arasındaki farkı ne kadar iyi söyleyebildiğini araştırmaya ve ayrıca multimodal sınıflandırmanın sınıflandırma sonuçlarını önemli ölçüde etkileyip etkilemediğini görmeye karar verdik. Bunu araştırmak için, akciğer kanserinin CT sınıflandırması ve SARS-COV-2, akciğer kanserinin X-ışını sınıflandırması ve SARS-COV-2 ve ardından kombinasyon akciğer kanseri ve SARS-COV-2'nin BT ve X-ışını sınıflandırması olmak üzere üç farklı akciğer kanseri ve SARS-COV-2 sınıflandırması gerçekleştirdik.

Bu deney için elde edilen sonuç, derin öğrenmenin SARS-COV-2 ile akciğer karsinomu hastalığı arasındaki farkı nispeten yüksek doğrulukla söyleyebildiğini, ancak multimodal görüntüleme sonucunda önemli bir gelişme gözlemlenmediğini gösteriyor.

Anahtar Kelimeler: akciğer kanseri, SARS-COV-2, Bilgisayarlı tomografi, Radyografi, Derin öğrenme, AlexNet

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List of Abbreviations

AI:	**Artificial Intelligence**
AUC:	**Area under Curve**
BCNN:	**Bayesian Convolutional Neural Network**
CNN:	**Convolutional Neural Network**
CT:	**Computerized Tomography**
DL:	**Decision Tree**
DL:	**Deep Learning**
GAN:	**Generated Adversarial Network**
HOG:	**Histogram-Oriented Gradient**
LDA:	**Linear Discriminate Analysis**
ML	**Machine Learning**
NN:	**Neural Network**
ODNN:	**Optimal Deep Neural Network.**
PSO:	**Particles Swarm Optimization**
PCR:	**Polymerase Chain Reaction**
RELU:	**Rectified Linear Unit**
ROC:	**Receiver Operating Characteristics curve.**
SIFT:	**Scale Function Transform**
SUM:	**Supporting Vector Machine**

CHAPTER I

Introduction

SARS-COV-2 and lung carcinoma are two distinct illnesses that are both fatal (Mallapaty,2020); Boyle, 2008). These diseases affect the lungs region recently, the SARS-COV-2 pandemic had a catastrophic consequence on almost every aspect of life. The Covid-19 pandemic emerged in a town called Wuhan in the eastern part of China. SARS-COV-2 is a respiratory infection that causes respiratory system dysfunction. It causes symptoms such as coughing and fever in the sickness early stages. (Wang et al., 2020) and it has a very high transmit ability rate (Shi et al.,2020) which made it very difficult to put under control. Due to this, there have been reportedly over 213million confirmed cases and 4million death (World Health Organization., n.d.). To diagnose the Covid-19 disease, medical professionals have been using PCR method which is both costly and laborious. It is reported that the PCR has low sensitivity and therefore, they suffer from false negative rates of results (Ai et al., 2020) which has further aided the spread of the disease. To put this under control, there is need for detection and diagnosis to be done faster and more accurate. This brought about the role of artificial intelligence (AI).

Lung carcinoma is also another form of respiratory disease which has been around for some times now. It has been identified as a lead cause of cancer death internationally. The manifestation of lung carcinoma in the body are easily shown through early signs and symptoms in most cases. (Jain et al., 2020). Lung carcinoma therapy is determined by the extent of dissemination across the lung's area. Possible treatments are chemotherapy, radiotherapy and surgery. Lung carcinoma causes are associated with smoking which causes growth of lungs tumor that could easily spread widely around the lung's region (Jain et al., 2020).

Over the years, artificial intelligence has gained wide popularity in the medical field and beyond because of its accurate detection and results which has helped improve health care across the globe. In the past, image classification utilizing machine learning technique like deep learning neural networks was employed for diagnosis. Deep learning models have been utilized in prediction and classification in medical circumstances such as breast cancer (Ragab et al., 2019), skin cancer (Kaymak et al., 2018), lung cancer (Xu et al., 2019), and brain tumor (Gao et al., 2017) and the results have been accurate.

In fighting against illnesses like SARS-COV-2 and lungs carcinoma, immediate, accurate and efficient screening of patients will play a greater role in such patient's survival. The CT and X-ray imaging has been outlined as one of the best techniques so far to easily detect these kinds of diseases because of their ability to disclose every suspected lung carcinoma module (Kassania et al., 2021) and alterations in chest radiographs and computed tomography imaging during the early stages of the illness (Jain et al., 2021). The computed tomography and chest radiographs images also helps to increase dataset size which makes classification more efficient and improve accuracy.

Deep learning

Deep learning is a set of ML techniques that centers primarily on automatic feature extraction and image classification and has demonstrated notable importance in a variety of applications. Notably in the health sector. (Sethy et al., 2020; Basu et al., 2020). DL develops procedures that are more accurate in predicting and classification of various illnesses using images. The primary rationale for employing deep learning techniques is because as the network becomes deeper, DL approaches learn by fabricating a more abstract representation of the input. Thence, the model gathers data automatically and gives more precise findings. Deep learning algorithms, in comparison to traditional machine learning algorithms, describe attribute using a succession of nonlinear functions that are integrated in a combinational manner to improve the model's accuracy. There are different types of deep learning approach which are supervised, semi-supervised and unsupervised.

Supervised learning

Supervised learning is a technique of learning using labeled data. The environment has a number of inputs and matching outputs for supervised DL techniques. In supervised learning there are changes in the network parameters to approximate the desired outputs interactively. The agent can receive the right response to queries from the environment after successfully training a given data.

Semi-supervised learning

Semi-supervised learning relies on partially labeled data sets.

Unsupervised learning

Unsupervised learning is implemented without having to label the data. Under this method, the agent will learn the internal representation or critical characteristic that will allow it to detect linkages or structure in the data. Clustering, decrease of size, and generative processes are often considered in the unsupervised learning.

Feature learning

There are little differences in the feature learning of conventional ML and DL. Machine learning makes use of handmade features using multiple feature extraction algorithms such an invariant scale function transform (SIFT), histogram-oriented gradient (HOG), and much more. While in deep learning characteristics are automatically learned and expressed in several levels in a hierarchical way. This is the strength of a solid knowledge of traditional methods of machine learning.

Table 1

Feature Learning Approach Summary Table.

Approaches	Learning steps				
Rule based	input	Hand design feature	output		
Conventional ML	input	Hand design feature	Mapping from features	output	
Representative learning	input	Features	Mapping from features	output	
DL	input	Simple features	Complex feature	Mapping from features	output

Table 1 shows different learning approaches and learning steps of feature extraction in machine learning.

Transfer learning

Transfer learning is the process where a network is trained with large quantity of data in case of deep learning and the weights and biases during training. These values may be sent to additional testing networks or a comparable new model can be retrained instead if training a new one from scratch. The network might start with pre-trained weight.

AlexNet Architecture

There is more than one hidden layer in deep architectures. These hidden layers have helped to improve, and have a better impact on feature extractions. The performance of classification of images using deep networks has been shown to be higher compared to different approaches, which encourages everyone to adopt deep networks. AlexNet is a large network of 650,000 and 60 million characteristics of various neurons. In other to train these parameters, (Krizhevsky et al., 2017) has made several improvements. The AlexNet design consists of 8 layers, five layer of convolution and three fully-linked layers. In all convolution machine learning and viewing techniques AlexNet obtained statement-of-the-art recognition accuracy. It was a major accomplishment for visual identification and classification of problems in the ML and computer vision, and is a period in history in which interest in deep learning has rapidly risen.

Advanced training techniques in AlexNet dataset preparation

This is the process whereby data are being feed to the network. There are different types of operations that follow in other for the dataset to be prepared which are samples scaling, random cropping, mean distribution, flipping data and random cropping and many more are being used to prepare the dataset.

