# Chapter 4

## 4.1. Introduction

Coronavirus Illness (COVID-19) is an infectious illness caused by the SARS-CoV-2 virus. The vast majority of COVID-19 patients will have mild to moderate symptoms and will also be able to restore without treatment. On the other hand, some people will become quite sick and require medical attention. The two most frequent techniques for detecting Covid-19 are RT-PCR and RAT. The Rapid Antigen Test establishes whether or not such a person is infectious, whereas the RT-PCR reveals whether or not such a person is infected with the dead virus. In certain cases, negative RAT findings on later testing have led to a positive RT-PCR. Regardless of the fact that it could report a recovered individual as positive, the RT-PCR was considered as the most reliable test during the first wave. However, a high-resolution CT scan of the lungs reveals severe lung damage. Patients in the second wave have reported receiving negative results on their initial test, then positive results on their second or third test, or unreported results. This has created a concerning issue because COVID-19 is now misleading these RT-PCR testing. The failure of these tests is owing to a significant change in the virus's appearance and behaviour since last year. There have been mutations in the virus's spike protein, which the RT-PCR checks for. Despite the fact that CT scans have been shown to be more effective, the rising majority of patients and the associated rise in radiological tests make it difficult to trust on chest CT scans for every individual from diagnosis to discharge. Additionally, a large reliance on CT scans will pressure the radiography department, offering chest X-rays (CXRs) a much more realistic option for COVID-19 diagnostics [1]. Chest X-rays are beneficial in tracing the evolution of lung abnormalities while being less sensitive in recognizing beginning respiratory involvement in COVID-19 [2].

Machine learning offers a lot of help in recognising the disease through image analysis. Novel coronavirus infections can be classified using machine learning. .For identification or prediction of virus, machine learning requires a large amount of data for analysis. Supervised machine learning algorithms require annotated data to categorise the image into several classes. Over the last decade, great progress has been achieved in this area, with specific investigations being attempted. The pandemic has drawn researchers from all around the world to work on this field. Several researchers constructed machine learning models that classified X-ray images into COVID-19 or not using data generated in the form of X-ray images.

Using chest X-ray images, many researchers used deep machine learning systems to determine COVID-19. However, the majority of these studies [5-8] used a small dataset and only a few COVID-19 samples. As a result, applying their results from these studies is tricky, and there's no guarantee that the reported results will be replicated when these models are tested on a larger dataset. To evaluate the transfer learning technique for identifying COVID-19 X-ray images, a large database must be employed. The development of a deep learning algorithm that can reliably detect COVID-19 illness in an individual based on symptoms is urgently needed.

**Process in Traditional Machine Learning Model**

A. Data is loaded by the pandas package, which returns a data frame object with data, in the traditional machine learning model.

B. Remove the primary keys and distinct values columns, as well as any other columns with unique values.

C. To make it easier to model for data training, null values must be substituted with mode values.

D. Label encoding is the process of replacing categorical and text labels with normalised values.

E. Create a machine learning model and test it.

Deep learning, which is effectively a three-layer neural network, is a subset of machine learning. By allowing it to "learn" from enormous volumes of data, these neural networks try to mimic human brain activity, however they stop short of it. While a layer is made neural network can approximate something, increasing hidden layers can help improve and optimise accuracy. Using deep learning, a program model learns to do categorization tasks directly from images, text, or speech. Deep learning [9] algorithms can reach extraordinary accuracy, beating humans in some cases. To train models, multi

- layer neural network nodes and a massive number of annotated data are utilised. In traditional Machine Learning techniques, the majority of the necessary features must be set by a specific domain in order to reduce size of the dataset and make trends more visible for training methods to work. Deep Learning algorithms' most noticeable value is that they seek to learn high-level characteristics from data in a consistent manner. As a consequence, class and the separation of hard-core characteristics are no longer required.

