

Development Validation and Detection of Covid-19 using chest Radiography.

MSc Research Project
Data Analytics

Veeresh Shivabasappa Kumbi
Student ID: 20165749

School of Computing
National College of Ireland

Supervisor: Prof Aaloka Anant

National College of Ireland
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Student ID:	20165749
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Development Validation and Detection of Covid-19 using chest Radiography.

Veeresh Shivabasappa Kumbi
20165749

Abstract

Covid19 or Coronavirus, is a dangerous condition that has put many people's lives at risk by directly harming the lungs. A medium-sized, coated single-stranded RNA virus. This virus is around 120 nm long and contains one of the biggest RNA genomes. This paper gives a brief overview of the recent development in systems using deep learning methods. Although this method is time consuming and complicated which would take 6-12 hours to get the results. In early infected patients due to low virus loads. This method is prone to show false negative results in fewer cases. The study aims at building a CNN model to detect the virus with explainability. In the field of health care, explainability plays a vital role as this would help the practitioners to make sensitive approach. By the result obtained using this model would be used to lessen the burden on doctors and prioritise the tests and treatments. Earlier models relied on tiny datasets, which might lead to overfitting. We created a model that could produce a binary classification F1-score of 84 percent and a multi-class classification F1-score of 78 percent.

1 Introduction

The novel corona virus came into light in Wuhan province on December 2019, China. It ended in spreading around the world very quickly it was initially found and transmitted from animals. The simplest way in which the virus spreads is by physical contact with infected person and by air. Virus enters the respiratory system destroys the lung cells and replicates within. (Hu et al.; 2020) It comprises of RNA cells and it is challenging to detect due to its mutation characteristics making it difficult to diagnose and treat. The common symptoms are as follows dizziness, cold, cough, shortness of breath, muscle ache and headache. The virus is so dangerous that it weakens the immune system resulting in death. Currently, the virus is leading to death of thousands around worldwide. (Lai et al.; 2020) The detection of virus at early-stage place and significant and vital role. Several ways have been proposed in order to detect the virus such as PCR, CBC's blood test and medical image methods. The reverse transcription polymerase chain reaction test is used to identify viruses. as insisted by WHO. However, this is time consuming process and is risky for infected people.

Medical imaging is carried out as the primary step. Then RT-PCR is conducted as the aid in detecting the virus. This in-turn help the physicians to assist on the necessary tests and diagnosis more accurately. There are two type of medical image techniques CT-scan and X-rays. By using X-ray, it is possible to detect the virus, it has advantage

of less harmful radiation on human cells and less cost. It is a challenge to treat covid virus for radiologist using X-ray as it relatively a complicated process using the images as the images contains pus accompanied with white spots which is problematic. There are chances where radiologist might mistakenly diagnose as tuberculosis.

Over the years, Study on Artificial intelligence has led to various development in the field on medical aiming to diagnose and treat various diseases related to tumours and cancer. In a decade, a branch of machine learning, Deep learning has leveraged large number of applications on artificial intelligence using data-processing matching level of human accuracy. Virus mutations that are 70% more transmissible as reported by WHO. This can be contained only when 60% of the population gets vaccinated. This study describes a method for detecting viruses using X-ray images. The following question has been developed and discussed in order to address the issue. “Is it possible to construct an explainable model that can identify covid 19 leveraging chest X-ray images using Deep Learning methodology?”

The main aim of the research is to detect the virus using chest X-ray images Also, Using Artificial Intelligence to identify Covid-19 from a chest radiography picture complements existing techniques such as fast antigen testing and RT-PCR to increase the precision of Covid-19 identification. The study’s goal is focused to designing an explainable model that the radiologist can understand to help in decision making; the model should be able to identify whether chest radiographs are Covid or not. In addition, the model’s findings are being compared to those of another model.

The significance of the research as the sensitivity of antigen test is less, and RT-PCR test is of high cost and time consuming. This would result in waste of productive time to find antigen tests are not accurate. This research paper argues that artificial intelligence can aid in the detection of the Covid-19 utilising readily available chest radiography. The results of this model’s detection of the Covid-19 can be designed to assist prioritise testing and treatments. Most older models employed tiny datasets to train their models; presently, better datasets are accessible to construct and train the model. Ease the strain on medical centers and doctors.

2 Related Work

To reduce mortality and spread of SAR-CoV-2 across the world public health social measures have been implemented. It includes measures such as social distancing, wearing-mask, Mass gathering, maintaining hygiene, sanitizing, etc. Few strategies have been followed to control the spread by prioritizing older age group who are exposed to outmost risk and front-line workers. WHO has also ruled out mandate vaccination which in turn would boost the immunity of the individual, which helps in keeping individual strong enough to fight the virus. In the section, we will be discussing about the symptoms, and diagnosis suggested by WHO. This section looks at how AI may help combat Covid-19 in a a range of methodologies, includes limiting the false news, contact retracing, protein sequence prediction, and even how artificial intelligence being revealed Covid-19 before it became a worldwide concern. We will then look into research work previously made in health care using AI. Specifically for chest X-rays and CT scan image classification. And later we will be discussing on the deep learning models that are built to detect covid-19 using chest sample its drawbacks and strength.

2.1 COVID-19

According to data, the COVID-19 virus mostly transmits from person to person among individuals in intimate contact (within about 6 feet, or 2 meters). The virus spreads by respiratory droplets produced when a virus-infected person coughs, sneezes, breathes, sings, or speaks. These droplets can be inhaled or fall in a person's mouth, nose, or eyes. When a person is exposed to tiny droplets or aerosols that remain in the air for many minutes or hours, the COVID-19 virus can spread. This is known as airborne transmission. The virus can also spread if you contact a virus-infected surface and then touch your lips, nose, or eyes. However, the danger is negligible. The COVID-19 virus can spread from an infected person who is asymptomatic. This is referred to as asymptomatic transmission. The COVID-19 virus can potentially be transmitted by someone who is sick but has not yet shown symptoms. This is referred to as presymptomatic transmission. The majority of infected people will have mild to moderate symptoms and will recover without needing to be hospitalised.