Network initiation

The initialization process is a very important task in deep learning because of its impact on the recognition accuracy (Rumelhart et al., 1986; Sutskever et al., 2013). In the past, the majority of the networks had been randomly initialized training a CNN for complicated classification task with high dimensionality data gets challenging since weights need not to be symmetrical owing to the back-propagation method. As a result, good starting strategies are critical for training this type of data.

Batch normalization

Batch normalization aids deep learning process acceleration by moving inputs samples decreasing internal correlation. The inputs are converted into a null mean and unit variance linearly. For inputs that are whitened the network covered more quickly and improves regularization in training, which will affect its accuracy. As data is whitened externally the whitening has no influence on the training of the model.

Activation function

Rectified linear unit is a common activation function (RELU) which was presented in 2010, addresses the vanishing gradient problem. DL techniques have a difficulty when it comes to training the fundamentals. The idea is simple to maintain all numbers above zero and set zeros to all negative values (Nair & Hinton., 2010). AlexNet was the first to employ activation, which was a game changer (Krizhevsky et al., 2017). Because the activation function is so important in learning the weight for deep architecture there are several improved versions that is proposed by different literature that will help provide better accuracies.

Pooling layer

There are two distinct approaches which have been utilized for deep network implementation in the pooling layer: max and average pooling. The idea of the average pooling layer was originally utilized in LeNet (LeCun et al., 1998) while max pooling layers was employed by AlexNet in 2012 (Nair & Hinton., 2012). Currently there are proposed pooling approaches in the literature.

Regularization approaches

There are different types of regularization techniques for deep CNN have been presented during the last few years. Hinton introduced the easiest but most efficient techniques called “dropout” in 2012 (Hinton et al., 2012). In dropout a portion of randomly selected activations inside a layer is set to zero (Srivastava et al., 2014) instead of removing the activation, a subset of weights inside the network layers is made zero. As a consequence, each of the layers are allocated as random picked subset of units from the layer before it (Wan et al., 2013) There are also techniques proposed in the literature.

Optimization methods

There are different optimization techniques such as Adam and much more (Ruder et al., 2016). Some activation functions have been enhanced in the areas of the additional variable momentum, which will have increased training and testing accuracy.

Medical imaging

The process of imaging the interior of a person for medical evaluation and intervention, as well as visual portrayal of the function of certain organs and tissues, is known as medical imaging technology. Medical imaging aims to show interior structure that are concealed behind the skin and bone, and also to detect and cure illness. It also helps create a database of normal anatomy and physiology allowing anomalies to be identified. There are different types of medical imaging procedure which include radiography, ultrasound, computerized tomography and much more.

Image pre-processing

Image pre-processing is the act of executing image processing on a dataset using machine learning technologies at the point of input. The goal of picture pre-processing is to improve features by eliminating undesired aspects of the image and to increase image quality.

Augmentation

The process of transforming data to create a more diverse dataset is known as data augmentation. It is usually done by generating image in most cases by rotation, translation, flipping and cropping which helps to increase dataset for training. Data argumentation is part of re-processing tools.

Image classification

Classification involves the procedure of predictively modeling problems in accordance with a class label. Classification involves training dataset from both input and output for the purpose of learning. Predictive accuracy is used as the only assessment criterion in the great majority of publications in classification model evaluation (Huang & Ling., 2005; Japkowicz & Shah., 2011).

Dataset

A dataset is a set of data that is utilized in an ML operation.

Research aims.

The primary focal point in this study is to look at the use of DL networks, specifically Alexnet to classify SARS-COV-2 and lung carcinoma. Alexnet is known to have a very good predictive and training interactions among other CNN. The classification is to evaluate the ability of Alexnet to classify CT and radiograph images of lung carcinoma and SARS-COV-2 images with an excellence performance. This would be of huge significance in the medical field that would help ease the pressing need for deploying AI models and tools for efficient and effective decision making, and also improve diagnosis of SARS-COV-2 and lungs carcinoma.

Research objectives.

The general focal point in this study is to derive an excellent technique of detecting diseases like lung carcinoma and SARS-COV-2, using artificial intelligence tools like machine learning classification tools to differentiate between CT scans and X-ray scans of both diseases because of the similarities in image structures.

Specific objectives.

1. To diagnose the nature of the disease.
2. To distinguish between a SARS-COV-2 Computed Tomography scan and lung carcinoma Computed Tomography scan.
3. To distinguish SARS-COV-2 radiographs from lung carcinoma radiographs.
4. To perform image simulations to prove it.

Contributions.

The thesis' key contributions are to inspect the usage of machine learning in medical imaging classifications by utilizing a pre-trained network named Alexnet to distinguish between lung carcinoma and SARS-COV-2 (CT and X-rays) images, in which we were able to achieve the following:

1. We successfully used a classification frame work which involves deep neural network. In this case, AlexNet

2. To aid automation and detection of SARS-COV-2 and lung carcinoma diseases.
3. This DL model was able to distinguish between SARS-COV-2 and lung carcinoma in which we used parameters like accuracy, sensitivity and specificity, to see how well they perform despite the similarities in medical imaging datasets of both (CT and X-ray) scans.
4. The results were evaluated using four datasets which includes covid 19 CTS, covid 19 X-rays, lung cancer CTS and lung cancer X-rays.

Summary

This chapter contains the basic knowledge and concept of the diseases SARS-COV-2, lung carcinoma and DL fundamentals that will be adapted in this study also further explains the aim and goal of the work and its contributions.

CHAPTER II

Literature Review

The impact of Covid-19 and lung cancer to human life has been disastrous which has led to a lot of damaging impact which includes loss of life. Due to the inability to test, detect these diseases at early stages. Over time we have seen the deployment of artificial intelligence to solve most of the challenges that deals with diagnoses, identification and detection problems.

(Hemdan et al.,2020) hypothesized a DL structure which is named Covidx-Net which has the ability to auto diagnose and detect SARS-COV-2 in X-ray images which was aimed to assist radiologist in more efficient manner. This Covidx-Net contains several different architectures of neural network models which includes a modified (VGG19) and a second version of GoogleNet. The deep neural network could differentiate between positive and negative cases.

A survey was carried out on DL in relation to medical imaging analysis by (Litjens et al., 2017) which reviews major deep learning pre-training on medical imaging and was able to summarize and analyze the major contribution of deep learning to medical field. Different deep learning main feature that was covered were, image classification, object detection, registration, segmentation and other related importance of deep learning in medical areas like ritual, digital pathology, pulmonary, abdominal, breast Musculoskeletal and neuro.

(Lakshmanaprabu et al., 2019) created an automated diagnostic and classification model for lung cancer (CT) images. This was done by analyzing CT lung images with the assistance of an optimal Deep Neural network (ODNN) and linear discriminate Analysis (LDA). It was able to extract feature of CT lung images with it dimension the reduced with the LDA for the purpose classifying the lung nodules into malignant or benign. The result achieved for the proposed classifier were good.

An investigation into a (CAD) based frame work was utilized to classify breast carcinoma by (Chougrad et al., 2018). Deep learning was used to expand and prepare the systems using transfer learning method was used with a little dataset of medical images. Transfer learning method was used to train the CNN which resulted to a very productive outcome in which its accuracy was 98.94%.

(Ghoshal et al., 2020) investigated how uncertainty in deep learning is affected by drop weight using (BCNN). During this investigation they used BCNN to enhance the performance of recognition and diagnoses of combination of human and machine using public dataset of covid Xray images. In their prediction they were able to show that uncertainty in result correlate with its accuracy.

(Xie et al., 2020) conducted a survey which summarized the process that has been made on incorporating medical domain knowledge into Architectures on various tasks completed like illness diagnosis organ, irregularity identification and organ segmentation for different kind of medical knowledge that has been used and also the modes of integration.

