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

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***Abstract*—The year 2020 will certainly be remembered for the outbreak of COVID-19 pandemic. With the first case being reported in December 2019, the SARSCoV2 virus has proved to be one of the most deadly virus which has affected the human civilization. Relatively high contagious rate and asymptomatic patients also being carrier of the virus makes it more dangerous. The only way to get a control on the outbreak is rapid testing. With the present testing mechanisms being costly and time consuming the end of this pandemic doesn't seems near. These challenges motivates us to come up with a system which can be effective in testing large population size and at the same time be less time consuming. We have proposed a Deep Convotuional Neural Network based ensemble architecture for extracting features from Chest X-Ray images and later classifying them into three categories namely- Community Acquired Pneumonia(CAP), Normal and COVID-19. We have shown that applying such technique can give better performance. Our ensemble network uses three pre-trained DCNN networks namely- NASNet, MobileNet and DenseNet. The low level features extracted from the three DCNN architectures are later concatenated and applied to a classifier for final classification. We have achieved an accuracy of 91.99% which is slightly better than the state of the art performances.**

***Index Terms*—COVID-19, Chest X-Ray, DCNN, ensemble model**

I. Introduction

The first case of COVID-19 was detected in the Wuhan province of China back in December 2019 and started spreading all across the world since then. The World Health Organization or WHO has declared it a pandemic in 11th March 2020. Today on October the 12th we have 7.18 million cases and 110,135 people have succumbed to the deadly virus world wide. The spread of this disease seems uncontrollable even after different part of the world had been under harsh lock down at different point of time. The R0 value is a parameter which measures how contagious an infectious disease is and thus it is one of the important scalar to study how the contagious disease has progressed. R0 can be used to find out the transmission and decline rate of that particular disease. Data suggests that the R0 value which changes with geography, population density and other important social measures followed in a community is higher than the deadly virus outbreak of 1918. The rapid spread of a disease of this kind demands a highly accurate point-of-care COVID-19 screening [1]. 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]. Though the countries are giving most importance to testing but again the large scale testing is somewhat impossible with the given high cost and non scalable testing equipment.

Researchers in the field of bio-medical image processing and Artificial Intelligence have tried to find a solution with the available resources. [3]–[5] have displayed great potential with Computed Tomography (CT) images for detection of COVID-19. The wide availability of Chest X-Ray (CXR) in diverse health care settings makes it an attractive option for rapid, accurate yet inexpensive point-of-care screening in primary care clinics.

II. Related Works

Convolutional Neural Networks(CNN) has time and again proved to be the best machine learning algorithm for image classification and recognition task. For almost all bio-medical image classification problems researchers have used CNN. Like for lung cancer [7], blood cancer [8] and breast cancer [9] researchers have reported state of the art performance using CNN structures. Detection and classification of COVID-19 from both Chest X-Ray and CT images being an image classification task, also attracted researchers to train deep learning models on the largely public datasets available. Li et. al. [1] presented COVID-MobileXpert, a DCNN based mobile application that can used for point-of-care COVID-19 screening from given noisy snapshots of chest X-ray image. Goodwin et. al. [10] have used twelve most common pre-trained DCNN structures to compare the results obtained for classification of Chest X-Ray images into healthy, Community acquired pneumonia(CAP) and COVID-19. The highest accuracy obtained by them is 88.4% using Densenet201 architecture. In [11] the researchers have used inception migration-learning model to detect COVID-19 from 453 CT images and achieved an accuracy of 73.1%. [12] have also used Chest CT images for detection of COVID-19. They have reported an AUC of 0.96.

TABLE I: Number of images in each class

	CAP	Normal	COVID-19
Train	4836	7081	175
Validation	605	885	20
Test	605	885	20

The work presented in [13] has used both Chest X-Ray and CT images to train a simple modified AlexNet structure. They have reported an accuracy of 94.01%. With every passing day people are coming up with more and more deep learning architectures but we are yet to achieve cent percent accuracy.

A. Motivation and Contribution

Developing an efficient, less expensive and accurate testing mechanism for COVID-19 has been the motivation for this work. With researchers performing various experiments on Chest X-Ray images, we too aim to develop a deep learning structure for contributing in the direction of developing an Artificial Intelligence system for detection of COVID-19. In the proposed framework we have tried to exploit the transfer learning technique for obtaining better performance. The main contributions are summarized below

- A framework based on DCNN architecture and transfer learning for the correct detection of COVID-19 and classification of Chest X-Ray images into CAP, COVID-19 and non-COVID-19 classes is proposed.
- To throughly study the concept of transfer learning on three different pre-trained DCNN structures.
- To compare the performance of the proposed model with other works present in the literature.

