# Simultaneous Detection of Covid-19 and Its Pneumonia using Multitask Learning

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***Abstract:*** *With the rapid growth of Severe Acute Respiratory Syndrome Coronavirus 2 (SARS-CoV-2) or Covid-19 into a pandemic, quick and efficient alternative testing methods were needed. Although Viral Nucleic Acid tests are the primary and standard method of testing, the time-consuming process, and the lack of availability of test kits in certain areas have been problematic for the quick diagnosis of the disease. Therefore, using radiologic modalities such as chest X- rays and Computerized Tomography (CT) were studied due to their wider availability because of their usage in the diagnosis of other diseases. This research is based on chest X-rays and tests the usage of deep multitask convolutional neural networks (CNN) to detect both Covid-19 and Covid-19 related pneumonia conditions in a patient simultaneously. Usage of chest X-rays allows for wider availability for usage in rural areas, where computerized tomography facilities are rare. Current results from separate custom CNN models with same layer structure but different task specific features, give an accuracy of 94% on Covid-19 detection and 90% accuracy on Covid-19 pneumonia detection. As a novelty, this paper suggests that a multitask learning based CNN model in the same architecture would be viable to detect both conditions from a single neural network, simultaneously. The simultaneous detection of Covid-19 and Covid-19 pneumonia in a patient is a further extension to traditional testing methods and allows for more effective treatments from the beginning.*

## 1. Introduction

In the history of the world known to humankind, there have been large number of infectious diseases that have gone on to become epidemics and pandemics. These infectious diseases are mostly disorders caused by micro living organisms, such as bacteria, viruses, fungi, or parasites. Some of these some have even been able to threaten the existence of humankind. Few examples for these can be given as the black death pandemic (1346-1353), which is claimed to have taken lives of over 50 million people (*Black Death - Effects and consequences of the Black Death | Britannica*), the flu pandemic (1918) caused by influenza (*History of 1918 Flu Pandemic | Pandemic Influenza (Flu) | CDC*, 2019), which claimed lives of around 50 million people among many others.

The Severe Acute Respiratory Syndrome Coronavirus 2 (SARS-CoV-2) or most known as Covid-19 disease is known to have started spreading in the Wuhan Province of the People's Republic of China. SARS-CoV-2 first became an epidemic and was mostly spread across the same province which it started from. The first confirmed case of this disease was reported in around December of 2019. But gradually it was spread to some of the most populous areas in China and then started to show cases in countries that were geographically far away from the place it started from. The number of infections started to rise day by day to the point that on 30th January 2020, The World Health Organization had to declare it as a "Public Health Emergency of International Concern" and declared the disease as a global pandemic on 11th March 2020. (*Coronavirus disease (COVID-19) pandemic | WHO*) As of the time of writing this, 513,396,993 cases have been reported and 6,261,084 deaths have happened worldwide because of Covid-19.(*COVID Live - Coronavirus Statistics - Worldometer*, no date) Up to now, there have been reports of five new variants with new mutations of the base virus. These new variants tend to have their own unique characteristics, basically on top of what the base virus had.

The common symptoms of Covid-19 include fever, cough, tiredness, sore throat, aches and pains, diarrhoea, loss of taste and smell etc. Serious symptoms may be difficulty in breathing, shortness of breath, chest pain, loss of speech or mobility. In the Covid-19 pneumonia, the lungs can be gradually filled with fluid and become inflamed, leading to breathing difficulties, which can become severe and could require oxygen supplies and ventilators. The Covid-19 pneumonia can cause additional symptoms such as increased heart rate and low blood pressure. These additional conditions are the ones that causes the severity of infections in patients with chronic diseases. This pneumonia variant tends to hold both lungs and is the main cause for the majority of Covid-19 deaths.(*COVID-19 Lung Damage*, 2022) Although this pneumonia does not often cause any lasting lung damage depending on the severity of the infection. This can result in breathing difficulties, even after the disease has passed. To detect the Covid-19 pneumonia condition, additional testing needs to be done after a patient is detected positive for Covid-19. This requires additional time, which could be the time it needs to save another life.