(Rajinikanth et al., 2020) introduced a technique to extract SARS-COV-2 infections from using CT images using Otus's based image threshold and harmony Search with watershed-segment which result was based on the size of infection the severity of the disease with respect to the lung.

(Wu et al., 2021) implemented a procedure of DL classification and segmentation of SARS-COV-2 infection images of CT scan of 200 patients. The results during the classifications were sensitivity of 95% and specificity of 93% were relatively good

(Chatterjee et al., 2020) classified Covid-19 and health subjects by using chest Xray dataset images. This was done using different type of deep learning model which were ResNet 34, ResNet 18, DenseNet 161, inception ResNet V2, and inception v_3. In this paper classification was done by images in other to predict the different pathologies that were present for each patient. The deep neural network model was studied using various techniques such as saliency, occulusion, Deep Lift and more which further concludes that ResNets is said to be the most interpretable model.

(Pahar et al., 2021) developed a SARS-COV-2 cough classifier which could differentiate between SARS-COV-2 coughs and negative SARS-COV-2 coughs. This was done with the aim to reduce the workload in SARS-COV-2 testing centers and to lessen the level of outspread of the SARS-COV-2. Publicly available datasets were used which contain samples from 6 continent both the positive and negative dataset indicated that SARS-COV-2 positive patient are 15%-20% shorter than normal cough. This was done using a leave P-out cross-validation scheme which was used to train and deduce different ML classifiers such as convolutional neutral network (Res Net

50), long, short term memory (LSTM), support vector machine (sum) and more others which there result shows that all the classifiers identified SARS-COV-2 coughs and Res Net 50 classifiers was the best to differentiate between positive SARS-COV-2 coughs and health coughs.

(Zheng et al., 2020) were able to develop a weak supervised deep learning software using 3D CT to detect SARS-COV-2. Pre-trained segmented lung region images were used to feed the 3D deep neural network in other for it to deduce the chance of SARS-COV-2 disease. The deep learning algorithms was successfully able to ascertain the SARS-COV-2 disease accurately well in chest CT dataset without needing annotation for training.

(Ella et al., 2020) introduced a model of classification which helps vectors gadget classifiers differentiate between a corona affected Xray images from other images. The model was a multi-level thresholding and SVM which was able to classify accurately with good result.

(Xue & Salim., 2021) developed a self-supervised learning framework in which a differing pre-train stage is used to train a feature called Transformer-based encoder with non-labelled data. A robust learning mechanism with respiratory sounds representation was included and then the pre trained encoder was fine-tuned in the downstream phase in other for it to classify cough. There were also different masking rates that was used to enhance the cough classification's performance.

(Pal & Sankarasubbu., 2021) proposed a model of an AI diagnosable framework which was developed through cough sounds feature with symptoms metadata. This was done by using 30,000 audio segments, 328 sounds of cough from a wide range of patients with different cough classes which were healthy cough, Bronchitis, Asthma, and SARS-COV-2. The outcome suggest that the proposed framework can differentiate between SARS-COV-2 cough and non SARS-COV-2 cough.

(Ausawalaithong et al., 2018) proposed model was aimed to provide assistance in detecting the diagnosis of the cancer. This was done using 121-layer CNN with some transfer learning techniques for classification of lung cancer from chest Xray dataset. The proposed model was trained using lung nodule dataset and further trained using lung cancer dataset to solve the small dataset problem, the result was good and also the proposed model can locate lung nodules by providing heat map for identification.

(Abbas et al., 2021) build a deep CNN known as (DeTraC) for classification of chest Xray images of covid 19. DetraC helps tackle irregularities challenge in image dataset using a mechanism called decomposition mechanism which aim is to investigating its class boundaries. The result had an accuracy of 93.1% which shows that it was able to detect Covid-19 Xray images from normal and others respiratory disease more accurately.

(Jiang et al., 2020) presents and adaptive feature selection guided Deep Forest (Afs Df) for SARS-COV-2 classifications using chest CT data. In this study they started by extracting location-specific property from CT scans, in which they captured the high-quality representation traits with a very little quantity of data deep forest prototype, which was used to learn small-scale data with high level depiction of the characteristics. Furthermore, they introduced a feature selection technique that is dependent on the trained deep forest prototype to feature redundancy that may be adaptively integrated with SARS-COV-2 classification prototype. They used a data set of 1495 SARS- COV-2 patient which cut across over 1027 communities of pneumonia patients, and their result was remarkable with accuracy of 91.79%.

(Singh et al., 2020) created a CNN that was used to classify Covid-19 infected individuals as infected (+ve) or not (-ve). In addition, the initial variable of CNN are modified by many objectives (MODE). Comprehensively experimenting with the suggested and competitive ML approaches on CT images in chest was carried out. A comprehensive examination reveals that the prototype presented can distinguish chest CT images with high precision.

(Apostolopoulos et al., 2020) were able to evaluate the efficacy of CNN architectures for medical image classification that have been present in recent times in which transfer learning method was used. The identification of different abnormalities in little medical datasets was a doable aim for transfer learning, and the results were outstanding. There were two datasets used in evaluation. To begin they collected 1427 X-ray images, which includes covid 19 confirmed cases of 224 images, pneumonia bacterial of 700 images and normal conditions of 504 images which were put together from X-ray dataset publicly available in medical sources. Investigation showed that DL combined with X-ray imaging may select significant biomarkers associated to the Covid-19 illness, with good accuracy, specificity and sensitivity being achieved.

(Chowdhury et al., 2020) presented a robust technique for automatically detecting Covid-19. Pneumonia from chest Xray images using pre trained DL model which has the ability to optimize the accuracy of the ability to detect. The authors developed an open database by gathering and merging different public database and gathering images from publication that were recently published, which it comprises of 423 Covid-19 images, 1485 viral pneumonia images and also 1579 normal chest images. Different pre- trained deep CNN was developed and validated utilizing the transfer learning approach. The different networks were trained to recognize two types of pneumonia which were (i) Covid-19 pneumonia; and the normal (ii) Covid-19 pneumonias with normal, viral with or without image augmentation. For the different systems the classification accuracy, precision, specificity and sensitivity were great.

(Jaiswal et al., 2020) worked on employing pre trained DL models as an automated method for Covid-19 identification diagnosis in chest CT images. A proposed method for classification of Covid-19 infected patients was formulated on a DL and transfer learning called DenseNet 201. This method extracts features from the dataset ImageNet in which it uses convolutional neural network with learning weight of its own. Extensive tests were carried out to assess the proposed model performance using CT scans from Covid-19 chest images. According to comparative evaluations of the proposed model. It shows the proposed model had more supervisor performance over other competitive alternatives.

(Song et al., 2021) utilizes deep learning to investigate the ability of DL to discriminate between Covid-19 patient and others. They gathered chest CT images of 88 Covid-19 images, 86 healthy people and 100 bacterially infected pneumonia patients. They created a system for deep learning CT diagnosis and their prototype was able to precisely identify Covid-19 from bacterial pneumonia with a good AUC value of 0.95 and accuracy of 0.79.

(Degerli et al., 2021) offers a distinctive method to identify Covid-19 from chest radiographs by creating the so-called infection maps, which can be used to detect joint location and severity. To achieve this they gathered 119, 316 chest radiographs comprising of 2951 Covid-19 samples in the biggest dataset in which a new collaboration method was used with ground truth segmentation mask on the images.

They concluded that the cutting- edge segmentation network can learn to locate Covid-19 infection in a more accurate way.

