COVID-19 detection from chest X-Ray images using ensemble of CNN models

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- Declared a pandemic in February 2020, COVID-19 is one of the most contagious disease known till date.[1]
- The World Health Organization or WHO has declared it a pandemic in 11th March 2020. Today we have more than 9 million cases and 110,135 people have succumbed to the deadly virus world wide.
- The gold standard screening approach based on Reverse Transcription Polymerase Chain Reaction (RT-PCR) shows good accuracy but is subject to considerable cost and slow turnover time constraints, rendering it not scalable to the ever-increasing population at risk. [2]
- The end of the pandemic is possible only with mass testing and isolation.

[1] https://www.who.int/

[2] Anne Dinnocenzio , Tom Murphy. No covid-19 testing at home yet but quicker options coming. https://www.nytimes.com/aponline/2020/04/05/health/bc-us-med-virus-outbreak-testing.html, 2020.

Problem Formulation

Scenario

- Development of an Artificial Intelligence based system for detection of COVID-19.
- Given the availability of X-Ray machines in all primary health care centers, we have decided to develop an AI for COVID-19 detection using Chest X-Ray images.

Challenges

- The Chest X-ray dataset available for COVID-19 is too less and thus testing on large dataset is not possible.
- Again training a DCNN from scratch is quite impossible.

Approach

- A re-sampling technique called under-sampling is used here.
- We have used the technique of transfer learning by which a DCNN trained on another dataset can be used for our task.

Motivation and Contribution

Motivation

- Developing an accurate and faster testing mechanism for COVID-19 detection was our primary motivation.
- With the availability of X-Ray machines in all primary health care centers, detection of COVID-19 from chest X-Ray images will surely boost up the testing process, and thus at the end of the day more tests can also be performed.

Contribution

- An ensemble based on pre-trained DCNN structures is proposed.
- The performance of the ensemble model is compared with that of the individual counter parts.

[1] A. Bernheim, X. Mei, M. Huang, Y. Yang, Z. A. Fayad, N. Zhang, K. Diao, B. Lin, X. Zhu, K. Li et al., Chest ct findings in coronavirus disease-19 (covid-19): relationship to duration of infection,? Radiology, p. 200463, 2020.

Chest X-Ray images from our dataset

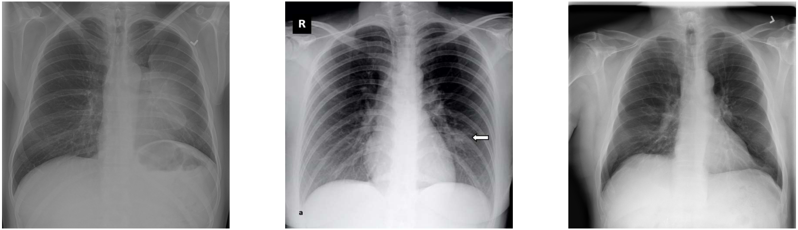
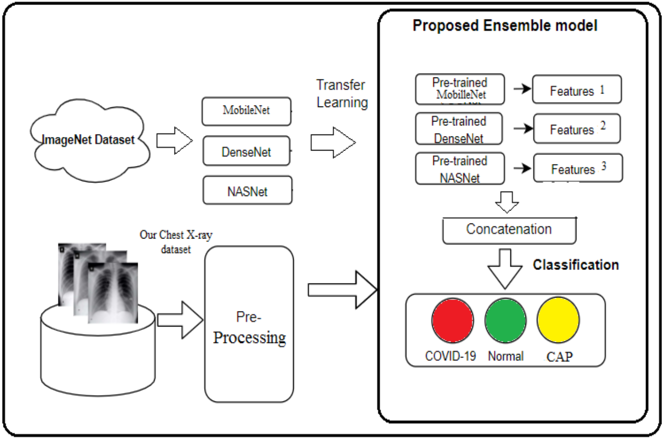


Figure 3: (a)CAP (b)COVID-19 (c) Normal Chest X-Ray images [1]

[1] Cohen, J. P., Morrison, P., Dao, L., Roth, K., Duong, T. Q., & Ghassemi, M. (2020). Covid-19 image data collection: Prospective predictions are the future. arXiv preprint arXiv:2006.11988.

