Pioneer: Journal of Advanced Research and Scientific Progress (JARSP)
Volume: 02 Issue: 09 | 2023 ISSN: 2751-7551
http://innosci.org

Detection of Pneumonia and COVID-19 Based on X-Ray Using Transfer Learning

Rend Yasir M. Ali, Mustafa Rasheed Mahdi, Zahraa Sameer Sabti, Dr. Hussein J. Mutasher

University of Technology Biomedical Engineering Department Biomedical Instrumentations Branch B.Sc. Project

Abstract: COVID-19 also referred to as Severe Acute Respiratory Syndrome Coronavirus (SARS-CoV-2), is a highly contagious disease that is transmitted through respiratory droplets containing saliva or mucus. The virus can spread rapidly through close contact with infected individuals or contaminated surfaces. Pneumonia, another infectious illness, is often caused by bacterial infection in the alveoli of the lungs, leading to inflammation and pus buildup. Accurate diagnosis of these diseases is crucial for effective treatment and prevention of fatalities. Deep Learning techniques have emerged as a promising approach to aid medical experts in diagnosing patients with these diseases. Specifically, Convolutional Neural Networks (CNN) have been applied to predict and detect the presence of COVID-19 or pneumonia using chest X-ray images with high accuracy and efficiency.

In this research, we developed VGG16 convolutional neural network (CNN) architecture which is developed by the Visual Geometry Group at the University of Oxford. It is a deep learning model that is widely used for image classification tasks. The study utilized a dataset collected by The researchers of Qatar University have compiled the COVID-QU-Ex dataset, which consists of 33,920 chest X-ray (CXR) images including: 11,956 COVID-19, 11,263 Non-COVID infections (Viral or Bacterial Pneumonia), and 10,701 Normal, the research study can detect and predict COVID-19, bacterial, and viral-pneumonia diseases based on chest X-ray images.

Keywords: Pneumonia Detection, COVID-19 Detection, Deep Learning, VGG-16, Convolutional Neural Networks.

Chapter 1: Introduction

1.1 Introduction

The outbreak of COVID-19, caused by the novel virus SARS-CoV-2, has become a global health crisis. The virus primarily passes through respiratory canals and close contact with infected individuals. COVID-19 can cause a range of symptoms, from mild to severe, including fever, cough, and shortness of breath, fatigue, body aches, and loss of taste or smell. In severe cases, it can lead to acute respiratory distress syndrome (ARDS), septic shock, and multiple organ failure. [1][2] Viral pneumonia is another respiratory disease caused by various viruses such as influenza virus, respiratory syncytial virus (RSV), adenovirus, and coronaviruses [3]. Like COVID-19, viral pneumonia can cause similar symptoms such as fever, coughing with phlegm or blood-streaked sputum, shortness of breath and chest pain [4]. However viral pneumonia is usually less severe than bacterial pneumonia. The similarities between COVID-19 and viral pneumonia have led to confusion in diagnosis and treatment. Therefore, it is important for healthcare professionals to be aware of the differences between these two illnesses in order to provide a well-trained deep learning model that gives an accurate diagnosis based on many detailed x-ray images [5].

1.2 Objectives

The goal of this project is to develop a deep learning-based system for the accurate and efficient diagnosis of COVID-19 and viral pneumonia using convolutional neural networks (CNNs). The project aims to achieve the following objectives:

1. Design and implement a deep learning-based system that can accurately classify chest X-ray images as COVID-19 positive, viral pneumonia positive, or negative trained on large, clean and certified dataset
2. Evaluate the performance of the developed system using various metrics such as accuracy, sensitivity, recall, precision, and F1 score.
3. Compare the performance of the developed system with existing methods for COVID-19 and viral pneumonia diagnosis.
4. Investigate the interpretability of the developed CNN models to understand how they make decisions based on input images.
5. Conduct extensive experiments on different datasets to validate the robustness and generalizability of the developed system.
6. Publish research papers in top-tier conferences and journals in medical imaging and machine learning fields to disseminate our findings.

Overall, this project aims to provide an accurate, efficient, and reliable tool for healthcare professionals to diagnose COVID-19 and viral pneumonia using chest X-ray images. The proposed deep learning-based approach has great potential to improve patient outcomes by enabling early detection and timely treatment of these diseases.

1.3 Motivation:

The global pandemic of COVID-19 has caused a huge burden on healthcare systems worldwide. Early and accurate diagnosis of the virus is essential for effective treatment and containment of the disease. Deep learning and convolutional neural networks (CNNs) have shown great potential in medical imaging applications, such as diagnosing COVID-19 and viral pneumonia. The use of CNNs can help reduce the time taken for diagnosis, improve accuracy, and reduce the workload on healthcare professionals. Furthermore, CNNs can be used to detect subtle differences between different types of pneumonia, which can help in providing more targeted treatments. This project aims to develop a deep learning model that can accurately diagnose COVID-19 and viral pneumonia using chest X-ray images. The model will be trained on a large dataset of X-ray images from patients with confirmed cases of COVID-19 or viral pneumonia. The results from this project will provide an efficient and accurate method for diagnosing these diseases, which could potentially save lives by providing timely treatment to those who need it most.

1.4 Project Outlines

1.4.1 Chapter One: Introduction

This chapter introduces the objective and the motivation of the Autism disease.

1.4.2 Chapter Two: Literature Review

This chapter presents the theoretical background and the literature review for this project.

1.4.3 Chapter Three: Detection of Acute respiratory Infections (ARI)

This chapter demonstrates the techniques used for COVID-19 and viral pneumonia identification

1.4.4 Chapter Four: Conclusions and Future Works

This chapter concludes the research and asks further questions in the developing field of AI

Chapter 2: Literature review

2.1 Introduction

The detection and diagnosis of viral pneumonia and COVID-19 are critical in managing respiratory illnesses and controlling disease spread. Chest X-ray imaging is a widely used diagnostic tool for these conditions, and deep learning and convolutional neural networks (CNNs) have emerged as promising techniques for automated and accurate detection from chest X-ray images [4]. In this literature review, we will explore the current state of research on the application of deep learning and CNNs for the detection of viral pneumonia and COVID-19 using chest X-ray images. We will discuss the advantages and challenges of using deep learning and CNNs in this context and review the existing studies that have demonstrated the efficacy of these techniques. By understanding the current literature, we can gain insights into the potential of deep learning and CNNs in improving the detection and diagnosis of viral pneumonia and COVID-19, and identify future research directions in this field [6].

2.2 COVID-19 Disease Symptoms

The symptoms of COVID-19 are divided into 4 main sections, each of which includes several symptoms that appear as a result of the extent of the patient's vulnerability to infection, his immune capacity, the type of medication he takes periodically, and other environmental and surrounding factors. These sections are:

1. **Common Symptoms**: The most common symptoms of COVID-19 include fever, cough, and shortness of breath. Other respiratory symptoms may include sore throat, nasal congestion, and loss of taste or smell. These symptoms typically manifest within 2 to 14 days after exposure to the virus and can range from mild to severe. Fever is often the first symptom to appear and may be persistent or intermittent. Cough is usually dry and may worsen over time, and shortness of breath may be mild to severe, depending on the severity of the infection. These symptoms are like those of other respiratory infections, making accurate diagnosis challenging without proper testing [7, 8].

