

Corona Virus Detection and Classification with radiograph images using RNN

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Abstract

We're working on detecting the symptoms of Corona virus, also known as Covid-19, in this project. COVID-19 is a highly infectious disease that has been declared a Public Health Emergency and a Pandemic by the World Health Organization. The virus has infected over 25 million people worldwide, which has killed over 840,000 people and threatened the lives of millions more. COVID-19 is characterised by a dry cough, sore throat, and a high temperature. It is critical to find quick and accurate results for Covid-19 at this time in order to stop it in its early stages and avoid it from being a problem. Deep learning concepts are being used to analyse and classify symptoms from radiograph images. Chest radiographs are one of the early screening tests to assess the onset of disease since the infection seriously affects the lungs. In this proposal, we used a recurrent neural network model combined with a multi-level thresholding technique to detect Corona virus. One of the machine learning techniques for prediction is the RNN model. A Recurrent Neural Network is used to decide if the given images belong to Covid-19 during the classification process. This implementation is based on a publicly available dataset of radiograph images.

Keywords: Covid-19 Detection Corona Virus, RNN, Radiographic images, Machine Learning.

1 Introduction

The COVID-19 coronavirus, also known as SARS-CoV-2, has triggered a global crisis this will continue until the end of the year. COVID-19's cumulative incidence is steadily increasing day by day. Cloud

computing and Machine Learning (ML) can be very useful in monitoring the outbreak, forecasting its progress, and modelling strategies and policies to stop it from spreading. This study employs a more advanced mathematical model to assess and forecast the epidemic's progression. An improved ML-based model was used to forecast the potential hazard of COVID-19 in countries around the world. We show that fitting the Generalized Inverse Weibull distribution with iterative weighting yields a better fit for creating a prediction system. On a cloud computing platform, this has been applied with a more precise and real-time forecast of the epidemic's spread. A data-driven strategy with greater precision can be quite useful for a constructive response from the government and people. Finally, we recommend a collection of research opportunities and setting-up grounds for more practical applications. For this paper, we get inputs from the image dataset. To make a prediction, we must first figure out which algorithm can effectively classify a given image as favourable or unfavourable. Recurrent Neural Networks were used to identify them in this paper.

2 Literature Survey

Several studies in the literature have used X-ray data to demonstrate reasonable performance using various deep learning techniques [1]. DarkCovidNet, a model for early detection of COVID-19 that used 17 convolutional layers to perform binary and multi-class classification involving normal, COVID, and pneumonia cases, was proposed in.

COVID-19 features in radiograph data can be detected and monitored using existing deep learning models on CT scan images[1]. Using CNN architectures like VGG-16 to distinguish between COVID-19 and non-COVID-19 cases[1]. Deep learning was shown to be a viable technique for identifying COVID-19 from radiograph images in their experiments[1]. The trained approach is designed to distinguish COVID-19 cases from normal cases as well as pathological patients with similar symptoms from other respiratory disorders, such as pneumonia. For this reason, chest X-ray images from normal patients are grouped along with those from pathological patients with respiratory disorders other than COVID-19, and the method predicts Normal and COVID-19 groups. [2] In addition, we altered a network architecture to test the separability of the two types of chest X-ray images used in this study. To do this, we used a series of chest X-ray images from patients infected with COVID-

19, patients with other pathologies with similar characteristics to COVID-19, and healthy patients to train a model.

