Detection of COVID-19 from CT scan images using deep neural networks

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Introduction

Detection of any illness or disease is the main challenge for diagnosis of the patient. Moreover, it is helpful if a patient is diagnosed as quickly as possible for his/her treatment to yield the best results possible, especially for COVID-19. Image classification using neural networks is the best shot at early identification and detection of the disease.

Motivation

Detecting COVID using RT-PCR (Reverse Transcription Polymerase Chain Reaction) test is a time taking process. So, methods such as detection from X-Ray and CT scans were adopted and results from these were promisingly accurate. This is the reason that many organizations have initiated their work on developing machine learning models to detect COVID from sources such as X-Ray and CT scans.

SCOPE of the Project

A deep convolution neural network (DCNN) is to be proposed which detects COVID-19 in CT scan images of the patients. The model is made to include four pre-trained models, namely Inception, ResNet50, Xception, NASNetLarge to extract features from the CT scan images.

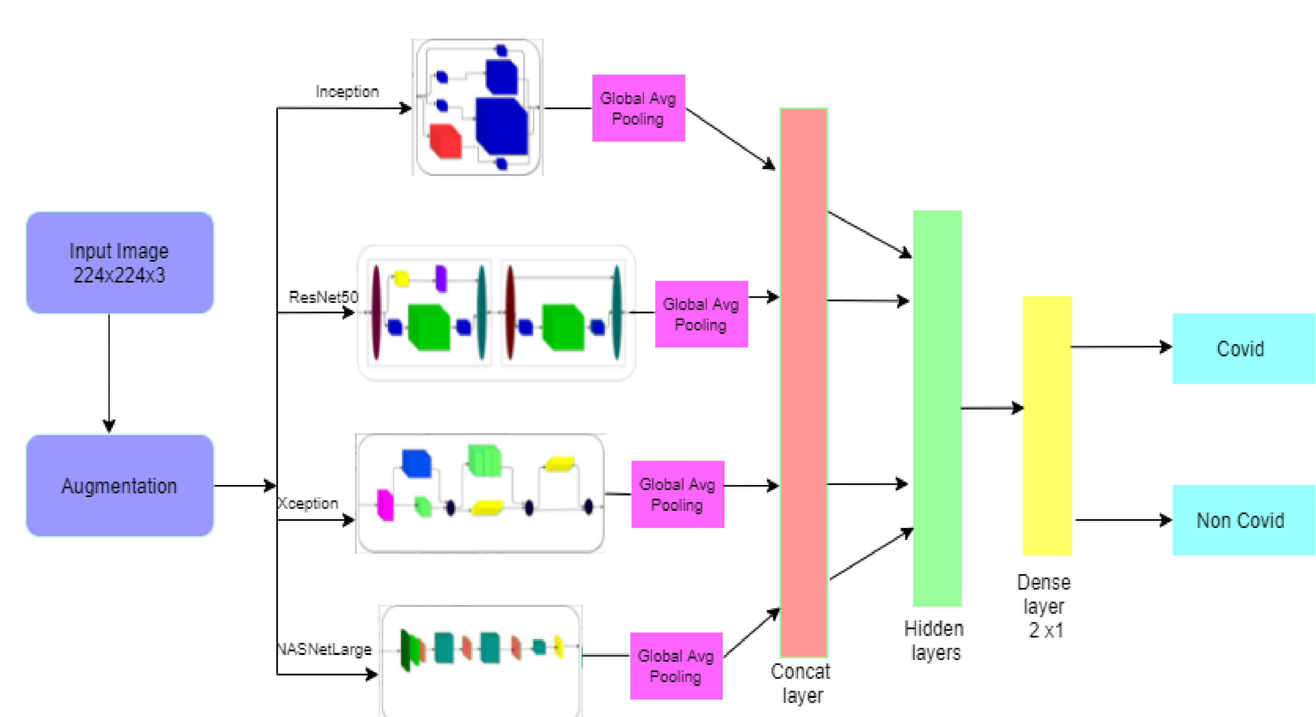
Methodology

The proposed model is a deep convolution neural network (DCNN) which is used to detect COVID-19 in CT scan images of the patients. The pretrained models used are InceptionV3, Xception, ResNet50, and NASNetLarge. These models are used as feature extractors which make use of the weights pre-trained on the ImageNet dataset. Then, these base models are fine-tuned to accommodate our dataset.

A Global average pooling 2d layers then replace the classification part of each model. The models are then fine-tuned on COVID CT scan images for better feature extraction by setting the “trainable” parameter to “false”. Training is done by providing the image data of shape 500x500x3 as input to the models. Output of these models are then passed to the global average pooling 2D layers. The outputs of these global average pooling layers are then concatenated.