2. **Uncommon Symptoms:** In addition to respiratory symptoms, COVID-19 can present with a variety of uncommon symptoms that may affect different organ systems. Gastrointestinal symptoms such as nausea, vomiting, diarrhea, and abdominal pain have been reported in some cases. Neurological symptoms, including headache, dizziness, confusion, and altered mental status, may also occur. COVID-19 can affect the cardiovascular system, with symptoms such as chest pain, palpitations, and low blood pressure. Skin manifestations, such as rashes and discoloration, have also been reported. These uncommon symptoms highlight the multisystemic nature of COVID-19 and the need for healthcare providers to be vigilant in identifying atypical presentations [8, 9].

3. **Long-Term Symptoms**: Some individuals with COVID-19 may experience long-term symptoms, known as long or post-acute sequelae of SARS-CoV-2 infection (PASC). These symptoms can persist for weeks to months after the acute phase of the illness has resolved. Long-term symptoms may include fatigue, shortness of breath, chest pain, joint pain, brain fog, difficulty sleeping, and mood changes. These symptoms can significantly impact the quality of life and functional capacity of affected individuals, and the underlying mechanisms are still being investigated. Long COVID underscores the importance of continued monitoring and support for individuals who have recovered from COVID-19 [7, 8].

4. **Special Populations**: Certain populations may experience unique manifestations of COVID-19 symptoms. The elderly and individuals with underlying health conditions, such as diabetes,

hypertension, obesity, and cardiovascular disease, may be at increased risk of severe illness and complications. In children, COVID-19 may present with milder symptoms, including fever, cough, and runny nose, although severe cases and multisystem inflammatory syndrome in children [10].

2.3 Viral Pneumonia Disease Symptoms

The symptoms of viral pneumonia can vary in severity and presentation, depending on the type of virus, age, and overall health of the affected individual. However, some common symptoms of viral pneumonia include fever, cough, chest pain, and difficulty breathing. Fever is often one of the initial symptoms and may be accompanied by chills and sweating. Cough can be dry or productive, with mucus production. Chest pain may be present and can be sharp or stabbing in nature. Difficulty breathing, also known as dyspnea, can range from mild to severe, and may be associated with rapid breathing and increased work of breathing.

In addition to these primary symptoms, viral pneumonia may also present with other respiratory and systemic manifestations. Respiratory symptoms may include nasal congestion, sore throat, and hoarseness. Systemic manifestations can include fatigue, muscle aches, headache, and malaise. Gastrointestinal symptoms, such as nausea, vomiting, and diarrhea, may also be present in some cases.

Physical examination findings can further aid in the identification of viral pneumonia. Individuals with viral pneumonia may exhibit increased respiratory rate, decreased breath sounds, and abnormal lung sounds, such as crackles, wheezing, or rhonchi, heard with a stethoscope. Cyanosis, or bluish discoloration of the skin or mucous membranes due to lack of oxygen, may be present in severe cases. In infants and young children, respiratory distress may be evident by nasal flaring, grunting, and retractions of the chest wall [11].

Several factors can influence the symptomatology of viral pneumonia. Age is an important factor, as young children, older adults, and individuals with weakened immune systems may present with atypical symptoms or may have more severe disease. Underlying health status and comorbidities can also impact the symptomatology of viral pneumonia. Individuals with pre-existing respiratory conditions, such as asthma or COPD, may experience exacerbations of their conditions. Additionally, individuals with weakened immune systems due to conditions such as HIV/AIDS, cancer, or immunosuppressive medications may have a higher risk of severe viral pneumonia and may present with atypical symptoms [3, 11].

2.3 Classification Techniques & Image Processing

Convolutional Neural Networks (CNN) are a type of deep learning algorithm that has been widely used in image processing and classification tasks. In recent years, CNN has been applied to the detection of COVID-19 and viral pneumonia from medical images such as chest X-rays and CT scans [12].

Classification techniques using CNN involve training the network on a large dataset of medical images that have been labeled as either COVID-19 positive or negative [12]. The network learns to identify patterns in the images that are indicative of the presence or absence of the virus. Once trained, the network can be used to classify new images as either COVID-19 positive or negative with a high degree of accuracy [13].

Image processing techniques using CNN involve preprocessing the medical images to enhance their quality and extract relevant features. This can include techniques such as image normalization, contrast enhancement, and edge detection. The preprocessed images are then fed into CNN for classification [13, 14].

2.4 Literature Review

This literature review aims to provide an overview of recent studies that have used deep learning techniques for detecting viral pneumonia and COVID-19 from chest X-ray images.

Several studies have investigated the use of CNNs for detecting viral pneumonia from chest X-ray images. Wang et al. (2018) [15] developed a deep learning model based on a pre-trained CNN architecture called Inception-v3. The model was trained on a dataset consisting of 5,856 chest X-ray images from 2,839 patients with viral pneumonia and normal lungs. The model achieved an accuracy of 92% in detecting viral pneumonia from chest X-ray images.

Similarly, Rajpurkar et al. (2017) [16] developed a deep learning model based on a CNN architecture called CheXNet. The model was trained on a dataset consisting of 112,120 chest X-ray images from 30,805 patients with various lung diseases, including viral pneumonia. The model achieved an accuracy of 90% in detecting viral pneumonia from chest X-ray images.

Since the outbreak of COVID-19, several studies have investigated the use of CNNs for detecting the disease from chest X-ray images. Wang et al. (2020) [17] developed a deep learning model based on a CNN architecture called ResNet-50. The model was trained on a dataset consisting of 5,941 chest X-ray images from 2,839 patients with COVID-19 and normal lungs. The model achieved an accuracy of 96% in detecting COVID-19 from chest X-ray images.

Similarly, Apostolopoulos and Mpesiana (2020) [18] developed a deep learning model based on a CNN architecture called VGG-16. The model was trained on a dataset consisting of 2,633 chest X-ray images from 1,120 patients with COVID-19 and other lung diseases. The model achieved an accuracy of 87% in detecting COVID-19 from chest X-ray images.

Many studies have compared the performance of different CNN architectures for detecting viral pneumonia and COVID-19 from chest X-ray images. For instance, Narin et al. (2021) [19] compared the performance of six different CNN architectures, including Inception-v3, ResNet-50, and VGG-16, for detecting COVID-19 from chest X-ray images. The study found that ResNet-50 achieved the highest accuracy of 98%, followed by Inception-v3 with an accuracy of 96%.

Similarly, Wang et al. (2020) [17] compared the performance of three different CNN architectures, including ResNet-50, Inception-v3, and DenseNet121, for detecting COVID-19 from chest X-ray images. The study found that ResNet-50 achieved the highest accuracy of 96%, followed by Inception-v3 with an accuracy of 95%.