Its most prevalent symptoms are:

- Raise in body temperature
- Continuous coughing
- Lack of energy
- loss of smell and taste

2.1.1 Diagnosis

In order to treat COVID-19, only one medicine has been licenced. COVID-19 is incurable. Antibiotics have little effect on COVID-19 or other viral infections. Researchers are testing a variety of therapeutic alternatives. Only one drug has been approved to treat COVID-19. COVID-19 is incurable. Antibiotics have little effect on COVID-19 or other viral infections. Researchers are testing a variety of therapeutic alternatives. The FDA has approved an emergency use licence for baricitinib, a rheumatoid arthritis medication, to treat COVID-19 in certain situations. Baricitinib is a COVID-19 antiviral and anti-inflammatory drug that appears to be effective. The FDA has given permission to baricitinib for the treatment of patients who are in need of supplementary oxygen.

2.1.2 Risk Factors

COVID-19 appears to be associated with the following risk factors:

- Close proximity to someone who has COVID-19.
- A sick individual coughing or sneezing on you

2.1.3 Treatment

So far, a number of medicines have been approved to treat COVID-19. Antibiotics are ineffective in the treatment of COVID-19 and other viral infections. A variety of therapeutic approaches are being tested by researchers. These medicine is prescribed to diagnose virus with all levels of severity. As part of the therapy, In order to expect a effective result ,this

medications should be made available once the individual starts to develop symptoms. In few cases this can be suggested to individual being hospitalised. Numerous patients are suffering from a mild illness that may be treated with supportive care. Supportive treatment is intended to relieve symptoms and may include the following:

- Antiinflammatory
- Cough medicine and cough syrup
- Drink plenty of water

2.2 Scope of AI in detection of Covid19

Timely identification and medication are critical in controlling the COVID-19 pandemic, since they are one of the most effective remedies. Using antigen detection technology is now the standard for categorising respiratory viruses. As a result of the virus, substantial work has gone into improving this technology as well as looking for additional options. These approaches, on the other hand, are typically extremely time taking and expensive have a low genuine positive rate, and necessitate the use of particular materials, equipment, and instruments. Using technologies in conjunction with AI frameworks is a straightforward approach for virus identification. In the literature, This is known as mHealth or mobile health. Another recommendation for COVID-19 detection is to utilize artificial intelligence (AI) approaches for the interpretation of medical data , which have recently emerged in a number of coronavirus research papers. (Ohata et al.; 2020) Infected individuals showed abnormalities in chest Xray images. Influenced by the research, Author designed a deep learning model with three datasets Normal, Covid infected and non-covid infected images. The dataset was trained with 13,975 images of 13,870 patients. Many ML and DL techniques were used in building models. Designed Convolutional model performed with an accuracy result of 93.3%. (Panwar et al.; 2020) (Wang et al.; 2020) , The cost of CT scan is more compared to that of X-ray, there is greater amount of research work that is being involved in detecting Covid 19 using chest images.

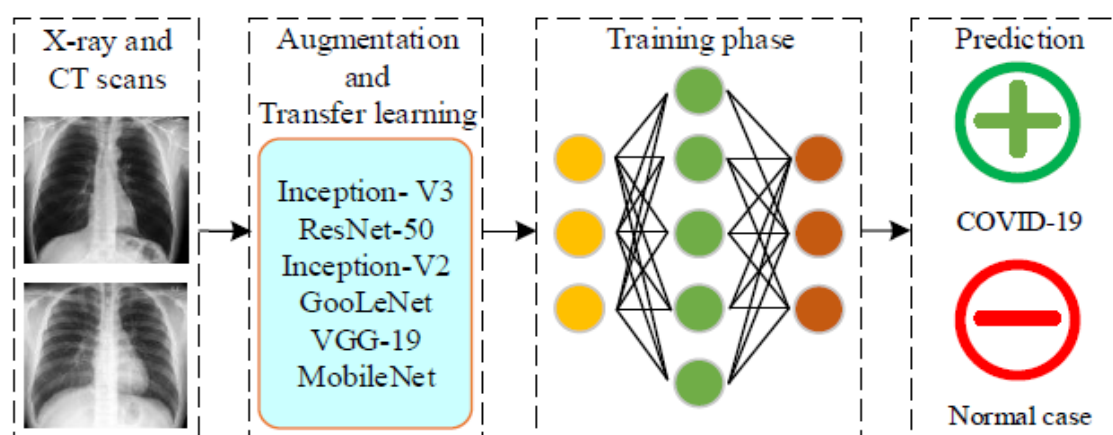


Figure 1: A diagram of DL-based frameworks for the COVID-19 detection and diagnosis (Panwar et al.; 2020) .

In the fight against covid pandemic, more importance and care is given to research to achieve best and efficient way to diagnosis and provide treatment in order to reduce the impact of virus.

2.2.1 Covid tracing using AI

Considering the increased possibilities Mass gatherings and high-density activities such as sports matches, conferences, and amusement parks are typically mentioned among the greatest events for extensive virus transmission. Because pure risk suppression is impractical in many aspects of life, a risk assessment approach that is more balance is necessary. Research Benjamin and his team proposed a machine learning model through which the events were traced using Bluetooth signal and cutoff the high risk activities. The DL based framework is explained in Figure 1

2.2.2 Use of AI in early diagnosis of Covid

The most widely utilised AI-based tool diagnosis, analysis, screening, categorization, medicine repurposing, prediction, and forecasting, as well as insights into where current research is heading (ML). Artificial intelligence research and development has dramatically improved COVID-19 screening, treatment, and prediction, resulting in greater scale-up, faster reaction, the most reliable, and efficient outcomes, and, in certain circumstances, surpassing humans in some healthcare tasks