A machine-learning strategy in which a model created for one job is utilised as the framework for a model for another activity. Well before frameworks are a useful tactic in deep learning for vision - based applications processing applications, considering the massive computing and time assets required to create neural network models for some of these functions, and also the extremely large leaps in skill that they provide on related problems. Transfer learning is a method of having taken a framework that's been formally defined data - set and implementing it to a dataset consisting of fewer values. We suspend the earliest convolution layers of neurons for image recognition but only training the last several levels that generate a prediction. The theory is that the convolution layer extracts broad, low-level features like boundaries, patterns, and gradients that apply across images, while the subsequent layers recognize particular parts of an image.

To summarise, numerous recent studies utilising a transfer learning strategy to predict COVID-19 X-ray images from a labelled data have yielded promising results, but these must be confirmed on a larger dataset. The goal of this study is to see how accurate sophisticated detection of COVID-19 from thorax X-rays is before and after the convnets. 1427 thorax X-ray images are processed and used to train the classifier the CNNs in addition to do this. Due to the limited size of the samples attached to COVID-19, transfer learning is the preferable approach for training deep CNNs. This is due to the fact that cutting-edge CNNs are sophisticated models that require massive datasets in order to achieve effective feature extraction and classification.

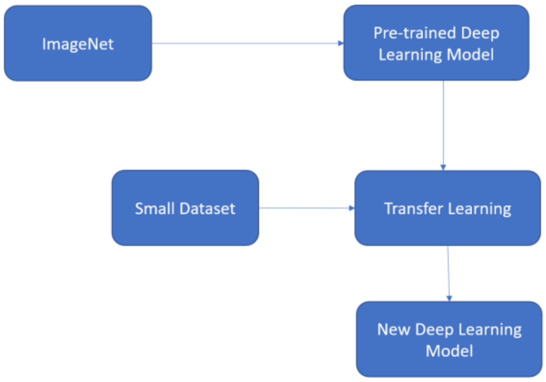


**Figure 4.1:** Transfer Learning

## 4.2. Related Studies

It is important to understand that a two-class classification means COVID-19 vs Normal, a three-class classification means COVID-19 vs Normal vs Pneumonia, and a four-class classification means COVID-19 vs Pneumonia Bacterial vs Pneumonia Viral vs Normal.

Utilising 224 COVID-19 images, Apostolopoulos and Mpesiana created a deep learning model with a level of performance of 98.75 percentage and 93.48 percent, correspondingly, utilising two and three classes [10]. The COVID-19 disease was detected automatically using a dataset of X-ray images from patients with common bacterial pneumonia, verified COVID-19 disease, and normal occurrences. They compared the performance of the popular Convolutional Neural Network designs for medical image categorization that have been proposed in recent years. The process known as Transfer Learning was used in this study. A total of two datasets were used. One is a dataset consisting of 1427 X-ray scans, with 224 images showing verified COVID-19 disease, 700 images showing verified common bacterial pneumonia, and 504 images showing normal conditions. Second is a collection of 224 images of COVID-19 illness, 714 images of bacterial and viral pneumonia, and 504 images of normal conditions. The information was gathered from publicly available X-ray scans in medical repositories. The findings reveal that using deep learning and X-ray imaging to derive important indicators connected to the COVID-19 disease is possible, with the best accuracy, sensitivity, and specificity being 96.78 percent, 98.66 percent, and 96.46 percent, respectively.

Wang et al. suggested a deep COVID-19 detection model (COVID-Net) that classified three categories with 93.3 percent accuracy (healthy, non-COVID-19 pneumonia, and COVID-19) [11]. This study introduces the use of COVID-Net, an open source and freely available deep CNN architecture tailored for the identification of COVID-19 cases from chest X-ray images. COVID-Net was one of the first open source network design features for automatically detecting COVID-19 from chest X-ray images when it was first released. It also presents COVIDx, an open access standard dataset composed of 13,975 chest X-ray images from 13,870 patient patient cases. Besides that, it explores how COVID-Net makes predictions using a modelling and analysis method in an effort not only to gain additional understanding into significant elements associated with COVID cases, which can assist health care professionals in enhanced testing, but also to review COVID-Net in a transparent and accountable manner to verify that it is making predictions based on chest X-ray images.