[2] Several researchers have been working on the virus since it first spread, developing a variety of methods for detecting and dealing with Covid-19. The use of x-rays in covid-19 prediction was inspired by the initial approaches used in pneumonia detection from chest x-rays using deep learning models [3]. It's also vital to provide a good dataset with confirmed covid19 patients' chest x-ray images. (3). **Transfer Learning** is a method in which we train a model for one problem and then use it for a few similar problems with minor changes. In the new model, one or more layers from the learned model are used. [3,4] Instead of clinical results associated with various conditions, a deep learning model will group X-ray images according to the scanning equipment used for the examination[2]. Furthermore, the vast majority of the photographs in these datasets were taken with fixed X-ray equipment. The capture equipment and acquisition technique affect the quality of chest X-ray images in terms of spatial resolution, contrast, presence of objects, and noise[2]. Furthermore, as RNN and other automated feature extraction techniques have become more popular, interest in early-stage feature extraction techniques has begun to wane. The Recurrent Neural Network architecture is a deep learning architecture that automatically extracts and categorises images from images. A hybrid model called fused perceptual hash based RNN was proposed to reduce the time it takes to classify CT images of the liver while maintaining accuracy. To solve the problem of medical image unbalance, a transfer learning technique was used. Reference 19 used an optimal deep neural network and linear discrimination analysis to analyse CT scans of lung images. Raw CT images were converted to low attenuation, and raw images and high attenuation patterns were rescaled. RNN was then used to re-sample and rate these three samples. Many researchers are working on this, beginning with the virus's result, and have discovered a number of methods for detecting covid-19 and curing it. The use of x-rays in covid-19 prediction was inspired by the initial approaches used in pneumonia prediction from chest x-rays using deep neural networks[3]. Instead of clinical results associated with various conditions, a

deep learning model will group X-ray images according to the scanning equipment used for the examination[2]. Furthermore, the vast majority of the photographs in these datasets were taken with fixed X-ray equipment. The capture equipment and acquisition technique affect the quality of chest X-ray images when it comes to spatial resolution, contrast, presence of objects, and noise[2]. Transfer Learning is a technique in which we develop a model for one problem and then apply it to a few similar problems with slight modifications[3]. In the new model, one or more layers from the learned model are used. It reduces the amount of time it takes to train a neural network for hyperparameter tuning. When we make use of pre-trained transfer learning models, we typically freeze just a few or none of the layers of the model. VGG (VGG 16 or 19)[3] and VGG (VGG 16 or 19) are two common transfer learning methodologies. The current infrastructure for detecting COVID-19 positive patients (e.g. small image data sources with expert labelled data set) is inadequate, and manual detection takes a long time[4]. With the increase in global incidences, it is expected that a Deep learning-based solution will be developed and combined with clinical practices to provide cost-effective, dependable, and simple automated COVID-19 detection to aid the screening process[4]. X-ray scans are widely used by radiologists to diagnose lung inflammation, swollen lymph nodes, and pneumonia. The COVID-19 virus infects the endothelial cells that line the lungs once within the body. X-rays may be used to determine a patient's lung health. X-ray analysis requires an expert and takes a long time[4,3]. Hybrid approaches to merging CNN and other ML algorithms are gaining popularity in the literature after outperforming current state-of-the-art in a variety of cases. Xiao-Xiao Ni et al. Created a Hybrid Algorithm that combined CNN and SVM to achieve a 95 percent digit recognition accuracy [5]. Ben Athiwaratkun et al. introduced various hybrid algorithms in his paper and demonstrated that they worked better [5]. By removing a multi-perceptron layer from CNN, Shaoqing Ren et al. used Faster R-CNN for feature extraction, and features were transferred to Random Forest, which performed better than CNN[5]. Various methods were used to analyse the chest X-rays, but the majority of them aren't very useful. Machine learning was used to help improve the