2.3 Deep Learning in classification of Images

Image classification is a complicated and thorough task that concentrates on number of criteria. Recent years have seen the emergence of a slew of innovative and valuable picture classification algorithms and methodologies, which researchers may be evaluated in terms of categorization accuracy and timeliness. Because there is no such thing as an optimal technique, a critical insight of a certain picture classification aim is to pick an appropriate procedure. Different methods may perform differently in certain jobs. Researchers should evaluate the data kind, data amount, and desired outcome while determining the best optimal approach for a certain task. In general, a classification system is created depending on the granularity of chosen remote sensing techniques, the user's objectives, compatibility with past work, available image-processing and classification methods, and time restrictions. Other deep learning neural networks, such as RNNs, are also discussed in the survey study. For example, (Li et al.; 2018) used LSTM models to include temporal information from subsequent segments to find foetal standard planes in US films. In cine-MRI of the heart, (Yang et al.; 2017) employed an LSTM-RNN and a CNN to detect end-diastole and end-systole frames. Artificial intelligence for diagnosis has recently garnered a lot of traction in the medical field. Deep learning algorithms can identify feature representation that can be used to automatically detect images. A convolutional neural network (CNN) is a deep learning system that can learn weights and biases to identify and separate images as input. A kernel is applied to the image, creating a convolved feature matrix, which is then pooled to represent the image's latent characteristics. To extract the most significant aspects from an image, convolution and pooling are employed several times. After being trained with adequate data, the CNN network learns weights and biases to categorise or segment images. Despite the fact that work on CNNs has been ongoing since the 1970s, (LeCun et al.; 1998) was the first to

successfully apply them in the real world to recognise handwritten numbers. When (Krizhevsky et al.; 2012) suggested AlexNet for the ImageNet competition, it was a defining moment. Deep Convolutional Networks are now the benchmark preferred technology for computer vision, notably in healthcare. Papers pertaining to deep learning in image analysis is explained Figure 2 Image processing in medical applications using deep learning originally surfaced at seminars and conferences, then in publications. The number of publications published in 2015 and 2016 increased dramatically is shown (Litjens et al.; 2017).

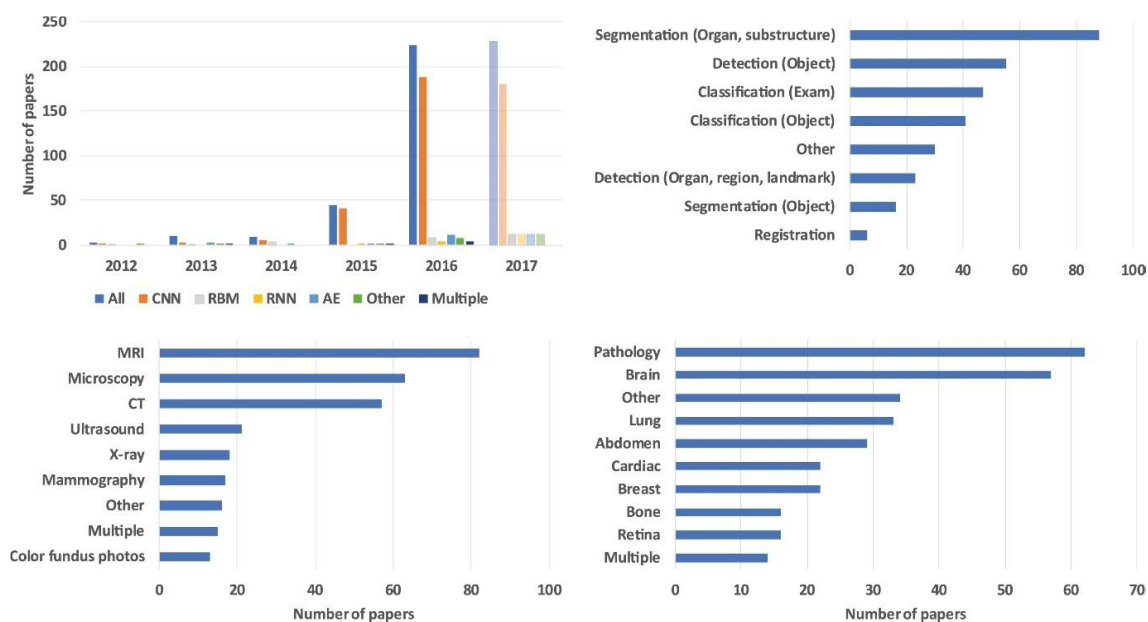


Figure 2: Papers on deep learning in medical image analysis are segmented.. (Pham et al.; 2020)

2.4 Ongoing art of CNN in detection of covid

In their study, Ozturk and colleagues (Ozturk et al.; 2020) present a technique for finding covid making use of a deep neural network and imaging tests. The study looks at how to use the DarkNet-19 model to identify Covid-19 using chest radiography. The classification model DarkNet-19 was created to detect the items. The proposed model employs DarkNet-19, a 19-layer convolutional network, There are five Maxpool layers, each with a different number of filters, sizes, and stride values. Convolution, LeakyRelu, and Batch Normalization are all DarkNet layers. LeakyRelu was employed in the model to prevent neurons from becoming dormant. The authors depend on a tiny dataset of 127 photos for their research. Despite the fact that the model has a 98 percent accuracy in predicting the existence of Covid-19, it is probable that it is overfitting to the restricted dataset. The model will have to be evaluated on a much larger set of data.

The researchers of (Alfaz et al.; 2021) used a bigger dataset of 6432 chest radiography images, 490 of which were Covid-19 positive. Augmentation is used to overcome the data's class imbalance and reduce overfitting. Augmentation methods such as picture sharing, rotation, and zoom are used. To circumvent the problem of dying neurons, LeakyRelu activation is utilised. Three alternative deep neural network models are tested. Inception

net v3, Xception net, and ResNext were the models employed. The proposal compares the performance of these three models and concludes that Xception net produces the best results for identifying Covid-19 from chest radiography images. The dataset distribution is shown in Figure 3 For Covid-19 detection, Xception net has a precision of 0.99 and a recall of 0.92. The authors make no attempt to explain the concept, and they explicitly state that the model is intended for research purposes.

	Train	Test
Healthy Person	1345	238
Covid-19 Infected Patient	490	86
Pneumonia Infected Patient	3632	641

Figure 3: Dataset Distribution (Alfaz et al.; 2021)

for classifying the chest radiography images the authors of (Ouchicha et al.; 2020) suggest a CVDNet model who split the dataset into 3 classes . Normal, pneumonia, and Covid-19 are the three groups. The dataset was taken from the COVID-19 repository on Kaggle. There are 219 Covid-19 CXRs among the 2905 chest radiographs. Cropping and resizing the photos are used to preprocess the data. To categorise photos, they use a ResNet model. The article activation function is leakyRelu, it basically gives an overview on the model which uses dual parallel layers. Batch normalisation, and Adam optimizer. The Model is validated using five-fold method with an F1-score of 96.68 percent, the model can detect the Covid-19. The performance of the model using CVDNet on each fold is explained in Figure 4

