Covid Pneumonia detection on Chest X-Rays using Convolutional Neural Network

MSc Research Project
Data Analytics

Pavan Doddaiah Kalpana
Student ID: 19201613

School of Computing
National College of Ireland

Supervisor: Dr. Christian Horn

National College of Ireland
Project Submission Sheet
School of Computing

Student Name:	Pavan Doddaiah Kalpana
Student ID:	19201613
Programme:	Data Analytics
Year:	2021
Module:	MSc Research Project
Supervisor:	Dr. Christian Horn
Submission Due Date:	31/01/2022
Project Title:	Covid Pneumonia detection on Chest X-Rays using Convolutional Neural Network
Word Count:	7,253 (Including references)
Page Count:	22

I hereby certify that the information contained in this (my submission) is information pertaining to research I conducted for this project. All information other than my own contribution will be fully referenced and listed in the relevant bibliography section at the rear of the project.

ALL internet material must be referenced in the bibliography section. Students are required to use the Referencing Standard specified in the report template. To use other author's written or electronic work is illegal (plagiarism) and may result in disciplinary action.

Signature:	
Date:	31st January 2022

PLEASE READ THE FOLLOWING INSTRUCTIONS AND CHECKLIST:

Attach a completed copy of this sheet to each project (including multiple copies).	☐
Attach a Moodle submission receipt of the online project submission, to each project (including multiple copies).	☐
You must ensure that you retain a HARD COPY of the project, both for your own reference and in case a project is lost or mislaid. It is not sufficient to keep a copy on computer.	☐

Assignments that are submitted to the Programme Coordinator office must be placed into the assignment box located outside the office.

Office Use Only	
Signature:	
Date:	
Penalty Applied (if applicable):	

Covid Pneumonia detection on Chest X-Rays using Convolutional Neural Network

Pavan Doddaiah Kalpana
19201613

Abstract

The emergence of a coronavirus outbreak caused by a new virus known as SARS-CoV-2 happened around the beginning of 2020. Covid-19's sudden explosion and unregulated worldwide spread reflect the weaknesses of current healthcare facilities in dealing with public health crises in a timely manner. Organizations in health care are frantic for decision-making technology to deal with such a virus and to aid them in having sufficient real-time guidance to prevent its spread. 1. Bigdata, 2. Internet of Things(IoT), 3. Machine learning, 4. Artificial Intelligence (AI) are few technologies and we also have other cutting-edge technology that can improve traditional health-care practices. In this context, artificial intelligence offers smart solutions for the detection of coronavirus-induced symptoms for care, prevention, and support for drug manufacturing. This study examines AI strategies employed in various applications to combat the breakout of covid-19 and describes the key goal of artificial intelligence research in this unusual battle.

1 Introduction

A significant concern across the globe is the coronavirus (covid-19) outbreak in late 2019. So huge was the magnitude of the epidemic that the World Health Organization (WHO) was forced within a month of its wide-scale spread to declare it a pandemic. With the major interruptions of many industries, such as supply chain, industry, insurance, agriculture, transport, and tourism, the spread of the virus triggers the global economic shock, forcing governments and owners to stop operations on a global scale.

As the number of infections increases, dramatic lock-downs and curfews have been introduced by many governments around the world, asking for social isolation and working from home to slow the virus's spread. Every effort is being made to ensure support for patients as well as stop the spread of the deadly coronavirus. Technology-enabled solutions will help cope with the global health crisis as authorities scramble to solve these problems. The outbreak of covid-19 could force the current healthcare systems to their limits. There is currently a lack of a trusted data monitoring system that would immediately provide the information they need about possible outbreaks to relevant healthcare organizations. Much of the existing knowledge on the coronavirus comes from different sources, such as the public, hospitals, and clinical laboratories, with a significant amount of incorrect data without rigorous monitoring. For possible outbreak detection and quarantine, the use of untrusted information makes it difficult. Using human-dependent medicine methods to process coronavirus data with complicated patterns and huge volumes is very difficult.

Bigdata, machine learning, ai, IoT, and other emerging technologies have the potential to improve traditional healthcare approaches. Artificial intelligence(AI) may have a substantial influence on the administration and delivery of care in pandemic conditions in this regard. The purpose of this research is to give a complete assessment of the applications and use cases of coronavirus-specific AI technologies (covid-19) based on the fast-expanding literature and the most recent research projects.

The covid-19 epidemic has a direct impact on health-care systems' capacity to continue delivering life-saving care. While the rising demand for covid-19 treatment is straining health-care systems around the globe, it is vital to keep preventative and curative resources available, specifically for the most populations that areat risk such as the children, persons suffering with severe ailments, the elderly, the people with disabilities and minorities. Countries must strike the perfect balance in preserving crucial health care, and combating the covid-19 epidemic. Some of the works mentioned below show the key role played by AI as a strong weapon to assist the healt-care professionals in early detection of the disease. In the research paper Zhavoronkov et al. (2020), the author proposed utilizing the deep generative drug discovery model to uncover novel treatments. A high precision AI-based system is suggested in Hu et al. (2020) to track the covid-19 epidemic and improve health and policy interventions. IBM has announced the availability of a research resource that is cloud-based which is trained on the covid-19 open dataset (CORD-19) *COVID-19 Open Research Dataset Challenge (CORD-19)* (n.d.). Furthermore, IBM formally adopted its proposed AI drug research technology, from which 3000 new covid-19 molecules were obtained. To dynamically alter control settings based on outbreak methods, SIR model is presented. An improved auto-encoder system is being researched in order to simulate the transmission dynamics of covid-19. Using the WHO's empirical data, the model will attain an average error which is less than 2.5 percent. The architecture of AI4covid-19 is intended to take into consideration the domain experience of healthcare specialists Imran et al. (2020). Cough or sound signals, which cellphones can record, are examples of input data. 97.91% of the accuracy of classification is achieved for cough identification (covid-19). A framework for DeTraC focused on CNN is suggested in Abbas et al. (2021). Particularly, the notion of transfer learning is employed to employ well-executed deep learning models. A deep CNN model is created by gathering 13k+ chest X-ray pictures from 13k+ patients for covid-19 classification and the dataset Wang, Lin and Wong (2020). 93.3% test accuracy is achieved using the proposed CNN model. In the paper Schuller et al. (2021), computer vision applications for combating the covid-19 epidemic are given.. This study also addresses risk assessment and problems in data collection and model sharing.

The remaining portions of the thesis are arranged in the following way: Section 2 gives a review of the literature on how AI/ML is used to detect covid-19 in chest X-ray images. Section 3 describes the dataset and methodology utilized in this investigation to find covid-19. Section 4 describes the techniques we used to identify covid-19 patients using the x-ray images. Section 5 provides the outline of the experiments. Section 6 examines the evaluation of the models employed and the findings gained, and Section 7 concludes with the conclusions and future work.