The output of the concatenation layer is passed to batch normalization layer, output of which is passed to a dense layer of 64 units with swish activation. Then a dropout layer with a dropout rate of 0.2 and a batch normalization layer are added. On top of this, a dense layer of 32 units with swish activation and L2 regularization of rate 0.001, and a dropout layer are added. The output of this is passed to the classification layer which is dense layer of 2 units with SoftMax activation. After optimizing the categorical cross entropy with Adam optimizer, the model is evaluated using the metrics categorical accuracy, precision and recall.

Architecture of the proposed model:



Loss Function:

The loss function used for the model is categorical cross-entropy. It is a SoftMax activation in addition with categorical entropy loss. The formula for the Categorical cross-entropy loss function is given in equation:

$$CE = -\sum_{1}^{K} t_i \log(\hat{t}_i)$$

Where, $\hat{t}_i$ is the i^{th} value in the output, and t_i is the corresponding target value.

Softmax:

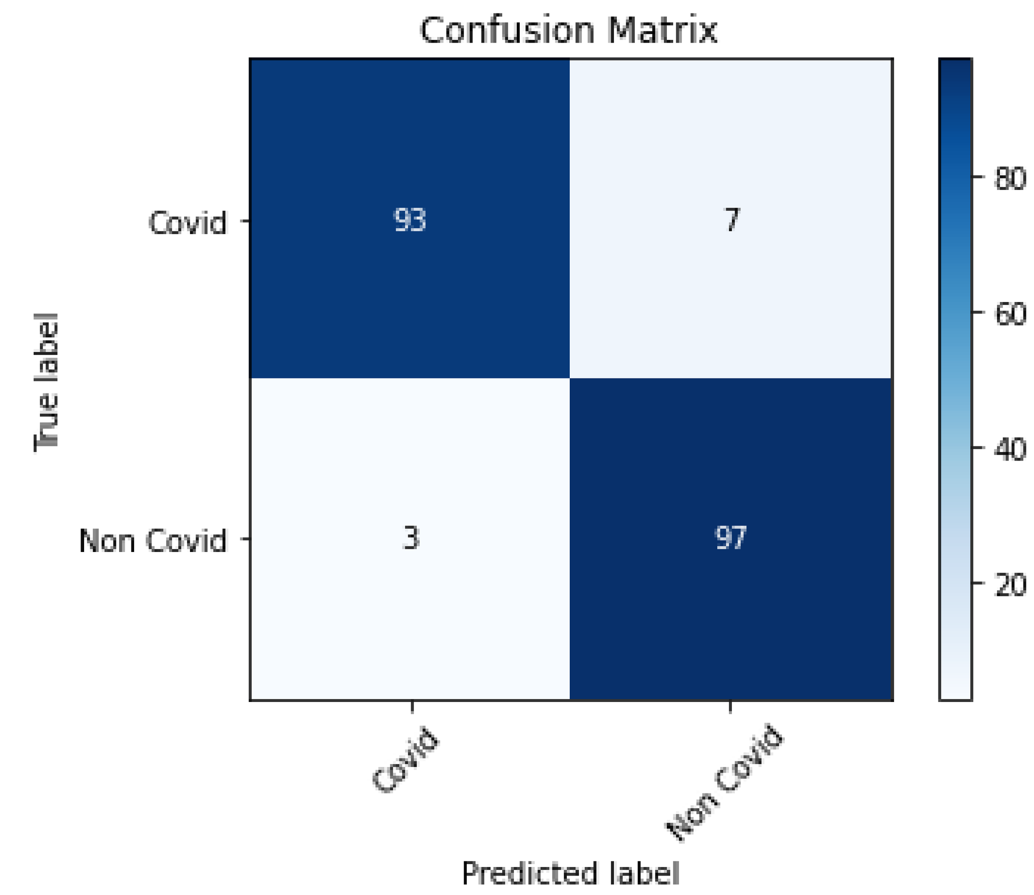
SoftMax function is used as the activation function for classification in the output layer of neural network, which is used in multi-class classification. The formula for the SoftMax function is given in equation:

$$\sigma(x)_i = \frac{e^{x_i}}{\sum_{j=1}^{K} e^{x_j}}$$

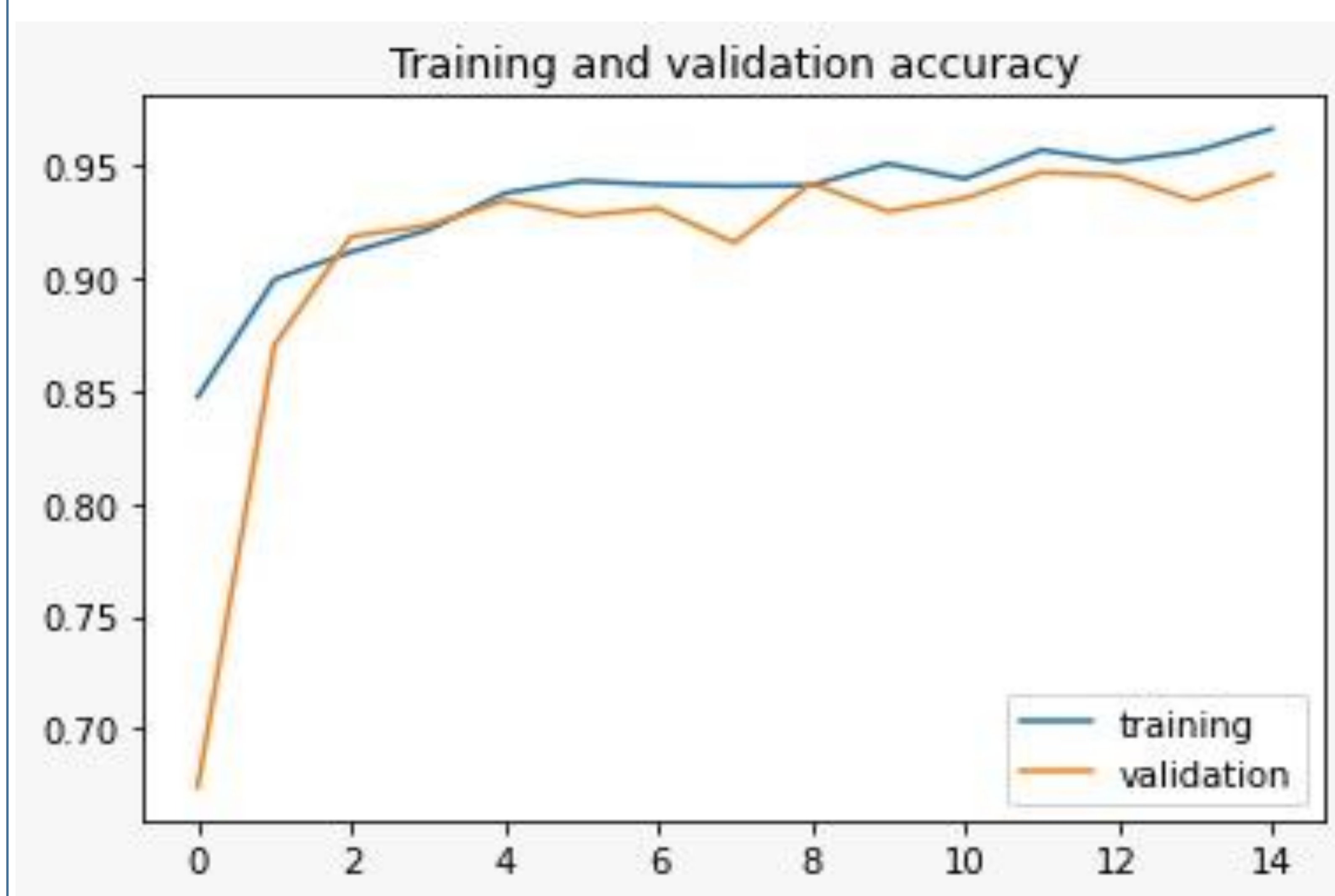
where, σ is SoftMax function, x is input vector, e^{x_i} is standard exponential function for input vector, K is number of classes in multi-class classifier, e^{x_j} is standard exponential function for output vector.

Results

Confusion Matrix for our proposed model



Graph for Accuracy of proposed model



Performance analysis

Performance Metric	Dataset	NASNetLarge	InceptionV3	ResNet50	Xception	Proposed Model
Accuracy	Training Set	90.21	89.47	86.16	91.36	96.63
	Validation Set	89.06	87.04	82.94	89.25	94.6
	Test Set	88.0	89.0	83.0	91.0	95.0
Precision	Training Set	92.39	92.23	89.5	93.41	98.08
	Validation Set	91.49	90.71	86.95	90.86	96.23
	Test Set	91.76	91.53	85.79	92.71	95.93
Recall	Training Set	86.93	85.36	80.48	88.38	93.58
	Validation Set	85.01	81.45	78.65	86.22	92.34
	Test Set	83.5	86.5	81.5	89.0	94.49

Conclusion

This model implements the concept of transfer learning by using 4 retrained models, namely NASNetLarge, Inception, ResNet50, and Xception. This model utilizes a data set containing 1616 COVID images and 1498 Non-COVID images for training, 1046 COVID and 1029 Non-COVID images for validation and 100 images of COVID and Non-COVID each for testing. The training accuracy is observed to be 96.63%, the validation accuracy to be 94.60%, and the testing accuracy to be 95%. The proposed model gave better values for accuracy, precision, and recall over individual base models.

References

[1] Anunay Gupta.,et al. Instacovnet-19: A deep learning classification model for the detection of COVID-19 patients using chest x-ray.

[2] Amine Amyar., et al. Multi-task deep learning based ct imaging analysis for COVID-19 pneumonia: Classification and segmentation.