Diagnosis of COVID-19 using artificial intelligence based model

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Abstract. Scientists have shown that early diagnosis of COVID-19 and self-isolation can help curb the spread of the virus. Hence, there is a need to develop methods for early and fast diagnosis of the disease. This research focuses on the development and use of an AI based model that would help medical professionals in easy and fast detection of COVID-19 that can be found in X-ray images, CT scan images, and patient symptoms. The model would then be deployed to the web for easy accessibility. To increase the confident level of decision made by the model, different data augmentation technique was deployed to create variance to the dataset and thereby increasing the accuracy and validation of the model. This project proposes the use of Convolutional Neural Network for classification purpose of both the X-ray image of the Lung of a positive and negative pneumonia patient. Further processes were done with CT scan images of both positive and negative COVID-19 patients. This eliminated biasness of the model. Lastly, symptoms of the disease were added to the model as conditional statement convolutional neural network model. The model was able to reach an overall accuracy of 95% for Pneumonia X-ray image and 89.65% for CT scan image of unseen data (test/evaluation). Artificial intelligence based model is therefore, encouraged for better, easier and more accurate diagnosis of COVID-19. Also, the accuracy of the model can further be improved by certain feature engineering technique and adding more complex deep neural network technique known as ensembles.

1. Introduction
After the outbreak of COVID-19 in December, 2019 in Wuhan, China, the virus has spread widely to neighboring countries such as Japan and South Korea and has taken a hit in some European countries such as Italy and Spain and finally set its shores in the Middle East and the United State with over 1million people all over the world being affected by the virus. Thousands of death has been recorded worldwide. More are expected to be affected according to statistics by the World Health Organization (WHO).

Corona virus is zoonotic, which implies the virus can be transmitted from animals to man [1]. The virus shows similarity with the SARS-CoV and MERS-CoV which were transmitted from bats and camels. The virus however is accompanied with different symptoms such as fever, dry cough, fatigue, sputum, shortness of breath, loss of smell, muscle aches, sore throat, chills and nasal congestion. Conjunctivitis (Pink eyes) has also been discovered to be associated with the virus in severe cases.
Recent studies show that the virus cannot be transmitted through vaginal or anal intercourse but are passed on through droplets from the nose and mouth of an infected person, most especially through kissing, coughing and sneezing. Different clinical trials such as plasma therapy are used as a means to manage the virus. Currently, WHO has accepted hydroxychloroquine for human trials in the treatment of COVID-19.

Pneumonia being one of the obvious symptoms of COVID-19 is known to be a fatal infection and inflammation of the respiratory tract which are usually caused by inhaled bacteria and virus both having the same properties of Streptococcus pneumoniae. The illness is usually associated with high fever, sharp chest pain, rapid breathing and cough with thick phlegm. Understanding the clinical implications on children, infant and older age groups are important in containing the spread of the virus. Radiography analysis from X-ray Scan and CT scan of the lung has played a vital role in early diagnosis and treatment of the disease. Decisions based on human intelligence are prone to errors [2].

Researchers all over the world have found means of implementing artificial intelligence for medical diagnosis and faster decision making, which in turn helps support the already made prediction by medical professionals [3].

Due to the high level of contingency of the virus, available data are hard to get resulting to other means of prediction. Getting fluid samples from infected persons is not advisable as the virus has shown the ability to survive on surfaces for a given period of time. This is why the molecular test method was accepted by scientists all over the world and is being conducted with great care [4].

Most research studies have shown to be bias as most models are based on only X-ray data of Pneumonia patient, leaving other factors out. It should be noted that Pneumonia can be caused by different factors such as flu (Influenza virus) which means diagnosis on only X-ray data is not totally acceptable.

This paper therefore looks into the use of X-ray images, CT scan images as well as other symptoms of COVID-19 to develop an AI model that will enable fast, easy and early diagnosis of the disease.