There are two main categories that have been used clinically to detect the disease. They are Viral tests and antibody tests. Out of these two classes, viral tests have been the most reliable, accurate and widespread used. This category includes the rRT-PCR(Real -time reverse transcriptase-polymerase chain reaction test) which is the primary testing method that has been clinically used across the world and is the most accepted to determine whether a person is currently infected or not. In addition to this, rapid tests, which is also a sub-type of viral tests have been used to detect the disease in patients. Although not as accurate as the PCR test, these rapid tests can give results within a maximum time of 20 minutes, compared to 5-6 hours it takes with PCR.

With the high infection rate of the disease and the high number of patients and deaths, there was need of increased capacity for testing methods to detect and diagnose the disease. Sometimes, when running under full capacity, although the processing time is 5-6 hours for a PCR test, there were delays up to 2-3 days for results. This was because the available capacity for testing machines was not enough to keep up with the large input of specimens from collection centres. This led to further loss of lives that could've been otherwise saved if the results were available quickly and efficiently. Also, both above-mentioned testing methods require the supply of a test kit per patient and since there is a cost involved per each test. When mass testing, this became a problem especially for the nations which has low purchasing power like Sri Lanka. These countries had difficulties of baring the costs of the testing kits and had to compete with other countries to secure supply because the test kit production was lagging the demand. Ultimately, these costs had to be passed on to the patients and if multiple tests had to be done, which is common for an infected patient, the cost can add up. Also, all these testing methods could only detect if patient is positive with the Covid-19 virus. These cannot detect if the patient is in the Covid-19 pneumonia condition at the time of the detection of the disease.

Radiologic methods, such as Chest X-rays and CT scans were being used to diagnose various diseases for a long period of time. Therefore, it is beneficial to try to find ways to combine the knowledge on both artificial intelligence and radiologic methods to find efficient, cost-effective, and less time-consuming methods to detect Covid-19 and Covid-19 related pneumonia conditions in suspected patients.

The aim of this research is to Build a Multitask Deep Convolutional Neural Network (MTDNN) based solution to simultaneously detect Covid-19 and Covid-19 related pneumonia in a single Chest X-ray image to enable quick, cost effective and more insightful diagnosis of Covid-19 patients. This will enable the patients to avoid delays in testing and reduce the cost per test. Further with the addition of simultaneous detection of Covid-19 pneumonia, more medical attention can be given from the beginning to the patients who requires.

This paper is structured as follows, Section 1 gives an introduction on to the research problem, section 2 gives a literature review on the related works. The following sections contain the methodology, current results, conclusion, and future works.

## 2. Literature Review

Research to find ways to leverage artificial intelligence methods in helping medical systems and personnel began from the early days of the Covid-19 pandemic. Because the detection and diagnosis of Covid-19 at the earliest stages of the disease, at the lowest cost possible was essential to limit the spread of the virus, these research works were deemed to be crucial. Accordingly, computing and medical researchers started using Deep learning methods to analyse radiology images to find accurate methods to diagnose Covid-19.(Ghaderzadeh and Asadi, 2021) There are two main radiology modalities that this research are based on. Around 57% of the research are based on CXR (Chest X-ray) imaging and 40% have been based on CT (Computerized Tomography) imaging.(Ng *et al.*, 2020) Aim of most of these studies has been to only detect and diagnose SARS-CoV-2. Researchers have also been able to differentiate between community acquired pneumonia cases from Covid-19 viral pneumonia using CT images of chest (Li *et al.*, 2020). Due to the limited data availability, transfer learning techniques have been used in most cases.

There are multiple proven model architectures that have been used widely in research work on the detection of Covid-19 in radiology images.(Ghaderzadeh and Asadi, 2021) MobileNetV1 and MobileNetV2 are image classification model architectures based on Convolutional Neural Networks (CNN) introduced by Google. In MobileNetV1 Depth Wise Separable Convolution was introduced and with MobileNetV2 removed non linearities in narrow layers and inverted residual structure of the model. These two models have shown highly capable in feature extraction and have achieved state of the art performances in object detection and semantic segmentation. Mohamed Abd Elaziz (Elaziz *et al.*, 2020) has used original MobileNet (MobileNetV1) for detection if Covid-19 and in research done in China, Jingwen Li (Li *et al.*, 2021) used MobileNetV2 on CT images to detect Covid-19 cases.

