COVID-19 DETECTION BASED ON DEEP LEARNING TECHNIQUE USING CHEST X-RAY IMAGES AND CT-SCAN DATASETS

A thesis

submitted in partial fulfilment of the requirement for the Degree of

Master of Technology in Computer Technology of

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By

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Certificate of Recommendation

This is to certify that the dissertation entitled — COVID-19 DETECTION BASED ON DEEP LEARNING TECHNIQUE USING CHEST X-RAY IMAGES AND CT-SCAN DATASETS has been carried out by Ipsita Das (University Registration No: 149851 of 2019-2020, Examination Roll No: M6TCT22018) under my guidance and supervision and be accepted in partial fulfilment of the requirement for the Degree of Master of Technology in Computer Technology. The research results presented in the thesis have not been included in any other paper submitted for the award of any degree in any other University or Institute.

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Certificate of Approval*

This is to certify that the thesis entitled — COVID-19 DETECTION BASED ON DEEP LEARNING TECHNIQUE USING CHEST X-RAY IMAGES AND CT-SCAN DATASETS ‖ is a bonafide record of work carried out by Ipsita Das in partial fulfilment of the requirements for the award of the degree of Master of Technology in Computer Technology in the Department of Computer Science and Engineering, Jadavpur University during the period of July 2019 to June 2022. It is understood that by this approval the undersigned does not necessarily endorse or approve any statement made, opinion expressed, or conclusion drawn therein but approve the thesis only for the purpose for which it has been submitted.

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Declaration of Originality and Compliance of Academic Ethics

I hereby declare that this thesis entitled — COVID-19 DETECTION BASED ON DEEP LEARNING TECHNIQUE USING CHEST X-RAY IMAGES AND CT-SCAN DATASETS‖ contains a literature survey and original research work by the undersigned candidate, as part of her degree of Master of Technology in Computer Technology.

All information has been obtained and presented by academic rules and ethical conduct.

I also declare that, as required by these rules and conduct, I have fully cited and referenced all materials and results that are not original to this work.

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Chapter 1

Introduction

Coronavirus (COVID-19) is a highly contagious disease that was proclaimed a pandemic by the World Health Organization (WHO) on March 11, 2020, due to its widespread spread over the globe[1]. COVID-19's worrisome rate of transmission and severity were also highlighted in the pandemic proclamation.

It is the first time a coronavirus has triggered a pandemic. It is described as a global health problem of the moment that has spread around the globe. However, the infection continues to spread at a breakneck speed[2]. While most persons infected with COVID-19 got mild to moderate respiratory illness, a few people acquired pneumonia, which was fatal. Illness and economic slowdown are two flaws that have a significant impact on human beings. Unfortunately, they have been brought to light by this novel coronavirus. The COVID-19 virus, as known, targets the lungs of a suspected patient and quickly mutates there. The infected lungs become irritated and filled with fluid in this situation. The results of a CT scan or X-ray imaging of an infected person indicate shadowy patches in the lungs known as Ground Glass Opacity[3]. Its spread rate is substantially higher than its forecast or detection rate due to its communicative character. There is a high demand for fast and reliable detection of COVID-19 suspicious patients in the absence of an intelligent diagnosis approach. However, the current methods for detecting this raging pandemic are only somewhat reliable and take a long time to complete. Reverse Transcription Polymerase Chain Reaction (RT-PCR), Computed Tomography (CT) Scan, and Chest X-Ray are the three types of COVID-19 testing procedures now accessible (CXR). RT-PCR is one of the more time-consuming approaches, whereas CXR can identify inflammation in the lungs, as well as its location, shape, and size, and CT-Scan is a more effective way to diagnose COVID-19 and Pneumonia because it provides a precise view of the air sacs. As a result, both CXR and CT-Scan pictures of the lungs are used in numerous experiments.

There is a common belief that senior persons with underlying medical issues such as cardiovascular disease, diabetes, chronic lung disease, renal or hepatic disease, and cancer are more likely to acquire serious illness. There is yet to be developed a specific COVID-19 vaccination or treatment. However, numerous clinical trials testing potential therapies are currently underway. Until June 11th, 2020, around 7.5 million infected patients were discovered in over 200 nations, with around 421 thousand deaths, 3.8 million recoveries, 3.2 million mild cases, and 54 thousand serious cases reported[4],[5]. The global spread of COVID-19 has quarantined a large portion of the world's population and devastated numerous industrial sectors, resulting in a global financial crisis. The most common symptoms of the novel coronavirus are fever, dry cough, myalgia, dyspnea, and headache, but in some cases, no symptoms are visible (asymptomatic), making the disease even more dangerous to public health[6]-[9]. The reverse transcript polymerase chain reaction (RT-PCR) is the gold standard for diagnosing COVID-19[5].Many countries are experiencing difficulties with an erroneous number of COVID-19 positive cases due to a paucity of test kits as well as a delay in the testing process outcomes of the tests[11].However, a lack of resources and strict test environment requirements limit the ability to screen suspicious cases quickly and effectively. Furthermore, in some cases, RT-PCR inspection produces false negative results. Unfortunately, the only way to effectively combat this communicable disease is through clinical vaccines and precise drug/therapy practices, both of which are currently unavailable[12]. COVID-19 has been identified as one of the most dangerous diseases posing a serious threat to human civilization. With the advancement of modern technology over the last few decades, ingenious solutions for disease diagnosis, prevention, and control that leverage smart healthcare tools and facilities have been developed [13]. Different imaging modalities, such as CT and X-ray, are thought to be among the most effective techniques for COVID-19 diagnosis. CT screening is preferred over X-rays when available because of its versatility and three-dimensional pulmonary view, even though X-rays are more affordable and widely available[14].

These traditional medical imaging modalities are critical in controlling the pandemic.

COVID-19 tests are currently hard to come by — there are simply not enough of them and they cannot be manufactured fast enough, which is causing panic.

Given that there are limited COVID-19 testing kits, need to rely on other diagnosis measures.

X-ray images are explored as doctors frequently use X-rays and CT scans to diagnose pneumonia, lung inflammation, abscesses, and/or enlarged lymph nodes.

Since COVID-19 attacks the epithelial cells that line our respiratory tract, X-rays can be used to analyze the health of a patient’s lungs.

Artificial Intelligence (AI), a rapidly evolving software technology in the field of medical image analysis, has also directly aided in the fight against the novel coronavirus by efficiently providing high-quality diagnosis results while dramatically reducing or eliminating the need for human intervention[15]. Deep learning and machine learning, two major areas of AI, have recently gained popularity in medical applications. Deep learning-based support systems for COVID-19 diagnosis are being developed using both CT and X-ray samples. Some of the systems are built on pre-trained models with transfer learning, while others are built on customized networks[16]. Machine learning and data science are two other areas where corona diagnosis, prognosis, prediction, and outbreak forecasting are actively used. Furthermore, big data from the Internet of Things (IoT) and smartphone technology are widely used to enable innovative solutions to control the spread of COVID-19[17].

1.1. Aim of the work

The aim of this thesis is to predict whether a person has COVID-19 or not, using deep learning technique. The prediction is performed using the clinical information of the patients. The goal is to identify whether a patient can potentially be diagnosed with COVID-19.

1.2. Objectives

The main objective of thesis are,

- Identifying the most appropriate deep learning technique for prediction to use on patient clinical information.
- Preparing a deep learning model that could make accurate predictions of COVID-19 in patients.
- Identifying the features that affects the prediction of COVID-19 in patients.

1.3. Research questions

To achieve the objectives of the thesis, there are some research questions that have been formulated:

1. **Which suitable deep learning technique can be used to predict COVID-19?**

Motivation: The motivation of the research question is to conduct a conjunctive literature study and experiment to see what are the appropriate deep learning algorithms that can be best applied to the given data and also to find out which algorithm gives us the best results in predicting COVID-19.

2. **What are the features that will influence the predictive result of COVID-19?**

Motivation: The motivation of this research is to conduct an experiment to identify the features that will influence the results of prediction of Corona virus in human beings.

1.4. Defining the scope of the thesis

This research focuses on the development of a deep learning model for predicting COVID-19 in patients. In this thesis, the type of identification of features is from the clinical information of patients that would influence the predictive result of COVID-19. This study does not focus on outer factors such as weather or any environmental factors that might influence results.

1.5. Outline

The thesis structure is divided into different chapters which are as follows:

- Chapter 1: This chapter contains the introduction to this thesis, aim and objectives, research questions, and motivation.
- Chapter 2**:** This chapter contains a summary of the works similar to this thesis.
- Chapter 3: This chapter contains methods.
- Chapter 4: This chapter experimental analysis like data processing, tools used during the experiment, and experimental setup details, results obtained.
- Chapter 5: This chapter contains the conclusion of the thesis and a discussion on possible future work
- Chapter 6: This chapter contains the references to the work.

Chapter 2
Literature survey

- A. M. Tahir et al.[18] constructed A. M. Tahir et al. created the largest benchmark dataset with 33,920 CXR pictures, including 11,956 COVID-19 samples, where ground-truth lung segmentation masks are annotated on CXRs using state-of-the-art segmentation networks, U-Net, U-Net++, and Feature Pyramid Networks (FPN). After an iterative approach, the constructed network achieved improved lung area segmentation performance, with an Intersection over Union (IoU) of 96.11% and a Dice Similarity Coefficient (DSC) of 97.99% .
- T. Rahman et al.[19] proposed a lung segmentation model that he compared to the usual U-Net model. On plain and segmented lung CXR pictures, six different pre-trained Convolutional Neural Networks (CNNs) (ResNet18, ResNet50, ResNet101, InceptionV3, DenseNet201, and ChexNet) and a shallow CNN model were studied, with an accuracy of 95.11%.
- By constructing so-called infection maps, A. Degerli et al.[20] proposed a unique method for the combined location, severity grading, and detection of COVID-19 from CXR images. The proposed method detected COVID-19 with a sensitivity of 94.96 % and a specificity of 99.88 %.
- M. E. H. Chowdhury et al.[21] proposed a robust method for automatically detecting COVID-19 pneumonia from digital chest X-ray pictures using pre-trained deep-learning algorithms with a 99.7% detection accuracy.
- Apostolopoulos et al.[22] reported 96.78% accuracy for COVID-19 detection from bacterial pneumonia and normal X-rays in a dataset of 1427 X-rays.
- Similarly, Abbas et al.[23] reported accuracy of 95.12% for COVID-19 classification from COVID-19, normal, and Severe Acute Respiratory Syndrome (SARS) CXR images using a pre-trained CNN model (DeTraC Decompose, Transfer and Compose) with a small database of 196 X-ray images.
- Minaee et al.[24] reported specificity and sensitivity of 90% and 97%, respectively using the ChexPert dataset. Despite the positive results, the dataset utilised to train machine learning (ML) models is tiny; yet, it demonstrates that deep ML models can be used to detect COVID-19.
- With a very small dataset, Khan et al.[25] investigated a restricted number of machine learning techniques for a four-class classification task (COVID-19, bacterial pneumonia, viral pneumonia, and normal).