2 Related Work

CNNs are being utilized to create computer-aided diagnostic (CAD) systems that will help in the evaluation of the medical images. The authors of Shin et al. (2016) employed a range of deep CNN architectures that can be pre-trained on the dataset of ImageNet and adjusted them using certain CT scans for thoracoabdominal lymph node detection and for the classification of interstitial lung disease. Their research shown that deep CNNs can solve CAD issues even while we have sparse training data. In the research paper submitted by Rajpurkar et al. (2017) presented the model known as CheXNet. CheXNet is for diagnosing multiple types of pneumonia using the X-ray images of the chest. The 1x2x1-layer model was trained on a massive data set of over 100,000 X-ray images that consisited of 14 different bronchial diseases. The ChecXNet model outperformed practicing radiologists in terms of detecting the virus with good performance. In the context of the covid-19 outbreak, much research has been carried on to develop an automated image-based diagnostic systems for finding covid-19. Following that, the author will go over the various methods for constructing dependable system for detection which will be based on the chest X-ray and CT-scan images. The techniques are divided into two categories that would be based on one of the two key notions.In one hand, a unique deep neural network architectures for covid-19 identification and recognition have been developed and tuned. According to the paper Wang, Lin and Wong (2020), COVID-Net is one of the first convolutional network that is designed for automatically detecting corona occurrences in the images of X-ray. For covid-19 cases, the network performed well, with an accuracy of 93.3 percent. The Coronavirus Recognition Network (CVR-Net) was proposed by Alshazly et al. (2021) as a CNN-based network for automatically recognizing covid patients from the x-ray images. The model was trained and tested using X-ray and computed tomography. The results define the accuracy ratings varied depending on the quantity of classes in the image dataset of x-ray, with the CT images in the dataset it has the mean accuracy of 78 percent. As detailed in Wang, Liu and Dou (2020), COVID-Net was further improved to improve its capacities to portray for a single picture modality and also to raise the computing efficiency of the network. Mukherjee et al. (2021) demonstrated a nine-layer architecture of customized CNN for detecting the positive cases of covid-19. They used CT scans and X-rays to train and evaluate their network. The network beat existing CNN designs, with the accuracy of 96.28 percent overall. Other deep neural networks, such as ResNet, Xception, and Capsule Networks are being proposed for equivalent assignment of automated covid-19 identification. In research paper Altan and Karasu (2020), to identify the covid-19 disease, the author developed a hybrid model using deep learning. To improve the performance of the model the author has implemented a chaotic optimization algorithm. Its low cost, high performance, and robustness outperform the other models. EfficientNet-B0, with a very low computation cost, is improved by applying a 2-D Curvelet transform to the chest X-ray images, and a feature matrix is constructed after analyzing the coefficients of the curvelet transform. By fine-tuning four typical pre-trained CNNs, Minaee et al. (2020) employed transfer learning to identify covid-19 infection. They carried out studies using 5000 chest X-rays on a predetermined X-ray image collection. The best approach in the experiment had an average specificity and sensitivity of 90 percent and 98 percent. Brunese et al. (2020) employed transfer learning with a VGG-16 network that was pre-trained to detect the covid from x-rays images of the chest. Using the dataset that was gathered from multiple sources utilizing X-rays captured for healthy, pulmonary diseases, an average accuracy of

97 percent was reported.

The magnitude of deep learning algorithms, chest computed CT images in identifying covid-19 pneumonia and influenza pneumonia was stressed by Zhou et al. (2020). The study included CT scans of covid-19 patients that were confirmed from multiple hospitals across China. Their research demonstrated the possibility of properly diagnosing covid-19 using CT scans, as well as the efficacy of the classification approach for comparison with the two forms of pneumonia. In the research paper Song et al. (2020), DeepPneumonia was created to identify covid-19 cases with 88 patients, bacterial pneumonia cases with 100 patients, and the healthy cases using CT scans (86 participants). The model was 86.5 percent accurate in distinguishing between bacterial and viral (covid-19) pneumonia and 94% accurate in distinguishing between covid-19 and healthy individuals.The authors of Jaiswal et al. (2020) used transfer learning combined with a pre-trained DenseNet201 network to differentiate between covid-19 patients and non-covid-19 people using CT images. The model had an accuracy of 96.25 percent. Handmade feature extraction techniques and traditional classifiers were rarely used in research. Pereira et al. (2020) used well-known texture descriptors to extract texture properties from X-ray pictures. To fuse the features with those generated from a pre-trained InceptionV3 Szegedy et al. (2016), several fusion approaches were applied. Following that, numerous classifiers were used to discriminate between the normal X-rays and various types of pneumonia. The outstanding classification approach had 83 percent of the F1-score. The researchers of Al-Karawi et al. (2020) proposed a technique for discriminating between the positive and the negative covid-19 patients obtained by the CT scans. Gabor filters were utilized to extract various texture properties from CT images, and the support vector machines(SVM) were trained for classification. The suggested approach from the authors was able to yield the accuracy of 95.37% and the sensitivity of 95.99 percent.

An attempt has been made to provide a reasonable solution to detect and label the tissues that are infected by a disease in Hatem (2020)'s research paper, where the author has developed the SegNet model as well as the U-Net model. The author has compared the performances of two deep learning models in identifying areas of affected x-ray images in a paper that he published. SegNet was even able to distinguish between infected tissues and healthy ones in the provided images after the comparison studies were made with multiple classification procedures for infected regions of the lungs. According to Barstugan et al. (2020), the covid-19 was diagnosed utilizing the X-ray images. They employed a variety of feature extraction algorithms to generate a feature set that properly excludes polluted locations. The dataset used in this study was handcrafted, and model worked brilliantly with the data, and also achieved 99.68 percent of classification accuracy. The model was also ran through the computerized tomography scans, and the results were promising. In the research study, Rahman et al. (2020) proposed a CNN-based transfer learning strategy for detecting and categorizing pneumonia kinds.They employed an X-ray picture collection for analysis. This dataset is used to train and test models. They claimed that the DenseNet201 method surpassed all others by efficiently training from a smaller set of difficult input, such as photos, with more generalization and reduced bias. Explainable Artificial intelligence is the most recent technology for producing outcomes that are intelligible to humans. XAI and CNN-based ensemble models were utilized to detect pneumonia in a study by Liz et al. (2021). These ensemble models produced superior outcomes when compared to basic models. Ensemble models produced a true positive rate of 0.73 and an Area under the ROC (receiver operating characteristic curve) curve of 0.92 on the target dataset. They pointed out that the model's outputs are contingent on the quality of the data; otherwise, the model will fail to discriminate regions other than the lungs. They proposed incorporating segmentation approaches in future study to increase the quality of their model. CNN approach is used to image data set consisting of computed tomography scans in another study by Wei et al. (2021). The model is assessed using metrics such as specificity, accuracy, and sensitivity, and the results are excellent. However, because the dataset size employed for model building is modest, model accuracy may suffer when large datasets are used. They proposed a training model with more sample data as part of future study. The research study of Manickam et al. (2021) uses a transfer learning method to identify pneumonia using the X-ray images of the chest. To extract the information from ImageNet datasets, they used transfer learning and pre-trained models such as InceptionResNetV2, InceptionV3, ResNet50. The accuracy of the InceptionResNetV2, InceptionV3, and ResNet50 is 92.40 percent, 92.97 percent, and 93.06 percent, respectively. They claim that their design outperforms existing pre-trained models. Training the model on a larger dataset might help it improve even more. Using residual thought methods and dilated convolution, Liang and Zheng (2020) proposes a method for identifying pneumonia in children using deep learning. Using the residual structure, and dilated convolution to compensate for loss of features, the author overcame the conditions of over-fitting and degradation. A large dataset is used to overcome the difficulty of training the model.

In the study done by Apostolopoulos and Mpesiana (2020), the distinction between ordinary pneumonia and covid-19 induced pneumonia was made utilizing the breakthrough neural network to get the greatest results. Transfer learning was utilized in this study to find anomalies in tiny x-ray pictures from a small medical dataset. According to the research, it was able to attain extraordinary outcomes by employing transfer learning. The scope of the research might be expanded by constructing a model that can distinguish between people with very moderate symptoms and those with pneumonia symptoms.Afshar et al. (2020) developed a distictive solution evolved from a deep neural network in a research article. They investigated the capsule systems in the research and came up with a model that could offer improved outcomes for tiny datasets and could serve as a substitute. The research paper Adhikari (2020), presented self-operating medical analysis network known as "Auto Diagnostic Medical Analysis," which uses pictures of x-rays and CT to locate anamolous areas and discard and label the tissue that is affected. DenseNet network has been proposed for identifying and classifying hazardous region of lungs. Khan et al. (2020) used an X-ray image of the chest for their study to determine if the images were infected with covid-19. The Xception architecture is used to build a deep convolutional neural network model.The outcome of the proposed model were thought to be outstanding to those of their previous research. The accuracy of 89.6 percent was achieved, 93 percent for precision, and 98.2 percent for recall rate for the covid-19 cases. For recognizing and segmenting the X-Ray images, the author of the study paper Hassantabar et al. (2020) used three separate types of deep learning algorithms. For diagnosis, two deep neural network (DNN) methods were used on the images with the random feature, and other convolutional neural network (CNN) method is used on the scanned images directly. In the research, the CNN model outperformed the DNN approach, producing more promising results.

In research paper Altan and Karasu (2020), to identify the covid-19 disease, the author developed a hybrid model using deep learning. To improve the performance of the model the author has implemented a chaotic optimization algorithm. Its low cost, high performance, and robustness outperform the other models. EfficientNet-B0, with a very low computation cost, is improved by applying a 2-D Curvelet transform to the chest X-ray images, and a feature matrix is constructed after analyzing the coefficients of the curvelet transform.