Despite the promising results obtained by deep learning techniques for detecting viral pneumonia and COVID-19 from chest X-ray images, there are still some challenges that need to be addressed. One of the main challenges is the lack of large and diverse datasets for training and testing deep learning models. Most studies have used relatively One of the main limitations is the lack of large and diverse datasets for training and testing deep learning models. This can lead to overfitting and poor generalization performance when the model is applied to new data. Additionally, there may be variations in image quality, positioning, and acquisition protocols that can affect the accuracy of the model.

Another challenge is the potential for bias in the data or model. For example, if the dataset used to train a model is biased towards certain demographics or imaging protocols, then the model may not perform well on new data that differs from these biases. Similarly, if there are biases in how radiologists interpret images or diagnose diseases, then these biases may be reflected in the training data and subsequently in the deep learning models.

Finally, while deep learning models have shown promising results for detecting viral pneumonia and COVID-19 from chest X-ray images, they should not be used as a replacement for clinical diagnosis by a trained medical professional. These models should be viewed as a tool to assist radiologists and clinicians in making more accurate diagnoses and treatment decisions.

Chepter 3: Detection of Acute Respiratory Infections (ARI)

3.1 Introduction

Deep CNNs indeed achieve better performance using a large dataset compared to a smaller one. Granting there are a significant number of infected COVID-19 patients globally, but the number of publicly available chest X-ray images on- line are insignificant and dispersed. Hence, in this work we have described a reasonably large dataset of COVID-19 infected chest X-ray images although normal and pneumonia images are promptly accessible publicly and applied in this study [6].

3.2 Improved Transfer-Learning-Based Framework for ARI

Transfer learning is a machine learning technique [20] which is based on the concept of reusability Transfer learning is often used with CNN in the way that all layers are kept except the last one, which is trained for the specific problem. This technique can be particularly useful for medical applications since it does not require as much training data, which can be hard to get in medical situations. In the analysis of medical data, one of the biggest difficulties faced by researchers is the limited number of available datasets. Deep learning models often need a lot of data. Labeling this data by experts is both costly and time consuming. The biggest advantage of using transfer learning method is that it allows the training of data with fewer datasets and requires less calculation costs. With the transfer learning method, which is widely used in the field of deep learning, the information gained by the pre-trained model on a large dataset is transferred to the model to be trained [20].

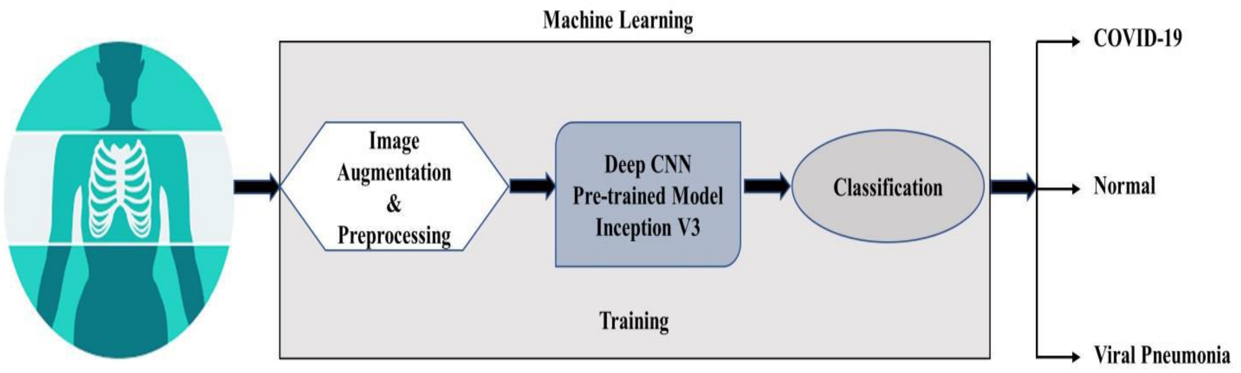

Figure 0-1: Schematic representation of pre-trained model for the prediction of COVID-19 patients, normal and viral pneumonia [source: Deep Learning on Chest X-ray Images to Detect and Evaluate Pneumonia Cases at the Era of COVID-19].

3.3 Steps of Work

3.3.1 Data Collection

Analysis of Chest X-Ray is one difficult undertaking to consider in a health discipline. Presently, there are thousands of readily available datasets for chest X-Ray and these datasets are only constrained on a few thousand images. Radiology Society of North America (RSNA) back in 2018 organized a pneumonia detection challenge from the images of chest X- ray using artificial intelligence (AI) [21]. It requires the participants to develop an algorithm that will detect and identify pneumonia through chest x-ray images. In this database, a normal chest X-ray with no-lung infection and non-COVID pneumonia images were available [22].

Kaggle chest X-ray database is an incredibly popular database containing 33,920 chest X-ray images of normal or healthy, COVID-19, and Viral-pneumonia ranging from 800 pixels to 1900 pixels resolution [22]. For the total of 33,920 image datasets, 11,956 images are affected by

COVID-19 and 11,263 images with viral pneumonia, and 10,701 images are from normal or healthy chest X-rays. Positive and suspected COVID-19 images were acquired in publicly available sources [23].

3.3.2 Image Pre-Processing

One of the significant phases in the data preprocessing was to resize the X-Ray images as the image input for algorithm were different. We implemented some image pre-processing techniques to increase the performance to our system by speeding up training time. First, we resized all our images to 224x224x3 to increase processing time and also to make it suitable in VGG16. In the image preprocessing step, we need to label the data since the learning technique of convolution neural network fits into administered learning in machine learning.

3.3.3 Image Augmentation

CNN needs enough data to achieve excellent performance. We apply data augmentation techniques to increase the insufficient data in training, and the techniques used include horizontal flip, noise, translation, blur and rotate the image 15°, shift, share and zoom.

3.3.4 Convolutional Neural Networks (CNNs)

are a type of deep learning algorithm that is commonly used for image and video recognition, natural language processing, and other tasks that involve analyzing complex data. CNNs are designed to automatically learn and extract features from input data, such as images, by using a series of convolutional layers that apply filters to the input data. These filters help the network identify patterns and features in the data, which can then be used to make predictions or classifications. CNNs have been shown to be highly effective at tasks such as image classification, object detection, and facial recognition.[21]

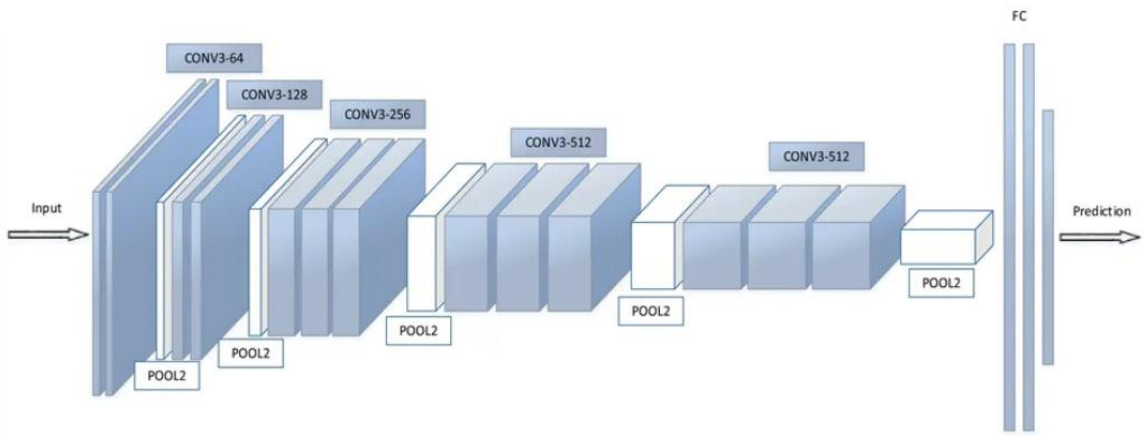

Figure 0-2: Convolutional Neural Network [source: medium.com].