- With the help of 2362 CXR images collected from four hospitals, Goldstein et al.[26] built a classifier to detect COVID-19 using a pre-trained deep learning model (ResNet50) and enhanced by data augmentation and lung segmentation, and achieved accuracy and sensitivity of 89.7% and 87.1 percent, respectively.
- Chowdhury et al.[27] proposed an ensemble of deep convolutional neural network (CNN) models named Efficient Convolutional Network (ECOVNet) to classify COVID-19, normal, and pneumonia using 16,493 CXR images using the transfer learning method and achieved an accuracy of 97%.
- Ashfar et al.[28] reported an accuracy of 95.7% using a Capsule network, called COVID-CAPS rather than a conventional CNN to deal with a smaller dataset.
- Yamac et al.[29] proposed the Convolution Support Estimation Network (CSEN), a compact CNN architecture that uses CheXNet as a feature extractor to categorize COVID-19, bacterial pneumonia, viral pneumonia, or normal CXR pictures. Using a dataset of 462 COVID-19 CXR images, the network achieved a COVID-19 detection sensitivity of 98 percent. Using a compact CSEN network, the same group of researchers presented a reliable warning system for diagnosing early-stage COVID-19 cases.
- On a smaller dataset, Ahishali et al. [30] demonstrated that CheXNet and CSEN had COVID-19 detection sensitivity of 97.1 percent and 98.5 percent, respectively.
- Furthermore, using 14,100 CXR images, Motamed et al.[31] proposed a randomized generative adversarial network (RANDGAN) that detects images of an unknown class (COVID-19) from known and labeled classes (normal and viral pneumonia) without the need for labels and training data from the unknown class of images (COVID-19) and achieved an area under the curve (AUC) of 0.77. It was discovered that combining multiple approaches can aid in improving COVID-19 detection performance.
- Degerli et al.[32] suggested a unique method for the joint localization, severity grading, and detection of COVID-19 from 15,495 CXR pictures by producing "infection maps," which can accurately localise and grade the severity of COVID-19 infection with 98.69 percent accuracy.
- Ahmed et al.[33] developed a novel CNN architecture for COVID-19 detection employing preprocessing stages called ReCoNet (residual image-based COVID-19 detection network), which was found to be highly useful for boosting distinctive COVID-19 signature. The suggested modular architecture was trained on 15,134 CXR pictures and achieved 97.48 percent accuracy, 96.39 percent sensitivity, and 97.53 percent specificity, respectively. A CNN-based multi-level preprocessing filter

block, a multi-layer CNN-based feature extractor, and a classification block make up the machine learning model. Transfer learning was a popular way to tackle such an issue in recent studies, and it yielded encouraging results.

- Kumar et al. [34] introduced the DeQueezeNet model, which classifies patients' X-ray pictures into positive and negative categories while identifying COVID-19. By pre-processing the X-ray pictures of positive COVID-19 patients and normal instances, the suggested model predicts the probability of the disease with 94.52 % and 90.48 % precision.
- Luján-Garca et al. [35] used chest X-rays to diagnose Pneumonia and further classify individuals as infected or not infected with Pneumonia. The suggested model takes into account 36 convolutional layers and has a precision score of 0.843.
- Due to the restricted quantity of data available, Apostolopoulos and Mpesiana [36] described the implementation of transfer learning in COVID-19 identification. They achieved a 96.78 % accuracy rate.
- Ozturk et al. [37] have made another breakthrough in COVID-19 classification by presenting a model for binary and multi-class categorization of diseases such as COVID-19, ordinary Pneumonia, and no-findings of any of them. With 17 convolutional layers, they achieved a binary classification accuracy of 98.08 percent and a multi-class accuracy of 87.02 %.
- Togacar et al. [38] used a fuzzy approach and stacking to minimize the noise in chest X-ray images for three different class values known as COVID-19, Pneumonia, and normal. They used the SqueezeNet as a model, analysing the correctness of reconstructed datasets at various levels, and obtaining significant accuracy in their results.
- For quick detection of COVID-19 situations, Panwar et al. [39] introduced the algorithm nCOVnet, which is based on the data leakage principle. The detection accuracy in their studies was 88 percent, but the authors did not provide a good picture of the detected COVID-19 cases on the CXR images.

Chapter 3
Methodology
3.1. Deep learning's role in detection/prediction
At a rate far above what standard methods of analysis can process, healthcare professionals generate and record massive amounts of data containing extremely significant signals and information. The RT-PCR test is one of the time-consuming and expensive procedures for detecting COVID-19 suspects, as all know. As a result, the best answer is to use a combination of deep learning classifiers and medical pictures to detect the COVID-19 virus quickly and accurately while analyzing CXR and CT-Scan images of the lungs. The suggested method in this research can directly assist radiologists in the rapid detection of COVID-19, which enhances the overall detection time and accuracy rate in CXR and CT-Scan pictures.

Deep Learning (DL) is a subclass of Machine Learning (ML) that allows computers to learn useful characteristics from raw data sets automatically [40]. Most of the deep learning breakthroughs in medical imaging have occurred since the development of the convolutional neural network (CNN). Because Deep Models like the Stacked Auto-Encoder (SAE), Deep Belief Network (DBN), and Deep Boltzmann Machine (DBM) all contain vector inputs [41], this is the case. Vectorization, on the other hand, removes the structural and configurational information accessible in neighboring pixels in medical imaging, and voxels are one of the most essential structural information. CNN can better exploit spatial and configurational information when given input in the form of 2D or 3D images [42].

One of the most common symptoms of COVID-19 and Pneumonia is a lung infection. Which can be observed on CXR and CT-Scan pictures of the lungs and could lead to a breakthrough in COVID-19 diagnosis. In this thesis for the result section deep learning classifiers and suggested a new technique for extracting characteristics from diverse radiology pictures in order to diagnose infection are used. On CXR and CT-Scan images of the lungs, the proposed algorithm enables the application of deep transfer learning and analyses the report of probable COVID-19 patients.

3.2. Classification of Deep Learning based on COVID-19 Diagnosis Systems

Complex problems can be explained using deep learning techniques by gaining knowledge from simple illustrations. The ability to learn accurate representations and the property of learning data in a deep manner where numerous layers are used consecutively are the major qualities that have made deep learning approaches popular[43]. Deep learning methods are widely used in medical systems such as biomedicine, smart healthcare, drug discovery, medical image analysis, etc. It has been commonly applied in the automated diagnosis of COVID-19 in patients in recent years. Data collection, data preparation, feature extraction and classification, and performance evaluation are all phases in deep learning-based systems in general. Fig.3.2.1 illustrates the general pipeline of a COVID-19 diagnosis system based on deep learning. At the data collection stage, the patients from the hospital environment are considered a participant. Patients from the hospital setting are considered participants during the data gathering stage. Although the data can take many various forms, imaging techniques such as CT and X-ray samples are used to diagnose COVID-19. Data preparation, which puts the data into an appropriate format, is the next important step. Data pre-processing encompasses procedures such as noise removal, scaling, and augmentation, among others. The data partitioning process divides the data into three sets for the experiment: training, validation, and testing. Generally, the cross-validation technique is utilized for data partitioning. The training data is used to develop a particular model that is evaluated by validation data, and the performance of the developed model is appraised by test data. The major step of deep learning-based COVID-19 diagnosis is feature extraction and classification. In this stage, the deep learning technique automatically extracts the feature by performing several operations repeatedly, and finally, the classification is done based on class labels (healthy or COVID-19). Lastly, the developed system is assessed by some evaluation metrics like accuracy, sensitivity, specificity, precision, F1-score, and so on. In this thesis paper, a taxonomy of classifying the COVID-19 diagnosis system is presented to facilitate the navigation of the landscape. Two alternative views are used, one for the deep learning algorithms used and the other for the imaging modalities used. The two types of deep learning approaches are pre-trained models with deep transfer learning and custom deep learning techniques. In addition, each deep learning-based diagnostic technique is classified into two categories: CT images and X-ray images. In this thesis paper, 45 COVID-19 diagnosis systems are looked in all. For COVID-19 diagnosis, 25 systems (55.55 percent of the total reviewed systems) applied pre-trained models, whereas 20 systems (44.45 percent of the total reviewed systems) used customized deep learning techniques.

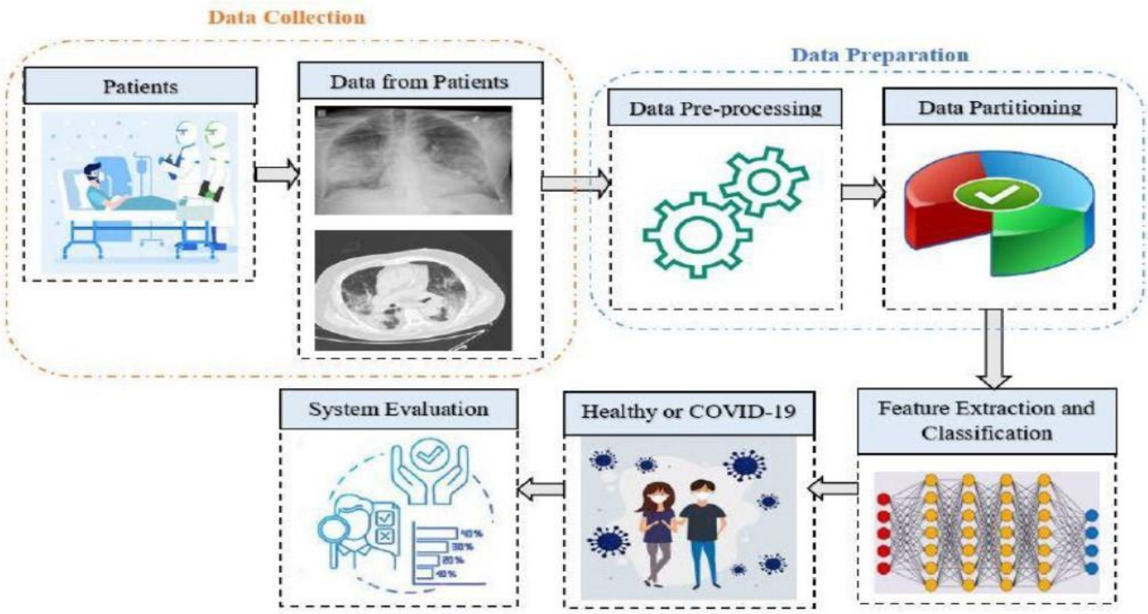

Fig. 3.2.1. A deep learning-based COVID-19 diagnosis pipeline.
[Islam, Md Milon, et al. "A review on deep learning techniques for the diagnosis of novel coronavirus (covid-19)." *IEEE Access* 9 (2021): 30551-30572.]

3.3. Pre-trained model with deep transfer learning

A pre-trained model has already been trained in fields related to the environment of the application. In transfer learning, weight and bias are transferred from a large trained model to a similar new model for testing or retraining. There are numerous benefits to using a pre-trained model with deep transfer learning. In general, training a model from scratch for large datasets is time-consuming and requires a lot of computing power[44]. Using a pre-trained model with transfer learning, the facility can accelerate convergence with network generalization[45]. There are numerous pre-trained models for the massive convolutional neural network (CNN) that are used in transfer learning.

A larger dataset usually outperforms a smaller dataset when using deep convolutional neural networks. In the case of deep CNN training with a small dataset, transfer learning can be applied. Transfer learning is a technique that employs a learned model from a big dataset, such as ImageNet, and Modifies the pre-trained networks' softmax and classification layers. The pre-trained weights are then used to train the network more quickly for an application with a smaller dataset[46]. This eliminates the need for a big dataset and shortens the training period that a deep learning system requires when built from the ground up. Despite the enormous number of COVID-19 patients infected around the world, the number of publicly available chest X-ray images is tiny and scattered. As a result, the authors have reported a rather large dataset of COVID-19 positive chest X-ray images in this investigation, whereas normal and viral pneumonia images are widely available and were employed in this analysis. The authors established a Kaggle database to make the database openly available to researchers all around the world, and the trained models were made available so that others might profit from this study.