On a dataset of 310 COVID-19, 657 pneumonia, and 284 healthy chest X-ray images, Khan et al. developed a CoroNet model to classify chest X-ray images that achieved an accuracy of 99 percent and 95 percent for 2-class and 3-class classification tasks, respectively [12]. CoroNet, a Deep Convolutional Neural Network model, was proposed in this research to detect COVID-19 infection from chest X-ray images automatically. It is built on the Xception architecture, which was pre-trained on the ImageNet dataset and then trained end-to-end on a dataset made up of COVID-19 and additional chest pneumonia X-ray images from two public repositories. CoroNet was trained and tested on the prepared dataset, and the evaluation demonstrates that the proposed method attained an accuracy rate of 89.6%, with precision and recall rates for COVID-19 cases of 93 percent and 98.2% for 4-class cases and 95 percent for 3-class classification (COVID vs pneumonia vs normal).

DarkNet, a CNN model that was proposed, has a performance rate of 98.08 percent for two classes and 87.02 percent for three classes. [13]. This research provided a new model for automatically detecting COVID-19 utilising raw chest X-ray images, resulting in accurate diagnoses for binary and multi-class classification. When the study's classification accuracy was tested, it came in at 98.08 percent for binary classes and 87.02 percent for multi-class situations. The DarkNet model was employed as a classifier for the YOLO (you only look once) real-time object identification system. They used 17 convolutional layers and applied various filters to each one.

Toraman et al. created a convolutional CapsNet based on chest X-rays and capsule networks for detecting COVID-19, with binary classification efficiency of 97.24 percent and 84.22 percent, respectively [14]. Using chest X-ray images and capsule networks, this study proposes a unique artificial neural network, convolutional CapsNet, for the automatic identification of COVID-19 disease. The suggested method combines binary classification and multi-class classification to deliver timely and effective testing methods for COVID-19 disease. For binary class and multi-class, the suggested method obtained accuracy of 97.24 percent and 84.22 percent, respectively.

[15] used pre-trained CNN networks and image augmentation to develop a reliable method for detecting COVID-19 pneumonia from chest X-ray images based on transfer learning. The networks were trained to perform binary and multiclass classification. This model had a 99.7 percent accuracy.

Using raw chest X-ray and CT scan images from one of the largest COVID-19 datasets, this study [16] used a CNN model named CoroDet for automatic COVID-19 detection. CoroDet consisting of a new 22-layer CNN model was created to be an accurate diagnostic tool for two-class classification, three-class classification, and four-class classification. Accuracy, precision, recall, F1 score, specificity, sensitivity, and confusion matrix. They compared the performance of the proposed model to ten current COVID detection algorithms to see how accurate it was. Their proposed model showed classification accuracy of 99.1 percent for two-class classification, 94.2 percent for three-class classification, and 91.2 percent for four-class classification.

## 4.3. Method

### Dataset

Our dataset has been constructed with chest X-ray images from publicly available repositories - Kaggle [17] [18] and GitHub [18].

### CNNs for Transfer Learning

CNN is used to analyse a fresh dataset of images of a significant difference and extract features using feature extraction information learned during initial training.


**Figure 4.2:** CNN Architecture

CNNs are made up of layers that turn an image into something that the learning model can understand. Convolutional layer produces a feature map by scanning the image many pixels at a time using a filter. Pooling layer reduces the amount of data created by the convolutional layer so that it may be stored more efficiently. Fully connected input layer flattens the outputs into a single vector. Weights are applied to the inputs provided by the feature analysis in a fully connected layer. Fully linked output layer determines the image class by generating final probability.

There are two common ways to make use of a pre-trained CNN's capabilities. The very first approach, based on feature extraction via transfer learning, is a technique that keeps a pre-trained model's basic architecture as well as all learnt weights. As a result, the which was before the model is solely developed to remove characteristics, which are then put into a new classification network. The second way is a more involved procedure that involves making exact changes to the form before the model in order to achieve the optimum results. Modifications to the design and parameter optimization might be included in these updates. Only particular data from the previous job is saved in this way, while fresh trainable parameters are added to the network. The new parameters must be educated on a large quantity of data in order to be useful.