VGG16 is a CNN architecture introduced in 2014 which is considered as one of the best modern vision models. VGG16 is deemed to be unique because it had its focus on having convolution layers of 3x3 filter with a stride 1 and always used same padding and maxpool layer of stride 2 with a 2x2 filter instead of having many hyper-parameters. This arrangement is consistently followed throughout the whole architecture of VGG16. It has 16 layers which have weights, and the architecture is pretty large due to its approximately 138 million parameters. In a research done based in Italy, Luca Brunese (Brunese *et al.*, 2020) used a slightly modified VGG16 architecture CNN model to achieve 97% accuracy on detection of Covid-19 in radiography images.

Resnet50 is also a CNN based architecture based on Residual Networks. Resnet50 has a total of 50 layers with 48 convolutional layers and 1 MaxPool and 1 average pool layers while the original Resnet (Resnet34) had 34 layers. This architecture is also proven to be one of the best in vision models. The use of 3-layer bottleneck blocks improved accuracy and made the training time lesser in the newer Resnet50 architecture. In a research done in China based on community acquired CT images (Li *et al.*, 2020), Resnet50 model was used to detect Covid-19 to achieve high accuracy.

Inception is a family of Network architectures which starts from and consists of newer iterations of the original Inception CNN architecture. It consists of iterations from Inception v1to Inception v4. Each version is an iterative improvement over the previous version which provides improvements in both speed and accuracy.(Mei *et al.*, 2020) Based on the research, for medical applications that includes feature extractions from vision sources, Inception v3 has been widely used due to its suitability.

Other than the CNN architectures mentioned above, Xception, DenseNet and GoogleNet architecture models have also been used in similar kinds of applications.(Wang *et al.*, 2020) In addition to these architectures, Linda Wang (Wang and Wong, 2020) has proposed a tailored CNN architecture for Covid-10 detection. named Covid-Net, which has been able to achieve comparable results to VGG-16 in the detection of Covid-19. After reviewing existing systems and similar medical applications that utilize image classifications, it can be noted that CNN approach would be the most suitable for an application like the proposed system. This is mainly because of the superiority in accuracy and efficiency of CNNs in classification tasks.

| Researc-h | Type | Radiogr-aphy mode | Architecture | Accuracy | Multitask learning Applied |
|---|---|---|---|---|---|
| Mohamed Abd Elaziz | Covid-19 detection | CXR | MobileNet | 94.09% | × |
| Jingwen Li | Covid-19 detection | CXR | MobileNetV2 | 92.78% | × |
| Lin Li | Covid-19 pneumonia detection | CT | Resnet-50 | 90% | × |
| Luca Brunese | Covid-19 detection | CXR | VGG-16 | 92% | × |
| Xueyan Mei | Covid-19 detection | CT | InceptionV2 | 70% | × |
| Shuo Wang | Covid-19 detection | CT | DenseNet121 | 80.3% | × |
| Jenita Manokaran | Pneumonia Differentiation | CXR | DenseNet201 | 94% | × |

Table 1: Summary of References

## 3. Methodology

### *A. Solution*

As a solution to the problems mentioned in the introduction, a multitask CNN based system is assumed to simultaneously detect Covid-19 and Covid-19 related pneumonia in a single chest X-ray image of a possible patient for quick, efficient, and cost-effective detection of Covid-19. The multitask CNN model is trained using two datasets, one for the training of the Covid-19 detection task and another for the classification of Covid-19 pneumonia, Normal Pneumonia and No Pneumonia patients. There is only a single type of input to the system. Those are chest X-ray images of a person that is suspected to have contracted with Covid-19. This input image can belong to either of positive or negative classes in the Covid-19 detection case. For the pneumonia detection case, this image can belong to one of Covid-19 pneumonia or Normal Pneumonia or No pneumonia classes. The input images will be used to train the multitask convolutional neural network. There are two classes of outputs from the system. One will be the results for the detection of Covid-19 positive/negative in the given chest X-ray image. Simultaneously, as another output, results for the detection of Covid-19 pneumonia/Normal Pneumonia and No pneumonia will be shown to the users.