Folds	Precision (%)	Accuracy (%)	Recall (%)	F1-score (%)
Fold 1	97.37	97.25	97.37	97.37
Fold 2	98.40	97.76	97.09	97.72
Fold 3	97.80	96.90	96.47	97.10
Fold 4	96.86	95.18	95.88	96.20
Fold 5	93.20	96.39	97.40	95.04
Average	96.72	96.69	96.84	96.68

Figure 4: The CVDNet’s performance on each fold. (Ouchicha et al.; 2020)

To identify the Covid-19, researchers (Yan et al.; 2020) used dataset with chest images. This collection contains 416 3D chest CT scans. The dataset was separated into

three sections by the researchers: 80 percent into trainset, 10% into test set, and 10% for validation . The authors offer a multi-scale technique based on the fact that radiographic the size of the attributes varies. position, and form. In order to generate images in multi-scale form , multi-scale spatial pyramid (MSSP) is applied. Decomposition to retrieve necessary information for advanced classification.They consider a multi CNN (MSCNN) module that receives input from the MSSP module.Each layer uses Efficient-NetB0 method. The suggested AI system has an accuracy of 87.5 percent in detecting the Covid-19. This model isn't explainable, as it's just trained and tested on a tiny collection of data. AI system architecture suggested is proposed in Figure 5

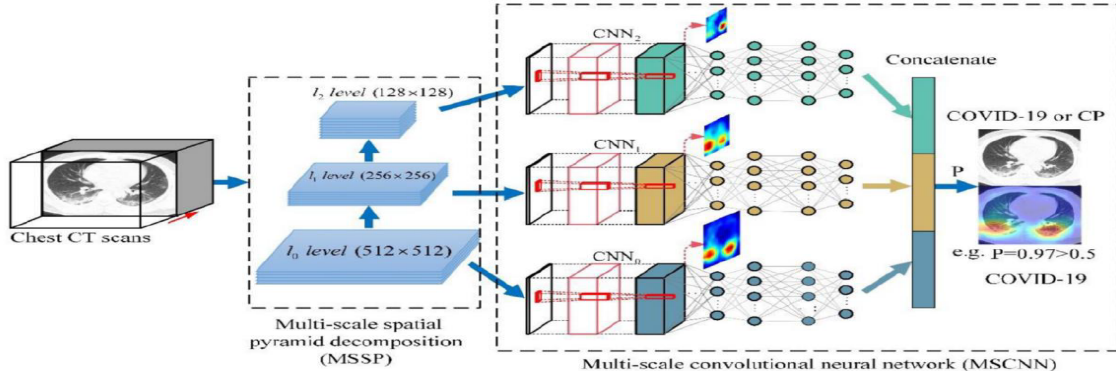


Figure 5: Architecture of the proposed AI system. (Yan et al.; 2020)

In their study (Chowdhury et al.; 2020), authors Chowdhury and his team. explore several dense neural networks that may be used to detect Covid-19. They assemble chest radiography pictures from a variety of data sets to create a comprehensive chest X-ray collection in an open-source dataset (Chowdhury et al.; 2020). They gathered data from six different sources. Along with normal radiographs and pneumonia radiographs, a subset of Covid-19 chest radiographs containing 423 pictures is created. The authors utilise techniques including scaling, rotation, and cropping to pre-process the data. The research examines eight different deep networks that have already been constructed. The study looks at eight distinct deep networks that has already been developed. They test several models using two forms of categorization: Binary classification and Multi-class classification. They use a binary categorization method to determine if chest radiographs are covid positive or negative. In a multi-classification scheme, they are classed as normal, infected, non-infected. CheXNet and DenseNet201 had the highest accuracy for both types of classifications, with 97.74 percent and 97.94 percent, respectively. respectively, according to the research.

In their study, the authors did not examine lung segmentation or the model's explainability. Performance metrics using various models is proposed in

Figure 6

3 Methodology

3.1 Data

To build a deep learning model the important aspect in the medical imaging platform would be data. Need for medical images of chest X rays would be the priority task

Schemes	Models	Accuracy	Precision (PPV)	Sensitivity (Recall)	F1 Scores	Specificity
Without image augmentation	SqueezeNet	95.19	95.27	95.19	95.23	97.59
	MobileNetv2	95.9	95.97	95.9	95.93	97.95
	ResNet18	95.75	95.8	95.75	95.78	97.88
	InceptionV3	94.96	94.98	94.95	94.96	97.49
	ResNet101	95.36	95.4	95.36	95.38	97.68
	CheXNet	97.74	96.61	96.61	96.61	98.31
	DenseNet201	95.19	95.06	95.9	95.04	97.87
With image augmentation	VGG19	95.04	95.06	95.03	95.04	97.51
	SqueezeNet	95.10	95.18	95.10	95.14	97.17
	MobileNetv2	96.22	96.25	96.22	96.23	97.80
	ResNet18	96.44	96.48	96.44	96.46	97.91
	InceptionV3	96.20	97.00	96.40	96.60	97.50
	ResNet101	96.22	96.24	96.22	96.23	97.80
	CheXNet	96.94	96.43	96.42	96.42	97.29
	DenseNet201	97.94	97.95	97.94	97.94	98.80
	VGG19	96.00	96.50	96.25	96.38	97.52

Figure 6: Performance metrics of different models. (Chowdhury et al.; 2020)

looking at the direction in which the project is been taking direction towards. Finally, we selected the datasets from Kaggle community an award-winning dataset. It contains 4 classes chest x-ray images of normal, pneumonia, lung opacity and covid-19 cases. ¹

The dataset contains 4 class of image samples

- Covid positive 3,616 image
- Normal 10,192 images
- Lung opacity of 6,012 images
- Viral pneumonia of 1,345 images

3.2 Data Description:

The dataset is found to be highly imbalanced. The images are in PNG format with size of 256*256. Usually, the images are always in DICOM format when converted later in jpeg or jpg format in order to access easily over the network. In this dataset normal x ray images are found to be higher than covid positive images.

3.3 Pre-processed Data

Portable Network Graphics (PNG) image is just a two-dimensional array of values ranging from 0 to 255 in each element (or pixel). Usually, Xray images have intensity ranging from 0 255. The photos were originally 255*255*1, but we adjusted them to 224*224*1. The pixel values are then divided each pixel's value by 255 to normalise the image. This aids in keeping pixel values inside the 0 to 1 range. This pixel rescaling solves the problem of gradient propagation. Data normalisation speeds up the convergence process when training the network. Normalization improves the efficiency of the training process.