3 Methodology

As the covid-19 epidemic spreads over the world, access to first-hand CT imaging and clinical data is important for directing clinical choices, deepening our understanding of the virus's infection patterns, and developing systematic models for early detection and urgent medical intervention. A critical strategy is to develop a comprehensive database with free access to CT scans and clinical symptoms linked to covid-19 to aid in the global fight against the virus. As indicated in the Related Work section, various datasets have been created and made available to academics, physicians, and data scientists to conduct a competitive research study on covid-19. For this project, we used the covid-19 Radiography Database[1]. 3616 covid-19 positive cases were added to the database in the second update, along with 6012 lung opacity (non-COVID lung infection), 1345 viral pneumonia, and 10,192 normal images. Because the dataset is open to the public, it will not create any ethical difficulties. Personal information about any individual is not collected in the dataset released on Kaggle. The collection solely comprises several types of x-ray pictures.

3.1 Experimental Settings

To verify the distribution of the three classes was constant across folds while evaluating the performance of our models, we concluded the performance of the model by cross validating against the test data splitted from the actual dataset. The concluding performances of the models were determined by averaging the values obtained by the five networks on their respective test folds.

Data augmentation methods were effectively employed to enhance the number of training samples in order to improve generalization. We avoided affine adjustments such as rotation and shearing since they were proven to hinder performance. In the end, the images were normalized using the mean and standard deviation of the ImageNets dataset. We employed a set of optimization parameters for each deep network.

A batch size of 32 was used along with a high weight decay of 1 for regularization. Tensorflow was used to implement the networks, which were trained for 100 epochs.

3.2 Evaluation Metrics

We validated the method based on the following parameters to evaluate its performance: how accurate the model is at classifying X-ray images.

[1]`https://www.kaggle.com/tawsifurrahman/covid19-radiography-database`

Precision: What proportion of the anticipated positives are true positives? The precision value ranges from 0 to 1.

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

Recall: What proportion of the total positive is true positive? It is equivalent to TPR (true positive rate).

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

F1 Score: It's the harmonic mean of recall and precision. It considers both false positives and false negatives. As a result, it performs well on a skewed dataset.

$$F1\ score = \frac{2}{\frac{1}{Precision} + \frac{1}{Recall}} = \frac{2 * (Precision * Recall)}{(Precision + Recall)}$$

4 Design Specification

System Architecture:

The procedure begins by importing a chest X-ray scan picture with the help of CV2. During preprocessing, the image will be converted to grayscale, resized to 224 x 224, and converted into a 1D array. In a 75:25 split, the dataset is divided into two halves for training and testing. The dataset contains 8900 pictures, divided into 6675 for training and 2225 for testing. To improve efficiency, we deployed five separate deep neural models based on CNN for this project.

Algorithms:

In the process of image classification, Convolutional Neural Networks (CNN), have benefited. To train the model, a large amount of training data must be collected. Because the model is naturally capable of extracting features via filters, the success of the deep-learning model is significantly reliant on the number of images used to train it. Deep learning, on the other hand, may be employed in fields where the dataset size is not large by applying the concept of transfer learning. Transfer-learning is a strategy in which features are produced from specified data using a CNN model and are utilized to handle

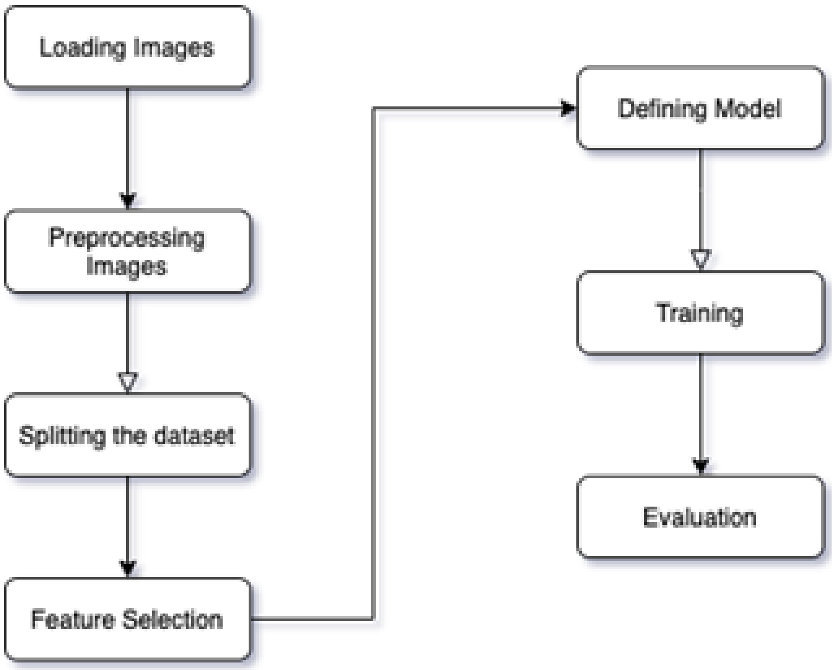


Figure 1: System Architecture

similar tasks, even when requiring fresh data (smaller dataset), and making the CNN from scratch is unfeasible. Training a model on a huge dataset, such as ImageNet, a pre-trained model for object identification and classification, is one of the most frequently used methods for transfer learning in the medical industry. The capacity of a deep-learning model to retrieve domain-specific information influences the model's selection for transfer learning.

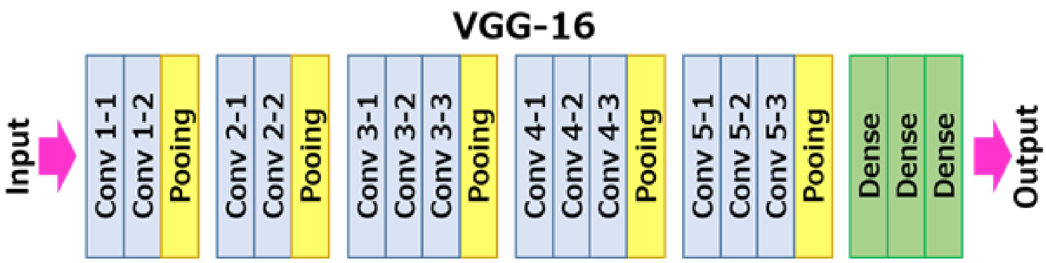
Two phases are used to achieve transfer learning: feature extraction and parameter adjustment (optimization strategy). The pre-trained model saves the newly extracted features from the training dataset during feature extraction. Second, in order to maximize a model's performance in the current area of application, the model architecture must be rebuilt and updated in tandem with parameter tuning. The drawback of a restricted dataset is solved, and the computational cost is lowered, by using this pre-trained model.

MobileNet, InceptionV3, ResNet50, VGG16, and VGG19 were utilized as pre-trained models. The models were trained on the ImageNet dataset earlier before being applied to the X-ray data collection..

4.1 VGG16

VGG16 model is one of the convolutional neural network. A dataset of over 14 million images categorized into over 1,000 classes in ImageNet, the model obtains an accuracy of 92.7%. It was one of the most celebrated model that entered in the year 2014 ILSVRC.