### *B. Datasets*

First, datasets consisting of Chest X-rays of the patients were acquired from publicly available online sources.(*COVIDx CXR-2*) The acquired datasets had all the images together and the training labels as a separate text files. This was problematic due to dealing with training labels in a separate file.

Therefore, for the ease of use, text files were first converted into CSV files. These files were then used in a python script to classify the images into separate folders according to their training classes. Figures 2 and 3 gives a summary of the datasets used in this research.

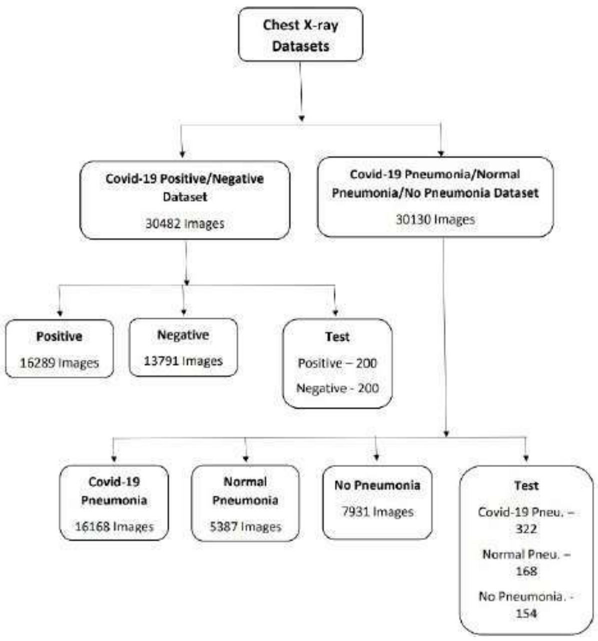


Figure 1: Summary of the datasets


Figure 2: Chest X-rays from the 3 classes of Pneumonia Detection dataset

The input images are pre-processed before being given to the CNN models. Every image is rescaled to 1/255 of the original size, sheared by 0.2 points, zoomed by 0.2 and horizontally flipped. To keep all the images in the same colour, the images are turned to the colour mode grayscale. The same pre-processing procedures are used for both the initial CNN models.

### C. Convolutional Neural Network Models

Then custom CNN models were built for each of the two training tasks to identify and test a suitable model to be later transformed into the multitask learning model. Both models need to share the architecture for the most part and then have the task specific layers at the final stages. The summary of the Custom CNN model used for the positive/negative detection of the Covid-19 is given in the figure 4. The model is built using Keras libraries on top of a TensorFlow backend. The libraries Scikit learn, NumPy and Pandas were also used for the solution on an anaconda virtual environment.

The model consists of Conv2d, MaxPooling2d, flatten and dense layers for the final layers. In this model, output layer has a single node, because the classification is binary. The output layer uses a ‘sigmoid’ activation function. ‘Adam’ optimizer and the loss function of ‘binary cross entropy is used to compile the model.

```
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d (Conv2D)             (None, 498, 498, 32)      320

 max_pooling2d (MaxPooling2D  (None, 249, 249, 32)     0
 )

 conv2d_1 (Conv2D)           (None, 247, 247, 32)      9248

 max_pooling2d_1 (MaxPooling  (None, 123, 123, 32)     0
 2D)

 conv2d_2 (Conv2D)           (None, 121, 121, 32)      9248

 max_pooling2d_2 (MaxPooling  (None, 60, 60, 32)       0
 2D)

 conv2d_3 (Conv2D)           (None, 58, 58, 64)        18496

 max_pooling2d_3 (MaxPooling  (None, 29, 29, 64)       0
 2D)

 conv2d_4 (Conv2D)           (None, 27, 27, 64)        36928

 max_pooling2d_4 (MaxPooling  (None, 13, 13, 64)       0
 2D)

 flatten (Flatten)           (None, 10816)             0

 dense (Dense)               (None, 128)               1384576

 dense_1 (Dense)             (None, 64)                8256

 dense_2 (Dense)             (None, 1)                 65

=================================================================
Total params: 1,467,137
Trainable params: 1,467,137
Non-trainable params: 0
_________________________________________________________________
None
```

Figure 3: Layers of the Covid-19 positive/negative model

The second CNN model features the same architecture for the most of it but differs in the latter layers. This is to keep a uniform architecture between the two models as much as possible. The output layer of the Covid-19 pneumonia, Normal Pneumonia and No Pneumonia classification model has 3 output nodes in the final layer. This is to accommodate the 3-class prediction. The output layer uses a 'softmax' activation function and a loss function of ‘Categorical Crossentropy’ is used int this model.

