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RESEARCH ARTICLE

Intermediate Learning-Based Attention Regulated Densenet for Diagnosis of Covid-19

Roshan Shetty[1]*, S N Prasad[2], D V Manjunatha[3], V Veeraprathap[4], Vasudev Shahapur[5], M S Shwetha[6]

1 Reaserch Scholar, School of ECE, REVA University. Bengaluru & Dept. of ECE, Alva's Institute of Engineering & Technology, Moodbidri, Karnataka, India
2 Department of Electrical and Electronics Engineering, Manipal Institute of Technology Bengaluru, Manipal Academy of Higher Education Manipal, 576104, Karnataka, India
3 Sr.Professor, Department of ECE, Alva's Institute of Engineering & Technology, Moodbidri, Karnataka, India
4 Department of ECE, Alva's Institute of Engineering & Technology, Moodbidri, Karnataka, India
5 Department of CSE, Alva's Institute of Engineering & Technology, Moodbidri, Karnataka, India
6 Department of ECE, Alva's Institute of Engineering & Technology, Moodbidri, Karnataka, India

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* **Corresponding author**.

roshan564956@gmail.com

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Abstract

Objectives: The AI-based Computer-Aided-Diagnosis of Chest X-Rays related to COVID-19 is very essential. Here we present an Attention regulated Pre-trained DenseNet-121with intermediate transfer learning as a Chest X-Ray image classifier to classify images according to three labels: COVID-19, pneumonia, and normal. **Methods**: We are proposing a new Attention regulated ImageNet pre-trained DenseNet-121 neural network architecture, which is retrained on NIH ChestX-ray14 data as an intermediate database before the actual COVID-19 database. We also fine-tuned the last layer of this neural network with a suggested novelty called the output neuron-keeping technique. Before feeding the Covid-19 data we removed all other neurons corresponding to Chest X-ray14 pathology classes except the "No finding" and "Pneumonia" classes. A new third neuron with random weights and bias is created in the final layer to detect Covid-19 pathology. A DenseNet-121 is supported by a GRAD-CAM-based attention mechanism in achieving detection accuracy and localization of pathologies. The used Covid-19 dataset is a combination of 370 Pneumonia, 1255 Normal, and 439 COVID-19 Chest X-Ray images. We randomly took 50 pictures from each class for testing purposes, the remaining images are augmented more to improve DenseNet performance on a small COVID-19 dataset. **Findings**: Our state-of-art model achieved 98.6% test accuracy since it misclassified one out of 50 Covid-19 images, and one out of 50 Pneumonia images, but all 50 normal Chest X-Ray images are classified with 100% accuracy. We compared our model with the other three state-of-the-art models, particularly under three-class classification problems (Pneumonia,

Covid-19, and Normal). The experimental result shows that the proposed model outperforms the existing three models by obtaining an accuracy of 98.6%. The GRAD-CAM generated heatmaps improved the interpretation of the infections. **Novelty:** The intermediate transfer learning, neuron keeping, and attention-regulated DenseNet are the highlight of the proposed work in achieving detection accuracy. The GRAD-CAM generated heatmaps indicate future research on COVID-19 diagnosis to analyze the severity of the infection**.** We believe this model may bridge the medical community and Artificial Intelligence gap.

Keywords: Chest XRay14; Covid19 diagnosis; DenseNet121; GradCam; Neuron keeping

1 Introduction

Early detection and isolation are required to fight against COVID-19, and to stop speeding in the community[(1)]. Apart from RT-PCR, another method is an analysis of radiology images such as Chest X-rays and CT from radiologists[(2)]. One study says radiologists can identify only 65% of COVID positive images due to the diversity of COVID-19 infections in the lungs[(3)]. Nowadays AI-based Deep Learning (DL) algorithms under Computer-Aided-Diagnosis (CAD) are assisting radiologists in the analysis of medical images. A type of DL called Convolution Neural Network (CNN) is a popular choice in any medical image-related task[(4)]. We selected a variant of CNN called DenseNet due to its success in various Chest X-Ray related applications[(5)]. A pre-trained DenseNet-121 is used as a Covid-19 feature extractor and classifier in this proposed work. The DenseNet-121 working is regulated with a Grad-CAM-based attention block to achieve pathology detection excellence. Figure 1 shows some Covid-19 positive images.