2. Methodology

2.1. Data augmentation
Data Augmentation (DA) is referred to as the process of artificially increasing the size of training dataset by creating a modified version of the image with little amount of variances. Data augmentation is usually carried out to improve the training accuracy of the dataset in order for the model to generalize better from different variance added to the image [5]. The variance added to the image are width shift range, shear range, height shift range, zoom range, horizontal and vertical flip. All these techniques are usually carried out on the image dataset to create more variables for the training dataset [6].

| Operation          | Values |
|--------------------|--------|
| Width shift range  | 0.2    |
| Height shift range | 0.2    |
| Shear range        | 0.2    |
| Zoom range         | 0.2    |
| Horizontal flip    | True   |

2.2. Data acquisition
This is the first step in the diagnostic system. The data collected are of 5 types namely: X-ray image of Lung, CT-scan of the lung, body temperature (fever), tiredness (vocal question) and dry cough like
questions. The image data of X-ray is about 5000 plus which was obtained from Kaggle.com. The X-ray image is of 3 classes namely: healthy lung image, pneumonia bacteria image and pneumonia virus image with each split equally. Also, Transverse CT scan image was obtained from github.com, 373 positive cases and 373 negative cases of the virus with total of 746 images.

2.3. Image pre-processing
Image processing is an image operation aimed at enhancing image quality, extracting specific features that are useful in further study of image. This process was done for both the X-ray and CT scan image.

The X-ray and CT scan image collected were in Grayscale form, which in turn helps the model read the image without issue. The RGB image is 3 times the size of a grayscale image which implies that the RGB has more intensity than that of Grayscale.

Histogram equalization is the technique used to adjust the image intensity in order to enhance the contrast. It gives the histogram representation of the image.

2.4. Convolutional neural network
The convolutional neural network works basically like the human optic eyes, it is a class of deep learning that is used to analyse visual image. The convolutional layer in neural network coverts images to pixels number for easy reading. The convolutional layer’s output volume is obtained by stacking activation maps of all filters along the deep axis. Although each filter’s width and height are less than the activation map’s input, only a limited local area of the input volume is related to each neuron [6].

2.5. Model building
Building the model requires lots of understanding of how the optical works in understanding pattern to determine which kind of image it sees. Basically there are 3 layers for Building a convolutional neural network layer. Namely; Convolution, Max-pooling and fully connected layers. But the model requires lot of experience, with the formula $y = Xw + b$.

2.6. Pre-trained model
The fundamental concept for pre-trained model is to use an already existing model and adjust the model to fix a specific task like fine-tuning. Tensor flow Keras API has been made with different documentation for both computer vision and natural language programming. Some of the pre-trained models for computer vision are XCEPTION, VGG16, VGG19, RESNET, INCEPTIONV3 and MOBILENET. MOBILENET pre-trained learning was used for this research due to the fact it is lighter to use and can easily be interfaced with other application such as mobile android app and so on.
The mobile Net is a convolutional neural network developed by researchers in the world that is trained on more than million images from the image net database with over 1000 output or label assigned to it. The MobileNet is made up of 28 layers, which are the hidden layer that contains the following layouts: fully connected input, max pooling, convolutional and so on.

Table 2. Mobilenet architecture

| Type / Stride | Filter Shape    | Input Size      |
|---------------|-----------------|-----------------|
| Conv / s2     | 3 x 3 x 3 x 32  | 224 x 224 x 3   |
| Conv dw / s1  | 3 x 3 x 32 dw   | 112 x 112 x 32  |
| Conv / s1     | 1 x 1 x 32 x 64 | 112 x 112 x 32  |
| Conv dw / s2  | 3 x 3 x 64 dw   | 112 x 112 x 64  |
| Conv / s1     | 1 x 1 x 64 x 128| 56 x 56 x 64    |
| Conv dw / s1  | 3 x 3 x 128 dw  | 56 x 56 x 128   |
| Conv / s1     | 1 x 1 x 128 x 258| 56 x 56 x 128   |
| Conv dw / s2  | 3 x 3 x 128 dw  | 56 x 56 x 128   |
| Conv / s1     | 1 x 1 x 128 x 256| 28 x 28 x 128   |
| Conv dw / s1  | 3 x 3 x 256 dw  | 28 x 28 x 256   |
| Conv / s1     | 1 x 1 x 256 x 256| 28 x 28 x 256   |
| Conv dw / s2  | 3 x 3 x 256 dw  | 28 x 28 x 256   |
| Conv / s1     | 1 x 1 x 256 x 512| 14 x 14 x 256   |
| 5x Conv dw / s1| 3 x 3 x 512 dw | 14 x 14 x 512   |
| Conv / s1     | 1 x 1 x 512 x 512| 14 x 14 x 512   |
| Conv dw / s2  | 3 x 3 x 512 dw  | 14 x 14 x 512   |
| Conv / s1     | 1 x 1 x 512 x 1024| 7 x 7 x 512    |
| Conv dw / s2  | 3 x 3 x 1024 dw | 7 x 7 x 1024    |
| Conv / s1     | 1 x 1 x 1024 x 1024| 7 x 7 x 1024   |
| Avg Pool / s1 | Pool 7 x 7      | 7 x 7 x 1024    |
| FC / s1       | 1024 x 1000     | 1 x 1 x 1024    |
| Softmax / s1  | Classifier      | 1 x 1 x 1000    |