Then after testing the performance of the two models, the Multitask CNN model is to be built. This is designed to use the same layer scheme as the previous CNN models built for testing. It is designed to have two branches in the last layers to accommodate the binary and 3-class

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prediction tasks. The model is to be trained simultaneously for the two tasks using the two datasets.

## 4. Results and Discussion

For the current results, the first custom Covid-19 Positive Negative Detection CNN model was trained using the dataset. It was able to give training accuracies of 97.7% for 20 epochs 97.85% for 25 epochs. After training for 25 epochs, it was able to give a testing accuracy of 94% for unseen data in the test dataset. For both instances, the batch size was set to 32. Figures 4 and 5 given below show the training accuracy, training loss plots for 25 epochs.

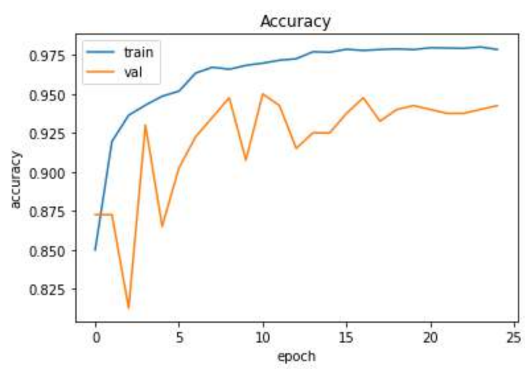



Figure 4: Training Accuracy Plot for the Covid-19 Detection

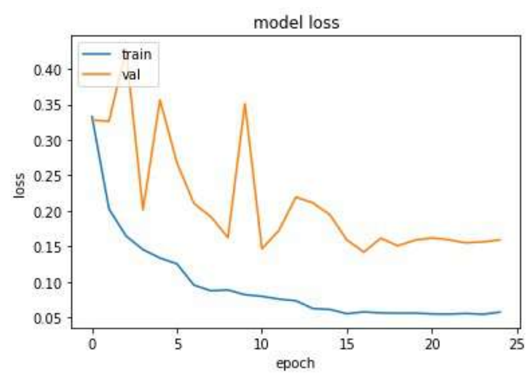



Figure 5: Training loss Plot for the Covid-19 Detection

The following figure 6 and 7 shows the classification report and confusion matrix for the Covid-19 Positive/Negative detection CNN model when trained for 25 epochs and tested with unseen data.

| | precision | recall | f1-score | support |
|---|---|---|---|---|
| Negative | 0.92 | 0.97 | 0.94 | 200 |
| Positive | 0.97 | 0.92 | 0.94 | 200 |
| accuracy | | | 0.94 | 400 |
| macro avg | 0.94 | 0.94 | 0.94 | 400 |
| weighted avg | 0.94 | 0.94 | 0.94 | 400 |

Figure 6: Classification Report for the Covid-19 Detection

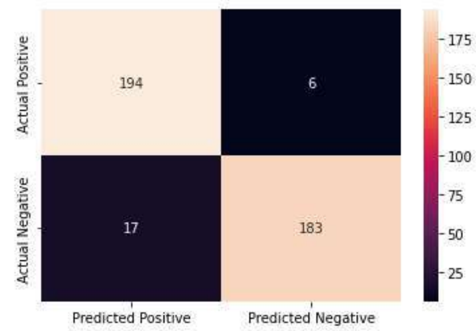



Figure 7: Confusion Matrix for the Covid-19 Detection

Then the same model was modified to accommodate the 3-class prediction of Covid-19 Pneumonia/ Normal Pneumonia and No Pneumonia Detection. The modification which was first made gave an accuracy of 91.9% for 20 epochs and 92.2% for 25 epochs and the batch size was set to 32. But the model did not do well with unseen data, with a low 27% accuracy on testing data. Therefore, further modifications were made on the model and again trained for 32 epochs. At that time the model was able to give a training accuracy of 91.9% and the testing accuracy was 90% on unseen data. The following figures provide Training accuracy, loss, the classification report and the confusion matrix when the model is trained for 32 epochs and tested.