(Sakib et al., 2020) proposed DL-CRL system utilizes radiograph (DARI), generic data enhancement approaches for generation of synthetic Covid-19 contaminated chest X-rays, for training a robust model, to adaptively use the generated adversarial network (GAN) and general dataset enhancement. Their custom-designed, coordinated neural system (CNN) model on DL-CRC includes actual and synthetic Xray data percent. The accuracy of the result of covid 19 recognition was 93.94 percent compared to 54.55 percent when data augmentation was not used. They went further to validate their result by comparing them in depth multipath and hybrid CNN paradigms with commonly used CNN models, notably DenseNet, ResNet and inception-ResNet v2. The result shows that Covid-19 determine can be automated to quickly detect and provide a reliable result in comparison to other diagnostic prototype.

(Kamal et al., 2021) gave a detailed assessment of 8 pre-trained prototype. A total number of 760 images were used which belong to 5 different and distinct classes. Training testing and validation of this prototype was done on those chest X-ray images, pre-trained and fine-tuned models in ImageNet dataset were accurate and coherent. The test accuracy of a time tuned DenseNet 121 was 98.69% which 4 different class classification was done containing bacterial pneumonia healthy, Covid-19 and viral pneumonia. Also, the fine-tuned models had greater test accuracy for the classification which contains SARS, Covid-19 and healthy chest images. The research outcome appears that just 62% of total parameters retrained to attain such precision.

(Narin et al., 2021) proposed a method for detecting corona virus pneumonia-infected patient in which chest Xray images were used. Convolutional neural network models which include ResNet 152, ResNet 101, ResNet 50, Intception-ResNet v_2 and Inception v_3 were utilized and five-fold cross validation was constructed. They created three distinct binary classifiers with four classes which were viral pneumonia, bacterial pneumonia, normal and Covid-19. Based on the performance of the introduced pre trained CNNs they concluded that ResNet 50 produced the best result.

(El-Kenawy et al., 2020) proposed two optimizing methods to pick features and classify Covid-19. There are three cascading phases in the proposed structure which are (1) Characteristics are retrieved on the CT scan which Will be done by AlexNet

(2) the proposed method for selection which was guided by WOA. WOA is referred to as stochastics fractal search (SFS) optimization Algorithm. (3) Designated property are balanced and finally a voting classification guided by WOA based on particles swarm optimization (PSO) adds predictions from various classifiers to the most popular class. This raises the probability of showing substantial disparities between classifiers i.e., supporting vector machine (SVM), Neural networks (NN), decision tree (DT) and K-Nearest Neighbor (KNN). The introduced prototype is tested with two datasets which are positive and negative Covid-19 clinical results. The result metrics was quite better in comparison to other voting classifiers.

(Jin et al., 2020) introduced an Al structure for quick Covid-19 diagnosis & an extensive statistical analysis was performed. They evaluated their algorithm on a big dataset with over 10,000 CT images from Covid-19, non-viral pneumonia and non-pneumonia dataset. The CNN based system was able to outperform the reader study that involved 5 radiologists.

(Pham., 2020) offer an examination of 16 pre-trained Covid-19 CNN utilizing a large public CT database of SARS-COV-2 and non-SARS-COV-2 samples. The outcome of the finding demonstrates that the CNNS produced very good results in classification task with only 6 training epoch and out of the 16 CNNS, Dense Net 201 is the best among them and also shows that transfer learning which includes input of image slice without using a data augmenter gives better classification.

(Zheng., 2020) used a DL-based model which was weakly supervised to form their own model named DecovNet. In other to examine possible infections by the Covid-19, the lung area was segmented also they used a Pre-trained VNet, which were Input into a 3-D Deep Neural Network. The lung masking helps Minimize background information and identify the illness better. To achieve this, they went through these stages which were stage 1. A Normal 3D conversion with a kernel dimension of 577 which included; a batch normal layer and a pooling layer. Stage 2. A fully linked 3D layer (FC) with SoftMax Enabling capability was used in each ResBlock which comprises of 2 3D residual blocks. 499 CT images were utilized for training 131 CT both positive and negative Covid-19 images which they achieved an accuracy of 90.1 percent.

(Li et al., 2020) offered a new way to train Covid-19 classification networks effectively and efficiently utilizing a minimal amount of Covid-19 CT reviews and a bad sample archive. A new self-monitored technique of learning is specifically designed to extract features from positive and negative cases of Covid-19 samples. Furthermore, the negative samples are produced by calculating the earth mover's distance between the characteristics and features and then generate soft labels for negative samples.

(Nishio et al., 2020) aims was to design and validate a diagnostic system for classification of pneumonia SARS-COV-2, healthy and non-SARS-COV-2 images of chest radiographs. They used data sets collected from two public database, which contained a combined number of 1248 chest radiograph images. The diagnostic structure employed VGG 16 as a pre-trained model, as data augmentation techniques combined with tradition method and mixing. The VGG 16 model was compared to some other type of pre-trained models. Data augmentation techniques were not evaluated. Training/test/validation was used when the diagnostic system was constructed and evaluated. The computer aided diagnostic system had an accuracy of 83.6%.

After a thorough review of different literature, it has been clearly revealed that there has been so much work done to the classification of medical related subject in terms of lung carcinoma and SARS-COV-2 it illustrates that DL prototype have performed well in areas of differentiating, distinguishing and detection with good accuracy. But nevertheless, there are still some limitations in these classifications, in which we look into in our work such as classification of SARS-COV-2 and lung carcinoma. Knowing the similarities in both SARS-COV-2 and lung carcinoma medical imaging is difficult to differentiate from physical image the difference between both CT images and both X-ray images. We decided to investigate if AlexNet (a leading DL model) would be able to differentiate and classify them with good accuracy.

Theoretical framework

The major point under this section is to outline the process behind this work. As earlier outlined in the main goal which is to distinguish between SARS-COV-2, lung carcinoma CT and X-ray will be done through deep learning classification process in which some certain percentage of dataset will be trained. Training is the process by which a machine learns through some deep learning feature extraction methods and techniques. After the images have been trained, it will go through the testing process which is an intentionally designed dataset is used to detect flaws associated with the machine learning process and also to check the system performance for evaluation purposes after which the overall system will be evaluated based on the aim of the research and the performance of the system.

CHAPTER III
METHODOLOGY

Overview

The goal to further enhance medical imaging diagnoses has become a great task because of the current challenges being faced in the aspect of diagnosis of respiratory samples and disease. The currently available methods are expensive and sometimes require a lot of time (Shibly et al., 2020) Therefore, automation of diagnosis to many illnesses recently has been done through AI, which has great accuracy and effectiveness in automatic classification and detection of problems through different ML methods. Machine learning refers to models that can learn and make decisions quickly and more efficiently based on huge quantity of data input samples. Based on data analysis, AI can execute tasks that requires human intelligence, for instance transition, voice recognition, graphical perception, and others.

In this part, we'll look at how deep learning performs in this classification process. To accomplish this goal, we will divide our data analysis into three scenarios (i) SARS-COV-2 and lungs carcinoma CT image classification (ii) SARS-COV-2 and lungs carcinoma CT mixed with X-ray for each. (iii) SARS-COV-2 and lung carcinoma X-ray dataset.

Preprocessing

All images in this dataset were resized to a measurement of 227 X 227 X 3. This is done in order for our deep learning model to train faster and learn better.

Classification

To reach our aim of determining if the DL system can distinguish between SARS-COV-2 and lung carcinoma from computed tomography and radiographs images, we must employ the classification approach. The image classification will help the computer to analyses the image using its algorithm to detect which class it falls into. The deep learning algorithm in this case is AlexNet. AlexNet is a CNN architecture, it has a learnable parameter of eight layers which composes of five-layer Max pooling with three fully connected layers. This layer uses RELU activation except the output. We pre-trained the network using ImageNet dataset, which comprises of around one million images.

IMPLEMENTATION

We used deep learning architecture to train the images on Intel (R) Core™ i3-4005u CPU @ 1.70GHZ with MATLAB framework.