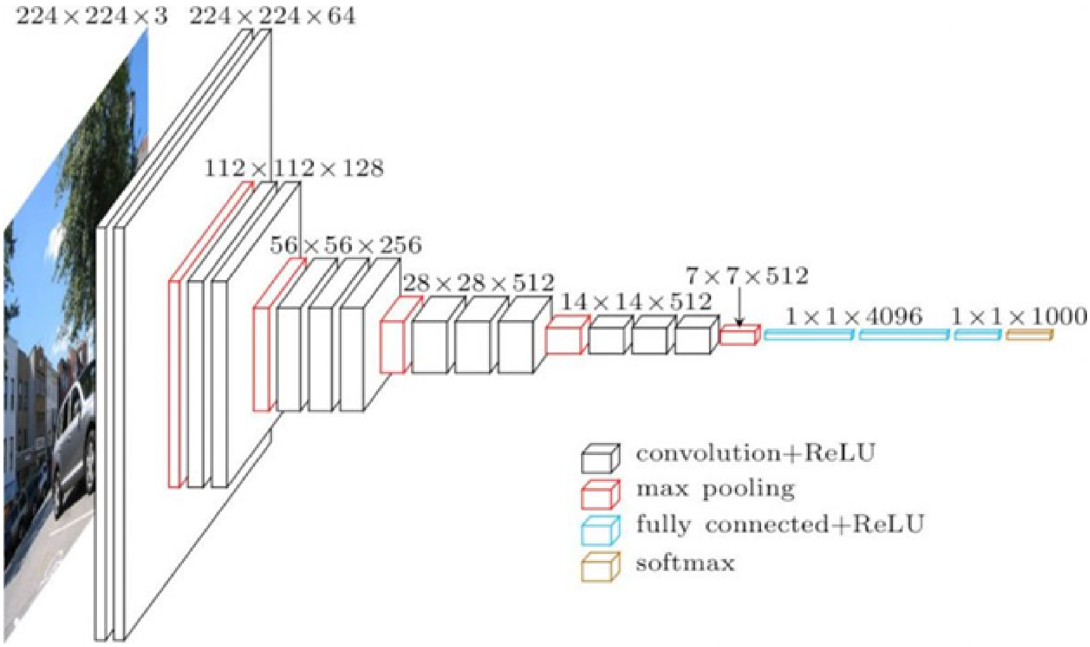
The cov1 layer receives a fixed-size 224 x 224 image as input. The image is processed using the layer of convolution, the filters are set to a complete narrow flexible field of 3x3



Source: `https://neurohive.io/en/popular-networks/vgg16/`

Figure 2: Architecture of VGG16

which is the smallest size that sufficiently captures the concept of left/right, up/down, and center). Furthermore, in one of the configurations, it includes 11 convolution filters, which can be regarded as a linear modification of the input channels which is followed by the non-linearity. The convolution stride is fixed at 1 pixel, and the spatial padding of the convolution layer input is set to one pixel in order to maintain the spatial resolution after convolution, i.e. the padding is one pixel for all 3x3 convolution layers. To conduct spatial pooling, five max-pooling layers are added after numerous conventional layers. Note: Not every convolutional layers are followed by max-pooling. Stride 2 is used to do max-pooling across a 2x2-pixel frame.



Source: `https://neurohive.io/en/popular-networks/vgg16/`

Figure 3: Convolution layers in VGG16

Following a stack of convolutional layers, three Fully Connected (FC) layers are added (the depth of which varies according to architecture). The first two layers have 4096 channels, whereas the third uses 1000-way ILSVRC classification and hence has 1000 channels which will be one for each class. There is also a soft-max layer at the end. The configuration of the entirely connected layers is the same in all networks. Each buried layer is non-linear in terms of rectification (ReLU).

4.2 ResNet50

We chose ResNet-50 due to its performance in various image recognition tasks; in particular, it outperforms VGGNet19 and DenseNet121 in terms of time and memory consumption. ResNet-50 is a version of ResNet, a convolutional neural network, with 50 layers. There are 48 convolutional layers, which include 1 MaxPool layer and 1 Average Pool layer in total. The architecture of ResNet-50 is presented in detail in Figure 5. ResNet is based on the deep residual learning framework. Even when extremely deep neural networks are deployed, they address the vanishing gradient problem. Despite its 50 layers, Resnet-50 has only about 23 million trainable parameters, which is much fewer than earlier designs.

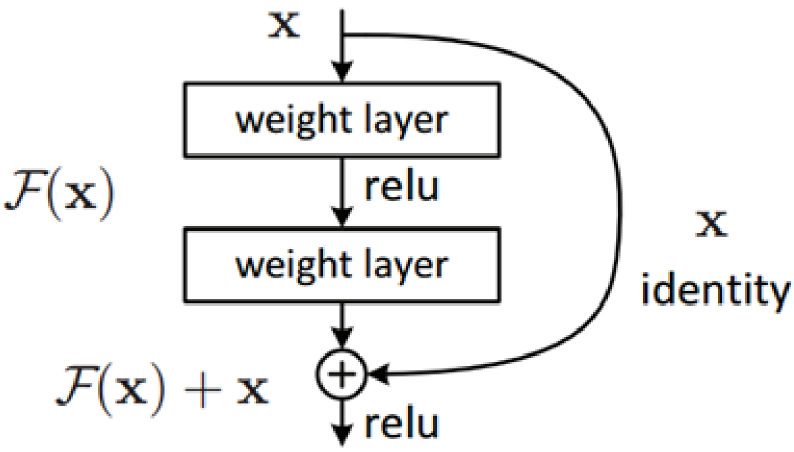
While the rationale for its performance is still being debated, the easiest way to understand it is to define residual blocks and to know how they work. Considering a neural network block that has an x input and the purpose of learning the real distribution of H(x). As an illustration, let us write the differences, or in other words, residuals, between these two as follows:

$$\mathbf{R(x) = Output \text{ - } Input = H(x) \text{ - } x}$$

Reorganizing it,

$$\mathbf{H(x) = R(x) + x}$$

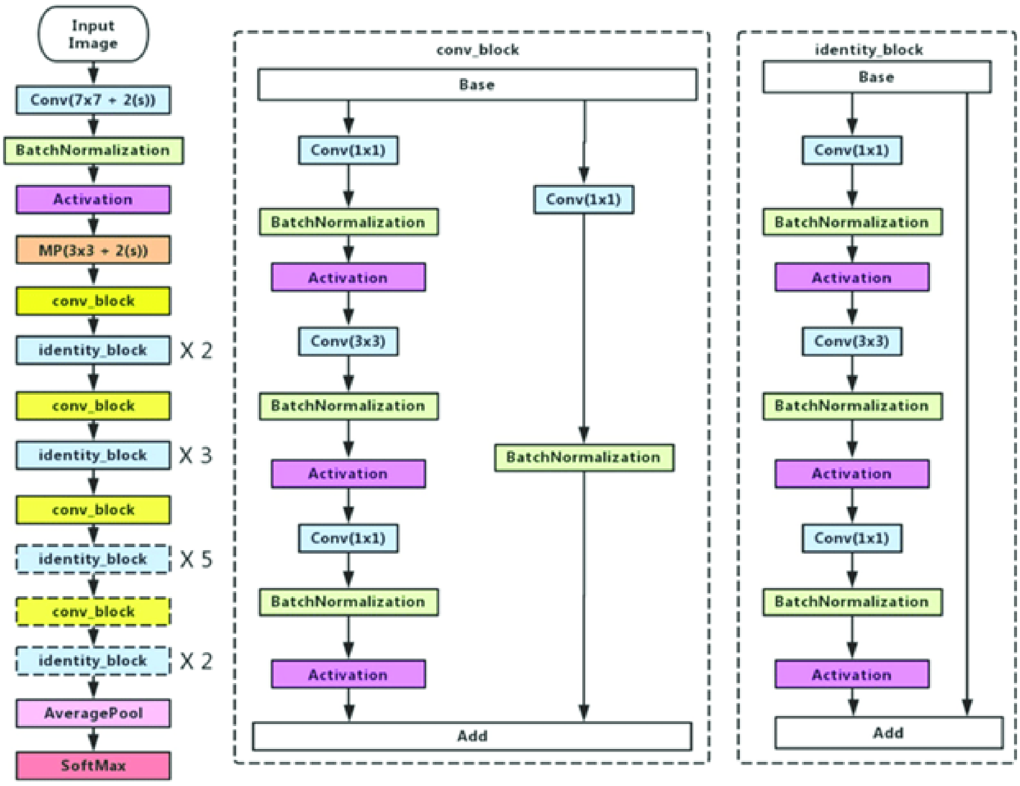
The residual block is attempting to discover the real value of H(x).



Source: `https://www.analyticsvidhya.com/blog/2020/08/top-4-pre-trained-models-for-image-classification-with-python-code`

Figure 4: Learning layers

Taking a closer look at the picture above, we see that the layers are learning the residual, R, as a result of the identity link caused by x. The layers in a conventional network learn the actual output (H (x)), whereas the layers in a residual network learn the residual (R (x)). It has also been observed that learning the leftover of the output and input is less difficult than memorizing the input alone. As a result, because they are eliminated from the design and add no complexity, the identity residual model allows for the reuse of activation functions from earlier layers.