3.4. Convolution Neural Network

The approach of Convolution Neural Networks (CNNs) and Transfer Learning is described in this section. Except for convolution operations, which take place in one or more layers of CNNs, CNNs are quite similar to vanilla Neural Networks. Eq.3.5.1 shows the layer of a simple neural network.

$$z^{[1]} = g(W^{[1]} a^{[0]} + b^{[1]}) \quad (3.5.1)$$

where $z^{[1]}$ indicates the current layer, $a^{[0]}$ represents the first or input layer, $W^{[1]}$ represents the first layer's weights, and $b^{[1]}$ represents the bias. Input, convolution, pooling, fully connected, and output layers are shown in Fig.3.5.1. The type of data in the input layer is CXR or CT-Scan pictures. Fig.3.5.1. shows the convolution layer, pooling layer, and connected layer separately. The example of the convolution operation on a 6 x 6 matrix employing a 3 x 3 filter and a stride of 2 is also discussed in Fig. 3.5.2. A stride value is used to control the movement of the filter window on the input matrix. The next layer after the convolutional layer is a pooling layer, which is used to reduce the network's computational loss. Here, some common pooling functions are looked like average, L2 norm, minimum, and maximum pooling. Fig.3.5.3. shows an example of a max-pooling procedure. Next to the pooling layer is the completely connected layer, which is represented in Fig.3.5.4. and in which each neuron is entirely connected to each neuron of the flattened version of the previous layer.

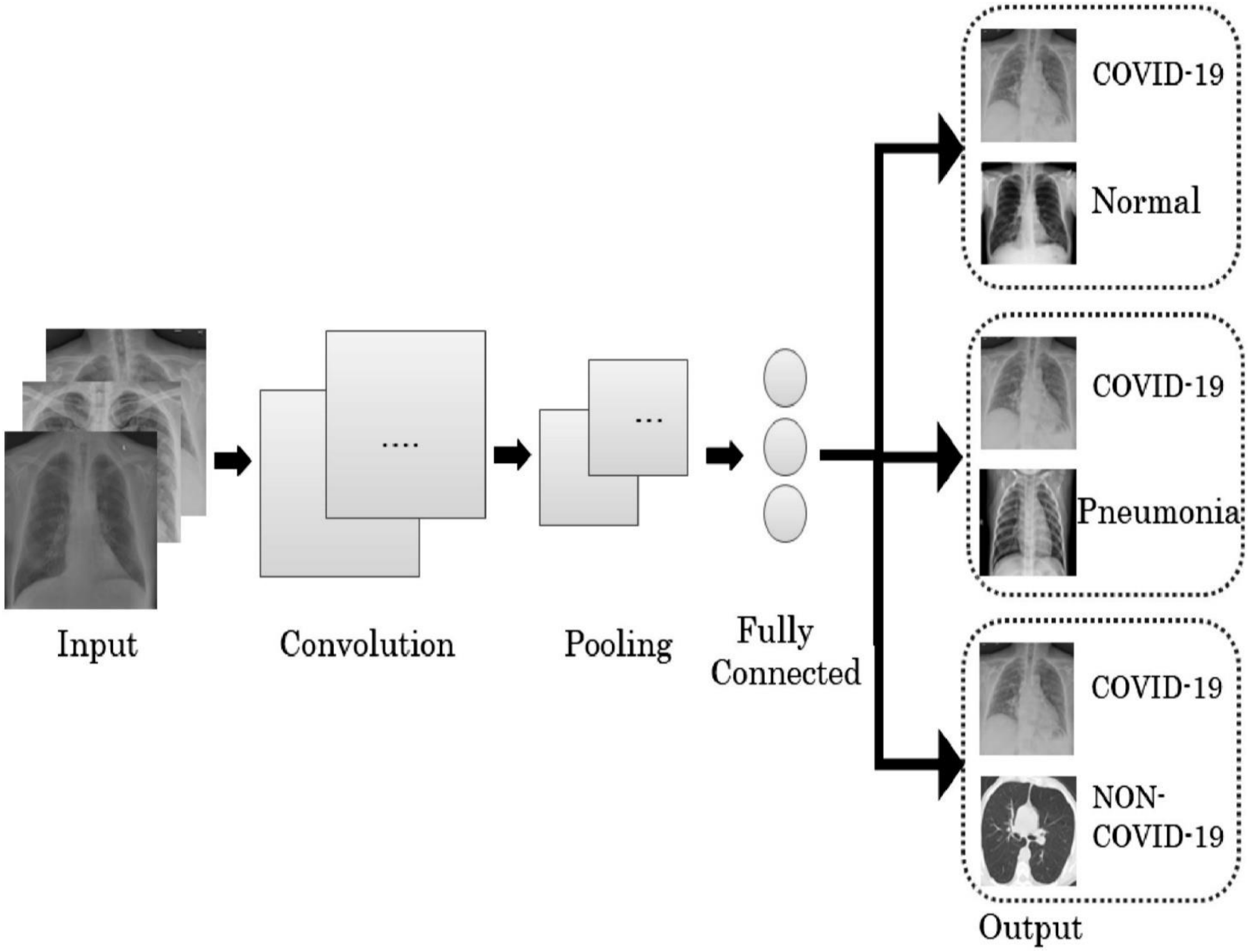

Fig 3.5.1. A primitive CNN architecture for binary COVID-19 image categorization.

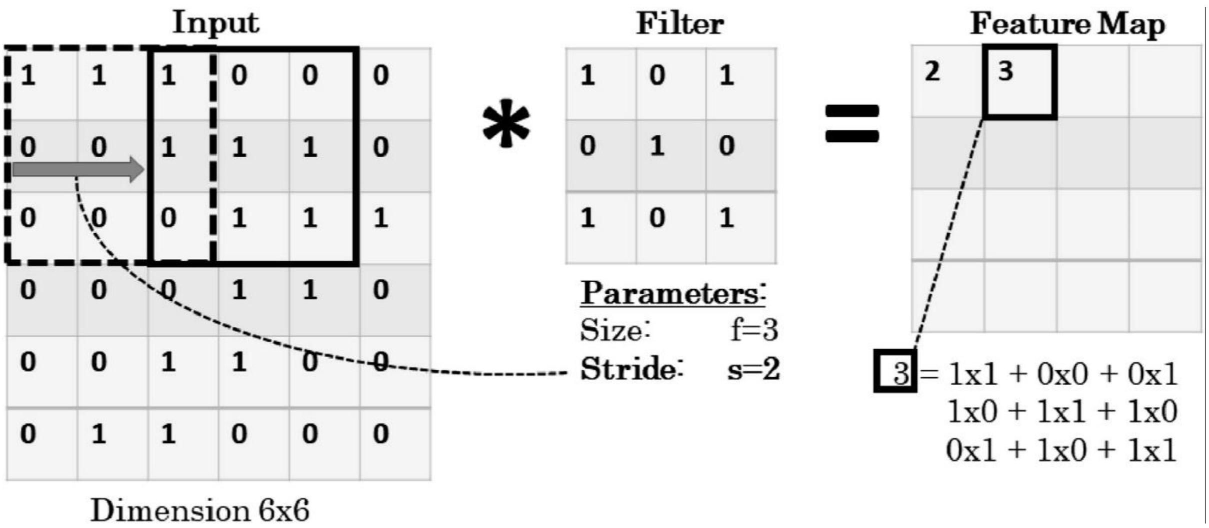

Fig 3.5.2. A sample of the convolution operation with filter size =3, and stride = 2.

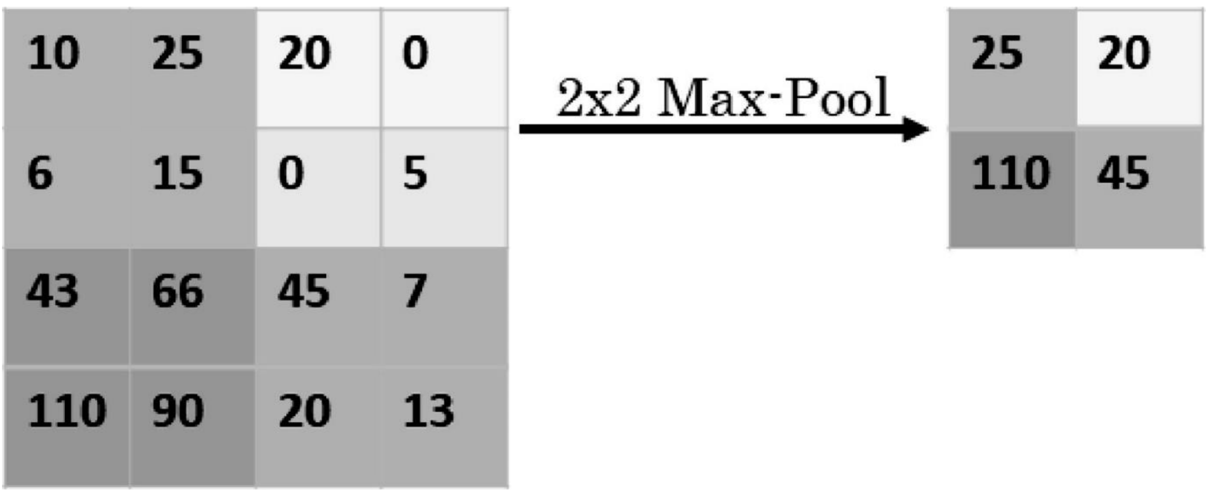

Fig 3.5.3. A max-pooling procedure with a 2x2 window size is an example.