Our Model



Block diagram The diagram shows the working of our proposed model

Table 1: Details of the proposed Architecture

Layer(type)	Output shape	# of parameter
MobileNet(model)	1024	20,025,923
DenseNet(model)	1920	18,321,984
NASNet(model)	1056	4,269,716
concatenate_6 (Concatenate)	5536	0
dropout(Dropout)	5536	0
dense(Dense)	256	1,417,216
dense_1(Dense)	3	768
Total Parameters		65,838,391
Parameters trained		1,417,984

Global Pooling algorithm

- CNNs takes the convolutional layers as a feature extractor to extract the high-level feature maps, and inputs these feature maps into the fully connected layers to stretch a long feature vector, and then is fed into Softmax classifier. The shortcoming is that the fully connected layer has too many parameters, which reduce the speed of training and easily result in overfitting. [1]
- Instead of down sampling patches of the input feature map, global pooling down samples the entire feature map to a single value. This would be the same as setting the pool size to the size of the input feature map. [2]

2

[1] Lin, Min, Qiang Chen, and Shuicheng Yan. "Network in network." arXiv preprint arXiv:1312.4400 (2013).

[2] S. H. Kassani, P. H. Kassani, M. J. Wesolowski, K. A. Schneider, and R. Deters, "Breast cancer diagnosis with transfer learning and global pooling", arXiv preprint arXiv:1909.11839, 2019

Global Pooling Contd.

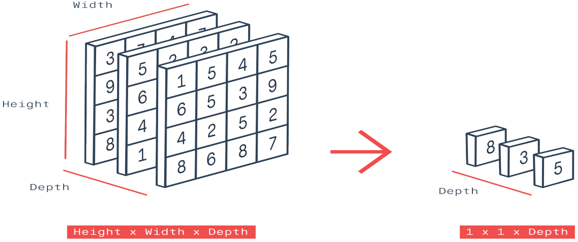


Figure 1: Image showing the concept of Global Pooling [2]

[2] Image Source : https://peltarion.com/knowledge-center/documentation/modeling-view/build-an-ai-model/blocks/2d-global-average-pooling

Results Obtained

Table 2: Comparison of accuracy with individual models and with state of the art structures (A three class classification problem)

Architecture	Accuracy	Description
NASNet	84.23%	Plain Model
MobileNetV2	86.78%	Plain Model
DenseNet201	87.67%	Plain Model
Goodwin et. al [1]	89.23%	DenseNet Architecture
Ozturk et. al. [2]	87.20%	Xception Architecture
Asif et. al. [3]	89.60%	DarkNet Architecture
Our model	**91.39**%	Ensemble model

2 3

[1] Goodwin, Brian D., Corey Jaskolski, Can Zhong, and Herick Asmani. "Intra-model Variability in COVID-19 Classification Using Chest X-ray Images." arXiv preprint arXiv:2005.02167 (2020).

[2] T. Ozturk, M. Talo, E. A. Yildirim, U. B. Baloglu, O. Yildirim, and U. R. Acharya, ?Automated detection of covid-19 cases using deep neural networks with x-ray images,? Computers in Biology and Medicine, p. 103792, 2020.

[3] A. I. Khan, J. L. Shah, and M. M. Bhat, Coronet: A deep neural network for ...est x-ray images, Computer Methods and

A binary classification problem

In the second part of our experiment we have considered the classification task as two class problem. We have divided the dataset into COVID and non COVID class. For that the images belonging to CAP and normal class are fused together to form non COVID class.

Table 3: Comparison with the individual models, a binary classification problem

Architecture	TPR	FPR	FNR	PPV	F1
NASNet	0.63	0.012	0.37	0.539	0.678
MobileNetV2	0.75	0.021	0.25	0.334	0.455
DenseNet201	0.73	0.019	0.27	0.338	0.457
Our model	**0.82**	0.009	0.18	0.539	0.648

Conclusion

- The framework presented in this manuscript uses an ensemble of three most common and up-to-date DCNN structures for detection and classification of Chest X-Ray images.
- The combination of features extracted from the three DCNN structures namely NASNet, MobileNet and DenseNet leads to a better generalization performance than single classifier as counterparts.
- The results obtained by our framework not only outperformed the individual DCNN architectures but also some of the state-of-the-art models presented in the literature.


Thank you!