III. Proposed Methodology

In this section the proposed method for classification of Chest X-Ray images into Normal, Community Acquired Pneumonia(CAP) and COVID-19 is explained. The problem with bio-medical image processing is the unavailability of large data size. Due to which training a DCNN structure from scratch is not advisable. Given the pre-trained DCNN which are trained on natural images, the features learned can be used for classifying medical images using a technique called transfer learning [14].

For classification of bio-medical images like Chest X-Ray images, various aspects like texture, compactness, roundness, circularity etc plays a very important role [25]. So in the proposed framework, three most common and up-to-date pre-trained DCNN architectures are adopted for the classification of the Chest X-ray images. The proposed ensemble structure will ensure that all the descriptors required for proper classification of the images are included. We have experimentally proved that employing such schemes provides better performance than the individual models.

As shown in figure 2 the ensemble of three well known DCNN structures namely NASNetMobile [15], MobileNetV2 [16] and DenseNet [17] are used for extracting the features from the input images which are concatenated and applied to a fully connected classification layer.

Before concatenating the features extracted from the DCNN, Global Average Pooling is applied. The motive behind adding a Global Average Pooling layer after every pre-trained DCNN is to reduce the final feature length and thus reducing the number of neurons in the input layer of the final classifier. This is beneficial as this significantly reduces the number of parameters and thus the chance of the network getting over fit is drastically reduced. [26]

A. Dataset Description

Since the outbreak of COVID-19 researchers has uploaded lot of clinically proven Chest X-Ray dataset on Internet. The Chest X-Ray dataset used for our experimentation is from Cohen et. al [18]. The same was acquired on 17th April 2020. Table 1 gives the total number of images used for train,test and validation set respectively. The dataset was partitioned and compared as given in [21]. Few examples of the Chest X-Ray images from Cohen et. al. [18] are shown in Figure 1.

As classifiers are generally biased towards majority class, so a re-sampling technique called under-sampling is used here. In under-sampling, examples from majority classes are randomly deleted until the dataset becomes equal.

B. Data pre-processing

For pre-processing Zero mean normalization is used to get rid of uneven lighting condition and also to make all input pixels values between 0 and 1 and thus speeding up the convergence of the training model [19].

C. Ensemble model for features extraction

Initially features were collected from the three DCNN structures which are trained on ImageNet dataset [20] separately. The proposed algorithm concatenates the features extracted from all three of them before classification. The details of the feature length and parameters are given in table II A brief description of the three DCNN structures used in our model is given below :

1) NASNet: Introduced in the year 2018 by Google Brain, they proposed the idea of search space which enables transferability [15]. They searched for the best convolutional layers which they called cells for solving the classification problem on CIFAR10 dataset and then applied several stacks of that cells for solving the ImageNet [20] classification problem.

2) MobileNet: Introduced by Howard et. al. [16] in the year 2017, the network is basically for mobile and embedded vision applications. MobileNets uses depthwise separable convolutions for its light weight deep neural network structure.

3) DenseNet: Introduced in the year 2018 by Huang et. al. [17], densely connected Covolutional Network connects each layer in a network to every other layer in a feed-forward style. This revolutionary work made possible to design more deeper and more accurate Convolutional Neural Network.