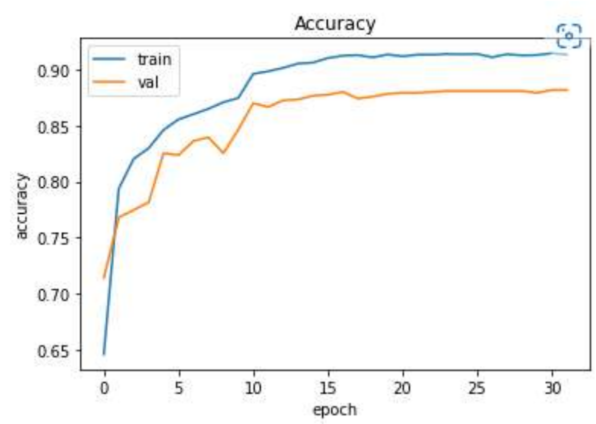
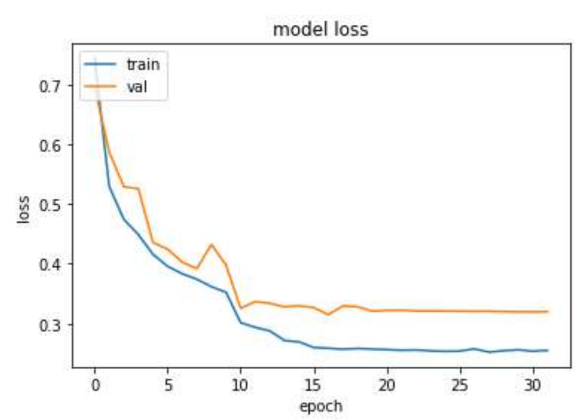



Figure 8: Training Accuracy Plot for the Pneumonia Detection



100

Figure 9: Training loss Plot for the Pneumonia Detection

| | precision | recall | f1-score | support |
|---|---|---|---|---|
| COVID-19 | 0.96 | 0.94 | 0.95 | 322 |
| normal | 0.85 | 0.88 | 0.86 | 154 |
| pneumonia | 0.83 | 0.83 | 0.83 | 168 |
| accuracy | | | 0.90 | 644 |
| macro avg | 0.88 | 0.88 | 0.88 | 644 |
| weighted avg | 0.90 | 0.90 | 0.90 | 644 |

Figure 10: Classification Report for the Pneumonia Detection

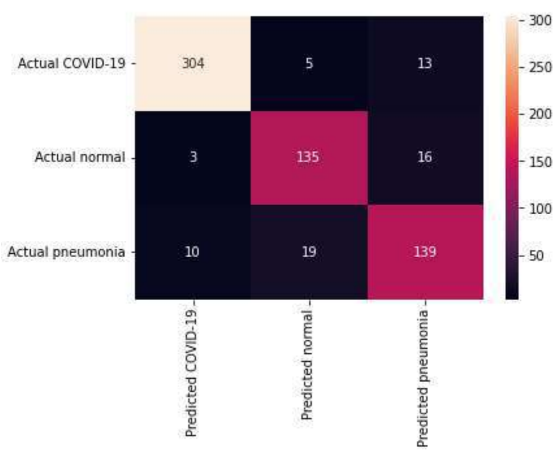



Figure 11: Confusion Matrix for the Pneumonia Detection

## 5. Conclusion And Future Works

The testing results for both the training tasks are above 91%. Therefore, the current testing for the two separate models is within acceptable levels. Therefore, it can be deemed suitable to use this architecture and design of the model to be used when building the final multitask learning model. Although the results that will come out of the multitask CNN model can slightly vary from the above results, these results provide the confirmation to proceed in the direction the research has already tested.

As future works, the final multitask model needs to be built and tested in the architecture that the current results confirmed to be suitable. Then it might be needed to adjust the model to get the highest accuracy possible. Once the multitask model is built and tested, then the model is expected to be connected to a web application to provide users, who can be identified as doctors and support medical staffs to have intuitive and easy access to the model to check the results in real-world applications. With further improvements in dataset size and quality of the images, the accuracy of the model could also be increased in the future.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