algorithms, but the systems' accuracy was poor [5,6]. Deep learning and the Convolution Neural Network (CNN) began to have an impact in 2007 and things began to change [5]. Deep learning algorithms have an inherent weakness in that they need a large data set to train[5]. One of the most widely used techniques for diagnosing pneumonia is chest radiography (X-ray) [6]. A chest X-ray is a simple, low-cost, and widely used clinical procedure [6]. In contrast to computed tomography (CT) and magnetic resonance imaging (MRI), a chest X-ray exposes the patient to less radiation [2,6]. Making the right diagnosis from X-ray pictures, on the other hand, necessitates expert expertise and experience [5,6]. A chest X-ray is much more difficult to diagnose than other imaging modalities like CT or MRI. COVID-19 can only be detected using a chest X-ray by a specialized physician. There are fewer experts who can make this diagnosis than there are general practitioners. In many countries around the world, even in normal times, the number of doctors per person is inadequate. According to 2017 statistics, Greece has the most doctors per 100,000 people, with 607 doctors. This figure is much smaller in other countries [6]. The health system will collapse in the case of a disaster, including the COVID-19 pandemic, that necessitates simultaneous emergency care due to a lack of hospital beds and medical personnel. COVID-19 is also a highly infectious disease, with physicians, nurses, and caregivers being especially vulnerable. Early diagnosis of pneumonia is critical for both slowing the spread of the virus and ensuring the patient's recovery [6]. Computer-aided diagnosis (CAD) helps doctors to diagnose pneumonia from a chest X-ray more rapidly and reliably [6]. Artificial intelligence approaches are becoming more common in the medical field because of their ability to work with large datasets that surpass human capacity [6]. In-

tegrating CAD methods into radiologist diagnostic systems decreases doctors' workload while also enhancing accuracy and quantitative analysis [6]. Several deep learning-based methods for classifying lung diseases have been proposed and evaluated to be effective at the human level [7]. Almost all of these techniques, on the other hand, are designed to diagnose

particular diseases like pneumonia [5,7], tuberculosis [7], and lung cancer [7]. Meanwhile, researchers are working on a unified deep learning system for accurately detecting several common thoracic diseases [7]. Reverse transcription polymerase chain reaction[8] confirms the diagnosis of COVID-19. The importance of chest radiography (CXR) is still a hot topic of debate. Present CXR studies on COVID-19 include a range of terms as well as different evaluations of its sensitivity and specificity. This can lead to CXR results being misinterpreted, rendering comparisons between examinations and study studies difficult [8,6]. We recommend terminology for consistent CXR reporting and severity assessment of individuals under investigation for COVID-19, patients with a verified diagnosis of COVID-19, and patients who may have radiographic symptoms of COVID-19, in order to satisfy this need for accuracy. When the diagnosis of COVID-19 is not suspected clinically, results characteristic or indicative of COVID-19 are found[8]. The most common imaging test in the country is chest radiography, which is essential for screening, diagnosing, and treating a variety of life-threatening diseases [9]. From enhanced workflow prioritization and clinical decision support to large-scale screening and global population health initiatives, automated chest radiograph interpretation at the level of practising radiologists could provide significant benefit in a number of medical settings[9]. The most popular image analysis requested is chest X-rays (CXRs). CXR ComputerAided Diagnosis (CAD) has gotten a lot of attention in the scientific community, both before and after the success of deep learning [10]. A recent effort has been made to build a new generation of CAD systems for the identification and visualization of common thoracic diseases from CXR images using advances in machine learning, especially deep learning [11,10,8]. The area of time series forecasting known as spatial-temporal time series is concerned with variables that shift over time and space. Disease forecasting, such as COVID-19, would benefit from spatial-temporal forecasting because it analyses patterns and provides a reliable predictor for decisionmakers all over the world, ability to make their decisions at the right time[12].

A Neural Network is made up of layers that are

3 Experiments Neural Network

linked to operate on the structure and function of the human brain. It contains an input layer, one or more hidden layers, and an output layer make up a neural network. One or more function variables (or input variables or independent variables) denoted as x_1, x_2, \dots, x_n make up the input sheet. One or more secret

nodes or hidden units make up the hidden layer. In the diagram above, a node is actually one of the circles. The output variable, too, is made up of one or more output units

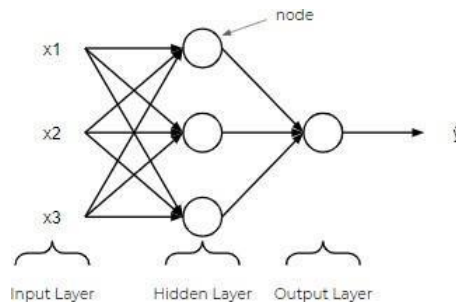


Fig. 1: simple neural network

Popular Neural Networks

- Feed-Forward Neural Network: Regression and classification problems in general.
- Convolutional Neural Network: Used to detect objects and classify images.
- Deep Belief Network: In the healthcare industry, it's used to detect cancer.
- Recurrent Neural Network: Speech recognition,

voice recognition, time series prediction, and natural language processing are all possible applications.