2.7. Training and validating dataset

Training of X-ray Pneumonia dataset was split into training, validation and test. The Training dataset had 70% of the 5000 images and the remaining 30% was shared equally among the Validation and Test set. A total of 100 epochs was done on the training dataset. The same process was repeated with the CT scan COVID-19 dataset of 746 images. The data were split to validation set to prevent over fitting of the model, in which the model becomes bias, due to lack of variance. Over fitting occurs when the model over train without enough data and parameter to checkmate the training accuracy. Training of data are done in the neural network model, which allows the model understand the image pattern better. With some different hyper parameters such as learning rate, epoch, batch size and cross validation.
3.0. Results
The results obtained after 100 epoch of training are as follows:
The performance of the model was evaluated based on the prediction accuracy, sensitivity of the test dataset i.e. (true positive rate), and specificity (True negative rate) to prevent over fitting of the model. Confusion matrix was used to evaluating the performance of the model on test data. The matrix contains four sections namely: the True positive (TP), True negative (TN), False positive (FP) and False negative (FN).

Other values gotten are Precision/Exactness of classifier and F-measure- Weighted average of precision and recall.
Specificity, Sensitivity and overall accuracy can be gotten from the formula below:
Recall or Sensitivity (True Positive rate) = \( \frac{TP}{TP+FN} \)
Specificity (True negative rate) = \( \frac{TN}{TN+FP} \)
False Positive Rate (FPR) = 1 - Specificity = \( \frac{FP}{TN+FP} \)
Overall accuracy = \( \frac{TP+TN}{TP+TN+FP+FN} \)

3.1. Data visualization of model
The visualization of the model was carried out in two forms: the Accuracy and the Loss.
From the above figure it can be seen that the accuracy of the training and validation set after 100 epoch increases as data is trained.

The loss of the model decreases as training is done.
3.2. Confusion matrix
This topic of statistical classification is in this area of machine learning. It is often called an error matrix by showing various layouts that allow the output of an algorithm to be visualized, typical in most managed learning.
The confusion matrix of the Pneumonia data is in 4 different layouts which indicate different situation. 917 images was set aside to be used as testing by the model with 247 TP (True Positive), 5 FP (False Positive), 635 TN (True Negative) and 30 FN(False Negative). This indicates the model performance fair.

The same process was carried out on the CT scan image of COVID-19 data and the result was gotten below. The results are as followed: TP = 12, TN=3, FP=14 AND FN=0

The confusion matrix without normalization:

\[
\begin{bmatrix}
12 & 3 \\
0 & 14
\end{bmatrix}
\]
Table 3. Evaluation test of x-ray data

| Output | Precision | Recall | F1-score | Support |
|--------|-----------|--------|----------|---------|
| 0      | 0.89      | 0.98   | 0.93     | 252     |
| 1      | 0.99      | 0.95   | 0.97     | 665     |
| Accuracy |          |        | 0.96     | 917     |
| Macro average | 0.94      | 0.97   | 0.95     | 917     |
| Weighted average | 0.96      | 0.96   | 0.96     | 917     |
| Overall accuracy | 0.9618320610687023 |

From the result above the overall test accuracy gotten for X-ray image is 96.18%.