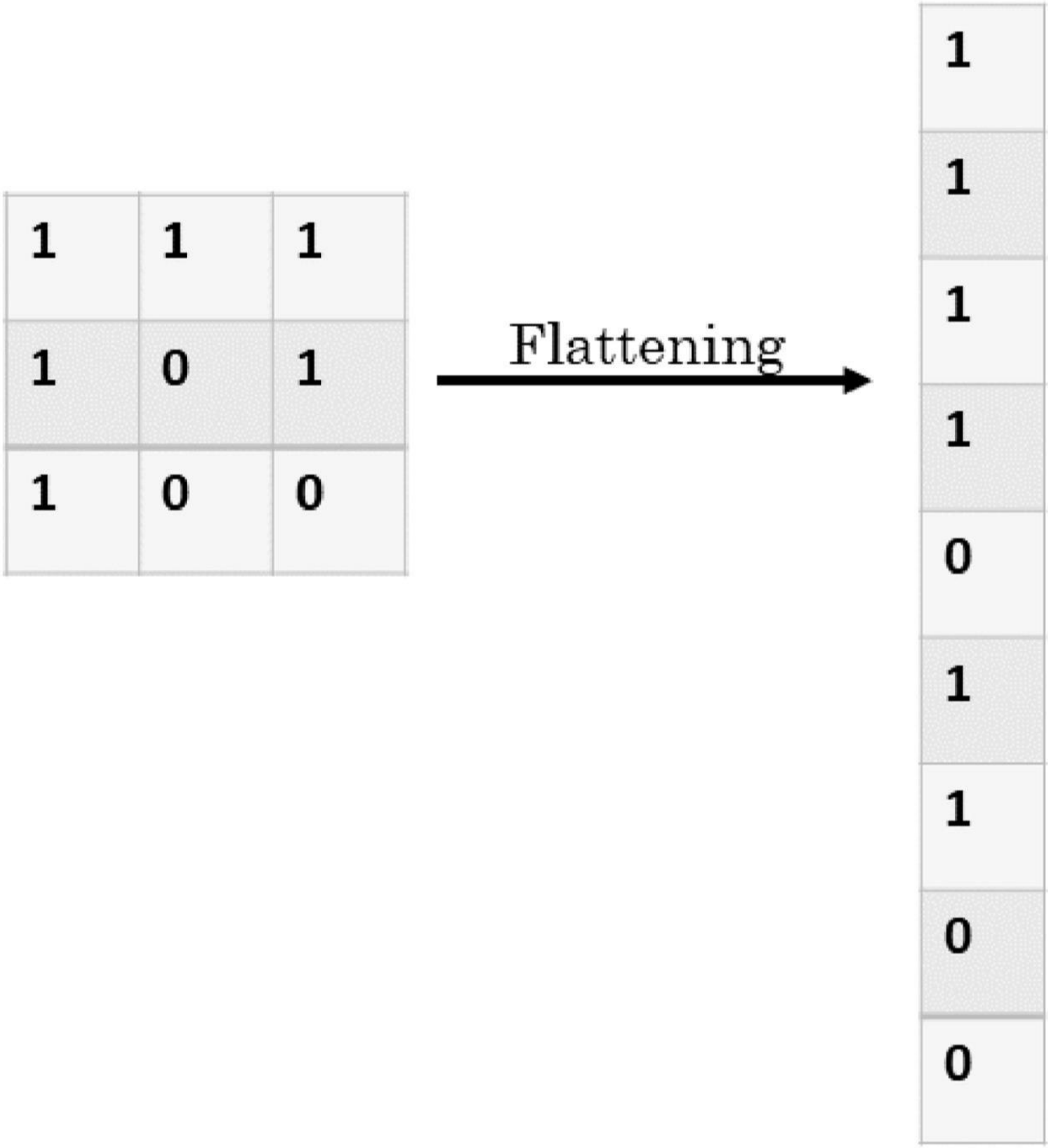

Fig 3.5.4. An example of the flattening procedure.

3.5. VGG-16

A convolutional neural network is also known as a ConvNet, which is a kind of artificial neural network. A convolutional neural network has an input layer, an output layer, and various hidden layers. VGG16 is a type of CNN (Convolutional Neural Network) that is considered to be one of the best computer vision models to date. The creators of this model evaluated the networks and increased the depth using an architecture with very small (3 × 3) convolution filters, which showed a significant improvement on the

prior-art configurations. They pushed the depth to 16–19 weight layers making it approx —138 trainable parameters. The basic architecture of VGG-16 is shown in Fig.3.6.1.1.
VGG16 is an object detection and classification algorithm which is able to classify 1000 images of 1000 different categories with 92.7% accuracy. It is one of the popular algorithms for image classification and is easy to use with transfer learning.

3.5.1. VGG-16 architecture

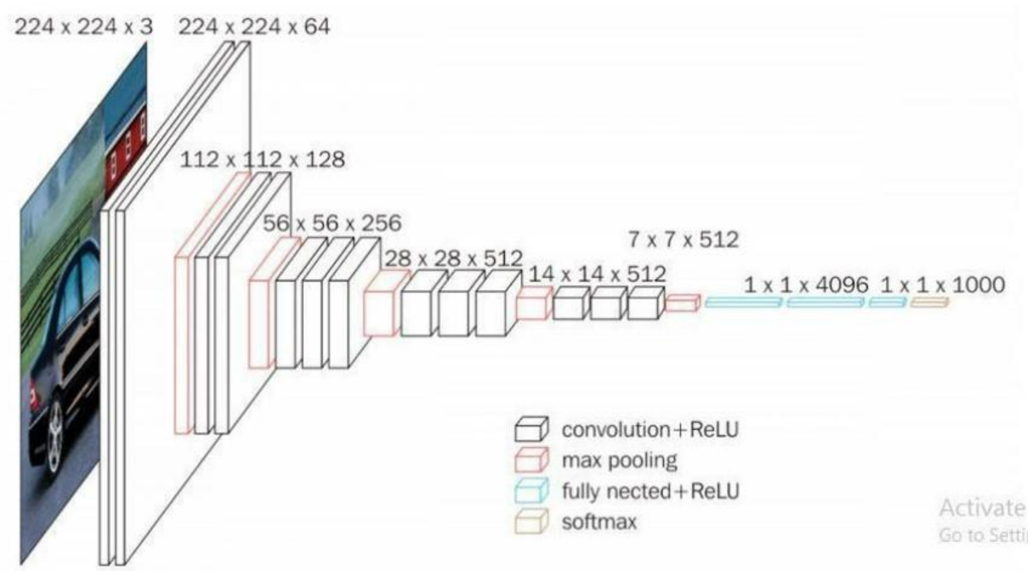

Fig.3.6.1.1. Basic VGG-16 architecture

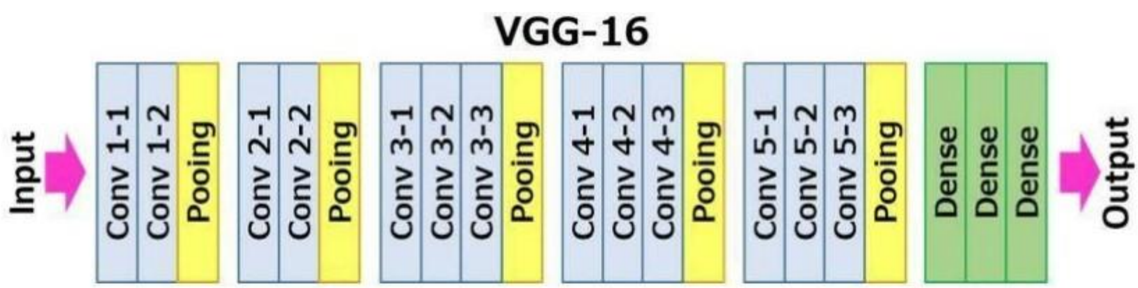

Fig.3.6.1.2. The 16 in VGG16 refers to 16 layers that have weights. In VGG16 there are thirteen convolutional layers, five Max Pooling layers, and three Dense layers which sum up to 21 layers but it has only sixteen weight layers i.e., the learnable parameters layer.

- The 16 in VGG16 refers to 16 layers that have weights. In VGG16 there are thirteen convolutional layers, five Max Pooling layers, and three Dense layers which sum up to 21 layers but it has only sixteen weight layers i.e., the learnable parameters layer. This is shown in Fig. 3.6.1.2.
- VGG16 takes input tensor size as 224, 244 with 3 RGB channel
- Most unique thing about VGG16 is that instead of having a large number of hyper-parameters they focused on having convolution layers of 3x3 filter with stride 1 and always used the same padding and max pool layer of 2x2 filter of stride 2.
- The convolution and max pool layers are consistently arranged throughout the whole architecture

3.6. Convolution Module

The convolution module is used in which there is the 4th pooling layer of the VGG-16 model. The scale-invariant convolution module captures the interesting clues of the image. The interesting clues are extracted from the mid-level layer (4th pooling) that is more appropriate to CXR images. However, the features from other layers (higher or lower) are not appropriate to CXR images because such images are neither more general nor more specific. Thus, in the first input the 4th pooling layer to the attention moduleis used. After that, the result of that module is concatenated with 4th pooling layer itself.

3.7. Fully Connected (FC) Base Layer

To represent the concatenated features achieved from attention and convolution block into one-dimensional (1D) features, fully connected layers are used. It consists of three layers such as flatten, dropout, and dense. In our method, the dropout is fixed to 0.5 and set the dense layer to 256.

3.8. Softmax Classifier

To classify the features extracted from the FC layers,and the softmax layer is used. For the softmax layer which is the last dense layer, the unit number depends on the number of categories (e.g., three for a dataset having three categories, four for the dataset with four categories, etc.). The softmax layer outputs the multinomial distribution of the probability scores based on the classification performed. The output of this distribution is

$$P(a = c|b) = \frac{e^{b_k}}{\sum_j e^{b_j}}, \tag{3.8.1.}$$

where *b* and *c* represents the probabilities that are retrieved from the softmax layer and one of the classes of the dataset used in our proposed method, respectively. Fig. 3.9.1. depicts the suggested model's general block diagram. In the next sections, we'll go through each of the basic blocks in detail. Fig. 3.9.2. describes model summary with VGG16 as the base model.

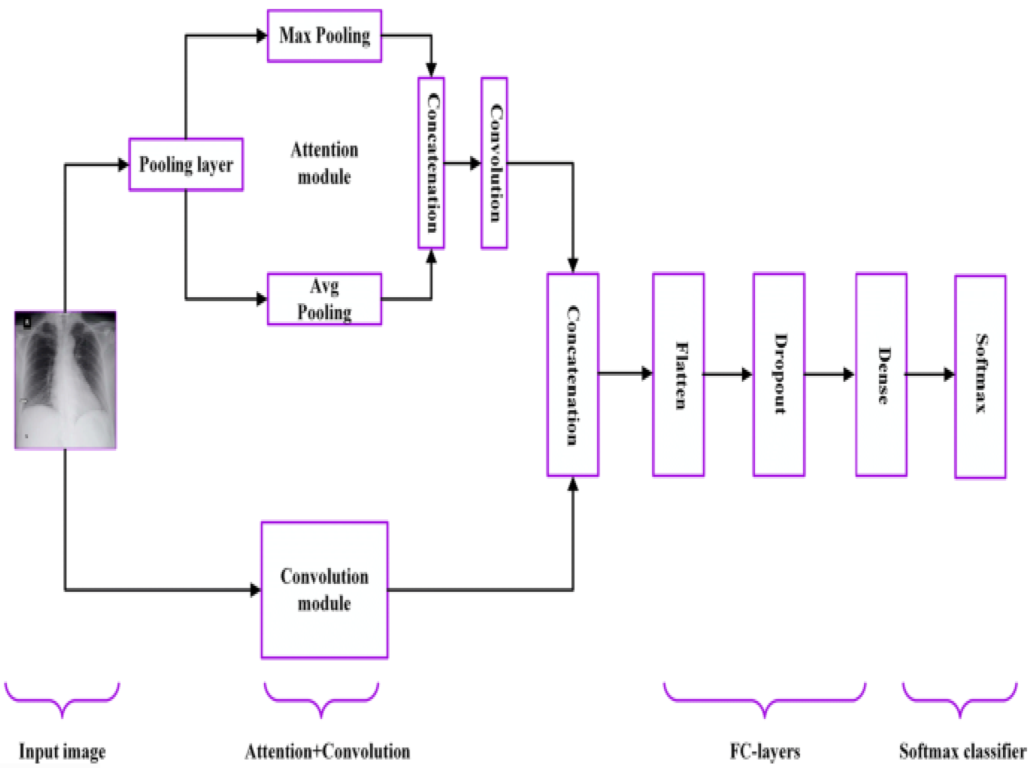

Fig.3.9.1. The VGG16 model's network configuration for COVID-19.