Source: `https://www.researchgate.net/figure/Left-ResNet50-architecture-Blocks-with-dotted-line-represents-modules-that-might-be_fig3_331364877`

Figure 5: Convolution layers for ResNet50

4.3 MobileNet

Separable convolutions of Depth-wise are used by MobileNet. When compared to the network with ordinary convolutions of the same depth in the nets, it immensely lowers the number of parameters. As an outcome, lightweight deep neural networks are created. Two procedures are used to create a depthwise separable convolution. This convolution was inspired by the concept that the depth and spatial dimension of a filter may be detached hence the name "separable." The channel-wise DK x DK spatial convolution is a depth-wise convolution. Assuming we have five channels in the Figure 6, then we will have five DK x DK spatial convolutions. It will be a map of a single convolution that will be applied to every input channel individually. As a result, the number of output channels is always equal to the number of input channels.

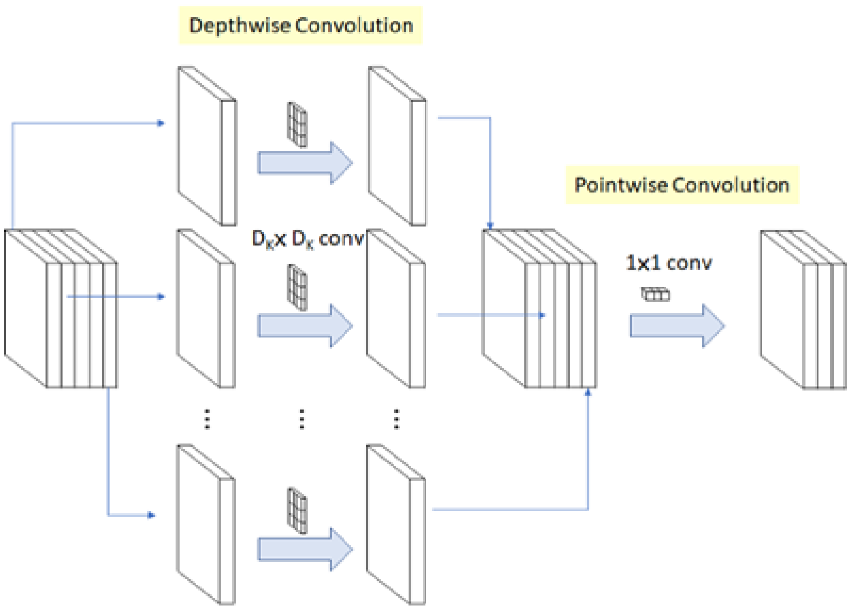


Figure 6: Convolution layers in MobileNet

Pointwise convolution is a 1 x 1 kernel size convolution that simply mixes the information produced by depthwise convolution.

The key difference between the MobileNet design and a typical CNN is that instead of a single 3x3 convolution layer, the batch norm and ReLU are used. The convolution was divided into two parts by Mobilenet: a 3x3 depth-wise convolution and a 1x1 pointwise convolution.

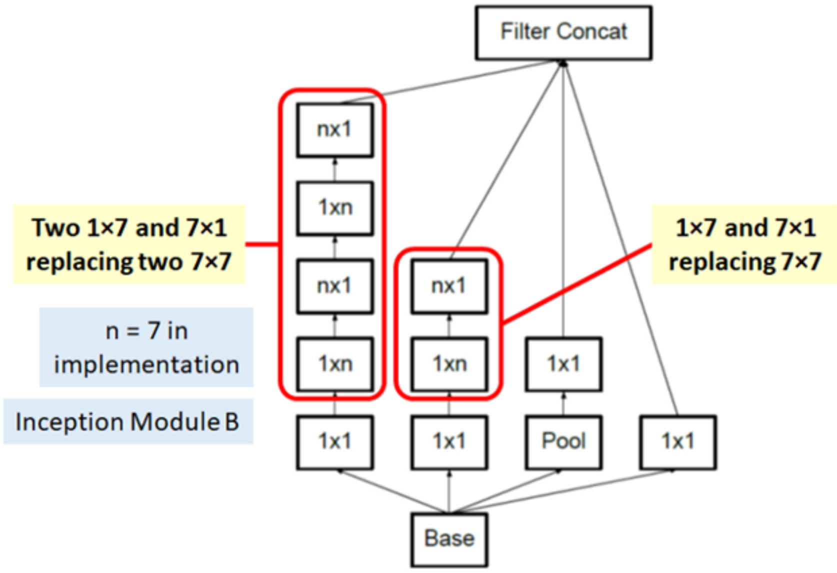
4.4 Inception V3

When compared to earlier generations, Inception V3 is built on factoring convolutions to anticipate and comprehend pictures. Convolutions are used to reduce the number of connections/parameters while preserving network efficiency.

Two 3x3 convolutions are equivalent to one 5x5 convolution in the following way: By employing a single layer of 5x5% filtering, the total number of parameters equals 5x5=25. By employing two layers of 3x3 filters, the total number of parameters is 3x3+3x3=18. The number of parameters has decreased by 28%. A similar approach has been discussed previously on VGGNet.

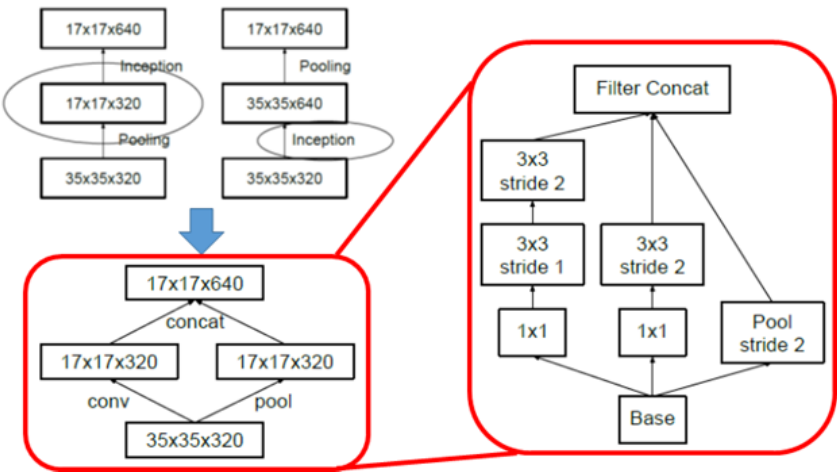
Traditionally, feature map reduction is accomplished by the use of max pooling. However, the disadvantage is that either max-pooling followed by a convolution layer is exorbitantly greedy, or the convolution layer succeeded by max-pooling is exorbitantly expensive. The following is a proposal for a more efficient grid size reduction:

With the efficient grid size decrease, convolution with stride 2 produces 320 feature maps. Max pooling generates 320 feature maps.These two sets of feature maps are then merged to get 640 feature maps, which are then sent to the next level of the inception



Source: `https://sh-tsang.medium.com/review-inception-v3-1st-runner-up-image-classification-in-ilsvrc-2015-17915421f77c`

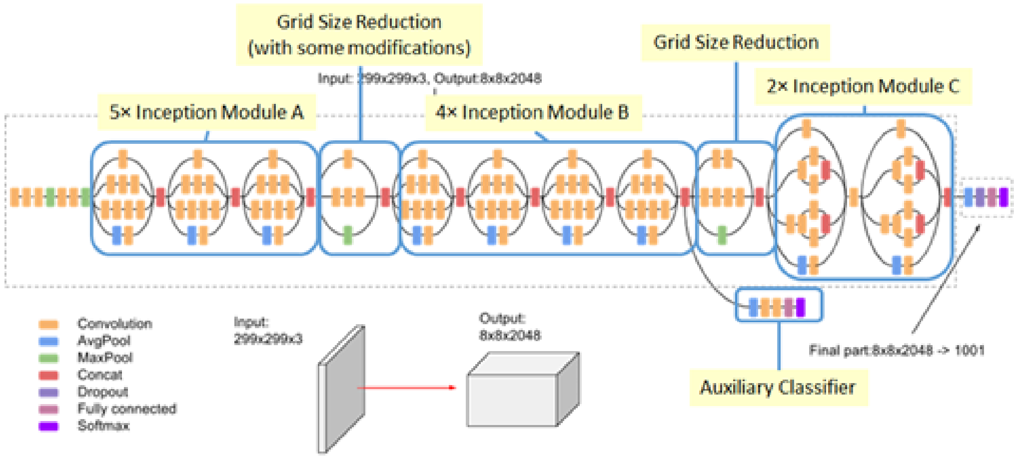
Figure 7: Layers in Inception V3



Source: `https://sh-tsang.medium.com/review-inception-v3-1st-runner-up-image-classification-in-ilsvrc-2015-17915421f77c`

Figure 8: Grid size reduction in Inception V3

module. This efficient grid size reduction results in a less expensive but still efficient network. A common use of vision networks is post-classification of detection, as shown



Source: `https://sh-tsang.medium.com/review-inception-v3-1st-runner-up-image-classification-in-ilsvrc-2015-17915421f77c`

Figure 9: Architecture of Inception V3

in the Multibox context. This involves analyzing a relatively tiny region of the picture containing a single item with contextual information. The objective is to identify whether the patch's central portion matches any object and, if so, to find the object's class. The issue is that things are frequently small and low-resolution. A question raises at this time as to how to handle input with a lower resolution correctly.