Recurrent Neural Network

The output from the previous step is used as input in the current step in a rnn.

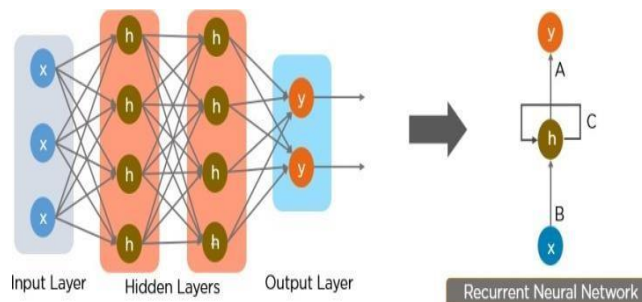


Fig. 2: Simple Recurrent Neural Network

Applications of Recurrent Neural Networks

- Time Series Prediction: An RNN can be used to solve any time series problem, such as forecasting

stock prices in a specific month.

- Natural Language Processing: An RNN for Natural Language Processing can be used to perform text mining and sentiment analysis (NLP).

- *Machine Translation:* If the input is in a single language, RNNs can be used to translate the input into multiple languages as output.

Advantages of Recurrent Neural Network

- An RNN remembers every piece of knowledge over time. It is only useful in time series prediction because it has the ability to remember previous inputs. This is referred to as Long Short Term Memory (LSTM).
- Even convolutional layers are used with recurrent neural networks to extend the effective pixel neighbourhood.

Disadvantages of Recurrent Neural Network

- Problems of gradient disappearing and bursting.
- It is extremely difficult to train an RNN.
- When using tanh or relu as an activation feature, it won't be able to process very long sequences.

Long Short Term Memory

LSTM (Long Short Term Memory) networks are a form of RNN that can learn long-term dependencies and are commonly referred to as "LSTM." LSTM was developed with the goal of preventing long-term dependency. It is their innate ability to recall

information for long periods of time. LSTM retains the error that can be back-propagated across time and layers. They allow repeated networks to continue to learn by sustaining a more constant error over a large number of stages (over 1000), thus opening up a channel for remote connections between causes and consequences. LSTM stores data in a gated cell outside of the recurrent network's normal flow. A cell's contents can be saved, written, or read. The neuron makes decisions about what to store and makes it possible to read and write by opening and closing gates. The layers are as follows:

1. *Tokenization:* This isn't an LSTM network layer, but rather a necessary transformation of our phrases into tokens (integers).
2. *Embedding Layer:* Transforms our term tokens (integers) to the required size for embedding.
3. *LSTM Layer (Long Short Term Memory):* Unknown state and number of layers discovered.
4. *Completely Connected Layer:* Mapping the output of the LSTM layer to the output size desired.
5. *Sigmoid Activation Layer:* In this layer, all output values will be translated to values ranging between 0 and 1.
6. *Output:* The final network's development is considered the final time stage of Sigmoid production.

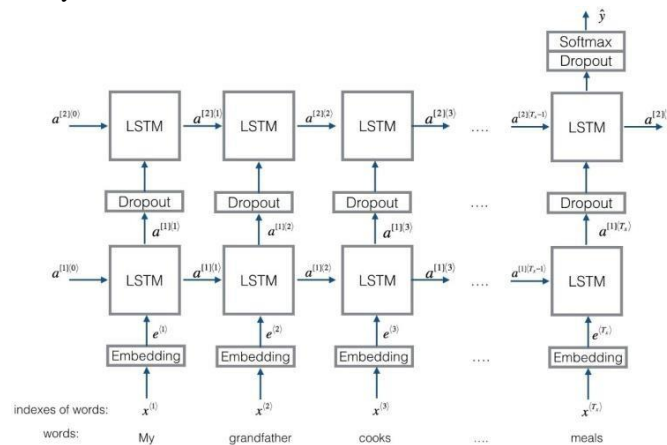


Fig. 3: Long-short term memory architecture

Memory Cell

This is a specialised neuron that is responsible for recognizing long-term dependencies. The LSTM employs a vector that moves from one cell to the next in its inner state. The LSTM is smart enough to figure

out just how long it would take to recall old data and skip the step of figuring out how to link new information to old memories.