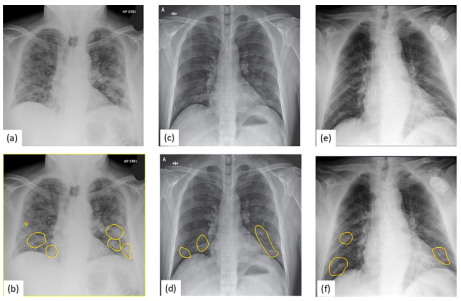

Fig 1. Images of Covid-19 with radiologists marking

In fact, in all CNNs efficiency purely depends on the volume of data we feed as input[(6)]. Our Covid-19 input data volume is less, so NIH Chest X-Ray14 data is used as intermediate training data for our network before learning from Covid-19 data. Our Covid-19 dataset contains Covid positive images along with Pneumonia and some Healthy images. The final layer neurons corresponding to the "Normal" and "Pneumonia" classes of NIH Chest X- Ray14 are kept as it is. This is because the NIH Chest X-Ray14 database already has these two classes. We believed that this will enable our model to learn more information from ChestX-ray14 before learning from Covid-19 data. While training with the Covid-19 dataset a new neuron for Covid-19 pathology is created along with other two retained neurons.

We resized images to standard 224×224x3, but resizing images reduces the resolution of the image or loss of details in an image[(7)]. In fact, the resolution is very

critical for diagnosis, especially for pathologies such as Covid-19 with very diverse lesion areas. Hence our GRAD-CAM visual attention mechanism will assist DenseNet to pay more attention to abnormal regions of the resized images rather than to the entire image[8]. Much research is already done on CNN-based thoracic disease diagnosis using Chest X-Ray14 images. For example, author[9] proposed attention-regulated DenseNet-121 with adaptive augmentation training for the classification of 14 thoracic diseases with the same dataset. Their model performance score on all 14 pathologies reached an average AUC score of 93%.

The significant contribution of this research work is (1) Attention-regulated DenseNet with intermediate transfer learning and neuron keeping at the final layer of DenseNet. (2) The Grad-Cam-based visual attention mechanism to support DenseNet, and to generate pathology localization heatmaps to judge the severity of the infections in the lungs.

Now we will review some of the AI researcher's work on Covid-19 Chest X-Ray diagnosis. Two DenseNet blocks with different kernel sizes are employed in a model called CrossDenseNet[10], which is used as a 3-class classification model. They are Covid-19, pneumonia, and normal class. A Covid-Net[11] model got promising results, with a test accuracy of 92.6%. It is one of the first open-source deep learning networks made public to detect COVID-19 from chest X-rays. This architecture design was created via a human-machine collaborative design strategy with mixed convolution layers and grouping configurations. They did four class classifications of chest X-Rays. They are Normal images, Bacterial infection, non-COVID-19 Viral, and COVID-19 Viral.

The author[12], developed a three-player framework, first is pre-trained DenseNet-121 to extract features from the Chest X-ray8 database, and the second player is fine-tuned resident fellow network that learns image features to distinguish COVID-19 from pneumonia and/or healthy images with a small amount of COVID-19 cases, the third player is the network to perform on-device COVID-19 patient triage and follow-up. The second network is fine-tuned with only 179 Covid-19, 179 Pneumonia, and 179 Normal Images, which got 84.3% accuracy. The large gap between natural images and the medical images of the first player and specific diseases such as COVID-19 in the second player made knowledge acquisition less effective in this work.

The author[13], extracted Chest X-Ray image features from 13 different pre-trained CNN models and fed them to the SVM classifier individually. The model ResNet50 with SVM is performing better compared to other remaining models with 95.33% of accuracy. The experimental studies were implemented using the MATLAB 2019a deep learning toolbox, with only 127 Covid-19, 127 Pneumonia, and 127 Normal images. They have not done any provision for the interpretation of infections on the images or attention mechanism in their model.

One more DenseNet-based approach with Grad-CAM interpretation was developed by the author[14]. They achieved 96.4% accuracy with the softmax classifier and Tensor Flow tool. Their database has 6045 pneumonia, 8851 normal images, and only 238 Covid-19 images. Less Covid-19 images created an imbalance in the dataset. To overcome this, they augmented the COVID-19 images in the training set only. They did both 2-class and 3-class pathology detection, they are COVID-19, healthy, and pneumonia classes.

2 Methodology

2.1 Dataset

2.1.1 NIH Chest X-Ray14

The Chest X-ray image database with over one lack of images made public by NIH (National Institute of Health). This database contains, a total of 14 thoracic diseases and some healthy images also. Figure 2 shows the pathology class distribution of the Chest X-Ray14 dataset. The data augmentation is carried out by us, by applying random horizontal flips on the training set before feeding them to the DenseNet. The augmentation process is carried out online.