DATASET

To carry out this investigation to differentiate between SARS-COV-2 and Lung carcinoma we used a public data set that included the SARS-COV-2 computed tomography dataset of (Yang et al., 2020), lung carcinoma computed tomography dataset of (Alyasriy et al., 2020), SARS-COV-2 chest radiographs dataset of (Rahman et al., 2020), Lung carcinoma chest radiographs dataset of (Shiraishi et al., 2000; Wang et al., 2017).

We utilized datasets from (Yang et al., 2020) which had 561 images of positive SARS-COV-2 computed tomography scans, (Alyasriy et al., 2020), which comprises of 561 malignant lungs carcinoma cases.

In addition, we utilized 161 Xray images from the SARS-COV-2 X-ray dataset (Rahman et al., 2020), and 161 X-ray images from the lung carcinoma X-ray dataset (Shiraishi et al., 2000; Wang et al., 2017).

We then merge 161 CT images with 161 X-ray images for the SARS-COV-2 and Xray datasets for the CT and X-ray image combination.

This results in lung carcinoma (CT & X-ray) 322 images as well as SARS-COV-2 (CT & X-ray) 322 images.

Table 2 contains the various dataset used and the number of train and test images used.

Table 3 shows the amount of augmented images that were trained and tested.

Figure 1 shows dataset sample of SARS-COV-2 and lung carcinoma CT and X-ray images

Table 2

No Of Image Used.

ILLNESSES	IMAGE DATASETS	IMAGE TRAIN	IMAGE TEST
SARS-COV-2 CT	(Yang et al., 2020)	393	168
LUNG CARCINOMA CT	(Alyasriy et al., 2020)	393	168
SARS-COV-2 X-RAY	(Rahman et al., 2020)	113	48
LUNG CARCINOMA X-RAY	(Shiraishi et al., 2000; Wang et al., 2017)	113	48
SARS-COV-2 (CT & X-RAY)	(Yang et al., 2020), (Rahman et al., 2020)	226	96
LUNGS CARCINOMA (CT & X-RAY)	(Alyasriy et al., 2020), (Shiraishi et al., 2000; Wang et al., 2017)	226	96

We also used augmentation method such as rotation and flipping for each dataset to get the augmented images.

Table 3

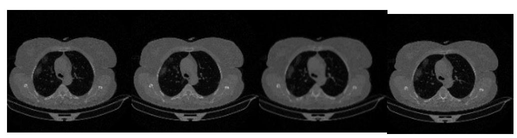
No Of Augmented Images Used.

ILLNESSES	DATASETS	TRAIN	TEST
SARS-COV-2 CT	(Yang et al., 2020)	1965	168
LUNG CARCINOMA CT	(Alyasriy et al., 2020)	1965	168
SARS-COV-2 X-RAY	(Rahman et al., 2020)	565	48

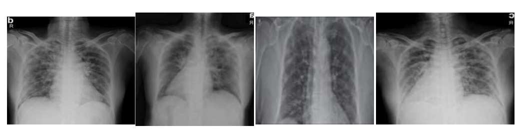
LUNG CARCINOMA X-RAY	(Shiraishi et al., 2000; Wang et al., 2017)	565	48
SARS-COV-2 (CT & X-RAY)	(Yang et al., 2020), (Rahman et al., 2020)	1130	96
LUNG CARCINOMA (CT & X-RAY)	(Alyasriy et al., 2020), (Shiraishi et al., 2000; Wang et al., 2017)	1130	96

Fig 1

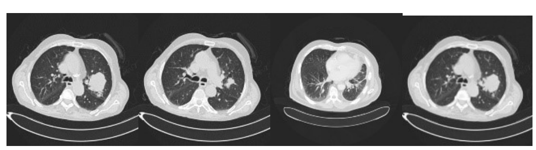
Image Dataset for SARS-COV-2 and Lung Carcinoma.



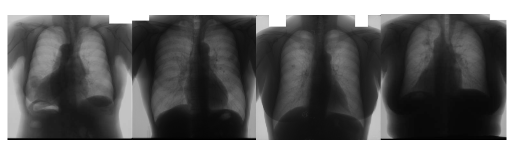
(a) SARS-COV-2 CT images.



(b) SARS-COV-2 X-ray images



(c) Lung carcinoma CT images



(d) Lung carcinoma X-ray images

PERFORMANCE INDICES

Different performance indices were used to determine the outcome of the classifier in relation to the goal to be achieved which were sensitivity, specificity, accuracy and AUC values

SENSITIVITY

The sensitivity was actualized by the percentage of SARS-COV-2 dataset which were rightly identified.

True positive (TP) – represents the no of SARS-COV-2 dataset that were rightly identified

False Positive (FN) – represents no of SARS-COV-2 dataset that were wrongly identified.

C- represents the total number of SARS-COV-2 dataset that were tested

$$\text{SENSITIVITY} = \frac{TP}{c} \text{ x } 100 = \frac{TP}{TP+F} \text{ x } 100\% \tag{1.1}$$

SPECIFICITY

The specificity was actualized by the percentage of lung carcinoma data which were rightly identified.

True Negative (TN) – depict numbers of lung carcinoma dataset that were rightly identified

False Negative (FN) – depict numbers of lung carcinoma dataset that were wrongly identified.

L- represents the total number of lung carcinoma dataset that were tested

$$\text{SPECIFICITY} = \frac{TN}{L} \text{ x } 100 = \frac{TN}{TN+F} \text{ x } 100\% \tag{1.2}$$

ACCURACY

The accuracy of a deep learning classification describes the deep learning model performance across all classes. It can be mathematically expressed as

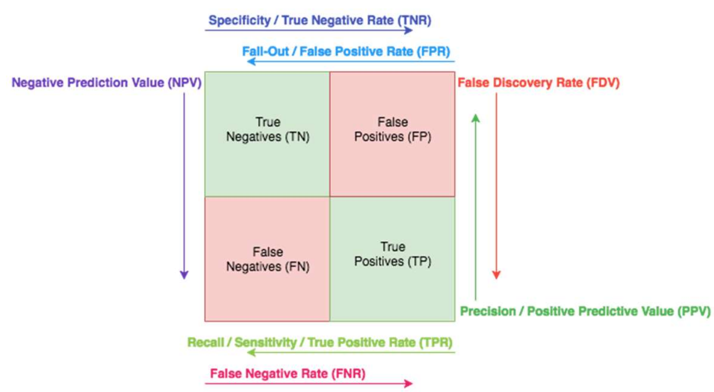
$$\text{ACCURACY} = \frac{TP+TN}{C+L} X\ 100\% \qquad (1.3)$$

CONFUSION MATRIX

Confusion matrix is a table that indicates how well the classification technique performs on a test dataset.

Fig 2

Confusion Matrix Diagram



TRAINING PROGRESS

When training the network in deep learning training progress often serve as a monitor that indicate how fast the network efficiency is been enhanced and whether the network is beginning to over fit.

ROC CURVE

The ROC curve was created by plotting the true positive (TP) against false positive (FP) at different threshold levels. The AUC is used to evaluate how well the classifier performs. For an excellent classifier AUC = 1 for a randomly assigned observation the AUC = 0.5.

SUMMARY

To further carry out our investigation we highlighted the DL methods that will be used and why we are going to use them such has preprocessing, classification, dataset and image augmentation also we indicated the parameters that will be used to pass judgement on the result derived from the experiment such has sensitivity, specificity, accuracy, confusion matrix and ROC curve.

CHAPTER IV

Findings and Discussion

Overview

To achieve the aim of the investigation we used three different scenarios in this experiment. These scenarios contains all prospect for substantiating the result of the experiment.