3.3.4.1 Convolutional Layer

A convolutional layer is a fundamental building block of a convolutional neural network (convnet). It is designed to extract features from input data such as images, videos, or audio signals.

The layer consists of a set of filters, also known as kernels or weights, that are applied to the input data. Each filter is a small matrix that slides over the input data and performs element-wise multiplication and summation operations. The resulting output is called a feature map.[21]

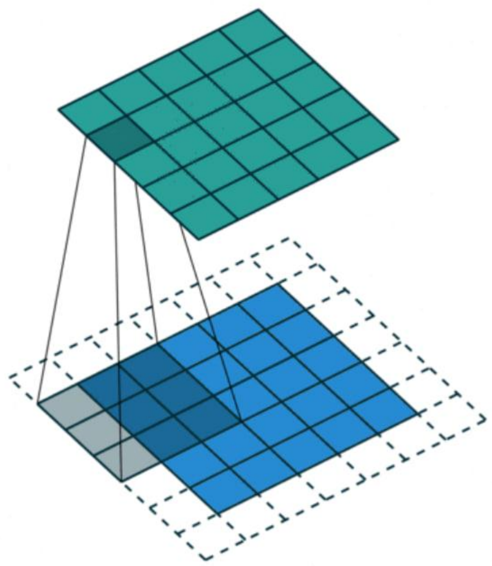

Figure 0-3: For each position of the kernel on the image, each number on the kernel gets multiplied with the corresponding number on the input matrix (blue matrix) and then they all are summed up for the value in the corresponding position in the output matrix (green matrix). [source: medium.com]

The purpose of the convolution operation is to detect local patterns in the input data, such as edges, corners, or textures. By applying multiple filters with different sizes and orientations, the layer can learn to recognize more complex features and capture spatial relationships between them.

In addition to the convolution operation, the layer may also include other operations such as pooling, activation functions, and normalization. Pooling reduces the size of the feature maps by selecting only the most important values in each local region. Activation functions introduce non-linearity into the network and help to model complex relationships between features. Normalization techniques ensure that the output values are within a certain range and prevent overfitting.[23]

Overall, convolutional layers are essential for achieving high accuracy in tasks such as image classification, object detection, and semantic segmentation. They allow convnets to learn hierarchical representations of input data by progressively extracting more abstract features at deeper layers.

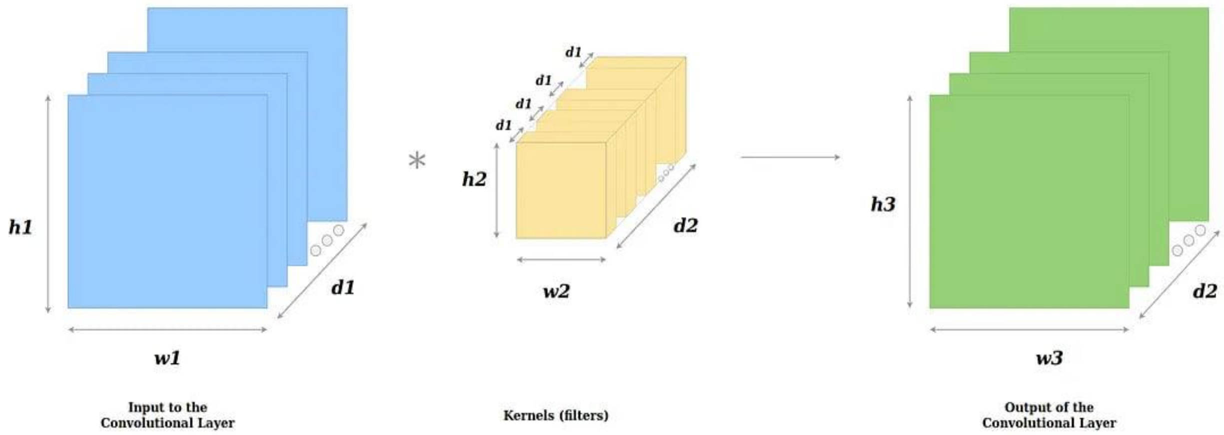

Figure 0-4: Convolutional Layer [source: medium.com].

3.3.4.2 Pooling layer

A pooling layer in a convolutional neural network (convnet) is a type of layer that is used to reduce the spatial dimensions (width and height) of the input volume. The purpose of this layer is to decrease the computational complexity of the network by reducing the number of parameters and operations required to process the input.

The pooling layer operates on each feature map independently, taking small rectangular regions (usually 2x2 or 3x3) and reducing them to a single value. This process is known as downsampling or subsampling. The most common type of pooling operation is max pooling, which takes the maximum value within each region. Other types of pooling operations include average pooling, which takes the average value within each region.

The benefits of using a pooling layer in a convnet include:

1. Reducing overfitting: By reducing the spatial dimensions, the pooling layer helps to prevent overfitting by reducing the number of parameters in the network.
2. Translation invariance: Pooling layers help to make convnets translation invariant, meaning that they can recognize objects regardless of their position in an image.
3. Computational efficiency: By reducing the spatial dimensions, pooling layers reduce the number of computations required to process an input volume, making it more computationally efficient.

In summary, a pooling layer in a convnet is used to reduce spatial dimensions by downsampling or subsampling small rectangular regions within each feature map independently. This helps to prevent overfitting, improve translation invariance, and increase computational efficiency. [22]