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d (Conv2D)              (None, 68, 68, 128)       3584
_________________________________________________________________
max_pooling2d (MaxPooling2D) (None, 34, 34, 128)       0
_________________________________________________________________
dropout (Dropout)            (None, 34, 34, 128)       0
_________________________________________________________________
conv2d_1 (Conv2D)            (None, 32, 32, 64)        73792
max_pooling2d (MaxPooling2D) (None, 34, 34, 128)       0
_________________________________________________________________
dropout (Dropout)            (None, 34, 34, 128)       0
_________________________________________________________________
conv2d_1 (Conv2D)            (None, 32, 32, 64)        73792
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 16, 16, 64)        0
_________________________________________________________________
dropout_1 (Dropout)          (None, 16, 16, 64)        0
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 14, 14, 64)        36928
_________________________________________________________________
flatten (Flatten)            (None, 12544)             0
_________________________________________________________________
dense (Dense)                (None, 16)                200720
_________________________________________________________________
dropout_2 (Dropout)          (None, 16)                0
_________________________________________________________________
dense_1 (Dense)              (None, 2)                 34
=================================================================
Total params: 315,058
Trainable params: 315,058
Non-trainable params: 0
```

Fig.3.9.2. Model summary with VGG16 as base model

In addition, the output obtained is influenced by the classes used to train the suggested model. In this thesis it is classified the output into four categories in this study, which can be identified as follows:

- **COVID-19:** by studying CXR and CT-Scan pictures, COVID-19 positive cases are discovered.
- **Pneumonia:** describes the patches of Pneumonia infection that have been observed in CXR images of patients.
- **Non-COVID-19:** This category comprises radiological images of patients who tested negative for COVID-19. However, these patients may have additional lung infections, according to the descriptions supplied for the relevant dataset.
- **Normal:** The radiological scans of various cases that are neutral or negative to COVID-19, Pneumonia, and other pulmonary infections are included in this category.

3.9. Image Analysis using Grad-CAM

To make deep learning more comprehensible and explainable, a lot of effort is being done. It is essential to make the deep learning model more interpretive in various deep learning applications connected to medical imaging. Selvaraju et al. have developed a technique known as Gradient Weighted Class Activation Mapping (Grad-CAM)[54], which allows deep learning models to be explained. Grad-CAM gives a visual explanation for any deeply linked Neural Network, which aids in learning more about the model while performing detection or prediction tasks.

Gradients in neural networks are vectors whose magnitude is the partial derivative of the function f(x) and which are directed towards the function's highest rate of growth. Grad-CAM employs class specificity to build localization maps of the significant portions of the picture based on this information flowing through a general convolutional network, making black-box models more accessible by showing visualizations that validate output predictions. Grad-CAM, to put it another way, combines pixel space gradient visualization with class discriminative properties. The assumption of the Grad-CAM model is that the final score as described below can always be expressed as a generalized linear combination of pooled average feature maps which depends on the following parameters: weights for a particular feature map, number of pixels in the activation map, etc. The final feature convolutional map of the input image is activated for different channels with respect to the class. That is to say, weighing every channel in the feature with the class gradient with respect to that channel. The global average pooling over two dimensions(i,j) for the gradient of respective class output with respect to the feature map is the spatial score of a specific class. The resulting value is multiplied with the feature map along with channel axis k and the resultant is pooled along its channel dimension. The spatial score map is hence of size i*j which is normalized to positive region predictions using the nonlinear ReLU transformation. The score for a class k correlates directly with the importance of the class-specific saliency map which hence impacts the final prediction output. Guided Grad-CAM is Grad-CAM integrated with existing pixel space visualizations to provide high-resolution class discriminative visualization. These are used in conjunction to solve image categorization and visual question answering challenges. Grad-CAM has the inherent ability to locate even the tiniest of objects. The backpropagation technique in the Guided Grad-CAM variation, which modifies the backward RELU pass to only send positive gradients to positively activated regions, improves localization but reduces Grad-class CAM's discriminative capacity. The guided backpropagation algorithm helps obtain coarse localization as well as high-resolution visualization highlighting regions that enable generated caption in the image captioning space.

As shown in Fig.3.10.1. the Grad-CAM takes a simple image as input and applies detection techniques using the proposed model. Grad-CAM is applied to any of the Conv layers after the projected label has been derived using the complete model. In most cases, the last Conv layer is the one that will be utilized to apply Grad-CAM.

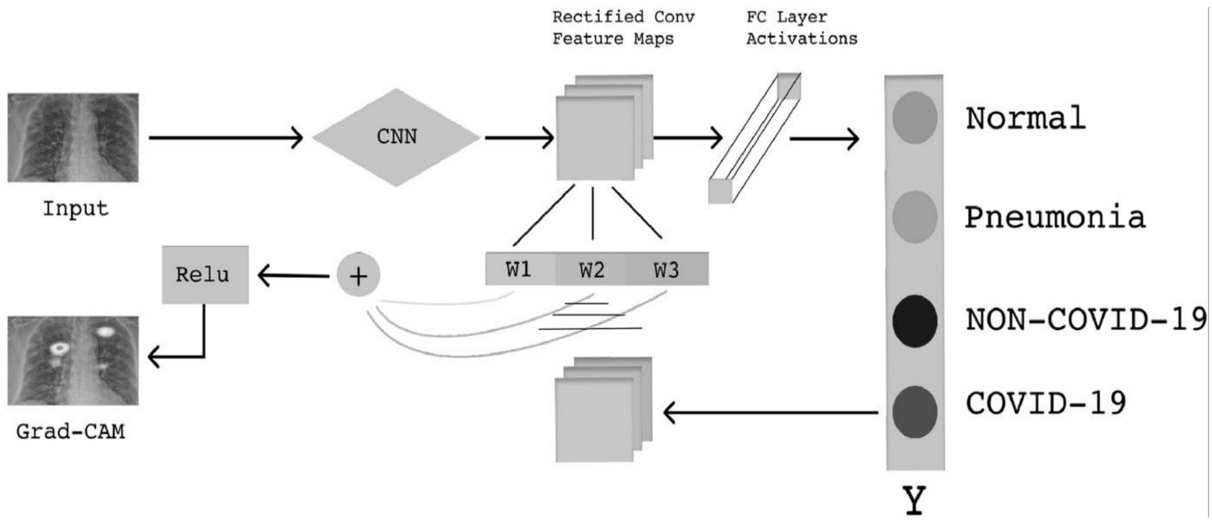

Fig.3.10.1. Gradient Weighted Class Activation Mapping is explained in a simple illustration(Grad-CAM). Panwar, H., Gupta, P. K., Siddiqui, M. K., Morales-Menendez, R., Bhardwaj, P., & Singh, V. (2020). A deep learning and grad-CAM-based color visualization approach for fast detection of COVID-19 cases using chest X-ray and CT-Scan images. *Chaos, Solitons & Fractals*, *140*, 110190.

3.10. Evaluation of performance

In Table 4.5.2 the confusion matrix to calculate the precision, recall, F-measure score, and accuracy of the model for evaluation is used. These were calculated using the parameters and equations listed below.

I. **True Positive(TP)**: If COVID-19 is identified in a COVID-19-affected person.
II. **True Negative(TN)**: If a person's NON-COVID-19 status is appropriately identified.
III. **False Positive (FP)**: depicts an inaccurate detection in which a healthy person is found to have COVID-19.
IV. **False Negative (FN)**: represents incorrect detection where a person infected with COVID-19 is detected as a normal one.

The following performance metrics have been calculated using the confusion matrix parameters.

- **Precision** COVID-19 accurate positive detection fraction is calculated. It is computed by Eq. 3.10.1.

$$Precision = \frac{TP}{TP+FP} \times 100\%$$
(3.10.1)

- **Recall** yields the proportion of total relevant examples correctly identified by the model, which determines how good all the positives are. Eq. 3.10.2 is used to compute it.

$$Sensitivity/Recall = \frac{TP}{Predictive\ Results(TP+FN)} \times 100\%$$
(3.10.2)

- **F-Measure** is a harmonic mean of recall and precision. It is calculated from Eq.3.10.3.

$$F - Measure = 2 \cdot \frac{Precision \cdot Recall}{Precision + Recall}$$

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

$$Accuracy = \frac{TP+TN}{Total\ no.\ of\ predictions}$$
(3.10.3)

3.11. Proposed Algorithm

The proposed deep transfer learning technique focuses primarily on binary image classification in order to identify the various Radiograph and CT-Scan pictures for rapid and accurate COVID-19 identification. The proposed algorithm considers the pre-trained weights to extract simple features and then learns the pattern of COVID-19 cases obtained from the patients' CXR and CT-Scan images. The suggested technique's key characteristic is that it uses completely connected layers with extra levels in the VGG-16 model. It, like other algorithms, takes into account the input dataset. CXR and CT-Scan pictures were used in this study, which included cases of COVID-19, NON-COVID-19, Pneumonia, and Normal. The dataset is represented using δ_n where n represents the n^{th} class. Because we're dealing with binary picture classification, the class value will be n=2. However, for multiclass image classification, n should be less than 2. The proposed algorithm's main steps are as follows:

3.11.1. Step 1. Create the datasets for training and testing-