Approach 1: Pre-trained model

From the available models, a pre-trained source model is selected. Many institutions introduce open source models based on vast and difficult datasets, which can be added to the list of available models. The model can then be utilised as the basis for a model on the next task. Depending on the modelling method, this could include using all or sections of the model. The model may need to be tweaked or fine-tuned based on the input-output pair data available for the task at hand.

Approach 2: Development of a model

You must select a relevant predictive analysis problem involving a large amount of data in which the input data, output data, and/or knowledge gained during the transfer from input to output data are all linked in some way. The next stage is to develop a competent model for the problem analysis. When compared to a simple existing model, the model must perform better with higher accuracy to indicate that some feature learning has occurred. The model fit on the analysis problem can then be applied to the second task of interest to create a model. This may include employing all or parts of the model, depending on the modelling method adopted. Model should be adjusted. It's possible that the model will need to be tweaked on the input-output pair of the next task.

We are going ahead with Approach 1: Pre-trained model. ImageNet is a database of over 15 million high-resolution images that have been categorised into over 22,000 classes. (Large Scale Visual Recognition Challenge) ILSVRC works with a subset of ImageNet that includes roughly 1000 images in each of 1000 categories. A total of 1.3 million training images, 50,000 validation images, and 100,000 testing images are available. ILSVRC CNNs were used to test approaches for large-scale object recognition and image categorization.

We have adopted VGG19, Inception, Xception, Inception ResNetV2 and MobileNetV2. The parameters - Layer Cutoff and Neural Network, were identified as important after referring to a previous study, but there are a plethora of other options that might be studied in future study to see if they contribute to performance improvement. The Layer Cutoff parameter, which starts at the bottom of a CNN, corresponds to the number of badly trained layers. The remainder of the levels that are nearer to the extracted feature are made trainable to enable further extracting information from the final convolution layer. The variable Neural Network refers to the classifier that is inserted at the bottom of the CNN and is used to classify the retrieved data. It is defined by the entire number of hidden nodes and the entire number of nodes. All CNNs have some hyper-parameters in common

VGG19 - The VGG19 model is a variation of the VGG model that has 19 layers in total (16 convolution layers, 3 fully connected layers, 5 MaxPool layers and 1 SoftMax layer). Other VGG variations include VGG11, VGG16, and more.

18 - Layer Cutoff

1024 nodes  - Neural Network

Inception - When broken down into its constituent parts, the Inception module is simple to deconstruct and interpret. It can achieve high-performance gains on Convolutional Neural Networks, effectively utilise computing resources with less increase in computation load for the higher yield of an Inception network, and obtain features of the input data at different scales utilising different convolutional filter sizes.

249 - Layer Cutoff

1000 - Neural Network

Xception - Xception is a 71-layer deep CNN design.

120 - Layer Cutoff

1000, 750 nodes - Neural Network

Inception ResNet v2

730 - Layer Cutoff

No - Neural Network

MobileNetV2 - MobileNetV2 is a CNN design that aims to be mobile-friendly. It is built on an inverted residual structure, with residual connections between bottleneck levels. As a source of non-linearity, the intermediate expansion layer filters features with lightweight depthwise convolutions. Overall, MobileNetV2's architecture includes a fully convolutional layer with 32 filters, and 19 residual bottleneck layers.

10 - Layer Cutoff

1000, 750 nodes - Neural Network

To prevent overfitting, a Drop - outs layer is applied to Neural Network models with two hidden layers. An optimization strategy was used to create the CNNs. The training lasted 10 epochs and was divided into 64 batches.

## Performance Metrics

We are utilising the confusion matrix to evaluate our approach:

In the field of machine learning, the confusion matrix is a tool that can be used to perform predictive analysis. The confusion matrix is mostly used to evaluate the performance of a classification-based machine learning model. Parameters used in our testing approach are listed below:

(a) True Positives (TP),

(b) False Negatives (FN),

(c) True Negatives (TN), and

(d) False Positives (FP) (FP)

Instances that were correctly identified as COVID-19 positive are denoted by TP, whereas cases that were incorrectly labelled as COVID-19 positive are denoted by FP. FP denotes instances that were correctly identified as COVID-19 negative, whereas FN denotes cases that were wrongly classified as COVID-19 negative. The accuracy, sensitivities, and precision of the model are calculated using these parameters.