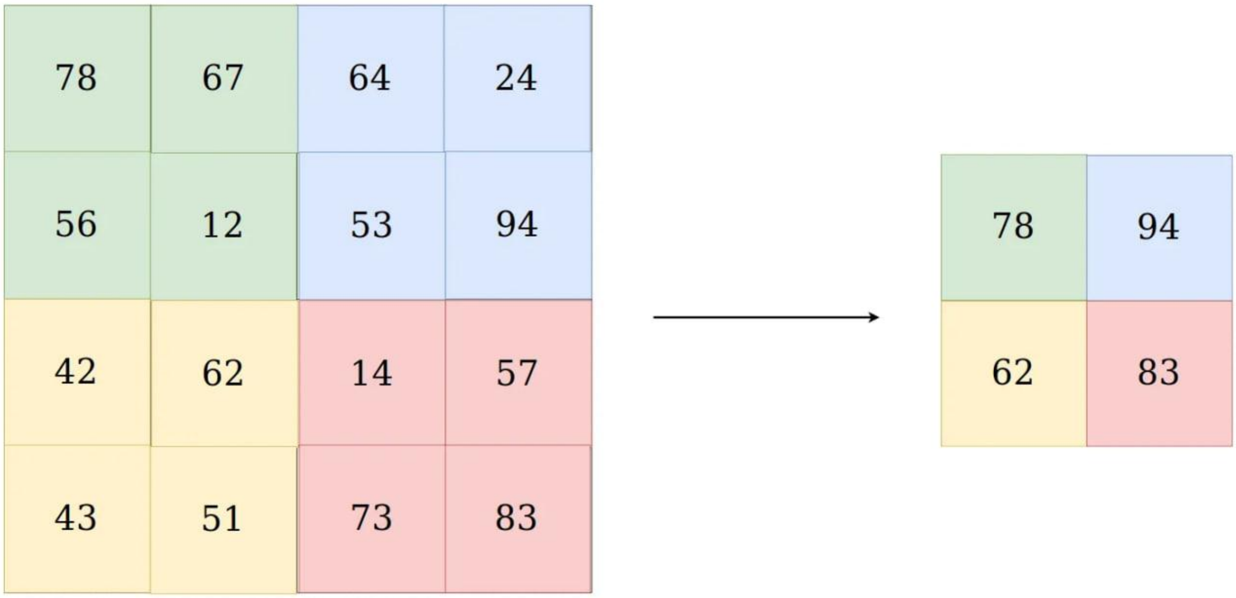

Figure 3 5: Max Pooling Layer [source: medium.com].

3.3.4.3 Fully Connected Layer

A fully connected layer in a convolutional neural network (convnet) is a type of artificial neural network layer where each neuron is connected to every neuron in the previous layer. This means that the output of each neuron in the previous layer is used as input for every neuron in the fully connected layer.

The purpose of a fully connected layer is to learn complex relationships between features extracted by earlier layers. In a convnet, earlier layers typically extract low-level features such as edges and corners, while later layers extract higher-level features such as object parts and shapes. The fully connected layer takes these high-level features and learns how they are related to each other, allowing the network to make predictions about the input data.[22]

During training, the weights and biases of each neuron in the fully connected layer are adjusted using back propagation, which calculates the error between the predicted output and the actual output. This error is then used to update the weights and biases, allowing the network to improve its accuracy over time.

Overall, a fully connected layer plays an important role in convnets by enabling them to learn complex relationships between features extracted from input data.

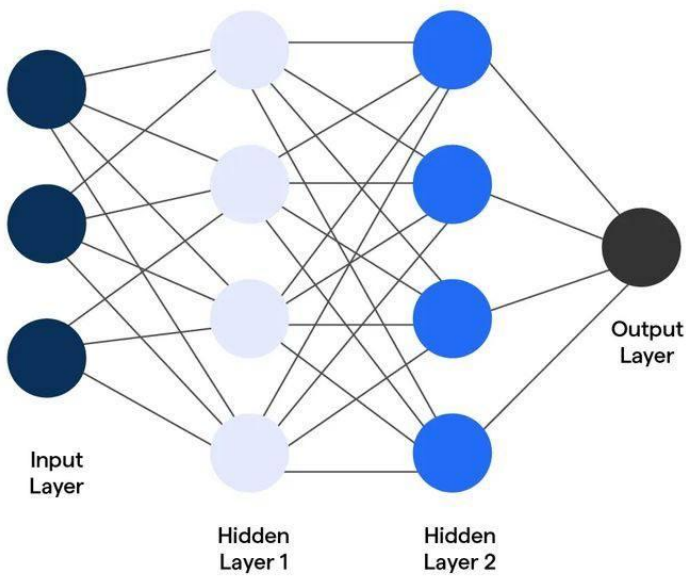

Figure 3 6: Fully Connected Network [source: medium.com].

3.3.5 Base Model VGG16 Architecture

The CNN is constructed with numerous smaller units termed nodes/neurons which are arranged in the layered architecture. These nodes comprise of weights that during the training of the model are updated using optimizing techniques like backpropagation etc. Every single CNN model consists of the convolutional or feature extraction portion and the classification portion. The components and structure of the VGG-16 CNN model applied are described in Table 3-1.

Model: "vgg16"		
Layer (type)	**Output Shape**	**Param #**
input_1 (InputLayer)	[(None, 224, 224, 3)]	0
block1_conv1 (Conv2D)	(None, 224, 224, 64)	1792
block1_conv2 (Conv2D)	(None, 224, 224, 64)	36928
block1_pool (MaxPooling2D)	(None, 112, 112, 64)	0
block2_conv1 (Conv2D)	(None, 112, 112, 128)	73856
block2_conv2 (Conv2D)	(None, 112, 112, 128)	147584
block2_pool (MaxPooling2D)	(None, 56, 56, 128)	0
block3_conv1 (Conv2D)	(None, 56, 56, 256)	295168
block3_conv2 (Conv2D)	(None, 56, 56, 256)	590080
block3_conv3 (Conv2D)	(None, 56, 56, 256)	590080

block3_pool (MaxPooling2D)	(None, 28, 28, 256)	0
block4_conv1 (Conv2D)	(None, 28, 28, 512)	1180160
block4_conv2 (Conv2D)	(None, 28, 28, 512)	2359808
block4_conv3 (Conv2D)	(None, 28, 28, 512)	2359808
block4_pool (MaxPooling2D)	(None, 14, 14, 512)	0
block5_conv1 (Conv2D)	(None, 14, 14, 512)	2359808
block5_conv2 (Conv2D)	(None, 14, 14, 512)	2359808
block5_conv3 (Conv2D)	(None, 14, 14, 512)	2359808
block5_pool (MaxPooling2D)	(None, 7, 7, 512)	0
Total params: 14,714,688 **Trainable params: 0** **Non-trainable params: 14,714,688**		

Table 0–1: The components and structure of the VGG-16 CNN model applied including flatten , dense , average pooling , maxpooling layers conv2D layers and overall parameters[source: code].

1. Convolutional Layer: This layer forms a basic building block for convolutional neural networks. This layer uses a fixed-size filter to extract several features. The inspection of images is done by transferring the filters per strides; in this case, there are 6 convolutional layers with the size of 32, 64, 64, 128, 128, 128 filters in the CNN model. Every layer uses 2D convolutional filters with a size of 3x3 and a stride of one.

2. Batch Normalization: It is used to improve the learning rate of the CNN model and this layer standardizes the input image. Batch normalization in a CNN model is applied after each convolutional layer.

3. Pooling Layer: Pooling is a method that downsamples the collected feature-map from a convolutional layer. Maxpooling and average-pooling are usually used and in every convolutional layer, a max-pooling with pooling filter-size of 2*2 utilized.

4. Activation: This function is a non-linear transformation of inputs that are applied at each end of a layer. ReLU or softmax is a common activation function that is applied at each end of the layer and in the final layer, there are two nodes used with an activation function.