According to popular belief, models with higher resolution receptive fields do significantly better at recognition. It is crucial, however, to distinguish between the impacts of greater first layer receptive field resolution and the effects of increased model capacitance and computation. We can use computationally considerably more efficient models to tackle more difficult jobs if we just change the input resolution without altering the model further. Naturally, these solutions already lose out due to the lower computing effort. To produce an appropriate evaluation, the model must examine imprecise clues and then "hallucinate" the fine features.

This is a computationally intensive operation. Thus, the issue remains: to what extent does increase input resolution benefit if computing effort is maintained constant? In the event of lower resolution input, one easy way to make sure consistent attempt is to reduce the strides of the first two layers or simply delete the network's initial pooling layer.

5 Implementation

The model is split into two stages: preprocessing stage and data augmentation stage, followed by transfer learning with pre-trained deep learning models like ResNet50, VGG16, VGG19, inceptionV3, and MobileNet. This study classifies X-ray images of the chest into several groups, including normal, covid-19, and pneumonia.

5.1 Pre-processing and augmentation of data:

A data augmentation strategy will be applied at this stage to address the issues that we face related to the model overfitting. Because of the extensive nature of the pre-trained model, there will be a significant risk of overfitting if the dataset is small. To bypass this constraint, fresh images were produced by augmentation of data. The augmentation of data strategy enhances the generalizability of the data, especially for the X-ray datasets. To resize the images, a dimension of 224 x 224 x 3 was used. Furthermore, random horizontal flipping was used to improve the models applicability to all probable locality of symptoms with respect to covid-19 in the X-ray images. The augmentation procedures were employed to attempt to improve the generality of the suggested model. The data upgrades were only done on the training dataset.

5.2 Transfer-Learning and Deep Neural Networks(DNN):

Convolutional Neural Networks (CNN), have benefited in the process of image classification. To train the neural network model, a large amount of training data must be collected. The success of a deep-learning model is significantly reliant on the number of images used to train it. Deep learning, on the other hand, maybe employed in fields where the dataset size is not large by applying the concept of transfer learning. Transfer-learning is a strategy in which features produced from the designated data using a CNN model are utilized to handle similar assignments, even those requiring new data (a small dataset), and making the CNN from scratch is unfeasible. Training a model on a big dataset, such as ImageNet, a pre-trained model for object identification and classification, is one of the most commonly utilized ways for transfer learning in the medical industry. The capacity of a deep learning model to retrieve domain-specific information influences the model's selection for transfer learning.

Two phases are used to achieve transfer learning: Firstly, feature extraction along with parameter adjustment also known as an optimization strategy. The pre-trained model saves the newly extracted features from the training dataset during feature extraction. Second, in order to maximize a model's performance in the current area of application, the model architecture must be rebuilt and updated in tandem with parameter tweaking. Using a pre-trained model avoids the drawback of a short dataset and reduces the computational cost.

6 Evaluation

On the chest X-ray imaging datasets under consideration, we illustrate and explain our results for recognizing covid-19 utilizing our finely-tuned deep neural networks. For each of the selected network designs, we give quantitative statistics as well as confusion matrices. Table 1 summarizes all the values of the assessment metrics achieved by the multiple networks on each X-ray image in the dataset. All the values are mentioned in terms of percentages, and the outstanding results are highlighted. On the chest X-ray image datasets under consideration, we illustrate and explain our results for recognizing covid-19 utilizing our finely tuned deep networks. For each of the selected network designs, we give quantitative statistics as well as confusion matrices(0: 'Normal', 1: 'COVID', 2:

"Viral_Pneumonia").

With 98.1 percent of an average accuracy and F1-score, **MobileNet** beats all other evaluation metrics. Furthermore, the model has an average **sensitivity of 96.2 percent**, which means that just two of the COVID-19 images are wrongly categorized as negative on an average. It also has the enough potential to detect all non-COVID-19 cases with just one being false positive, yielding a 96 percent specificity rate. The VGG19 model has the highest sensitivity score of 96.6 percent, with just one of the COVID-19 image labeled as negative on an average. The **Inception** model has the lowest performance compared to all other assessment metrics, with **97.4 percent** of average accuracy and **96.6 percent sensitivity scores**.

Table 1: Evaluation metrics of five models.

Evaluation Metrics				
Model	**Accuracy**	**Precision**	**Sensitivity**	**Specificity**
MobileNet	**98.1 ± 1.3**	**97.2 ± 2.0**	**96.2 ± 1.4**	**96.0 ± 2.2**
ResNet50	96.6 ± 0.4	95.6 ± 0.3	94.1 ± 0.6	95.6 ± 0.3
InceptionV3	93.6 ± 0.5	92.5 ± 0.8	92.8 ± 0.3	91.5 ± 0.8
VGG16	96.6 ± 0.8	96.1 ± 1.4	96.0 ± 0.2	95.9 ± 1.5
VGG19	97.4 ± 0.6	97.0 ± 1.0	96.6 ± 1.1	96.9 ± 1.1