Using the input dataset creates two needed sub-datasets. The first sub-dataset is a training dataset, which is used to fit the model for learning purposes using a sample of data. A set of samples is used to tune the various hyper-parameters for an unbiased evaluation of the classifier while selecting the number of hidden units in a neural network in the second sub-dataset of validation. Finally, a test sub-dataset is a random sample set that is used to evaluate the performance of a fully described model. Training, validation, and testing sub-datasets have split ratios of 60, 20, and 20 correspondingly.

3.11.2. Step 2. Prepare the base model and the new model-

As a basic model, VGG-16 on ImageNet with pre-trained weights is used in this phase. The suggested model has been developed to adapt and learn the basic features of computer vision (e.g., edges and boundaries), ensuring that the model does not have to learn from scratch each time it is used to train on CXR and CT-Scan image datasets.

3.11.3. Step 3. Update and store the trained weights-

These weights have been applied to detect cases of COVID-19. Forward propagation performs the calculation and obtains the output layer values from the input data. It goes through all of the neurons and covers each layer starting at the base. Eq.3.11.3.1 is then used to derive the binary cross-entropy loss function from the output values. The number of changes in the weights is counted as the backpropagation takes place. The computing process starts with the last layer and moves forward, starting with the backward layer and ending with the first layer. One iteration is made up of both forward and backward passes. A subset of the data set is passed and displayed as batch size (BS), which is also known as one epoch and indicates the passing of the whole data set at once, during this one iteration.

$$Cross\ Entropy = -(y\log(p) + (1-y)\log(1-p)) \qquad (3.11.3.1)$$

where p is the probability predicted by the model and y denotes the true value.

Chapter 4
Results and Discussion
4.1. Software Environment
Python

Python is a high-level and effective general-use programming language. It supports multi-paradigms. Python has a large standard library that provides tools suited to perform various tasks. Python is a simple, less-clustered language with extensive features and libraries. Different programming abilities are utilized for performing the experiment in our work. In this thesis, the following python libraries were used.

- Pandas - It is a python package that provides expressive data structures designed to work with both relational and labeled data. It is an open-source python library that allows the reading and writing data between data structures.
- Numpy - It is an open-source python package for scientific computing. Numpy also adds fast array processing capacities to python.
- Matplotlib - It is an open-source python package used for making plots and 2D representations. It integrates with python to give effective and interactive plots for visualization.
- Keras - Keras is a high-level, deep learning API developed by Google for implementing neural networks. It is written in Python and is used to make the implementation of neural networks easy. It also supports multiple backend neural network computations.
- Sklearn - It is an open-source python machine learning library designed to work alongside Numpy. It features various machine learning algorithms for classification, clustering, and regression.

4.2. About Dataset:
Computational technologies such as artificial intelligence (AI), data science, machine learning, and data mining are being actively employed to find a solution to the COVID-19 epidemic. For effective detection, these

algorithms are primarily reliant on datasets. Because COVID-19 is a novel condition, there is a limited amount of data to work with while doing trials. However, there are just a few public datasets that can be used to apply deep learning to radiological imaging. Cohen et al[20] 's data set is one of the most commonly utilized data sets for COVID-19 trials. For the purposes of this study, the following three datasets are used to run several experiments.

The posterior-to-anterior (AP)/anterior-to-posterior (PA) picture of a chest X-ray was employed in this study since radiologists use this view of radiography frequently in clinical diagnosis. To make a single database, six distinct sub-databases were used. The authors generated the COVID-19 database from gathered and publicly available records, whereas the normal and viral pneumonia databases were created from Kaggle databases. The authors have outlined the process of generating this dataset in the next section.

The following four major data sources were used to build the COVID-19 sub-database, which contains 423 AP/PA photos.

- Italian Society of Medical and Interventional Radiology (SIRM) COVID-19 DATABASE :

384 COVID-19 positive radiographic images (CXR and CT) with the variable resolution are reported in the SIRM COVID-19 database [21]. There are 94 chest X-ray images and 290 lung CT images among the 384 radiographic images. This database is updated at random intervals, and there were 71 verified COVID-19 instances recorded in this database as of May 10, 2020.

- Novel Corona Virus 2019 Dataset :

By gathering 319 radiographic images of COVID-19, the Middle East respiratory syndrome (MERS), Severe acute respiratory syndrome (SARS), and ARDS from published studies and online resources, Joseph Paul Cohen, Paul Morrison, and Lan Dao have built a public database in GitHub [22]. They have 250 COVID-19 positive chest X-ray images and 25 COVID-19 positive lung CT images with varied image resolutions in this database. However, the authors of this study took into account 134 COVID-19 positive chest X-ray images, which differ from the photos in the database that the authors compiled from various articles.

- COVID-19 positive chest x-ray images from different articles:

The authors were inspired to delve into the literature by the GitHub database, and more than 1200 pieces were published in less than two months. The authors noticed that the GitHub database did not contain the majority of the X-ray and CT images, but only a small number of them. Furthermore, the photos in the SIRM and GitHub databases are of varying sizes, depending on the resolution of the X-ray machine and the articles from which they were obtained. The authors were able to gather 60 COVID-19 positive chest X-ray photos from 43 recently published publications that were not mentioned in the GitHub database, as well as 32 positive chest x-ray images from Radiopaedia[23] that were not featured in the GitHub database.

- COVID-19 Chest imaging at thread reader:

A physician has shared 103 images for 50 different cases with varying resolutions from his hospital in Spain to the Chest imaging at thread reader[24]. Images from the RSNA-Pneumonia-Detection-Challenge database were combined with the Kaggle Chest X-ray Images database to construct the sub-databases for normal and viral pneumonia 1579 X-ray images and 1485 X-ray pictures, respectively.

- RSNA-Pneumonia-Detection-Challenge

The Radiology Society of North America (RSNA) held an artificial intelligence (AI) challenge in 2018 to diagnose pneumonia using X-ray pictures of the chest. Normal chest X-rays with no lung infection and non-COVID pneumonia images were present in this database[25].

- Chest X-Ray Images (pneumonia):

The Kaggle chest X-ray database is a popular one, comprising 5247 chest X-ray images of normal, viral, and bacterial pneumonia, with resolutions ranging from 400 to 2000 pixels[26]. There are 3906 photos from different people affected by pneumonia (2561 images for bacterial pneumonia and 1345 images for viral pneumonia) and 1341 images from normal subjects among the 5247 chest X-ray images. This database was utilized to construct the new database, which included chest X-ray images for both normal and viral pneumonia. Figure 1 shows a selection of chest X-ray images from the database, including normal, COVID-19 pneumonia, and viral pneumonia.

Two different experiments on three different radiology in this study. These tests can be divided into two categories: (1) Binary Image Classification on CXR of COVID-19 positive patients vs. CXR of Normal Patients; and (2) Binary Image Classification on COVID-19 positive patients' CXR vs. Pneumonia patients' CXR.

Fig.4.2.1 Sample X-ray image from the dataset: COVID-19 X-ray image (A), normal X-ray image (B), and viral pneumonia X-ray image (C).

4.3. Data Preprocessing

Data preprocessing is an important process in the development of a machine learning model. The data collected is often loosely controlled with out-of-range values, missing values, etc. Such data can mislead the result of the experiment.

- **Imputation of missing values** - In our data, missing values have been handled by using a simple imputer from the sklearn python package. The missing values are replaced by using the mean strategy.
- **Encoding Categorical Data**- The package of OneHotEncoder in python is used, this package handles categorical data by one-hot or dummy encoding scheme.

4.4.Experiment 1: COVID-19 vs normal