¹<https://www.kaggle.com/tawsifurrahman/covid19-radiography-database>

3.4 Proposed Model

The CNN algorithm is the most well-known and widely used deep learning algorithm. CNN has a basic advantage over its predecessors in that it recognises crucial aspects without the requirement for human interaction. It CNN design is basically inspired from human brain. In Cat brain visual cortex is structured by intricated sequenced cells which is duplicated by the CNN. A conventional CNN, similar to a multi-layer perceptron (MLP), includes numerous convolution layers before subsampling (pooling) levels, with FC layers as the last layers..

Benefits of employing CNN: The following are some of the advantages of employing CNNs in the computer vision environment over other standard neural networks:

- The key argument for using CNN is that it allows the network to improve generality while minimising overfitting. Its unique feature of weight sharing inturn reduces the number of paramaters that are trainable.
- feature extraction learning and classification layers concurrently leads in a model output that is both well-aligned on the extracted features.
- CNN makes the building of large-scale networks more easier than other neural networks.

Convolution layer, ReLU layer, Pooling layer, and dense layer sum to build a CNN design as shown in Figure 7: We will be discussing on the key terms that is used in CNN.

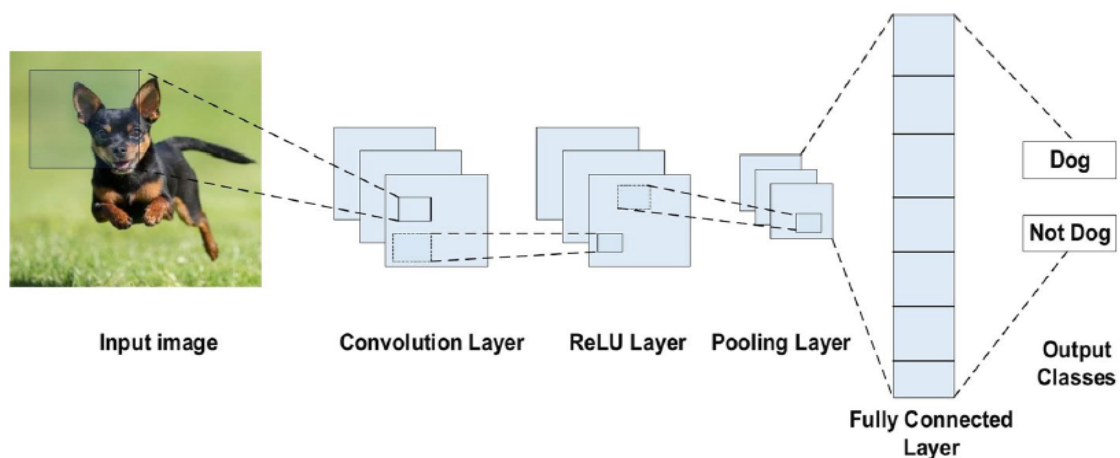


Figure 7: An illustration of a CNN Design for image classification.

3.4.1 Convolution

In CNN design, the convolutional layer is the most significant component. It is made up of many convolutional filters (called kernels). Convoluting the input image with these filters, which are represented as N-dimensional metrics, yields the output feature map. Input format of CNN is discussed first. The vector format is the input format of a traditional neural network, whereas the CNN's input is a multi-channelled picture. The gray-scale picture format, for example, is single-channel, but the RGB image format is three-channelled.

3.4.2 Stride and Padding:

In convolution, stride refers to the number of steps we make in each phase. It is one by default. We can see that the size of the output is smaller than the size of the input. Padding is used to keep the output dimension the same as the input. Padding is the symmetrical addition of zeros to the input matrix.

3.4.3 Pooling Layer

Pooling layer plays a fundamental role in subsampling the feature maps. These maps are created using convolutional techniques. This strategy depletes large feature maps in order to generate feature maps smaller. Since a result, Total CNN performance decreases; this is the pooling layer's main downfall, since it assists the CNN in evaluating the presence of input image, and concentrates on finding features exact location.

3.4.4 Fully Connected layer

When the feature analysis is complete and it is time to analyze, this layer gives random weights to the inputs and predicts an appropriate label. Fully connected layers are feed forward neural networks. The final Pooling Layer output is deflated and sent into the fully connected layer as the fully connected input. The preceding pooling or convolutional layer provides input to the FC layer. The FC layer output represents the final CNN output.

3.4.5 Model Configuration:

The ablation experiment was the initial step in the model's development. Ablation occurs when a model is overfitted to a small number of characteristics. We attempt to overfit the model with a limited training dataset. This allows us to determine if the network recognises the training data patterns. Firstly, we split the dataset into test and train datasets.

- Training dataset: The training data is a set of data that is used to understand how to employ technologies such as neural networks to learn and deliver advanced results.
- Validation dataset: A validation dataset is a subset of data from your model's training that is used to assess model competence while adjusting the model's hyperparameters. Procedures for making the most of your validation and test datasets while assessing your models
- Test dataset: The test set is a collection of data used to assess the model's performance using a performance measure. It is critical that no observations from the training set appear in the test set. If we achieve good accuracy on training dataset, but the model fails to produce a meaningful pattern result in overfitting.
- Regularization: Over-fitting is the most common problem with CNN models when it comes to achieving well-behaved generalisation. When a model performs extraordinarily well on training data but fails badly on test data, it is said to be over-fitted. Just fitted on the other hand, happens if the model fails to learn from training data but performs well on both training and testing data.

- Dropout: This is a commonly used generalisation approach. Neurons are dropped at random throughout every training session. As a result, The power of feature selection is divided uniformly throughout the whole set of neurons, pushing the model to learn a large number of independent features. The dropped neuron will not participate in back- or forward-propagation throughout the training phase. During the testing process, the full-scale network, on the other hand, is used to make predictions.
- Hyperparameter tuning: it is learning rate it helps to control on the weights in optimization algorithm. We experiment learning rate by setting the value to 0.1 and later by different learning rate
- Activation Function: The primary purpose of all sorts of activation functions in all types of neural networks is mapping the input to the output. The weighted summation of the neuron input and its bias is used to compute the input value. This implies that the activation function decides whether or not to fire a neuron in response to a certain input by producing the associated output.