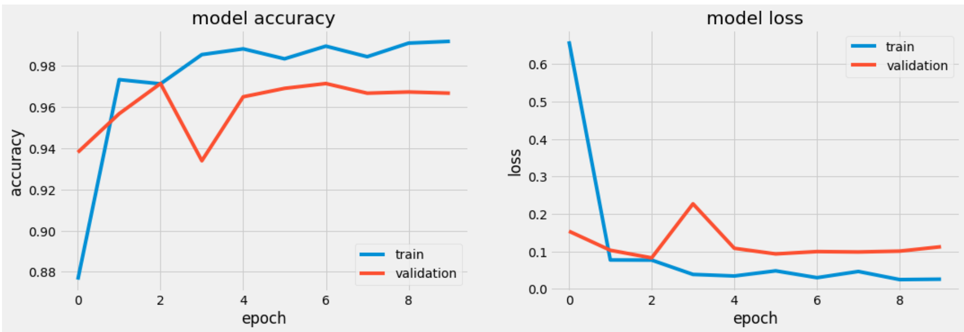


Figure 10: VGG16 Training Metrics

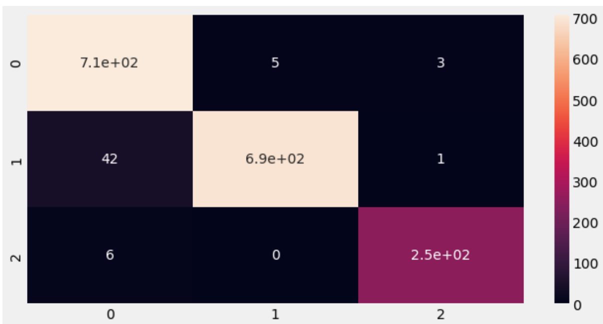


Figure 11: VGG16 Confusion Matrix

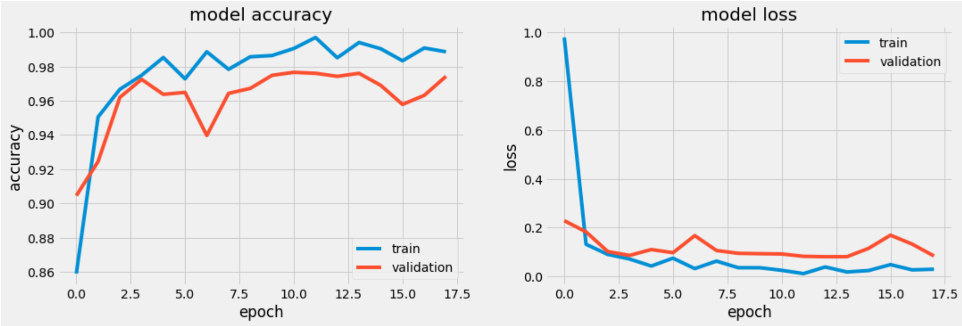


Figure 12: VGG19 Training Metrics

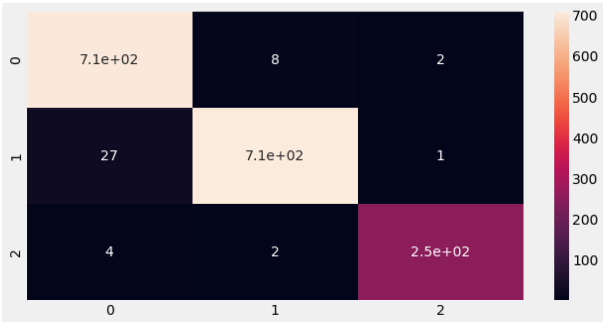


Figure 13: VGG19 Confusion Matrix

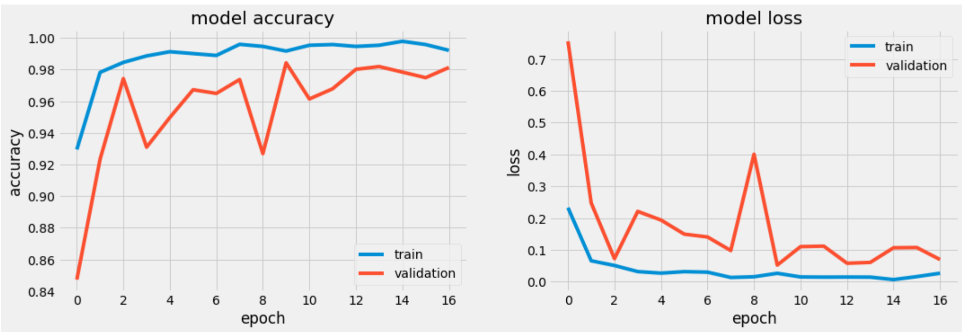


Figure 14: MobileNet Training Metrics

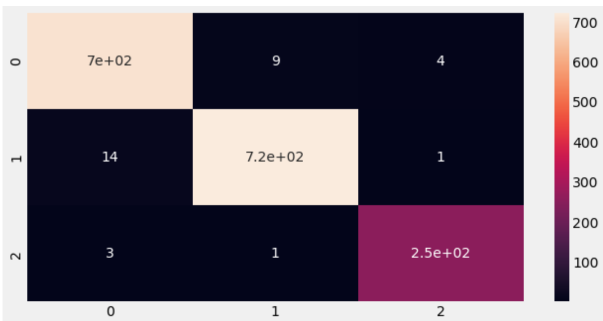


Figure 15: MobileNet Confusion Matrix

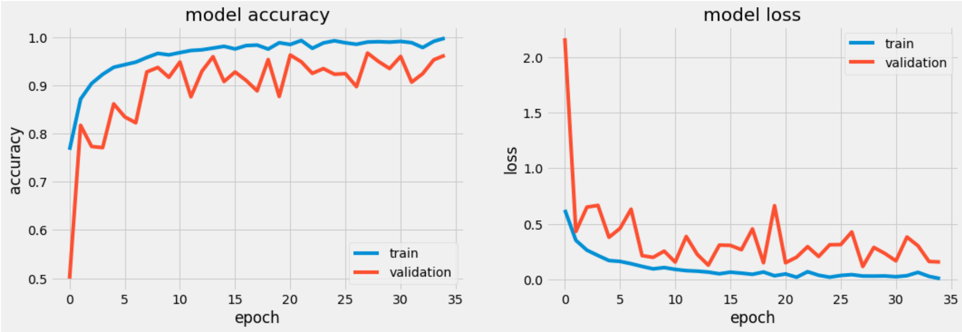


Figure 16: ResNet50 Training Metrics

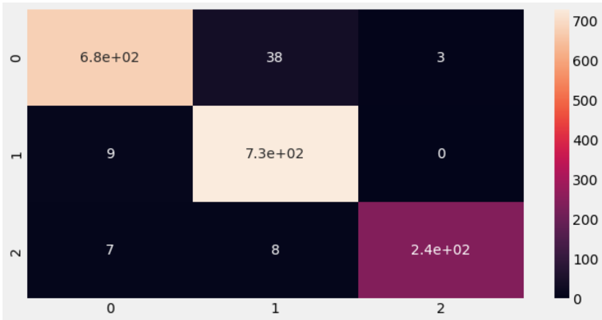


Figure 17: ResNet50 Confusion Matrix

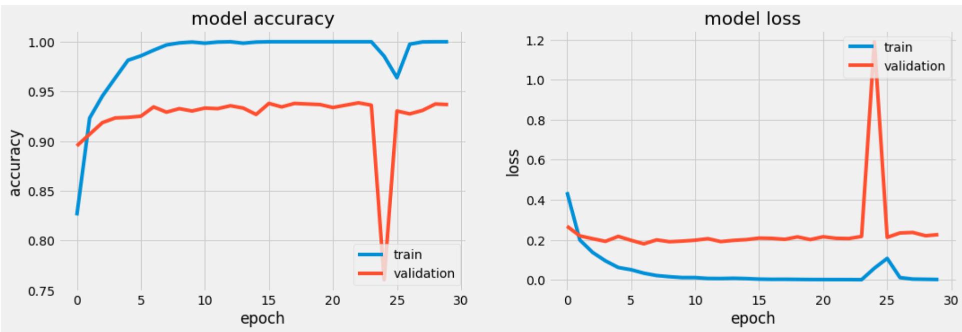


Figure 18: Inception Training Metrics

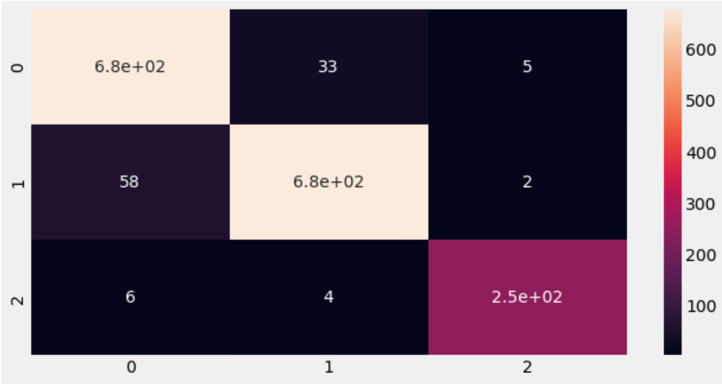


Figure 19: Inception Confusion Matrix

7 Conclusion and Future Work

Covid-19 widespread testing and early detection are key for limiting the present global epidemic. Time, cost, and accuracy are only a few of the factors that must be considered in any disease detection technique, but especially in covid-19 detection. To address these difficulties, this work presents a CNN based approach for detecting the covid-19 incidents in X-rays images of patients. The dataset with images was divided into three groups,and was used to train the CNN models. The MobileNet model outperforms the other four models stated. It outperforms the other models by having 98.3 percent of the accuracy and F1-score for the given dataset. This work can be enhanced by including multi-level of class classification and using a bigger dataset available. Finally, CNN has a high likelihood of detecting covid-19 in a small amount of time, resources, and money. While the proposed technique has yielded promising results, it has yet to be clinically confirmed. However, with such a high degree of accuracy, the suggested approach will definitely aid greatly to the rapid and quick identification of covid-19, reducing the overall testing time and cost.