5. Dropout: A technique applied to reduce the overfitting of the model. Certain nodes in the layer using the dropout method are randomly selected to be inactive on some occasions. This will prevent the model from getting excessively familiar with the data. The dropout of 0.1 was employed in the dense layers of the model for classification.

6. Dense Layers: The output of the convolutional-layer is further flattened and submitted as input to the dense-layer. The convolutional-layer task is to extract features and the role of the dense layer is for the classification of images. The CNN architecture has two dense layers with 512-nodes each and 2 nodes for the final layer.

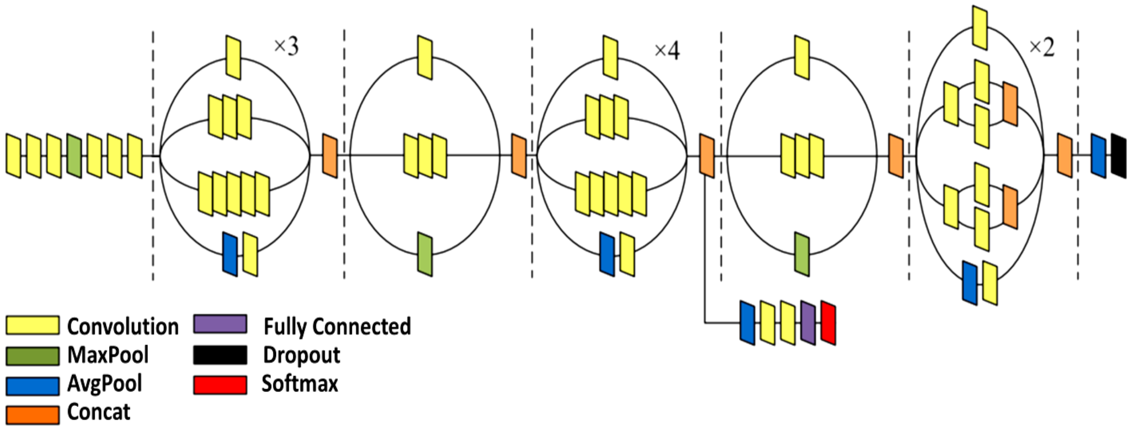

Figure 0-5: Defines the VGG16 model which performs convolution, pooling, softmax and fully connected procedures. Here a pre-trained neural network established for one task can be utilized as the initial point of another task [source: code].

3.4 Confusion matrix

A confusion matrix is a table that is used to evaluate the performance of a classification model by comparing the true labels of the data with the predicted labels generated by the model. The matrix consists of four cells, each representing a combination of true and predicted labels. The cells are:

- True Positive (TP): The number of instances that were correctly classified as positive (i.e., the model predicted positive and it was actually positive).
- False Positive (FP): The number of instances that were incorrectly classified as positive (i.e., the model predicted positive but it was actually negative).
- True Negative (TN): The number of instances that were correctly classified as negative (i.e., the model predicted negative and it was actually negative).
- False Negative (FN): The number of instances that were incorrectly classified as negative (i.e., the model predicted negative but it was actually positive).

The confusion matrix helps to evaluate how well a classification model is performing by providing information about its accuracy, precision, recall.

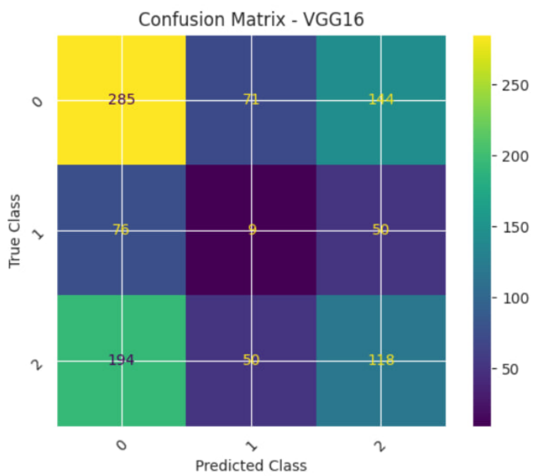

Figure 0-6: Confusion matrix [source: code].

These steps involve calculating the confusion matrix based on the true and predicted labels, creating a ConfusionMatrixDisplay object, plotting the confusion matrix, and customizing the plot with title, axis labels, and tick labels rotation. The resulting plot shows the confusion matrix for the predictions made by the VGG16 model

3.5 Results

Our system showed great results in the detection of these types of infections . This system can be used in developing-countries to aid short-staffed medical personnel, or for various other reasons.

The model showed results of overall accuracy, which shows the rate at which the model was accurate. Precision, which is the accuracy of the model in predicting a specific topic. Furthermore, recall is the ability of the model to detect a specific topic as shown in the figure 3-4.

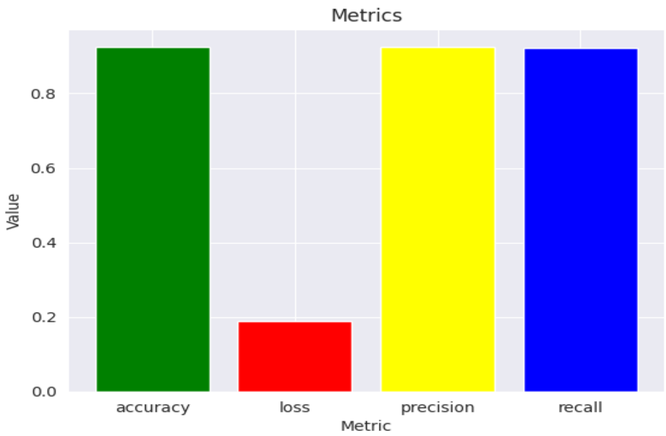

Figure 3 9: Shows overall accuracy of 93,88% , loss of 16% , Precision of 93,88% and recall of 93,78%[source: code].

Although, the model showed increasing in the accuracy and deceasing in the loss during the learning process (figure 3-5), which is considered to be prove that the model is accurate and not overfitted

Figure 3 10: loss and accuracy histogram [source: code].

3.6 Parallel Diagnosis

This CNN algorithm is a significant breakthrough in the field of radiology as it is capable of parallel diagnosis, which means that it can process multiple images simultaneously during the testing and prediction step. This feature allows the algorithm to show 15 related predictions in less than 2 seconds as shown in figure 5, which is a paradigm shift in the radiology field. The ability to process multiple images at once reduces the need for radiologists and decreases the time needed for diagnosis.

Moreover, this algorithm provides x-ray devices with the ability to give true and real-time diagnosis themselves. This feature can significantly improve patient outcomes by reducing diagnostic errors and improving treatment plans. Additionally, this technology can help healthcare providers manage their workload more efficiently by allowing them to focus on more complex cases while relying on automated systems for routine diagnoses.