This research investigates the LIME and GradCAM approaches for determining the model’s explainability. Tensorboard was utilised for visualisation, modelling, and training. Any target concept’s gradients to create a rough localization map for predicting the concept of essential spots of images is achieved by Grad-CAM class activation. LIME is model-agnostic, which implies that it may be used with any machine learning model. The method attempts to determine what the model is doing by varying the input of data samples and observing how the predictions change.

3.4.6 Evaluation

Using a chest radiograph, the model must be able to predict whether the person is infected or not. Accuracy, specificity, and sensitivity of the model are evaluated. To provide clear view of the model a classifier’s performance, a confusion matrix is constructed.

4 Design Specification

We have designed a model which is a two-dimensional convolutional neural network with convolution blocks and convolution layers, leaky relu activation, Batch normalisation, and max pooling. Dropouts have also been included to decrease the model’s overfitting between convolution blocks. After the convolution blocks, we added a flatten layer and two thick layers. The last thick layer, activated by softmax, is used for categorization. We used Adam optimizer and categorical accuracy as metrics during compilation, as well as categorical focus loss to reduce loss. GradCAM was used to compute the gradients that activate the neurons in the last layer, The output image results in a distinct localization map that indicates critical locations. The architecture has also been represented by graphing the model architecture with the plot model keras function. Design architecture is shown in Figure 8



Figure 8: Network Architecture

5 Implementation

5.1 Dataset Preparation

Image pre-processing: ImageDatagenerators are used to read and preprocess the image. To fetch and train the images we have used ImageDataGenerators. The images have spatial dimension of 256*256 pixels.

5.2 Dataset

When training a neural network, it is quite common to use the ImageDataGenerator class to generate batches of tensor image data with real-time data augmentation.

5.3 Exploratory Data analysis

Dataset totally includes 21,165 images of chest radiographs from four distinct classes. The dataset is shown to be severely unbalanced, with 3,616 Covid images, 6,012 Lung opacity ,10,192 normal images, and 1,345 viral pneumonias. Initially, we checked at the random samples and later converted the images to matrices. We then concentrated on the images of covid and normal.Images samples is shown in Figure 9 In the output layer, loss

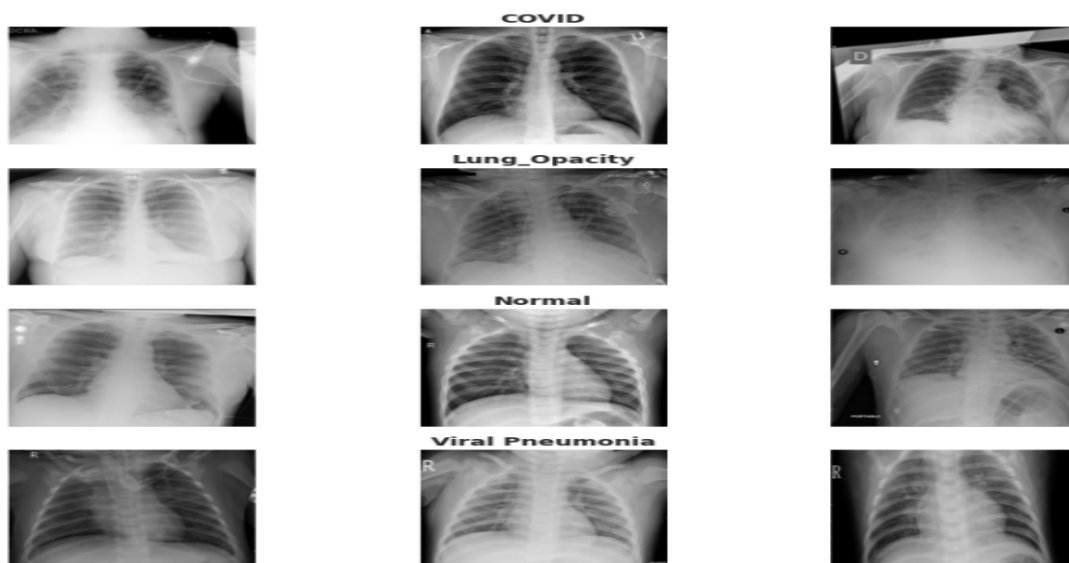


Figure 9: Image samples from 4 class

functions are used to determine the projected error throughout the training set. The CNN model contains samples. This deviation displays the discrepancy between the expected and actual outcomes, as well as the predicted outcome. The CNN learning procedure will then be used to optimise it. The loss function, on the other hand, uses two parameters to determine the error. The first parameter is the CNN estimated output. The second argument is the actual output. In various issue categories, several types of loss functions are used. While building a binary classification Model we employed cross entropy loss function. In addition, categorical cross entropy is used for multi-class categorization. The

neural network's bias and weights are changed during training depending on the loss in cross-entropy seen in backpropagation.

5.4 Explainability

Grad-CAM: Is a common method for generating a class-specific heatmap using a single input picture, a trained CNN, single class of interest. Grad-CAM may be used in any CNN architecture with differentiable layers. The heatmap is generated as a numpy array by the function `make_gradcam_heatmap`. To evaluate the model training outcomes, we created a confusion matrix. To limit the false negativity recall is outmost importance. Confusion matrix is useful to learn the specificity and sensitivity of the model. We have trained the model on validation loss and validation accuracy to build a best possible model

6 Evaluation

6.1 Binary Classification:

Initially we considered the covid and normal sample images for binary classification. Two class of samples were involved for experiment. The data was partitioned into test and train sets with a split of 0.2 using `Imagedatagenerators`. In the training dataset, we had 11,047 photos in train dataset and 2761 images from the test dataset. The dataset was extremely skewed. For all convolution layers, we used a kernel size of (3,3) and a stride of (1,1). Every convolution layer was followed by `LeakyRelu`. The maximum pooling layer is utilised with kernel size 2, stride 2, padding 0, and dilation 1 we utilise binary cross entropy as the loss function. As an optimizer, we employed SGD. We boosted our accuracy to 84% by switching to Adam as the optimizer. To speed up the model construction process, we used the Keras framework for model training and assessment instead of Pytorch. Keras allows for high-level abstractions for neural network training. `ModelCheckpoint`, `ReduceLRonPlateau`, `EarlyStopping`, and `TensorBoard` are among of the new callbacks. `ModelCheckpoint` has been added to preserve model checkpoints, with the best performing ones being utilised for model predictions later. When a plateau is reached for many epochs, `ReduceLRonPlateau` decreases the learning rate by the factor provided. The patience option specifies how many epochs we should wait before adjusting the learning rate. When the validation loss does not change, the model is stopped early with patience. The `TensorBoard` callback was added to allow visualisations to write events to the tensor board. Training performance is plotted in Figure 10

As we see, the initial training phase's peaks and valleys suggest that the model has experienced multiple local optima. After 10 epochs, the loss for the validation set stabilises, indicating that there is no expressive improvement in Model Accuracy Metric. The Learning Rate decrease and the model's ability to converge to a more stable solution are intricately connected.