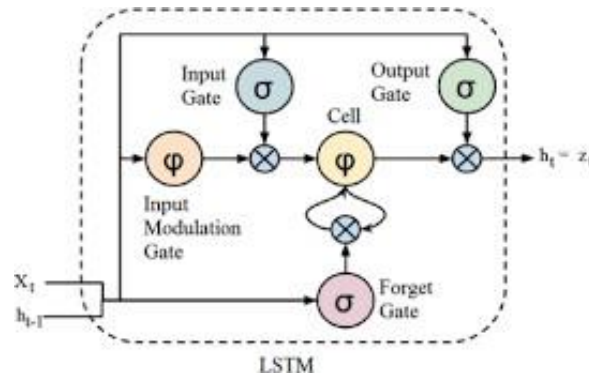


Fig. 4: Architecture of memory cell in LSTM

We'll construct an LSTM model using word sequences as data, with word ordering taken into account. To define terms, we'll use GloVe's 50-dimensional pre-trained word embeddings. Then, as an input, we feed the word embeddings into an LSTM, which predicts the most appropriate emotion for the text. Hidden states are output by the LSTM, which takes embedded words as input. The linear layer that transforms hidden state space into output space.

normal healthy conditions.

Applications of LSTM

- Robot control: Robust control is a controller design technique that directly addresses ambiguity. Robust control methods are designed to work properly when there are unknown parameters or disturbances in a given collection.
- Speech recognition: Speech recognition, also known as automatic speech recognition (ASR), machine speech recognition, or speech-to-text, is a feature that allows a computer programme to translate human speech into text.
- Handwriting recognition: Handwriting recognition (HTR) is the ability of a computer to obtain and interpret intelligible handwritten information from sources such as paper documents, images, touch screens, and other devices..

4 Proposed Methodology

In order to predict the Covid-19 disease, we implemented a few of the Artificial Neural Network concepts RNN in this paper. The traditional method of gathering the dataset (collection of CSV datasets) is delegated by collecting the image datasets. To be more specific, the dataset contains radiographic images of patients with pneumonia, Covid-19, and

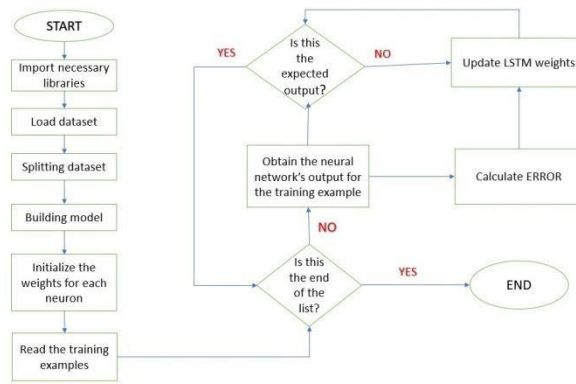


Fig. 5: FlowChart for implementation

Keras is used in order to perform the image classification for the dataset, these three types of images, as well as their names, are all translated to bytes and integers. and these are stored into XML file and are further split into training and testing. The data contains the images of three categories: Normal, Covid and Viral pneumonia. These data files are extracted into a list and converted as training and testing model. After conversion the data is stored in the xml file as bytes and integers. The xml file is used for comparing the Covid images and Viral pneumonia images with the Normal ones and gives the accuracy of barely 0.7. As compared to CNN model, RNN model shows a bit low performance, so this model shouldn't be considered for image classification.

than, training loss in most cases. Continue doing more training as long as the loss of validation is less than or even equal to the loss of training. If your training loss decreases but your validation loss does not, you should increase your training. When the lack of validity starts to rise, it's time to stop. With radiographic images, we got an accuracy of 86 percent, 93 percent with CT-Scan images, and 76 percent with X-Ray images. We conclude that using CT-Scan images for Covid-19 classification is better than using Radiographic images and X-Ray images after comparing the results of Radiographic images, CT-Scan images, and X-Ray images. The RNN model performs poorly as compared to the CNN model, so it should not be used for image classification.