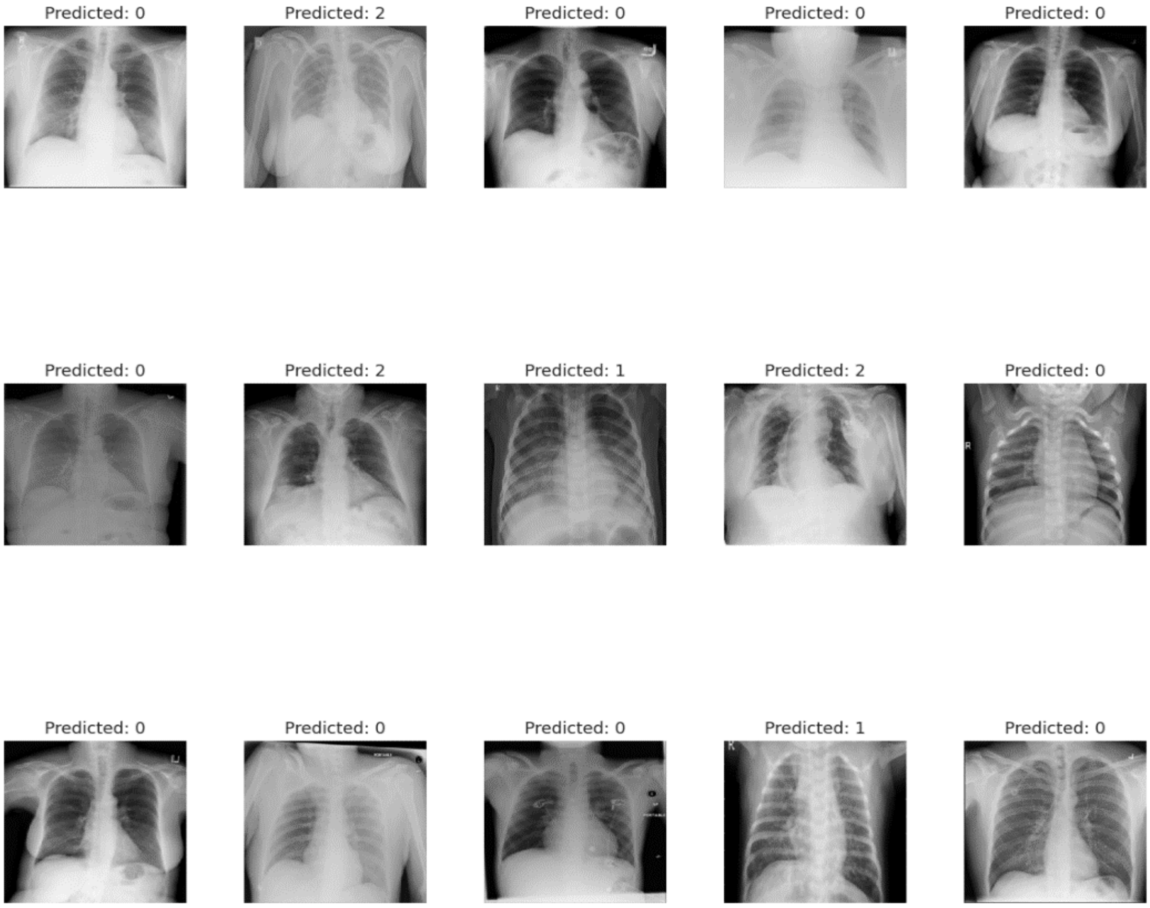

Figure 0-7: Parallel diagnosis with mapped results shows that each predicted 0 means COVID-19 diagnosed , predicted 1 is normal and predicted 2 is viral pneumonia [source: code].

3.7 Discussion

Pneumonia and COVID-19 are serious respiratory illnesses that require accurate and timely diagnosis for effective treatment. Traditional diagnostic methods often involve manual examination of chest X-ray images by medical professionals, which can be time-consuming and subjective. By leveraging the power of deep learning and transfer learning techniques, this project offers a potential solution to automate the detection process.[19]

Convolutional Neural Networks (CNNs) are well-suited for image classification tasks due to their ability to learn hierarchical representations from raw pixel data. The VGG16 architecture, originally developed for the ImageNet competition, has proven to be effective in various computer vision tasks. Transfer learning involves utilizing pre-trained models, such as VGG16, and fine-tuning them for specific tasks by retraining the last few layers.[16]

In this project, we trained the VGG16 model on a large dataset of chest X-ray images, including samples from both healthy individuals, pneumonia cases, and COVID-19 patients. The model was then fine-tuned to improve its performance specifically for pneumonia and COVID-19 detection. The achieved results are quite promising, with an accuracy of 93.86%, indicating that the model can effectively distinguish between normal, pneumonia, and COVID-19 cases.

The loss value of 18% indicates that the model has learned to minimize errors during training, further validating its effectiveness. The precision and recall rates of 92% imply that the model can accurately identify positive cases (both pneumonia and COVID-19) and minimize false positives and false negatives. These metrics are crucial for medical applications as they ensure reliable and trustworthy predictions.

The utilization of transfer learning in this project is noteworthy. By building on the pre-existing knowledge of the VGG16 model, the researchers were able to leverage the learned representations for better feature extraction. This approach is particularly advantageous when working with limited training data, as is often the case in medical image analysis. Transfer learning allows the model to generalize well and make accurate predictions even with a relatively small dataset.

However, it is important to consider the limitations of this project. While the reported accuracy, loss, precision, and recall values are impressive, it is essential to evaluate the model's performance on a separate validation or testing dataset. Additionally, the dataset used for training and fine-tuning should be diverse, representative, and of sufficient size to ensure generalizability of the model.

Moreover, the interpretation of the model's predictions is critical. The model's high accuracy and precision rates imply that it can reliably identify pneumonia and COVID-19 cases, but it is crucial to validate these predictions with clinical tests and expert medical opinions. AI models should be considered as supportive tools for healthcare professionals, assisting in diagnosis but not replacing their expertise.

In conclusion, the project "Pneumonia and COVIDBranch 19 Detection based on chest X Transfer Learning ray images using Convolutional Neural Networks" presents a promising approach for automating the detection of pneumonia and COVID-19 from chest X-ray images.

The use of the VGG16 architecture with 93.86% accuracy, 18% loss, and 92% precision and recall rates demonstrates the model's effectiveness in distinguishing between normal, pneumonia, and COVID-19 cases. However, further evaluation and validation on independent datasets, along with clinical validation, are necessary before deploying such models in real-world medical settings.

4 Conclusion and Future Work

4.2 Conclusion

The trained VGG-16 proposed in this research study for the COVID-19 detection and pneumonia detection on chest x-ray images using the CNN method have meaningful results. The developed CNN model was effective in extracting features from an x-ray image and forecast the occurrence or nonexistence of COVID-19, bacterial, and viral-pneumonia. Likewise, testing-data in the research was intensified through data augmentation techniques. In addition to the improvement of computer- related applications in the medical division, COVID-19 and pneumonia can be efficiently found employing chest radiographs with the support of CNN and deep learning technologies. Methodologies developed in the conduct of this research in which COVID-19, and viral-pneumonia can be forecast with greater accuracy, and in this case our study obtained 93,88% accuracy. The medical field through automated diagnosis is the essential area that will gain precisely from this research. Future studies can make better a performance of CNN architecture by tuning the hyper- parameters and transfer learning combinations. Improved complex network-structure might likewise be achievable to determine the best model for pneumonia and the COVID-19 detection system.