6.2 Confusion Matrix

Confusion matrix is plotted in Figure 11. The values of the Confusion matrix would be as follows:

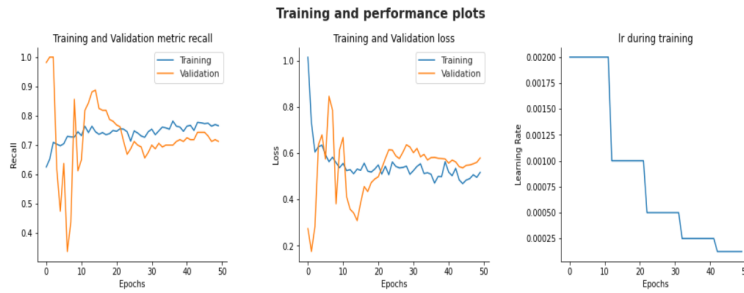


Figure 10: Training and performance plot

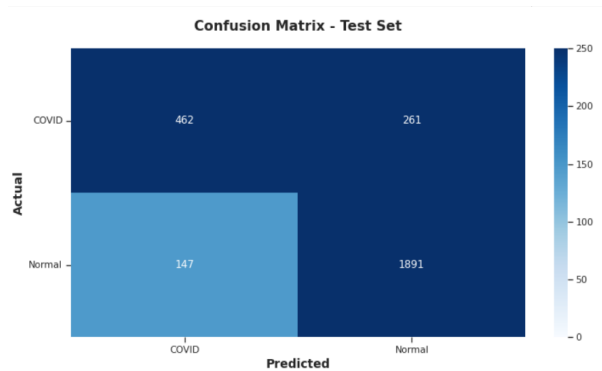


Figure 11: Confusion matrix

- True Positive = 462; Covid positive images were classified correctly .
- True Negative = 1891; Covid negative images were classified correctly
- False Positive = 261; Covid negative images were incorrectly classified as belonging to the covid positive class
- False Negative = 147; Covid positive images were incorrectly classified as belonging to the covid negative images.

Classification Report:				
	Precision	Recall	F1- Score	Support
Covid	0.68	0.76	0.72	723
Normal	0.91	0.87	0.89	2038
Accuracy			0.84	2761
Macro Avg	0.8	0.82	0.8	2761
Weighted Avg	0.85	0.84	0.85	2761

Figure 12: Classification Table

The performance of the model and its Classification table is proposed in Figure 12. Given the significantly greater number of true positive and true negative values in our dataset, this turned out to be a reasonably good classifier with an accuracy of 84 percent.

6.3 Multi-Class Classification:

The dataset consists of 4 classes of images. Covid, normal, Viral pneumonia and Lung opacity. Using imagedatagenerator we had divided the dataset into test and train with a split of 0.2. Because the dataset was very unbalanced, During execution, in order to use categorical entropy, we altered the loss function with the focused loss function. To deal with data imbalances, a loss function called focused categorical loss is used. We utilised the class weight parameter in model to compensate for class imbalances. To make the classifier strongly weight the few instances that are provided, use the fit function. Because it performed well, we used the previous model for binary classification as a base for testing the parameters with new data. Small batch sizes, As per the result we improved accuracy by slowing the training time. While a bigger batch size cut down on training time, it also cut down on accuracy. With Adam optimizer, we also determined that the learning rate 0.001 performed better for our dataset. Training performance values is plotted in Figure 13

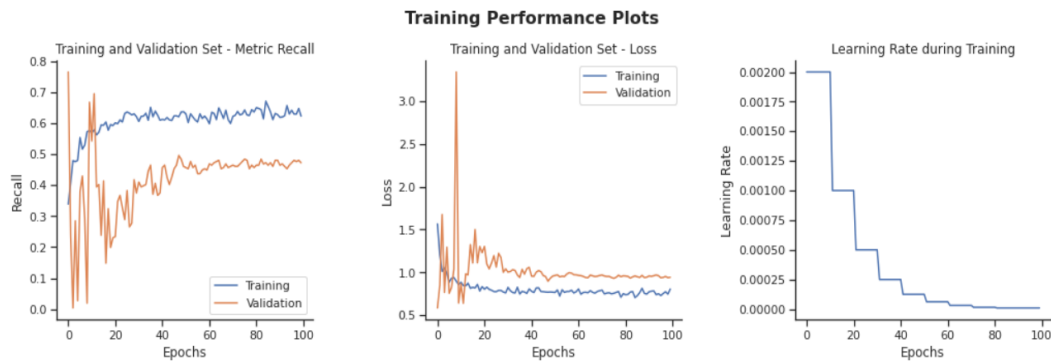


Figure 13: Training and performance plot

After 60 epochs, the loss for the validation set stabilises, indicating that there is no expressive improvement in Model Accuracy Metric. Overfitting may occur if the model is trained for a prolonged period of time. We would be caught in a Local Optima if we trained the model for fewer epochs, and we would be unable to generalise to fresh data.

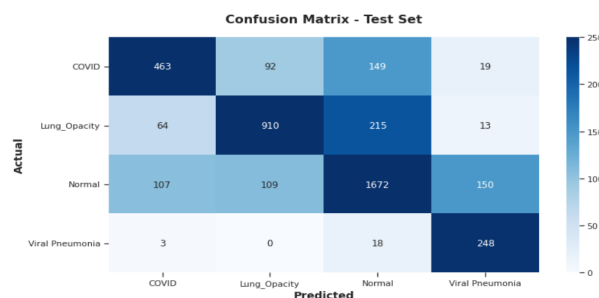


Figure 14: Confusion Matrix

From the confusion matrix plotted Figure 14, we arrive at a conclusion that viral Pneumonia is the class with misclassifications at a very low number. Normal samples are also misclassified as Lung opacity or Viral Pneumonia, Very less chances to be mistaken

as Covid-19. Lung Opacity is more often classified as Normal than as Pneumonia or lung opacity. Covid 19 if misclassified can be predicted as normal sample else lung opacity sample. It is less likely to be classified as Pneumonia. Throughout, the model can identify the samples.