2.1.2 Covid-19 data

We assembled this database by combining Chest X-Ray images of two different pathologies and some normal healthy images. We selected 439 Covid-19 front-view Chest X-ray images from the "Covid-19 Image Data Collection"[15] dataset. The second pathology is called Pneumonia, 1255 pneumonia images are collected from the CheXpert database[16]. The 370 healthy images are collected from the Montgomery and Shenzen databases[17]. This database contains front-view healthy images along with some tuberculosis images. We selected only healthy normal images from this database. Table 1 shows our accumulated Covid-19 database pathology count for the proposed work.

Accumulated 2064 images are divided into training, validation, and testing dataset. We randomly selected 50 each pneumonia, normal, and Covid-19 images as testing data. Out of the 1914 remaining images, 90% were made as training data, remaining as validation data. Here none of the images from the same patient were repeated. The parameters obtained from the ImageNet database have been applied to perform Covid-19 image normalization. Table 2 shows our accumulated COVID-19

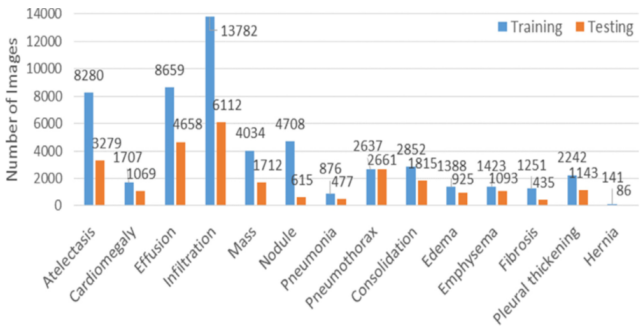

Fig 2. The 14-pathology class distribution in the ChestX-Ray14 dataset

Table 1. Accumulated COVID-19 database

Normal	370
Pneumonia	1255
COVID-19	439
Total	2064

database image division.

Table 2. Accumulated COVID-19 database image division

Testing	50 Covid-19, 50 Pneumonia, 50 Normal
Training	1722
Validation	192

We applied data augmentation for the Covid-19 dataset because such a small dataset affects Deep Neural Networks' performance due to overfitting. So we need to produce more instances of input data from the current dataset. This is done with the help of some common transformations on input data called as data augmentation. We did rotation of -40 to 40 degrees, translation of 32 pixels up-down left-right, and also a horizontal flipping. All augmentation done online before feeding them to proposed Deep Neural Network.

Table 3 shows details of Augmentation, we can observe a shortage of 360 Covid images with respect to other two classes. In order to create a balance, in every epoch, 360 each normal and pneumonia augmented image were left out randomly.

Table 3. Details of Augmentation

Pathology	**Images selected for Augmentation**	**Augmentation Count**	**Total Images after Augmentation**
Normal	288	30 times	8640
Pneumonia	1080	8 times	8640
Covid-19	345	24 times	8280
Total	1713	62 times	25560

2.1.3 Architecture

DenseNet models in various medical image classification problems, we selected pre-trained DenseNet-121 as a feature extractor. The

While intermediate training with the ChestX-ray14 database, we kept 15 neurons with sigmoid activation to classify 14 thoracic diseases plus one "No finding" class. Label prediction vector is denoted as F_d. While training with the Covid-19 dataset only neurons corresponding to Pneumonia and No finding classes are utilized along with new Covid-19 neuron. The remaining neurons are taken out. Figure 3 shows our model architecture.

Separate Grad-CAM based attention block is proposed here to regulate DenseNet with attention features. This further guide DenseNet to give more attention to highlighted infected areas rather than to the entire X-Ray image. The output from Dense-