Scenario 1: SARS-COV-2 and lung carcinoma CT image classification

To discern between SARS-COV-2 and lung carcinoma we carried out classification of SARS-COV-2 and lung carcinoma CT images. A total of 1122 images were utilized, which contained 561 SARS-COV-2 CT images and 561 lung carcinoma CT images.

A combination of 393 images each of SARS-COV-2 and lung carcinoma images were trained 393 and tested 168 each of SARS-COV-2 and lung carcinoma images were tested.

Table 4 contains dataset and train to test ratio of SARS-COV-2 and lung carcinoma CT classification.

Table 4

SARS-COV-2 And Lung Carcinoma CT Images Classification

DATASETS	TRAIN	TEST	TOTAL
SARS-COV-2 CT	393	168	561
LUNG CARCINOMA CT	393	168	561
TOTAL	786	336	1122

In this subsection, we used AlexNet to classify SARS-COV-2 and Lung carcinoma (CT) image datasets. In this regard, we utilized 561 SARS-COV-2 CT images with 561 lung carcinoma CT images for training and 168 SARS-COV-2 CT images with 168 lung carcinoma CT images to examine how well the system functioned. The dataset was gotten from (Yang et al., 2020) and (Alyasriy et al., 2020)

Following training and testing, the following results were obtained: sensitivity of 1, specificity of 1, accuracy of 1, and AUC value of 1.

Table 5 Presents the AlexNet experimental outcome in terms of accuracy, sensitivity, specificity, and AUC

Figure 3 Illustrates SARS-COV-2 and lung carcinoma CT classification confusion matrix

Figure 4 Illustrates the SARS-COV-2 ROC curve and lung carcinoma CT classification

Figure 5 Shows the training progress for the SARS-COV-2 and lung carcinoma CT classification.

Table 5

Results Of SARS-COV-2 And Lung Carcinoma CT Image Classification.

	ACCURACY	SENSITIVITY	SPECIFICITY	AUC
RESULTS	1	1	1	1

Fig 3

Confusion Matrix Of SARS-COV-2 And Lung Carcinoma CT Classification Result

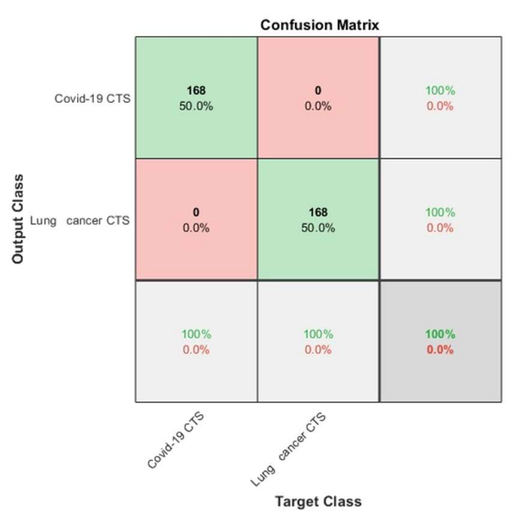


Fig 4

ROC Curve Of SARS-COV-2 And Lung Carcinoma CT Classification Result

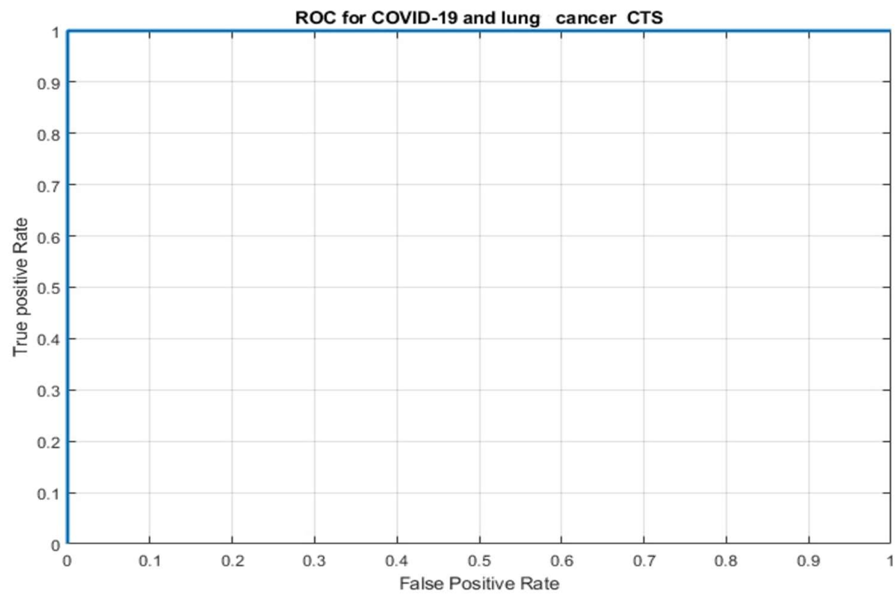
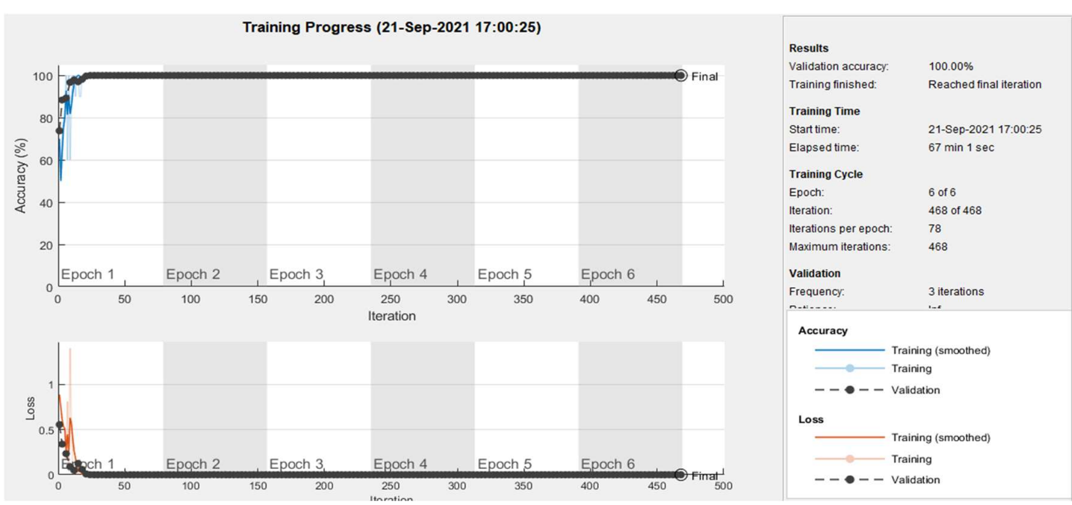


Fig 5

Training Progress Diagram For SARS-COV-2 And Lung Carcinoma CT Classification



Scenario 2: SARS-COV-2 and lung carcinoma X-ray image classification

In this scenario chest X-ray images of SARS-COV-2 and lung carcinoma was used for classification

Table 6

SARS-COV-2 And Carcinoma X-ray Images Classification

Illnesses	Train	Test	Total
SARS-COV-2 (Xray)	113	48	161
Lung carcinoma (Xray)	113	48	161
Total	226	96	322

Table 6 Contains dataset and train to test ratio of SARS-COV-2 and lung carcinoma X-ray classification.

To differentiate between SARS-COV-2 and lung carcinoma we carried classification of SARS-COV-2 and lung carcinoma x-ray images. In this regard 113 chest Xray images each were trained for both SARS-COV-2 and lung Carcinoma and also 48 chest X-ray images were tested. The dataset used were (Rahman et al., 2020) and (Shiraishi et al., 2000; Wang et al., 2017).

The results were as follows: sensitivity 0.89, specificity 1, accuracy 0.94, and AUC 0.99.

Table 7 Highlights the AlexNet experiment results for SARS-COV-2 and lung carcinoma X-ray classifications utilizing accuracy, sensitivity, specificity, and AUC.