References

Abbas, A., Abdelsamea, M. M. and Gaber, M. M. (2021). Classification of covid-19 in chest x-ray images using detrac deep convolutional neural network, *Applied Intelligence* **51**(2): 854–864.

Adhikari, N. C. D. (2020). Infection severity detection of covid19 from x-rays and ct scans using artificial intelligence.

Afshar, P., Heidarian, S., Naderkhani, F., Oikonomou, A., Plataniotis, K. N. and Mohammadi, A. (2020). Covid-caps: A capsule network-based framework for identification of covid-19 cases from x-ray images, *Pattern Recognition Letters* **138**: 638–643.

Al-Karawi, D., Al-Zaidi, S., Polus, N. and Jassim, S. (2020). Machine learning analysis of chest ct scan images as a complementary digital test of coronavirus (covid-19) patients, *MedRxiv* .

Alshazly, H., Linse, C., Barth, E. and Martinetz, T. (2021). Explainable covid-19 detection using chest ct scans and deep learning, *Sensors* **21**(2): 455.

Altan, A. and Karasu, S. (2020). Recognition of covid-19 disease from x-ray images by hybrid model consisting of 2d curvelet transform, chaotic salp swarm algorithm and deep learning technique, *Chaos, Solitons Fractals* **140**: 110071.

Apostolopoulos, I. D. and Mpesiana, T. A. (2020). Covid-19: automatic detection from x-ray images utilizing transfer learning with convolutional neural networks, Vol. 43, Springer, pp. 635–640.
URL: *https://link.springer.com/article/10.1007/s13246-020-00865-4*

Barstugan, M., Ozkaya, U. and Ozturk, S. (2020). Coronavirus (covid-19) classification using ct images by machine learning methods, *CEUR Workshop Proceedings* **2872**: 29–35.
URL: *https://arxiv.org/abs/2003.09424v1*

Brunese, L., Mercaldo, F., Reginelli, A. and Santone, A. (2020). Explainable deep learning for pulmonary disease and coronavirus covid-19 detection from x-rays, *Computer Methods and Programs in Biomedicine* **196**: 105608.

COVID-19 Open Research Dataset Challenge (CORD-19) (n.d.).
URL: *https://kaggle.com/allen-institute-for-ai/CORD-19-research-challenge*

Hassantabar, S., Ahmadi, M. and Sharifi, A. (2020). Diagnosis and detection of infected tissue of covid-19 patients based on lung x-ray image using convolutional neural network approaches, *Chaos, Solitons Fractals* **140**: 110170.

Hatem, A. S. . I. (2020). Covid-19 lung ct image segmentation using deep learning methods: U-net versus segnet.

Hu, Z., Ge, Q., Li, S., Jin, L. and Xiong, M. (2020). Artificial intelligence forecasting of covid-19 in china, *arXiv preprint arXiv:2002.07112* .

Imran, A., Posokhova, I., Qureshi, H. N., Masood, U., Riaz, M. S., Ali, K., John, C. N., Hussain, M. I. and Nabeel, M. (2020). Ai4covid-19: Ai enabled preliminary diagnosis for covid-19 from cough samples via an app, *Informatics in Medicine Unlocked* **20**: 100378.

Jaiswal, A., Gianchandani, N., Singh, D., Kumar, V. and Kaur, M. (2020). Classification of the covid-19 infected patients using densenet201 based deep transfer learning, *Journal of Biomolecular Structure and Dynamics* pp. 1–8.

Khan, A. I., Shah, J. L. and Bhat, M. M. (2020). Coronet: A deep neural network for detection and diagnosis of covid-19 from chest x-ray images, *Computer Methods and Programs in Biomedicine* **196**: 105581.
URL: *https://www.sciencedirect.com/science/article/pii/S0169260720314140*

Liang, G. and Zheng, L. (2020). A transfer learning method with deep residual network for pediatric pneumonia diagnosis, *Computer Methods and Programs in Biomedicine* **187**: 104964.

Liz, H., Sánchez-Montañés, M., Tagarro, A., Domínguez-Rodríguez, S., Dagan, R. and Camacho, D. (2021). Ensembles of convolutional neural network models for pediatric pneumonia diagnosis, *Future Generation Computer Systems* **122**: 220–233.

Manickam, A., Jiang, J., Zhou, Y., Sagar, A., Soundrapandiyan, R. and Samuel, R. D. J. (2021). Automated pneumonia detection on chest x-ray images: A deep learning approach with different optimizers and transfer learning architectures, *Measurement* **184**: 109953.
URL: *https://linkinghub.elsevier.com/retrieve/pii/S0263224121008885*

Minaee, S., Kafieh, R., Sonka, M., Yazdani, S. and Soufi, G. J. (2020). Deep-covid: Predicting covid-19 from chest x-ray images using deep transfer learning, *Medical image analysis* **65**: 101794.

Mukherjee, H., Ghosh, S., Dhar, A., Obaidullah, S. M., Santosh, K. and Roy, K. (2021). Deep neural network to detect covid-19: one architecture for both ct scans and chest x-rays, *Applied Intelligence* **51**(5): 2777–2789.

Pereira, R. M., Bertolini, D., Teixeira, L. O., Silla Jr, C. N. and Costa, Y. M. (2020). Covid-19 identification in chest x-ray images on flat and hierarchical classification scenarios, *Computer Methods and Programs in Biomedicine* **194**: 105532.

Rahman, T., Chowdhury, M. E., Khandakar, A., Islam, K. R., Islam, K. F., Mahbub, Z. B., Kadir, M. A. and Kashem, S. (2020). Transfer learning with deep convolutional neural network (cnn) for pneumonia detection using chest x-ray, *Applied Sciences (Switzerland)* **10**.

Rajpurkar, P., Irvin, J., Zhu, K., Yang, B., Mehta, H., Duan, T., Ding, D., Bagul, A., Langlotz, C., Shpanskaya, K. et al. (2017). Chexnet: Radiologist-level pneumonia detection on chest x-rays with deep learning, *arXiv preprint arXiv:1711.05225* .

Schuller, B. W., Schuller, D. M., Qian, K., Liu, J., Zheng, H. and Li, X. (2021). Covid-19 and computer audition: An overview on what speech & soundanalysis could contribute in thesars-cov-2 corona crisis, *Frontiers in digital health* **3**: 14.

Shin, H.-C., Roth, H. R., Gao, M., Lu, L., Xu, Z., Nogues, I., Yao, J., Mollura, D. and Summers, R. M. (2016). Deep convolutional neural networks for computer-aided detection: Cnn architectures, dataset characteristics and transfer learning, *IEEE transactions on medical imaging* **35**(5): 1285–1298.

Song, Y., Zheng, S., Li, L., Zhang, X., Zhang, X., Huang, Z., Chen, J., Zhao, H., Jie, Y., Wang, R. et al. (2020). Deep learning enables accurate diagnosis of novel coronavirus (covid-19) with ct images. medrxiv, *Preprint posted online February* **25**.

Szegedy, C., Vanhoucke, V., Ioffe, S., Shlens, J. and Wojna, Z. (2016). Rethinking the inception architecture for computer vision, *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 2818–2826.

Wang, L., Lin, Z. Q. and 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): 1–12.

Wang, Z., Liu, Q. and Dou, Q. (2020). Contrastive cross-site learning with redesigned net for covid-19 ct classification, *IEEE Journal of Biomedical and Health Informatics* **24**(10): 2806–2813.

Wei, J., Zhu, R., Zhang, H., Li, P., Okasha, A. and Muttar, A. K. (2021). Application of pet/ct image under convolutional neural network model in postoperative pneumonia virus infection monitoring of patients with non-small cell lung cancer, *Results in Physics* **26**: 104385.

Zhavoronkov, A., Aladinskiy, V., Zhebrak, A., Zagribelnyy, B., Terentiev, V., Bezrukov, D. S., Polykovskiy, D., Shayakhmetov, R., Filimonov, A., Orekhov, P. et al. (2020). Potential 2019-ncov 3c-like protease inhibitors designed using generative deep learning approaches.

Zhou, M., Chen, Y., Wang, D., Xu, Y., Yao, W., Huang, J., Jin, X., Pan, Z., Tan, J., Wang, L. et al. (2020). Improved deep learning model for differentiating novel coronavirus pneumonia and influenza pneumonia, *medRxiv* .