The proposed deep learning technique is used to classify COVID-19 infected instances from normal ones in this experiment. 3616 CXR images of COVID-19 infected patients from the COVID-chest X-ray-dataset and 10192 CXR images of normal patients from the CXR Image dataset for this study are used, the number of cases is shown in Fig 4.4.1.

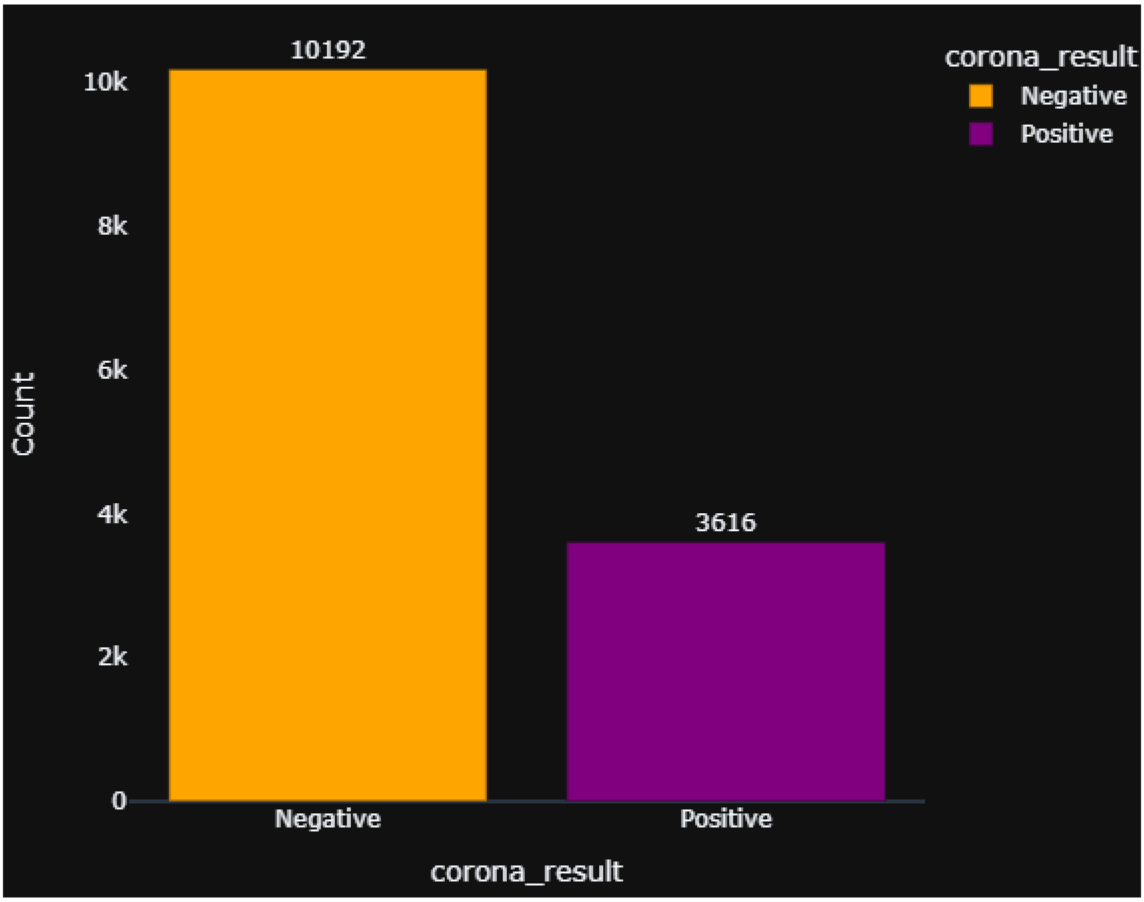

Fig. 4.4.1. Counts of corona result

4.4.1.Different Types of Image Augmentation

Image augmentation is a method of modifying existing images in order to generate additional data for the model training process. In other words, it is the technique of artificially increasing the dataset available for deep learning model training. Various types of Image augmentation techniques are shown in Fig. 4.4.1.1.

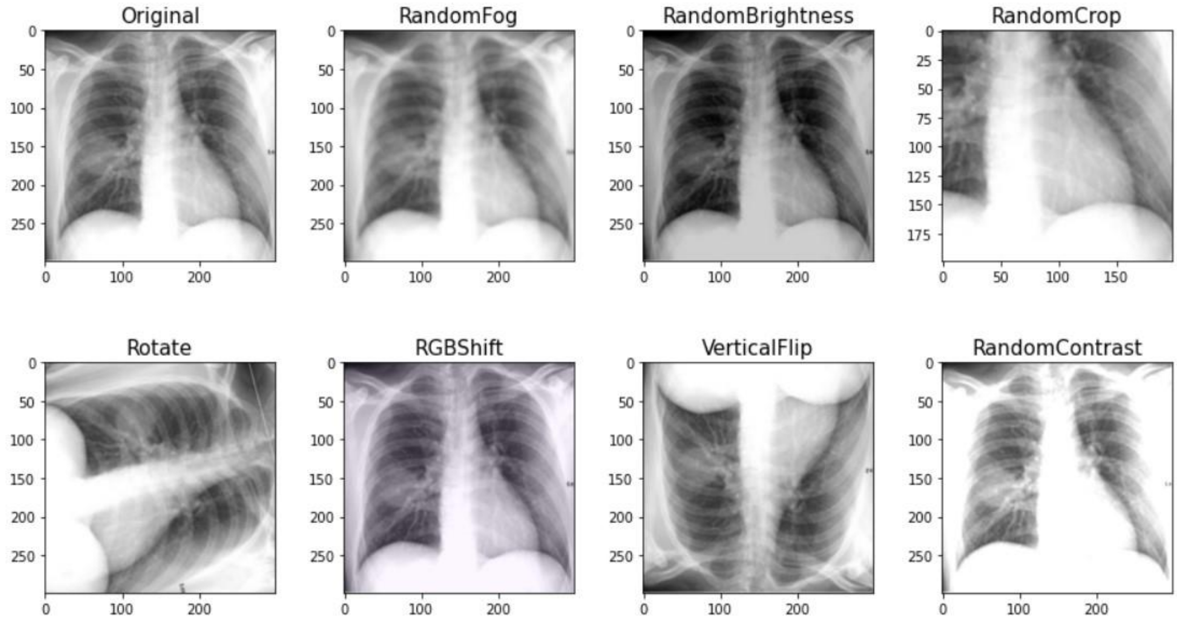

Fig. 4.4.1.1. Different types of Augmentation

4.4.2.Grad cam Image Analysis

- Positive-1 Sample Insight: In its Grad-CAM image, the blue colour highlighted section on the right mid part of it has opaque, indicating that it belongs to the COVID - Positive Category.
- Positive-2 Sample Insight: In its Grad-CAM image, the observation of the blue-green hue is highlighted section on the left bottom half of it, which is consolidation, and no Tree-Bud, hence it belongs to COVID - Positive Category.
- Negative-1 Sample Insight: The blue colour highlighted section between the Cardiac and Diaphragm can be seen in the Grad-CAM image, and no opacity was detected, hence it falls into the COVID - Negative Category.
- Negative-2 Sample Insight: The blue colour part of the Grad-CAM image highlights the Trachea, and no other opacity was observed, hence it falls into the COVID - Negative Category.

These analysis are highlighted below in Fig.4.2.2.1.

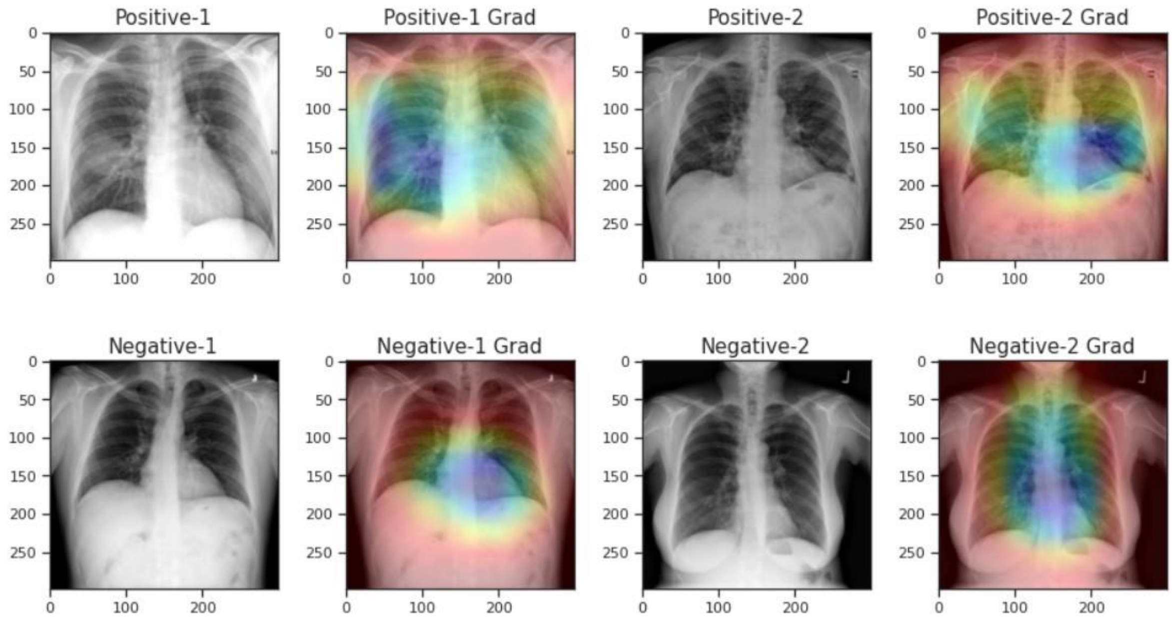

Fig.4.2.2.1. Grad cam covid 19 image analysis

For training, validation, and testing, the COVID-19 positive cases dataset distribution is 9941, 2762, and 1105, respectively. For training, validation, and testing purposes, the dataset distribution for Normal Patients is 8232, 1272, and 1069, respectively. Fig.11 displays the training accuracy, validation accuracy, training loss, and validation loss plots.
On the 30th epoch, the best results are acquired for the proposed model. The Train and Validation Accuracy Curves, as well as the Loss Curve, appear to be slightly overlapping. As a result, Overfitting is avoided, due to Dropout Regularization and Early Stopping Metrics. As a result, it stops at the 34th epoch, as seen in Fig.4.2.2.2.
The specificity of the proposed model is calculated by using this data. The proposed model has a specificity of 95.58 %. Using the CXR and CT-Scan images, each patient who visits the hospital and is COVID-19 Negative (i.e., True Negatives) can be recognized as Normal with high accuracy during the tests. Because of the good clarity of the pictures, the radiologist can also utilize a color visualization approach using Grad-CAM to make an expedient and confident choice. In Table 4.5.2, the recall, precision, and F1-score are also provided. By using the Grad-CAM technique, the suggested model has obtained an overall accuracy of 95.58%, as well as a better understanding of the deep learning model's

predictions. The confusion matrix of experiment 1 is shown in Table 4.4.2.1.

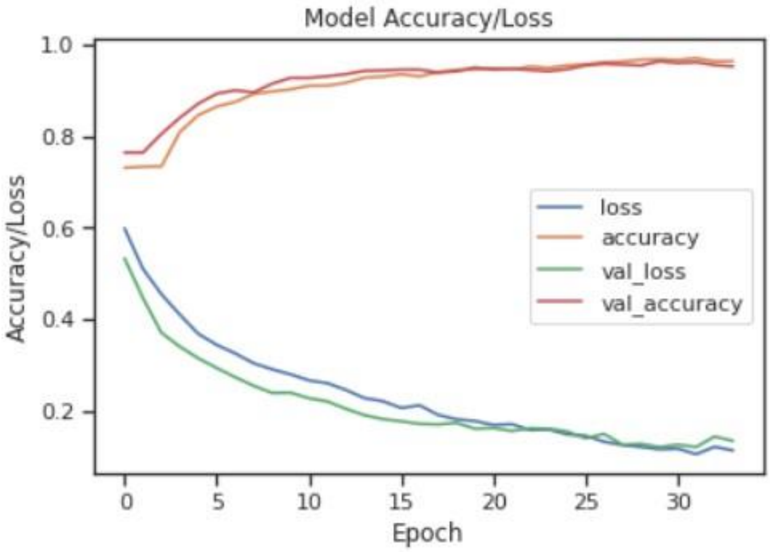

Fig.4.2.2.2. Experiment 1: Training loss, Validation loss, Training accuracy, Validation accuracy, and early stopping

<u>Table 4.4.2.1. Confusion matrix of Experiment 1</u>

		Predicted Class	
		Covid 19 (Class-1)	Normal (Class-2)
Actual Class	Covid 19 (Class-1)	TP= 7152	FN=135
	Normal (Class-2)	FP=45	TN=2609

4.5. Experiment 2: COVID-19 vs. Pneumonia

The goal of this study is to see if there is a connection between COVID-19 positive and Pneumonia cases. In the instance of pneumonia, CXR Images of Pneumonia are used, which were compiled roughly 1–2 years ago, well before the COVID-19 outbreak. In contrast, for COVID-19-positive patients, the same data as in Experiment-1 is used. The dataset split is performed in the same way as Experiment-1. The values for training accuracy, validating accuracy, training loss, and validation loss acquired after Experiment-2 are provided in the table below.

For COVID-19 positive patients, the obtained specificity is 96.45%. The proposed method can predict and detect COVID-19 patients (i.e. true positive) with 93.45 % accuracy from the data. The confusion Matrix was also used to assess memory, precision, and F-1 Score, as shown. The proposed model has an overall accuracy of 93.45% when it comes to successfully detecting COVID-19 cases. As a result it is shown in Fig 4.5.1.

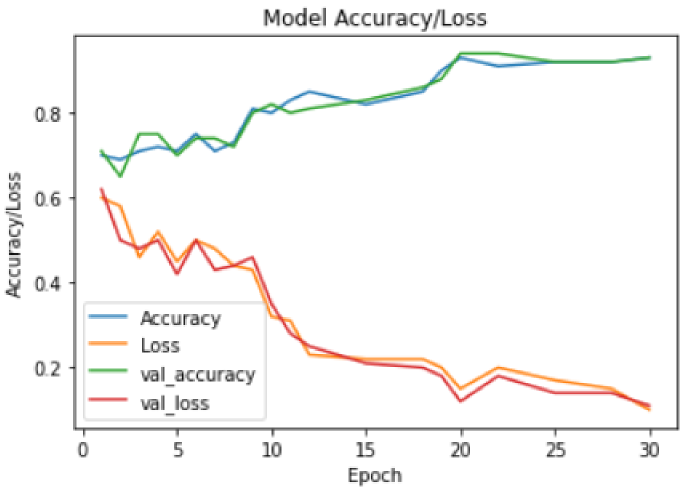

Fig.4.5.1. Experiment 2: Training loss, Validation loss, Training accuracy, Validation accuracy, and early stopping

Table 4.5.1. Confusion matrix of Experiment 2

		Predicted Class	
		Covid 19 (Class-1)	Pneumonia (Class-2)
Actual Class	Covid 19 (Class-1)	TP= 814	FN=30
	Pneumonia (Class-2)	FP=23	TN=238

Table 4.5.2. Binary Class Image Classification Evaluation

Exp.	**Class-1**			**Class-2**			**Overall Accuracy**
	Precision	Recall	F1 Score	Precision	Recall	F1 Score	
1.	97	97	97	92	90	91	95.58
2.	83	94	88	97	96	96	93.45

Chapter 5
Conclusion

COVID-19 is still a pandemic, with new records in terms of worldwide infection counts and death tolls being established every day. COVID-19 has already been detected thanks to the development of a consistent and accurate deep learning-based automatic diagnostic. The newest COVID-19 diagnosis work is described in this article, which uses deep learning algorithms to diagnose two types of imaging modalities: CT and X-ray samples. The COVID-19 diagnosis systems are discussed in this term paper, which is built on a pre-trained model with deep transfer learning and bespoke deep learning architecture. A two-leveled taxonomy was used to investigate the perspectives of deep learning techniques and imaging modalities. The studies are conducted on binary image classification to detect COVID-19 and Non-COVID-19 positive patients in this study. Furthermore, non-COVID-19 positive patients may have Pneumonia or other respiratory disorders, according to the analysis. The CXR and CT-Scan pictures of the chest have been used in several investigations to detect COVID-19 patients. The proposed approach has a detection accuracy of 95.58 % for COVID-19 cases, which is significantly faster than traditional RT-PCR testing. The weights produced from the proposed model's training during CT Scan image processing also give a substantial response to CXR images. In our tests, the Grad-CAM technique is used to apply a colour visualization approach to make the suggested deep learning model more interpretable and explainable. The results show that a patient with Pneumonia has a higher likelihood of being assessed as a False Positive using the proposed method. As a result, it is recommended that the model be trained on radiology pictures of patients with Pneumonia symptoms to detect COVID-19 instances reliably and with a higher recall. This will help to identify pneumonia patients who were previously identified as false positives as True Negative (just to clarify, COVID-19 cases are True Positive). In a real-time context, this results in an unbiased detection of COVID-19 cases. Deep learning algorithms cannot replace physicians or clinicians in clinical diagnosis, according to the findings of this study. Deep learning experts are expected to work with radiologists and medical professionals to develop adequate support systems for detecting COVID-19 infections, particularly in the early stages of the disease, or determining the severity of the infection shortly.

Chapter 6

References

[1]. (2020). *WHO Director-General's Opening Remarks at the Media Briefing on COVID-19_11 March 2020*. [Online]. Available: https://www.who. int/dg/speeches/detail/who-director-general-s-opening-remarks-at-themedia-brie_ng-on-covid-19_11-march-2020.

[2]. (2020). *Coronavirus Disease 2019 (COVID-19)*. [Online]. Available: https://www.cdc.gov/coronavirus/2019-ncov/need-extra-precautions/ people-at-higher-risk.html.

[3]. Hu, Qiongjie, et al. "Early CT features and temporal lung changes in COVID-19 pneumonia in Wuhan, China." *European journal of radiology* 128 (2020): 109017.

[4]. *Global COVID-19 Report*, World Health Organization, Geneva, Switzerland, Mar. 2020.

[5]. J. H. U. Medicine. (2020). *Coronavirus COVID-19 Global Cases by the Center for Systems Science and Engineering (CSSE) at Johns Hopkins University (JHU)*. [Online]. Available: https://coronavirus.jhu.edu/map.html.

[6]. Wang, Dawei, et al. "Clinical characteristics of 138 hospitalized patients with 2019 novel coronavirus–infected pneumonia in Wuhan, China." *Jama* 323.11 (2020): 1061-1069.

[7]. Chen, Nanshan, et al. "Epidemiological and clinical characteristics of 99 cases of 2019 novel coronavirus pneumonia in Wuhan, China: a descriptive study." *The lancet* 395.10223 (2020): 507-513.