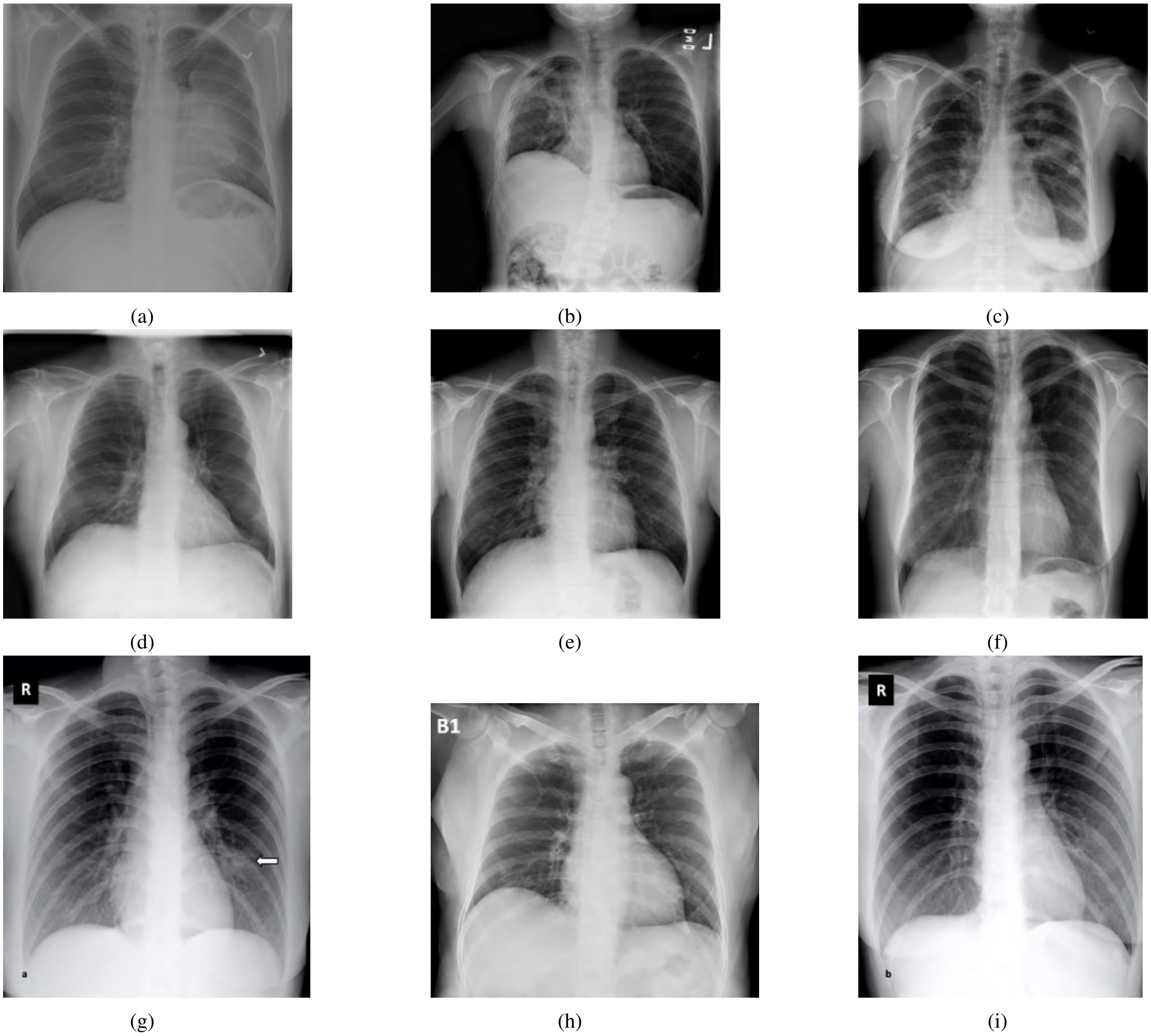

Fig. 1: Example of Chest X-Ray images as given in Cohen et. al. first row shows CAP, second row shows the normal and the third row shows the COVID-19 cases

TABLE II: 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

IV. Experimental Results and Discussions

The dataset was organized as given in Wang et. al. [21]. All the images were resized to 224 X 224 and the batch size was taken to be 32. The classification layer attached after the proposed model uses ReLU activation function. $\beta 1$ and $\beta 2$ of the Adam optimizer was set to be 0.6 and 0.8 respectively. The learning rate used for training is 0.01 and was trained up to 1000 epochs. The experiments were implemented in Python using Keras package with Tensor-flow as backend framework. Figure 3 shows the training progress. The performance of the proposed model is also compared with that of the three individual models of NASNetMobile [15], MobileNetV2 [16] and DenseNet [17] as shown in Table III. With NASNet an accuracy of 84.23% is obtained. Similarly an accuracy of 86.78% and 87.67% is obtained in case of MobileNet and DenseNet respectively.