5 Experimental Results

Validation loss should be similar to, but slightly greater

Results of Radiographic Images

Epoch	Loss	Accuracy	Val_Loss	Val_Accuracy
1	0.7313	0.6162	0.6861	0.6901
2	0.6225	0.6802	0.5742	0.7423
3	0.5860	0.7223	0.5106	0.7756
4	0.4788	0.7967	0.4541	0.8069
5	0.4401	0.8163	0.3749	0.8310
6	0.4208	0.8275	0.3853	0.8345
7	0.4008	0.8398	0.3475	0.8485
8	0.3697	0.8575	0.3241	0.8620
9	0.3607	0.8597	0.3175	0.8832
10	0.3638	0.8604	0.3088	0.9201

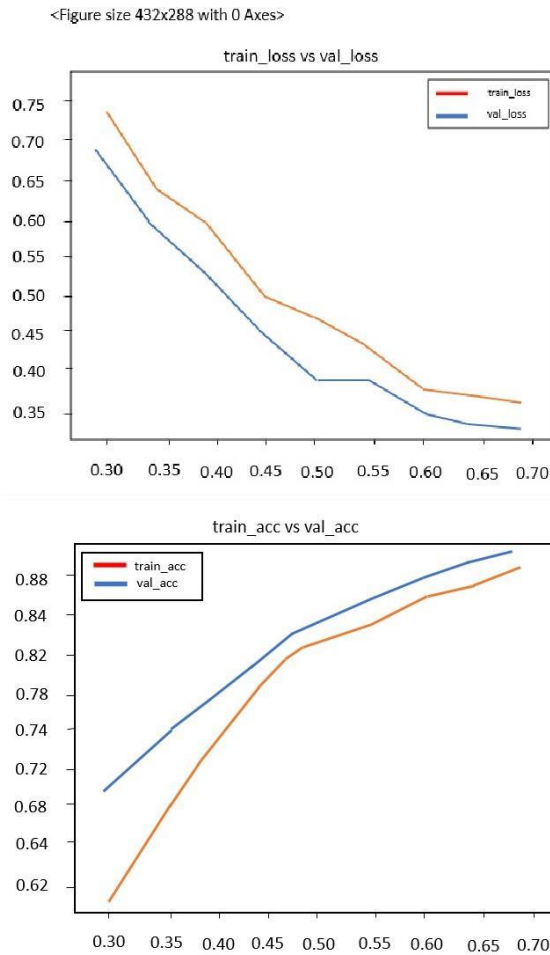
Fig. 6: Accuracy of Radiographic Images

	precision	recall	f1-score	support
COVID	0.92	0.84	0.91	812
NONCOVID	0.75	0.83	0.78	575
accuracy			0.86	1387
macro avg	0.86	0.87	0.86	1387
weighted avg	0.87	0.86	0.86	1387

Fig. 7: Model Results

```
[[654 185]
 [ 50 375]]
acc: 0.8620
sensitivity: 0.8583
specificity: 0.8540
```

Fig. 8: Confusion Matrix



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Fig. 9: Model graph

Results of CT-Scan images

Epoch	Loss	Accuracy	Val_Loss	Val_Accuracy
1	0.4469	0.7720	0.3117	0.8371
2	0.2771	0.8691	0.2290	0.8925
3	0.2328	0.8904	0.2076	0.9090
4	0.1958	0.9138	0.1906	0.9239
5	0.1736	0.9223	0.1714	0.9256
6	0.1492	0.9397	0.1629	0.9305
7	0.1407	0.9410	0.1660	0.9280