Table 4. Evaluation of CT-scan COVID-19 Image

| Output | Precision | Recall | F1-score | Support |
|--------|-----------|--------|----------|---------|
| 0      | 1.00      | 0.80   | 0.89     | 15      |
| 1      | 0.82      | 1.00   | 0.90     | 14      |
| Accuracy |          |        | 0.90     | 29      |
| Macro average | 0.91      | 0.90   | 0.90     | 29      |
| Weighted average | 0.91      | 0.90   | 0.90     | 29      |
| Overall accuracy | 0.896551724137931 |

From the result above the overall test accuracy gotten for CT-scan image is 89.65%.

3.3. Model performance

3.3.1. AUC and ROC. The performance of the classification problem, uses the AUC (Area Under the Curve) and ROC (Receiver Operation Characteristic) curve. It is important in evaluating metrics for checking model performance.

If the multi-class grouping issue requires to be tested or visualized, then we use the AUC curve and the ROC (Receiver Operating Characteristics) curve.

![Figure 9. AUC and ROC curve of x-ray pneumonia data](image-url)
The AUC curve is 0.950, it means there is 95.0% chance that model will be able to distinguish between NORMAL class and PNEUMONIA class.

![ROC curve](image)

**Figure 10. AUC & ROC curve of CT scan image**

The AUC curve is 0.900, it means there is 90.0% chance that the model will be able to distinguish between non-COVID-19 class and COVID-19 class.

3.4. Prediction

The result shows prediction and accuracy for a test sample of healthy X-ray and CT-scan images.

```python
img = cv2.imread('ttt/NORMAL2-IM-1346-0001.jpeg')
img = cv2.resize(img, (224, 224))
img = np.reshape(img, [1, 224, 224, 3])

classes = new_model.predict(img)
print(type(img), img.shape)
print(classes*100, '%')
print(converter(np.argmax(classes)))

<class 'numpy.ndarray'> (1, 224, 224, 3)
[[63.37964 36.620365]] %
NORMAL
```

**Figure 11. Performance of model**
Figure 12. Performance of model

4.0. Discussion

Early diagnoses of COVID-19 have shown to increase the chances of survival of infected persons. AI based model have also shown to help in faster decision making. The model was created to correctly diagnose COVID-19 based on image from frontal view of chest X-ray of pneumonia patient and CT scan of both positive and negative COVID-19 patient.

The algorithm used in developing the model starts with resizing the image to a standard size of 150x150 (Height by Width). Data Augmentation was performed on the image to increase the number of image and increase variance of image. With this, it helps to prevent over-fitting and overall data generalization. Image pre-processing was performed on the image to enhance certain features of the chest image, after which the processed image was passed to the Convolution Neural Network, which trains and help in identification of image. Further features were added to the model to reduce biasness of the model such as; fever, cough and tiredness.

One of the few limitation faced was the computing power of the system used for this project an intel®Core™ i3-3110M CPU @ 2.40GHz 8.00GB RAM. So, it is highly advisable to employ cloud computing platform such as colab for heavy computing task or a GPU enabled system. The deep learning approach is meant to help medical professionals prevent error when making final decision. It can be said to be a two way confirmation system by cross checking the neural network model and that of the medical professional. With this, it can be inferred that the neural network is meant to help medical professionals make accurate and fast decision.

5.0. Conclusion

The model passed the accuracy and validation tests with an overall test accuracy of 96.18% for X-ray image and 89.65% for CT scan images. The AUC curve shows that there is a 95.0% probability that the model will be able to distinguish between a normal class and pneumonia class. Also, there is a 90.0% probability that the model will be able to distinguish between NON-COVID-19 class from COVID-19 class. The model performed excellently well in predicting the diagnoses of the disease. AI based model is therefore, encouraged for better, easier and more accurate diagnosis of COVID-19. Also, the accuracy of the model can further be improved by certain feature engineering technique and adding more complex deep neural network technique known as ensemble.
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