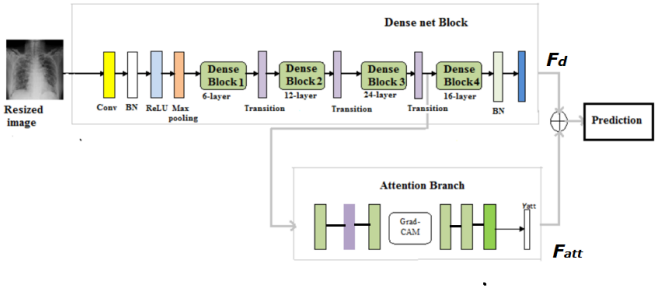

Fig 3. The architecture of the proposed model

unit 3 is taken as input to the attention block because deeper layers of DNNs contain rich semantic and visual details [18]. Before and after the Grad-Cam unit three convolution layers are stacked for further refinement of image feature maps. F_{att} is termed as a label prediction vector in the attention block. During the intermediate training database, we kept 15 neurons with sigmoid activation to classify 14 thoracic diseases plus one No finding class. While training with the Covid-19 dataset only neurons corresponding to Pneumonia and No finding classes are utilized along with new Covid-19 neuron. The remaining neurons are taken out. At the end, average predictions of both blocks F_{att} and F_d are taken to produce the diagnosis result.

3 Results and Discussion

3.1 Transfer Learning

It's a unique training strategy for new deep models using pre-trained models. The advantages of transfer learning are: performance enhancement; reduction in training time; and less training data may be enough for the new model. By doing this, learned DNN from the first dataset will generalize better on the second database. Transfer learning is very useful if the second dataset is smaller than the first dataset [19]. The DNN model output can be changed, by adding and removing neurons in the final layer with randomized weights and biases. Our Transfer learning contains three steps: (1) Train DNN on ImageNet, (2) Train with secondary dataset ChestX-Ray14, and (3) finally, train with our newly assembled Covid-19 dataset.

3.2 Neuron Keeping

The intermediate database Chest X-ray 14 and final database Covid-19 both share two common classes, they are "No finding" and "Pneumonia". So while preparing the last layer of DNN, we kept 15 output neurons in the last layer for the intermediate database. Before feeding, the Covid-19 database we removed all other neurons corresponding to Chest X-ray14 disease classes except the "No finding" and "Pneumonia" classes. This improved the DNN training speed and performance of a model on a smaller Covid-19 database. We Copied weights and biases of a neuron at the end of intermediate training, later those copied parameters are substituted to neurons, which were used to detect the same pathology "No finding", and "Pneumonia" under the Covid-19 dataset. A new third neuron with random weights and bias is created in the final layer to detect Covid-19 pathology from the Covid-19 dataset.

3.3 Experiment with ChestX-Ray14 data

The DNN was established by downloading the PyTorch version of a pre-trained DenseNet121.We added the 15^{th} neuron in the last layer to deal with the "No findings" class of the dataset. The sigmoid activation function of the last layer is maintained as it is. The intermediate ChestX-ray14 training started with 20 epochs and was carried out on two NVidia GTX 1080 GPUs. The Table 4 shows different learning parameters on intermediate dataset.

3.4 Experiment with COVID-19 data

The weights and biases of neurons that classified "No findings" and "Pneumonia" in earlier training is retained during training with the Covid-19 dataset. The Covid-19 dataset training started with 20 epochs and was carried out on the same two NVidia GTX 1080 GPUs. A stochastic gradient descent backpropagation algorithm with binary cross-entropy loss function is used to estimate training error in both datasets.

Table 4. Different learning parameters

Parameters	On Chest X-ray14
Momentum	0.9
Mini-batches	16 images
Learning rate	0.001
Maximum iteration number	500

The Covid-19 training has 4 stages: (1) except for the final layer, all other layer parameters are frozen at the beginning. The training started with 10 epochs, a learning rate of 0.001, and a weight decay of 0.01. (2) Unfroze all parameters, and increase epochs from 10 to 48. At the same time learning rate is decreased by a factor of 10 and it becomes 0.0001. (3) In every layer we decreased the learning rate to 0.00001 with the same settings. (4) Weight decay and early stop are taken out, again train a network with 48 epochs.

3.4.1 Performance Comparison

The proposed model achieved 98.6% test accuracy since it misclassified one out of 50 Covid-19 images, and one out of 50 Pneumonia images as shown in Table 5 in bold Black. But all 50 normal Chest X-Ray images are classified with 100% accuracy. We compared our model with the other three state-of-the-art models, particularly under three-class classification problems (Pneumonia, Covid-19, and Normal).

The first existing model is three player network with an accuracy of only 84.3%[12]. The large gap is observed between the natural images of imagenet database and the medical images of the Chest X-Ray8 database in the first player. A specific disease such as COVID-19 is used in the second player. This setup made the knowledge distillation less effective in the entire model. But in our proposed model much bigger Chest X-ray 14 database of 14 pathology distributions is used compared to the Chest X-Ray 8 dataset. Along with this, we did extensive data augmentation during training to acquire effective knowledge distillation. One more existing model got an accuracy of 95.3%[13] under the same three-class classification. But they haven't utilized the attention mechanism in their model. We incorporated the attention mechanism in our model, which created class discriminative attention maps of pathologies on the images. This attention map further guides the DenseNet feature extractor to achieve higher detection efficiency and indicates significant image regions that contribute to the predictions.