Classification Report:				
	Precision	Recall	F1- Score	Support
Covid	0.73	0.64	0.68	723
Lung Opacity	0.82	0.76	0.79	1202
Normal	0.81	0.82	0.82	2038
Viral Pneumonia	0.58	0.92	0.71	269
Accuracy			0.78	4232
Macro Avg	0.73	0.78	0.75	4232
Weighted Avg	0.79	0.78	0.78	4232

Figure 15: Classification Table

The performance of the model and its Classification table is proposed in Figure 15 Normal and Lung opacity have good and similar values of precision and recall that is above 78% which means the model is good at recognising and classifying the images. It is seen that lower results are found for covid as the precision and recall metrics differed highly. The F-score is balance between precision and recall. Precision and recall values are similar, Normal class show high score. Overall, to reduce the number of covid images incorrectly classified as normal images. It is termed to be a good outcome that all the metrics are above 75%. Result per class can be definitely be improved.

7 Explainability

Gradient-weighted Class Activation Mapping is a method that uses the gradients of irrelative target concept to create a coarse localization map that emphasises key locations in the image for concept prediction. Grad-CAM is a common approach for generating a class-specific heatmap using a given input image on a trained CNN Figure 16, Gradcam was used to activate the pixels in the resulting images which resulted in blank heatmap. In order to overcome this we rescaled the image between 0 and 1 dividing it with 255 resulted in lowering gradients. The model exhibits right activations around the lungs and appears to have undesired activations on the CXR image's right side. Lung segmentation would aid in identifying Covid-19 with greater accuracy.

8 Conclusion

There have been multiple attempts to use CXR to diagnose various illnesses using deep neural networks. During our literature study, we discussed a number of methods for detecting Covid-19 utilising CXRs. DenseNet, VGG are the pretrained models most research articles used to categorise .(Ozturk et al.; 2020) Transfer learning was used by the authors on DarkNet-19. Authors (Ohata et al.; 2020) used Inception netv3, Xception net, and ResNext models on tranfers model. These are complicated models that function as broad image classifiers in nature. These models have a number of flaws, including the fact that they lack explainability.

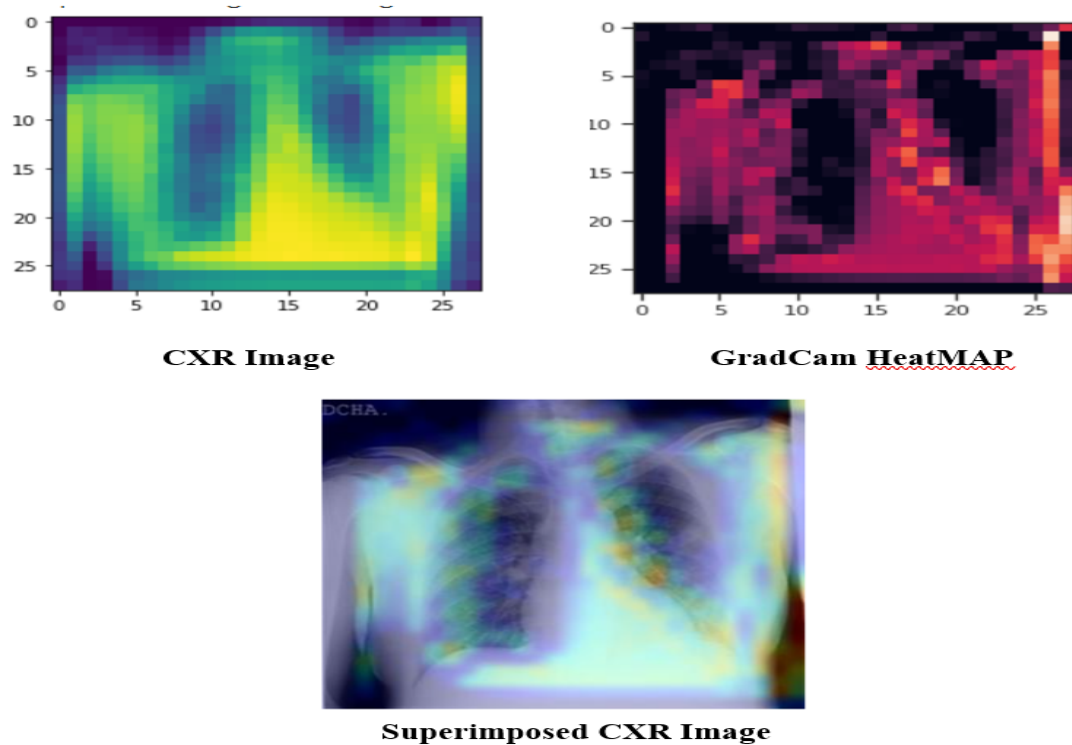


Figure 16: GradCam Activation CXR images

- The number of trainable parameters in DenseNet and ResNet is enormous, ranging from 20 to 40 million.
- models that are too generalised

This encouraged us to create a model that can classify CXRs as either Covid or non-Covid, as well as multi-class categorization. With just 2 million parameters, the proposed model is substantially lighter than pretrained transfer learnt models. The model's performance is excellent as well. For binary classification, Our model scored an f1-score of 84 percent, and in multi-class classification, model scored an f1-score of 78 percent.

9 Future Recommendations

Due to a surge in the second wave of Caronavirus-19, health infrastructure throughout the world is collapsing. Using deep learning to categorise the Covid-19 based on X-rays appears to be a potential way to help alleviate the strain on health infrastructure. With mutated viruses causing RT-PCR tests to lose sensitivity (Khan and Cheung, 2020), any technology that can enhance the RT-PCR is beneficial. The Covid-19 can be found using CT scans and CXRs. This methodology has the potential to relieve radiologists of some of their responsibilities. By removing unnecessary segments such as shoulders, image segmentation can increase the model's accuracy. Training on a larger and better dataset, as well as stratified K-fold validations, can enhance the author's model. To combat data shortage, many sampling approaches can be used. When making selections, it is necessary to consider non-CXR imaging information as well. Within the CXRs, noise

can be organised or random. Before we begin the training process, we should clean up and segment all of the CXR pictures.

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