Goodwin et. al. [9] also used the same dataset for

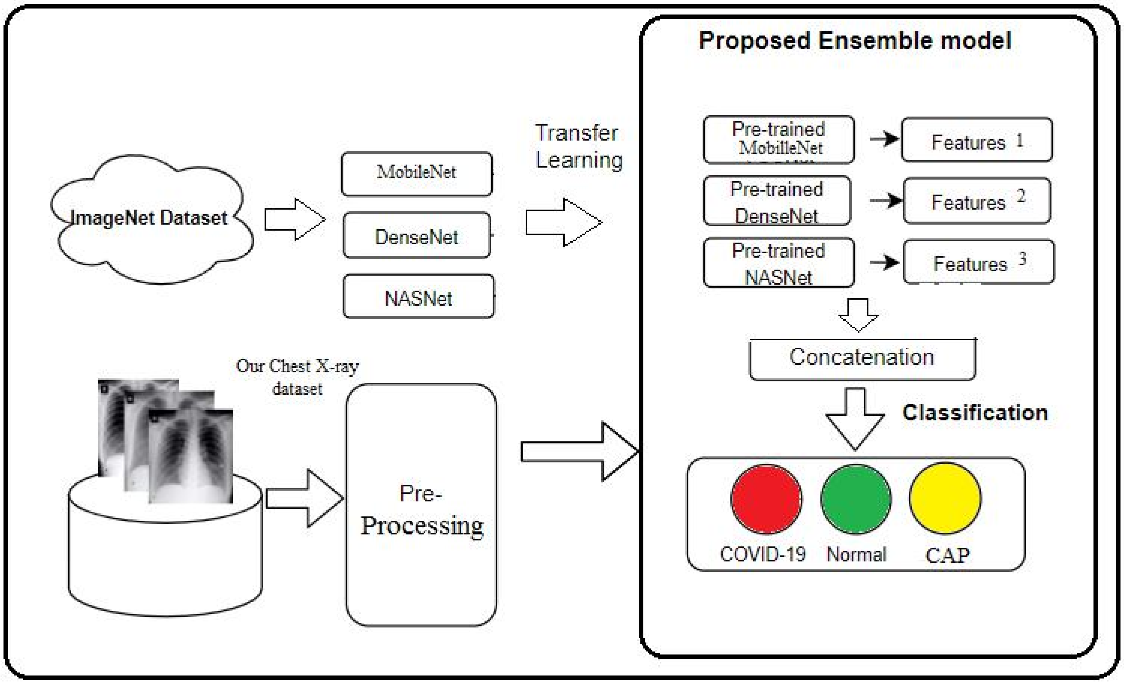

Fig. 2: Schematic illustration of our model

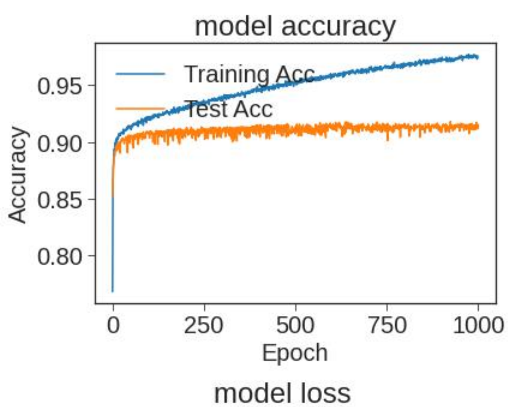

Fig. 3: The training progress of the proposed model

TABLE III: Comparison of accuracy (A three class problem)

Architecture	Accuracy
NASNet	84.23%
MobileNetV2	86.78%
DenseNet201	87.67%
Goodwin et. al [10]	89.23%
Ozturk et. al. [23]	87.20%
Asif et. al. [22]	89.60%
Our model	**91.39**%

TABLE IV: Comparison of 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

their experimentation. They have used the 12 most common pre-trained DCNNs and compared their performance. DenseNet201 reported highest accuracy. The ensemble of all the 12 models gave an accuracy of 89.4%. Our ensemble model gives an accuracy of 91.99% which is slightly better than their results. Asif et. al. [22] proposed a DCNN based on Xception model for classification of Chest X-Ray into COVID-19, normal and pneumonia classes. They have reported an accuracy of 89.6%. Ozturk et al. [23] proposed a CNN based on DarkNet architecture for the classification process. They have performed 5-fold cross validation and the average accuracy obtained by them is 87.02%. The results in terms of accuracy obtained by our ensemble model is slightly better than the individual models and also the state of the art models presented in the literature. More details are present in Table III. To check the robustness of the model, a 5-fold cross validation is also performed. An accuracy of 0.89 (+/- 0.03) is obtained.

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 IV provides the parameters computed after transforming the problem into two class classification problem. The parameters that we have used to compare our ensemble model with the individual architectures are TPR, FPR, FNR, PPV and F1 score. As shown in IV, the True Positive Rate obtained by our ensemble model is far better than the individual models.

V. 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. And most importantly the ensemble model takes a little over one second to classify the input test images, whereas each of the individual models takes less than a second. But this little delay can be afforded when accuracy of the model is our priority.

With the increasing number of cases, it is also important to ensure that no single COVID-19 patient goes undetected. The proposed method can assist the radiologists to have a deeper understanding of the critical aspects related to COVID-19. We strongly believe that once more training data becomes available, the accuracy will go up.

Source Code and Dataset

The Chest X-Ray dataset used for our experimentation is from Cohen et. al [18]. The same was acquired on 17th April 2020.The dataset was partitioned and compared as given in [21]. The same can be found at [24].

The source code for the ensemble model can be obtained from https://github.com/sagardeepdeb/ensemble-model

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