Fig. 10: Accuracy of ct scan

	precision	recall	f1-score	support
COVID	0.96	0.93	0.95	834
NONCOVID	0.86	0.92	0.89	375
accuracy			0.93	1209
macro avg	0.91	0.93	0.92	1209
weighted avg	0.93	0.93	0.93	1209

Fig. 11: Model Results

```
[[777 57]
 [ 30 345]]
acc: 0.9280
sensitivity: 0.9317
specificity: 0.9200
```

Fig. 12: Confusion Matrix

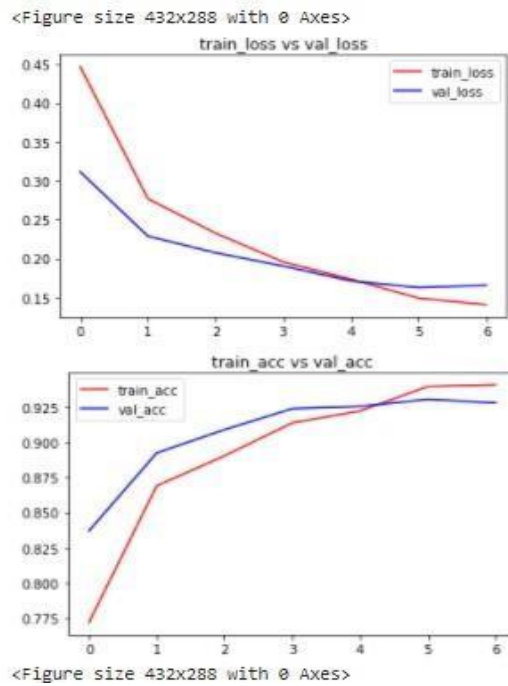


Fig. 13: Model graph

Results of X-Ray images

Epoch	Loss	Accuracy	Val_Loss	Val_Accuracy
1	0.6300	0.6494	0.5912	0.7051
2	0.5547	0.7249	0.5407	0.7331
3	0.5276	0.7432	0.5148	0.7510
4	0.5087	0.7580	0.5081	0.7617
5	0.4879	0.7634	0.4973	0.7638

Fig. 14: Accuracy of X-Ray scans

	precision	recall	f1-score	support
COVID	0.82	0.74	0.78	803
NONCOVID	0.70	0.80	0.75	628
accuracy			0.76	1431
macro avg	0.76	0.77	0.76	1431
weighted avg	0.77	0.76	0.76	1431

Fig. 15: Model Results

```

[[591 212]
 [126 502]]
acc: 0.7638
sensitivity: 0.7360
specificity: 0.7994
    
```

Fig. 16: Confusion Matrix

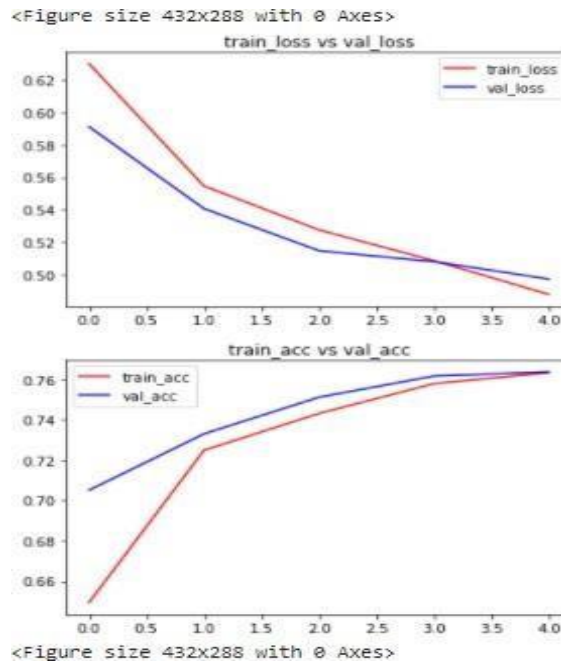


Fig. 17: Model graph

6 Conclusion

Covid-19 can be predicted in a variety of ways,

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