- (TP+TN)/(TP+TN+FP+FN) gives accuracy
- TP/(TP+FN) gives Sensitivity
- TN/(TN+FP) gives Specificity

Because of the data imbalance, deciding whether the classifier is superior at diagnosing COVID-19 illness is difficult. Misdiagnosis, especially in the instance of COVID-19, has the opportunity to have devastating consequences. As a result, the COVID-19 class parameters must be determined.

## 4.4. Results

COVID-19 samples from a large chest X-ray dataset were input into five well-known pre-trained CNN models: VGG19, MobileNetV2, Inception, Xception, and Inception ResNet v2. It was found that the VGG19 and MobileNetV2 CNNs tend to have the best classification accuracy when compared to the other CNNs. All of the CNNs appear to perform well in terms of accuracy and specificity, despite the dataset's imbalance. However, because those measures are highly dependent on the quantity of samples used to represent each class, a single evaluation will produce erroneous results. As a result, selecting the optimum model requires balancing accuracy, sensitivity, and specificity. Despite the fact that VGG19 has a higher accuracy, MobileNetV2 has a greater specificity than VGG19, depending on the original dataset findings, this is the most accurate mechanism for the specified classification task and data sample. True Positives (TP), False Positives (FP), True Negatives (TN), and False Negatives (FN) related to the COVID-19 class for the highest performing CNNs.

**Table 4.1:** Study of True Positives (TP), False Positives (FP), True Negatives (TN), and False Negatives (FN) Rate - Binary Classification (COVID-19 vs Normal)

| CNN | TP | FP | TN | FN |
|---|---|---|---|---|
| VGG 19 | 210 | 13 | 1192 | 13 |
| Mobile Net V2 | 222 | 35 | 1170 | 1 |

VGG19:

Sensitivity - 94.17%

Specificity - 98.92%

Accuracy - 98.18%

MobileNetV2:

Sensitivity - 86.38%

Specificity - 97.10%

Accuracy - 95.21%

MobileNetV2 provides fewer false negatives than VGG19, despite the fact that VGG19 achieves higher accuracy rate. False negatives can be extremely harmful because they mean patients are not treated for infections in a timely manner, so MobileNetV2 may be the best choice.

## 4.5. Conclusion

A deep CNN-based domain adaptation strategy for effectively identifying COVID-19 pneumonia is presented in this paper. Five major, efficient CNN-based learning algorithms for recognising normal and sick individuals using chest X-ray images were developed, tested, and reviewed. MobileNet v2 was found to outperform other deep CNN networks. The findings suggest that deep learning using CNNs can significantly improve the automatic identification and extraction of crucial information from X-ray images, which is important for COVID-19 diagnosis. Using existing Convolutional Neural Networks that have been trained on massive datasets, we can develop accurate deep models on small datasets to improve accuracy of COVID-19 detection. In this way, rather than developing our model from scratch, we can use pre-trained models with generalizable low-level features to train it. However, there are several limitations to this experiment. A more in-depth analysis, in particular, necessitates a greater quantity of patient data, notably COVID-19 data. After all, powerful deep learning models are typically trained on millions of images, which is difficult in the medical field. Furthermore, overfitting may occur when deep neural networks are trained on a small dataset, restricting generalisation. Depending on the potential deep learning models employed to recognize COVID-19 from chest X-ray images, deep learning can still be enhanced and then become a viable option in the battle against the pandemic. Increasing the number of images and employing preprocessing techniques will surely aid in the resolution of the problem. Overall, the proposed model vastly improves upon existing methods, and it may prove to be a low-cost, quick, and useful tool for medical workers to help in the detection and diagnosis of COVID-19 patients while reducing virus infection during the COVID-19 pandemic.

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