Although this project has the potential to significantly reduce the cost on patients and the healthcare system by providing an efficient and accurate method for COVID-19 and pneumonia detection through chest radiographs. With the use of CNN and deep learning technologies, automated diagnosis can be achieved, reducing the need for costly manual labor and multiple radiologists. Additionally, with further improvements in network structure and hyper-parameter tuning, this technology can become even more cost-effective in the future.

4.3 Future Work

The future work in diagnosing COVID-19 viral pneumonia using chest X-ray images and the VGG16 CNN transfer learning model holds immense potential in improving diagnostic accuracy and facilitating timely treatment. The utilization of transfer learning techniques, combined with large and annotated datasets, can enable the development of robust and efficient diagnostic systems. The integration of these systems into clinical practice can assist healthcare professionals in making informed decisions and managing the COVID-19 pandemic effectively.

Although, the aforementioned model has the potential to be implemented on CT-scan sliced images, thereby the details in every slice could enhance the learning parameters and ultimately improving the accuracy of the model while reducing loss. Furthermore, integration of the model with hospitals' PAC systems could facilitate efficient data storage and retrieval, encompassing images, diagnoses, and comparative results for patients over time.

References

1. World Health Organization. 2020. Coronavirus disease 2019 (COVID-19) Situation Report–196, [online] [cited 3 August 2020]. Available at: https://www.who.int/docs/default-source/coronaviruse/situationreports/20200803-covid-19-sitrep-196cleared.pdf?sfvrsn=8a8a3ca4_4.
2. Centers for Disease Control and Prevention. 2020. Interim Infection Prevention and Control Recommendations for Patients with Suspected or Confirmed Coronavirus Disease 2019 (COVID-19) in Healthcare Settings, [online] [cited 5 June 2020]. Available at: https://www.cdc.gov/coronavirus/2019-ncov/hcp/infectioncontrolrecommendations.html.
3. Jain, S., Self, W. H., Wunderink, R. G., Fakhran, S., Balk, R., Bramley, A. M., ... & Grijalva, C. G. 2015. Community-acquired pneumonia requiring hospitalization among US adults. New England Journal of Medicine, 373(5), pp. 415-427.
4. Chowdhury, M. E. H. et al. 2020. Can AI Help in Screening Viral and COVID-19 Pneumonia? IEEE Access, 8, pp. 132665-132676. DOI: 10.1109/ACCESS.2020.3010287.
5. Militante, S., Dionisio, N. Unpublished. Real-Time Facemask Recognition with Alarm System using Deep Learning.
6. Wang, L., Lin, Z. Q., Wong, A. 2020. COVID-Net: A tailored deep convolutional neural network design for detection of COVID-19 cases from chest X-ray images. Scientific Reports, 10(1), pp. 1-12. DOI: 10.1038/s41598-020-76550-z.
7. Centers for Disease Control and Prevention. 2020. Symptoms of coronavirus, [online]. Available at: https://www.cdc.gov/coronavirus/2019-ncov/symptoms-testing/symptoms.html.
8. CDC COVID Data Tracker Team. 2021. Demographic Trends of People Receiving COVID-19 Vaccinations in the United States. Available at: https://covid.cdc.gov/covid-data-tracker/#vaccination-demographic.

9. Huang, C., Huang, L., Wang, Y., et al. 2021. 6-month consequences of COVID-19 in patients discharged from hospital: a cohort study. Lancet, 397(10270), pp. 220-232.
10. Dong, Y., Mo, X., Hu, Y., et al. 2020. Epidemiology of COVID-19 Among Children in China. Pediatrics, 145(6), e20200702.
11. Jain, S., Self, W. H., Wunderink, R. G., Fakhran, S., Balk, R., Bramley, A. M., ... & Courtney, D. M. 2015. Community-acquired pneumonia requiring hospitalization among US adults. New England Journal of Medicine, 373(5), pp. 415-427
12. Wang, L., Wong, A., & COVID-Net Consortium. 2020. COVID-Net: A tailored deep convolutional neural network design for detection of COVID-19 cases from chest X-ray images. Scientific Reports, 10(1), 19549. DOI: 10.1038/s41598-020-76550-z.
13. Apostolopoulos, I. D., & Mpesiana, T. A. 2020. COVID-19: Automatic detection from X-ray images utilizing transfer learning with convolutional neural networks. Physical and Engineering Sciences in Medicine, 43(2), pp. 635-640. DOI: 10.1007/s13246-020-00865-4.
14. Ozturk, T., Talo, M., Yildirim, E. A., Baloglu, U. B., Yildirim, O., & Acharya, U. R. 2020. Automated detection of COVID-19 cases using deep neural networks with X-ray images. Computers in Biology and Medicine, 121, 103792. DOI: 10.1016/j.compbiomed.2020.103792.
15. Wang, X., Peng, Y., Lu, L., Lu, Z., Bagheri, M., & Summers, R. M. 2018. ChestX-ray8: Hospital-scale chest X-ray database and benchmarks on weakly-supervised classification and localization of common thorax diseases. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 2097-2106).
16. Rajpurkar, P., Irvin, J., Bagul, A., Ding, D., Duan, T., Mehta, H., ... & Ball, R. L. 2017. Mura dataset: Towards radiologist-level abnormality detection in musculoskeletal radiographs. arXiv preprint arXiv:1712.06957.
17. Wang, L., Lin, Z. Q., Wong, A., Zung, J., & Cao, X. 2020. COVID-net: A tailored deep convolutional neural network design for detection of COVID-19 cases from chest radiography images. Scientific Reports, 10(1), 1-12.
18. Apostolopoulos, I. D., & Mpesiana, T. A. 2020. Covid-19: automatic detection from x-ray images utilizing transfer learning with convolutional neural networks. Physical and Engineering Sciences in Medicine, 43(2), pp. 635-640.
19. Narin, A., Kaya, C., & Pamuk, Z. 2021. Automatic detection of coronavirus disease (COVID-19) using X-ray images and deep convolutional neural networks. Pattern Analysis and Applications, 24(1), pp. 1207-1220.
20. G. C. Platform. 2017. Image Classification Transfer Learning with Inception v3. Available at: https://codelabs.developers.google.com/codelabs/cpb102-txflearning/index.html#0.
21. Demner-Fushman, D., Kohli, M. D., Rosenman, M. B., Shooshan, S. E., Rodriguez, L., Antani, S., ... & McDonald, C. J. 2016. Preparing a collection of radiology examinations for distribution and retrieval. Journal of the American Medical Informatics Association, 23(2), pp. 304-310. DOI: 10
22. Alqudah, A. M., & Qazan, S. 2020. Augmented COVID-19 X-ray Images Dataset. Mendeley Data, v4. DOI: 10.17632/2fxz4px6d8.
23. Monteral, J. C. 2020. COVID-Chestxray Database. Available at: https://github.com/ieee8023/covid-chestxray-dataset.