Figure 6 Illustrates the confusion matrix of SARS-COV-2 and lung carcinoma X-ray classification.

Figure 7 Illustrates the ROC curve for SARS-COV-2 and lung carcinoma X-ray classification

Figure 8 Demonstrates the training progress graph for SARS-COV-2 and lung carcinoma X-ray classification.

Table 7

The Classification Result Of SARS-COV-2 And Lung Carcinoma X-ray Images.

	Accuracy	Sensitivity	Specificity	AUC
Results	0.94	0.89	1	0.99

Fig 6

Confusion Matrix Of SARS COV-2 And Lung Carcinoma X-ray Classification Result

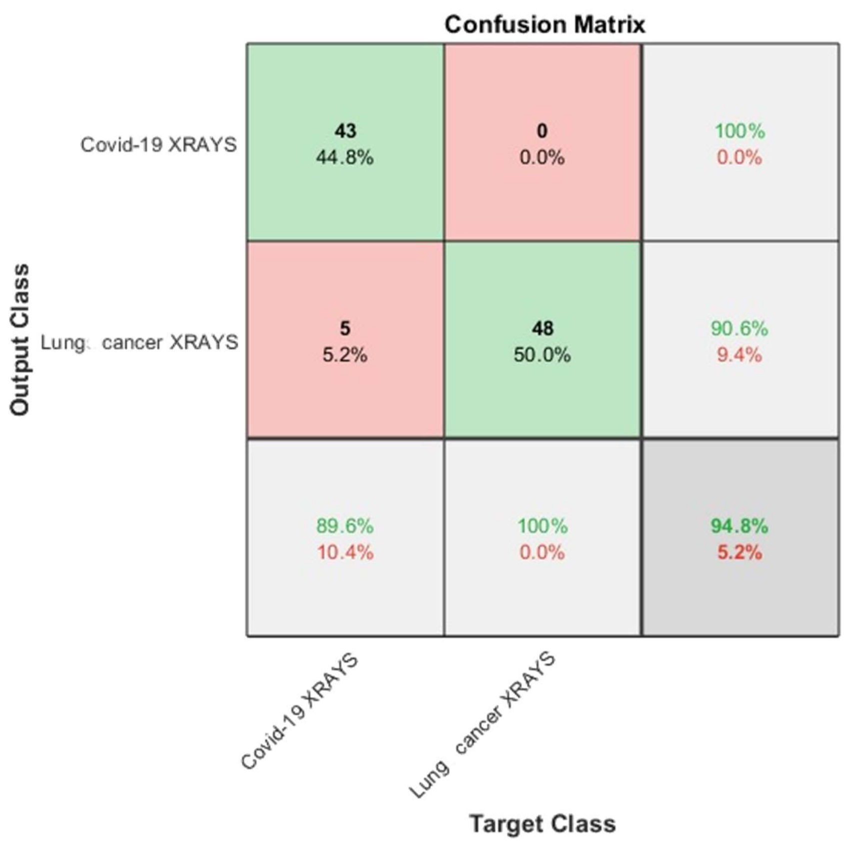


Fig 7

ROC Curve Of SARS-COV-2 And Lung Carcinoma X-ray Classification Result

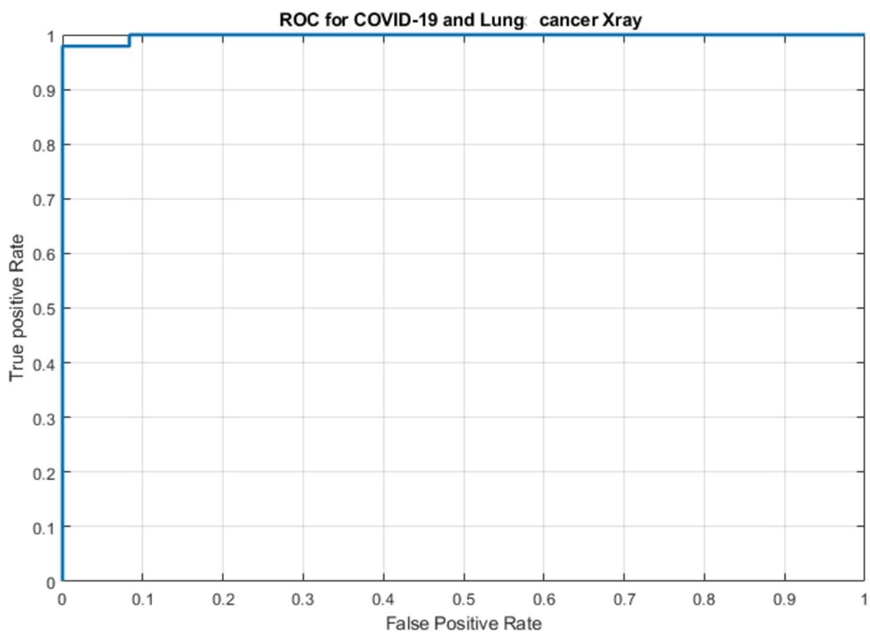
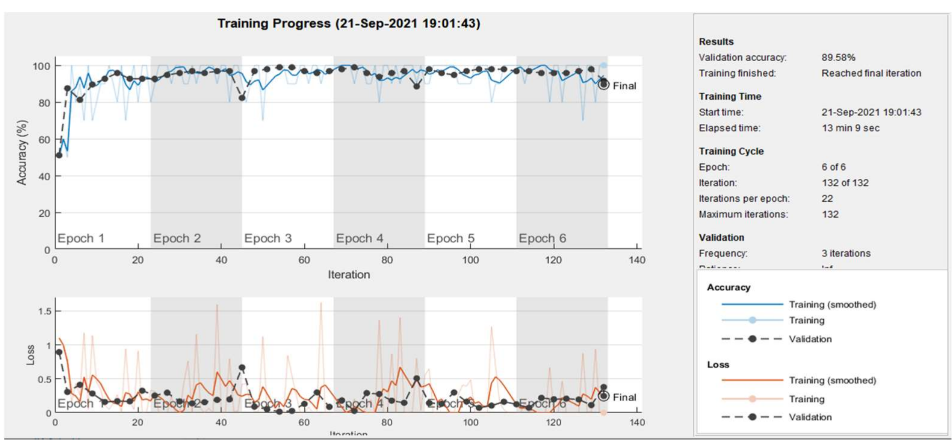


Fig 8

Training Progress Graph SARS-COV-2 And Lung Carcinoma X-ray Classification



Scenario 3: SARS-COV-2 and lung carcinoma CT and X-ray image classification

Chest CT images and X-ray images of both SARS-COV-2 and lung carcinoma were mixed together.

Table 8 contains dataset and train to test ratio of SARS-COV-2 and lung carcinoma CT & X-ray classification.

Table 8

SARS-COV-2 And Lungs Carcinoma CT & X-ray Images Classification

Dataset	Train	Test	Total
SARS-COV-2 (CT & Xray)	226	96	322
Lung carcinoma (CT & Xray)	226	96	322
Total	452	192	644

Using AlexNet, we classified SARS-COV-2 and lung carcinoma chest CT and X-ray images merged together. In this regard, 226 chest CT images with SARS-COV-2 and lung carcinoma were trained, and 96 chest CT images with SARS-COV-2 and lung carcinoma were evaluated. The dataset used were (Yang et al., 2020), (Alyasriy et al., 2020), (Rahman et al., 2020), and (Shiraishi et al., 2000; Wang et al., 2017).

The obtained results was sensitivity of 1, specificity of 0.91, accuracy of 0.95, and AUC of 0.99.

Table 9 Highlights the AlexNet experiment results for SARS-COV-2 and lung carcinoma CT & Xray image classification utilizing accuracy, sensitivity, specificity, and AUC.