[8]. Li, Qun, et al. "Early transmission dynamics in Wuhan, China, of novel coronavirus–infected pneumonia." *New England journal of medicine* (2020).

[9]. Huang, Chaolin, et al. "Clinical features of patients infected with 2019 novel coronavirus in Wuhan, China." *The lancet* 395.10223 (2020): 497-506.

[10]. Wang, W., Xu, Y., Gao, R., Lu, R., Han, K., Wu, G., & Tan, W. (2020). Detection of SARS-CoV-2 in different types of clinical specimens. *Jama*, *323*(18), 1843-1844.

[11]. A. J. News. (2020). *India's Poor Testing Rate May Have Masked Coronavirus Cases*. [Online]. Available: https://www.aljazeera.com/news/2020/03/india-poor-testing-rate masked-coronavirus cases-200318040314568.html.

[12] A. J. News. (2020). *Bangladesh Scientists Create 3 Kit. Can it Help Detect COVID-19*? [Online]. Available: HTML.

[13]. Kumar, Aishwarya, Puneet Kumar Gupta, and Ankita Srivastava. "A review of modern technologies for tackling COVID-19 pandemic." *Diabetes & Metabolic Syndrome: Clinical Research & Reviews* 14.4 (2020): 569-573.

[14]. Kanne, Jeffrey P. "Chest CT findings in 2019 novel coronavirus (2019-nCoV) infections from Wuhan, China: key points for the radiologist." (2020): 16-17.

[15]. Kim, Hyungjin, Hyunsook Hong, and Soon Ho Yoon. "Diagnostic performance of CT and reverse transcriptase-polymerase chain reaction for coronavirus disease 2019: a meta-analysis." *Radiology* 296.3 (2020): E145-E155.

[16]. Mei, Xueyan, et al. "Artificial intelligence-enabled rapid diagnosis of patients with COVID-19." *Nature medicine* 26.8 (2020): 1224-1228.

[17]. Islam, Md Milon, et al. "A review on deep learning techniques for the diagnosis of novel coronavirus (covid-19)." *IEEE Access* 9 (2021): 30551-30572.

[18]. Tahir, Anas M., et al. "COVID-19 infection localization and severity grading from chest X-ray images." *Computers in biology and medicine* 139 (2021): 105002.

[19]. T. Rahman, A. Khandakar, Y. Qiblawey A. Tahir S. Kiranyaz, S. Abul Kashem, M. Islam, S. Al Maadeed, S. Zughaier, M. Khan, M. Chowdhury, "Exploring the Effect of Image Enhancement Techniques on COVID-19 Detection using Chest X-rays Images," Computers in Biology and Medicine, p. 104319, 2021, https://doi.org/10.1016/j.compbiomed.2021.104319.

[20]. A. Degerli, M. Ahishali, M. Yamac, S. Kiranyaz, M. E. H. Chowdhury, K. Hameed, T. Hamid, R. Mazhar, and M. Gabbouj, "Covid-19 infection map generation and detection from chest X-ray images," Health Inf Sci Syst 9,1(2021), https://doi.org/10.1007/s13755-021-00146-8.

[21]. M. E. H. Chowdhury, T. Rahman, A. Khandakar, R. Mazhar, M. A. Kadir, Z. B. Mahbub, K. R. Islam, M. S. Khan, A. Iqbal, N. A. Emadi, M. B. I. Reaz, M. T. Islam, "Can AI Help in Screening Viral and COVID-19 Pneumonia?," IEEE Access, vol. 8, pp. 132665-132676, 2020, https://doi.org/10.1109/ACCESS.2020.3010287.

[22]. Nguyen, G., Dlugolinsky, S., Bobák, M., Tran, V., Lopez Garcia, A., Heredia, I., ... & Hluchý, L. (2019). Machine learning and deep learning frameworks and libraries for large-scale data mining: a survey. *Artificial Intelligence Review*, *52*(1), 77-124.

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

[24]. Cohen, J. P., Morrison, P., Dao, L., Roth, K., Duong, T. Q., & Ghassemi, M. (2020). Covid-19 image data collection: Prospective predictions are the future. *arXiv preprint arXiv:2006.11988*.

[25]. S.-I. S. O. M. A. I. Radiology. (2020). *COVID-19 Database*. [Online]. Available: https://www.sirm.org/category/senza-categoria/covid-19/

[26]. J. C. Monteral. (2020). *COVID-Chestxray Database*. [Online]. Available: https://github.com/ieee8023/covid-chestxray-dataset

[27]. (2020). *Radiopedia*. [Online]. Available: https://radiopaedia.org/search?lang=us&page=4&q=covid+19&scope=all&utf8=%E2%9C%93
[24]. C. Imaging. (2020). *This is a Thread of COVID-19 CXR (All SARS-CoV-2 PCR+) From my Hospital (Spain). I Hope it Could Help*. [Online]. Available: https://threadreaderapp.com/thread/1243928581983670272.html

[28]. X.Wang, Y. Peng, L. Lu, Z. Lu, M. Bagheri, and R. M. Summers, ``ChestXray8: hospital-scale chest X-ray database and benchmarks on weakly-supervised classification and localization of common thorax diseases,'' in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CPR)*, Jul. 2017, pp. 2097_2106.

[29]. P. Mooney. (2018). *Chest X-Ray Images (Pneumonia)*. [Online]. Available:https://www.kaggle.com/paultimothymooney/chest-xray-pneumonia

[30] Panwar, H., Gupta, P.K., Siddiqui, M.K., Morales-Menendez, R., Bhardwaj, P. and Singh, V., 2020. A deep learning and grad-CAM-based color visualization approach for fast detection of COVID-19 cases using chest X-ray and CT-Scan images. *Chaos, Solitons & Fractals*, *140*, p.110190.

[31]. 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), 635-640.

[32]. Abbas, Asmaa, Mohammed M. Abdelsamea, and Mohamed Medhat Gaber. "Classification of COVID-19 in chest X-ray images using DeTraC deep convolutional neural network." *Applied Intelligence* 51.2 (2021): 854-864.

[33]. Manage, Shervin, et al. "Deep-COVID: Predicting COVID-19 from chest X-ray images using deep transfer learning." *Medical image analysis* 65 (2020): 101794.

[34]. Khan, Asif Iqbal, Junaid Latief Shah, and Mohammad Mudasir Bhat. "CoroNet: A deep neural network for detection and diagnosis of COVID-19 from chest x-ray images." *Computer methods and programs in biomedicine* 196 (2020): 105581.

[35]. Shafahi, A., Najibi, M., Ghiasi, M. A., Xu, Z., Dickerson, J., Studer, C., ... & Goldstein, T. (2019). Adversarial training for free!. *Advances in Neural Information Processing Systems*, *32*.

[36].T. R. Muhammad E. H. Chowdhury, A. Khandakar, R. Mazhar,M. A. Kadir, Z. B. Mahbub, K. R. Islam, M. S. Khan, A. Iqbal, N. Al-Emadi, and M. Bin I. Reaz. (2020). *COVID-19 Chest X-Ray Database*.

[37]. Apostolopoulos, Ioannis D., and Tzani A. Mpesiana. "Covid-19: automatic detection from x-ray images utilizing transfer learning with convolutional neural networks." *Physical and engineering sciences in medicine* 43.2 (2020): 635-640.

[38]. Yamac, Mehmet, et al. "Convolutional sparse support estimator-based COVID-19 recognition from X-ray images." *IEEE Transactions on Neural Networks and Learning Systems* 32.5 (2021): 1810-1820.

[39]. Ahishali, Mete, Aysen Degerli, Mehmet Yamac, Serkan Kiranyaz, Muhammad EH Chowdhury, Khalid Hameed, Tahir Hamid, Rashid Mazhar, and Moncef Gabbouj. "Warning methodologies for covid-19 using chest x-ray images." *IEEE Access* 9 (2021): 41052-41065.

[40]. Motamed, Saman, and Farzad Khalvati. "Multi-class generative adversarial nets for semi-supervised image classification." *arXiv preprint arXiv:2102.06944* (2021).

[41]. Yamac, M., Ahishali, M., Degerli, A., Kiranyaz, S., Chowdhury, M. E., & Gabbouj, M. (2021). Convolutional sparse support estimator-based COVID-19 recognition from X-ray images. *IEEE Transactions on Neural Networks and Learning Systems*, *32*(5), 1810-1820.

[42]. Ahmed, Sabbir, et al. "Reconet: Multi-level preprocessing of chest x-rays for covid-19 detection using convolutional neural networks." *medRxiv* (2020).

[43]. Kumar, Saurabh, Shweta Mishra, and Sunil Kumar Singh. "Deep Transfer Learning-based COVID-19 prediction using Chest X-rays." *Journal of Health Management* 23.4 (2021): 730-746.

[44]. Luján-García, Juan Eduardo, et al. "A transfer learning method for pneumonia classification and visualization." *Applied Sciences* 10.8 (2020): 2908.

[45]. Apostolopoulos, Ioannis D., and Tzani A. Mpesiana. "Covid-19: automatic detection from x-ray images utilizing transfer learning with convolutional neural networks." *Physical and engineering sciences in medicine* 43.2 (2020): 635-640.

[46]. Ozturk, Tulin, et al. "Automated detection of COVID-19 cases using deep neural networks with X-ray images." *Computers in biology and medicine* 121 (2020): 103792.

[47]. Toğaçar, Mesut, Burhan Ergen, and Zafer Cömert. "COVID-19 detection using deep learning models to exploit Social Mimic Optimization and structured chest X-ray images using fuzzy color and stacking approaches." *Computers in biology and medicine* 121 (2020): 103805.

[48]. Panwar, Harsh, et al. "Application of deep learning for fast detection of COVID-19 in X-Rays using nCOVnet." *Chaos, Solitons & Fractals* 138 (2020): 109944.

[49]. Goodfellow, Ian, et al. *Deep learning*. Vol. 1. No. 2. Cambridge: MIT Press, 2016.

[50] Shin, Hoo-Chang, et al. "Deep convolutional neural networks for computer-aided detection: CNN architectures, dataset characteristics, and transfer learning." *IEEE transactions on medical imaging* 35.5 (2016): 1285-1298.

[51]. A. Elhassouny and F. Smarandache, ``Trends in deep convolutional neural networks architectures: A review,'' in *Proc. Int. Conf. Computer. Sci. Renew. Energies (ICCSRE)*, Jul. 2019, pp. 1_8, DOI: 10.1109/ICCSRE.2019.8807741.

[52]. Goodfellow, Ian, Yoshua Bengio, and Aaron Courville. *Deep learning*. MIT Press, 2016.

[53]. Selvaraju, Ramprasaath R., et al. "Grad-cam: Visual explanations from deep networks via gradient-based localization." *Proceedings of the IEEE international conference on computer vision*. 2017.