The existing model called COVID-DenseNet[14] achieved 96.49% and 93.71% accuracy under 2-class and 3-class classifications respectively. Under the three-class classification, their accuracy dropped further due to a very less number of COVID-19 images, which are only 238. This number is extremely small compared to the number of radiology images available for infected and healthy persons. This number is again too small compared to 6045 pneumonia and 8851 normal images. Further, they did augmentation of only COVID-19 images in the training set. Keeping this in mind, we have done augmentation of all three classes in our model.

The proposed method achieved higher accuracy of 98.6% than existing works of 84.3%[12],95.3%[13], and 93.71%[14] respectively. Figure 4 shows accuracy comparison of different existing models with ours.

Table 5. Prediction of Proposed Model

Test data		Proposed DenseNet Predictions		
Pathology	Images	Pneumonia	Covid-19	Normal
Pneumonia	50	49	01	00
Covid-19	50	01	49	00
Normal	50	00	00	50

A Grad-CAM uses the gradient of output to produce an attention map to highlight infected regions of the lungs. Figure 5 shows a true positive Covid-19 image and its Grad-Cam generated heatmap. We can see two colors red and blue on the map. The blue color indicates a normal part of the lung, and the red part indicates the Covid-19 infected region of the lung. Our model found Covid-19 infections in both lungs.

4 Conclusion

Attention-regulated DenseNet with intermediate transfer learning and neuron-keeping method gave promising results with an accuracy of 98.6%. This method could also be used in all types of medical image classification problems. The intermediate

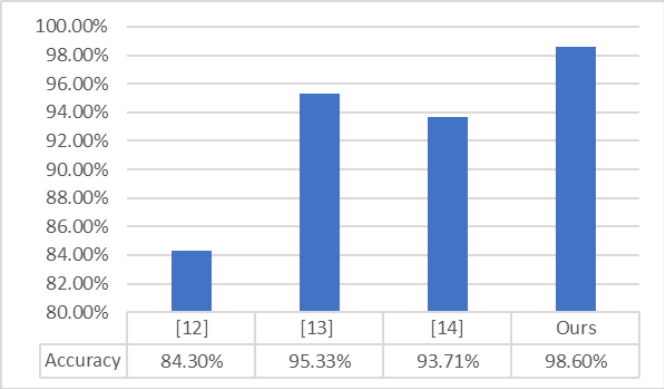

Fig 4. Comparison of proposed model with existing models

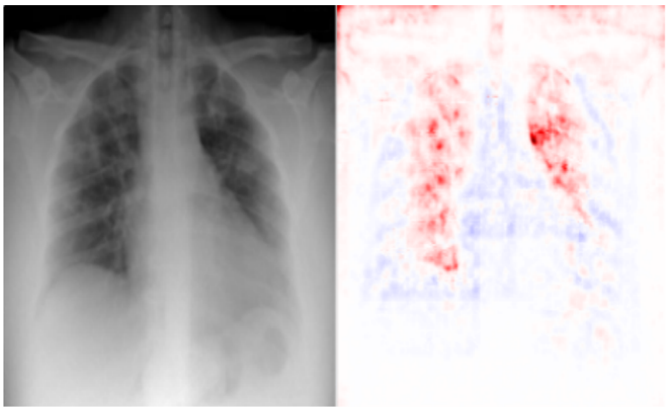

Fig 5. COVID-19 image and Grad-CAM generated heatmap of infections

transfer learning boosted the performance of a DenseNet even though our primary Covid-19 dataset is very small. The GRAD-CAM-based attention block guided our DenseNet-121 to achieve good classification accuracy. It gave a good interpretation of infected regions of the lungs to judge severity. We also admit that our assembled Covid-19 dataset is not ideal, and it is small. A much larger Covid-19 data from many sources would create a much better model. Furthermore, clinical validation is due in a real-world scenario. This proposed work shows that DL has the potential of becoming a more rapid, economical method for Covid-19 diagnosis than RTPCR. The GRAD-CAM-generated heatmaps improve the interpretation of the infections and indicate future research on COVID-19 diagnosis.

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