Figure 9 Illustrates the SARS-COV-2 and lung carcinoma mixed CT & X-ray classification confusion matrix.

Figure 10 Illustrates the ROC curve for SARS-COV-2 and lung carcinoma combined CT & X-ray classification

Figure 11 Demonstrates the training progress graph for SARS-COV-2 and lung carcinoma merged CT and Xray classification.

Table 9

SARS-COV-2 And Lung Carcinoma CT & X-ray Images Classification Result

	Accuracy	Sensitivity	Specificity	AUC
Results	0.95	1	0.91	0.99

Fig 9

Confusion Matrix Of SARS-COV-2 And Lung Carcinoma CT & X-ray Classification Result

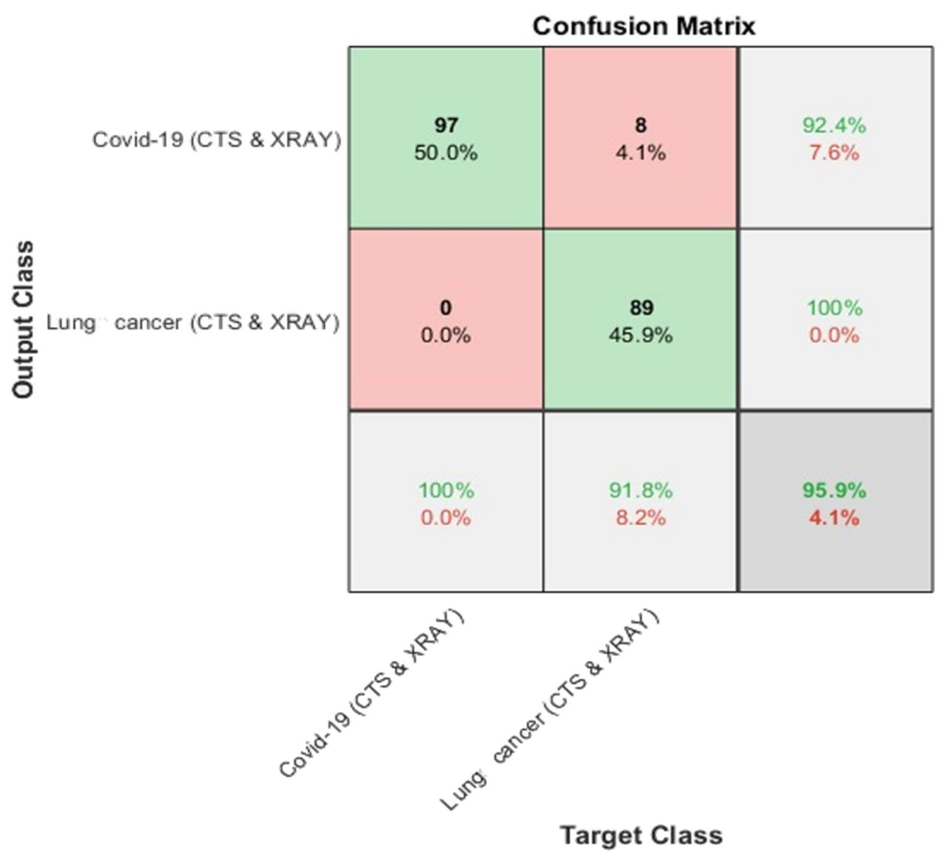


Fig 10

ROC Curve Of SARS-COV-2 And Lung Carcinoma CT & X-ray Classification Result

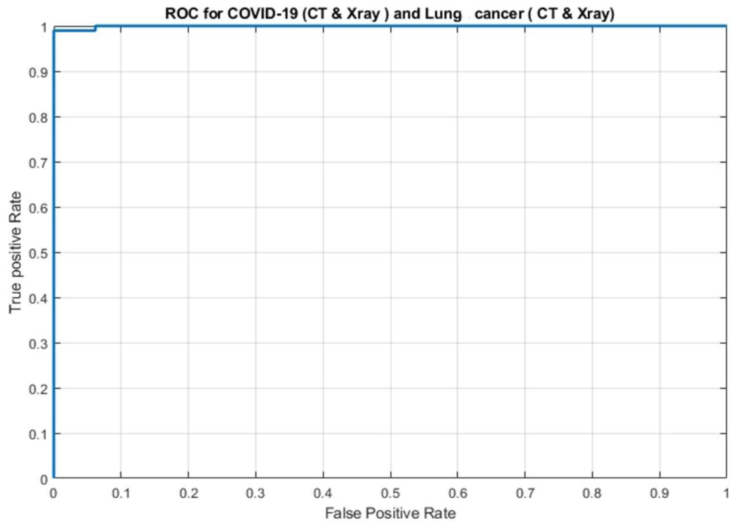


Fig 11

Training Progress Graph SARS-COV-2 And Lung Carcinoma Mixed CT & X-ray Classification

Summary

In this chapter detailed explanation of experiment carried out was discussed which were spited into three scenarios which were (i) distinguishing SARS-COV-2 from Lung carcinoma CT (ii) distinguishing SARS-COV-2 from Lung carcinoma X-ray (iii) distinguishing SARS-COV-2 CT & X-ray from Lung carcinoma CT & X-ray. Figures and table were used to show and explain the result.

CHAPTER V

Discussion

In this work we were able to investigate how well deep learning performs on medical images especially in detecting and identifying SARS-COV-2 and lung carcinoma chest CT and chest radiograph images, as well as the capacity to differentiate between both medical images. Three different scenarios were performed, the first was SARS-COV-2 and lung carcinoma in which we trained 392 CT chest images and test 168 chest CT images. Also, for the second we 113 chest CT mixed with Xray images were trained and 48 chest CT mixed with Xray images were tested. Finally, we trained 226 SARS-COV-2 and lung carcinoma chest Xray images and examined 96 chest Xray images for the third. The outcome of the DL classification are presented in chapter four. We were able to conclude from the results that deep learning architecture, specifically AlexNet, was able to differentiate between lung carcinoma and SARS-COV-2, with classification of SARS-COV-2 and lung carcinoma CT providing the best overall performance and no significant improvement to the classification as a result of the multimodal classification.

CHAPTER VI

Conclusion

Medical imaging with deep learning has helped to improve diagnosis of disease in many of its application overtime with good accuracies in its detection abilities and capabilities. Deep learning was used in SARS-COV-2 and lung carcinoma medical images of both CT and Xray's to investigate deep learning performs on images with comparable image structure. SARS-COV-2 and lung carcinoma have similar image structure for both different medical imaging. During the experiment, we utilized AlexNet, a DL architecture, to identify SARS-COV-2 and lung carcinoma CT and Xray images in three distinct circumstances which were SARS-COV-2 and lung carcinoma classification using CT images, SARS-COV-2 and lung carcinoma classification using both CT and Xray images merged together, and SARS-COV-2 and lung carcinoma classification using Xray images. The classification of SARS-COV-2 and lung carcinoma using CT scans worked well, with a 100% accuracy and an AUC value of 1 and classification of SARS-COV-2 and lung carcinoma using Xray images with accuracy of 94% and an AUC value of 0.99. This study found that deep learning architectures like as AlexNet can distinguish SARS-COV-2 images from lung carcinoma images using CT and Xray medical imaging, but that multimodal classifications had no significant improvement on the classification process. The result further suggest that DL can be applied to healthcare system especially the area of diagnoses and detection of disease like SARS-COV-2 and Lung carcinoma and could has well distinguish between diseases like SARS-COV-2 and Lung carcinoma.

Recommendation

To further improve the outcome of this experiment there is need for availability of Dataset because of the role datasets plays in image classification. Also there is need for consideration of other medical imaging procedures such as MRI images and Ultrasound. This will help broaden the application deep learning towards medical diagnosis.

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