Mobile Freeze-Net with Attention-based Loss Function for Covid-19 Detection from an Imbalanced CXR Dataset[*]

†

Santanu Roy[‡]
Christ (Deemed to be University)
Bangalore, India
santanuroy35@gmail.com

Rahul Khurana
Bharati Vidyapeeth's College of Engineering
New Delhi, India
rahulkhurana.rk59@gmail.com

ABSTRACT

In this paper, we present a novel framework, that is, Mobile Freeze-Net along with Attention-based Loss Function, for Covid-19 detection from a Chest X-Ray (CXR) dataset. First, we have observed that by freezing 50% of a Mobile Net-V2 model (means fine-tuning 50% layers from ImageNet dataset) has automatically removed the class imbalance problem from the CXR dataset considerably. We call this 50% frozen Mobile Net-V2 model as Mobile Freeze-Net. Secondly, we have proposed an Attention-based Loss function, which provides more attention to the class, having higher inter-class similarity. We have computed attention weights for each class from the statistical inference of the dataset itself, by employing a Monte-Carlo method and thereafter, we have incorporated those weights into WCCE loss function of Mobile Freeze-Net model. By utilizing Mobile freeze-Net, we have achieved testing accuracy, F1 score, precision and recall of 93%, 94%, 93% and 94% respectively. This is approximately 3-4% improvement compared to 100% fine tuning of Mobile-Net V2. Furthermore, we have achieved approximate 1-2% improvement of Mobile Freeze-Net, after incorporating Attention-based Loss function. For the validity of the proposed framework, we have conducted experiments with 10-fold cross validation. All these experimental results suggest that our proposed framework has outperformed other existing models considerably.

KEYWORDS

Mobile Freeze-Net, Attention-based Loss function, Covid-19 detection, Chest X-Ray (CXR) Images, Class Imbalance

ACM Reference Format:
Santanu Roy and Rahul Khurana. 2023. Mobile Freeze-Net with Attention-based Loss Function for Covid-19 Detection from an Imbalanced CXR Dataset: . In *Proceedings of ACM SAC Conference (SAC'23).* ACM, New York, NY, USA, Article 4, 3 pages. https://doi.org/10.1145/3555776.3577825

[*]Produces the permission block, and copyright information
[†]The full version of the author's guide is available as `acmart.pdf` document
[‡]

SAC'23, March 27 –March 31, 2023, Tallinn, Estonia

ACM ISBN 978-1-4503-9517-5/23/03…$15.00
https://doi.org/10.1145/3555776.3577825

1 INTRODUCTION

Covid-19 has been declared as pandemic by World Health Organization (WHO) [3] in March 2020. Since then, it was affecting on mortality and health of the global population considerably all over the world. Early automatic detection of Covid disease from Chest X-Ray (CXR) images has been the key to the survival of this pandemic [7]. Numerous researchers ([5], [7]) have come up with novel CNN architectures in order to detect Covid disease efficiently from CXR images. L. Wang et al. [7] designed a novel CNN architecture called Projection Expansion Projection Extension (PEPX) based on a human-machine collaborative design strategy. They called their architecture as Covid Net. Recently, S.Roy et al. [4] proposed a data-augmentation method called 'SVD-CLAHE Boosting' which is composed of both under-sampling and over-sampling, for alleviating class imbalance problem. A novel SVD-based contrast enhancement method is proposed by them for over-sampling, along with CLAHE 0.5, CLAHE 1.0. Mrinal Tyagi et al. [6] recently proposed Custom Weighted Balanced Categorical Cross Entropy (CWBCCE) on ResNet-18 model, in order to overcome class imbalance problem from an imbalanced CXR dataset. More number of works can be found in a review paper by Nayak et al. [2] for Covid-19 detection from CXR dataset.

The contributions of this paper are as follows:

(1) In this paper, we utilize a Mobile Freeze-Net, in which we freeze first 50% layers of pre-trained Mobile-Net V2 (from ImageNet) and train only last 50% layers of the model.
(2) We have proposed an Attention-based Loss Function, incorporated on the Mobile Freeze-Net to slightly improve its performance. The attention-weights of WCCE is chosen proportional to the inter-class similarity for each class which is computed based on Monte-Carlo method.
(3) For the validity of our proposed framework, we have performed 10-fold cross validation experiment.

2 DATASET

A Covid 19 dataset is taken from publicly available Kaggle website [1], in which there are four classes: Covid, Normal, Lung Opacity (LO) and Viral Pneumonia (VP), having number of images 3616, 10,192, 6012 and 1345 respectively. Standard CNN models have poor performance on this imbalanced dataset. Moreover, we observed that many images are miss-classified due to very higher inter-class similarity between Lung Opacity (LO) and Normal class.

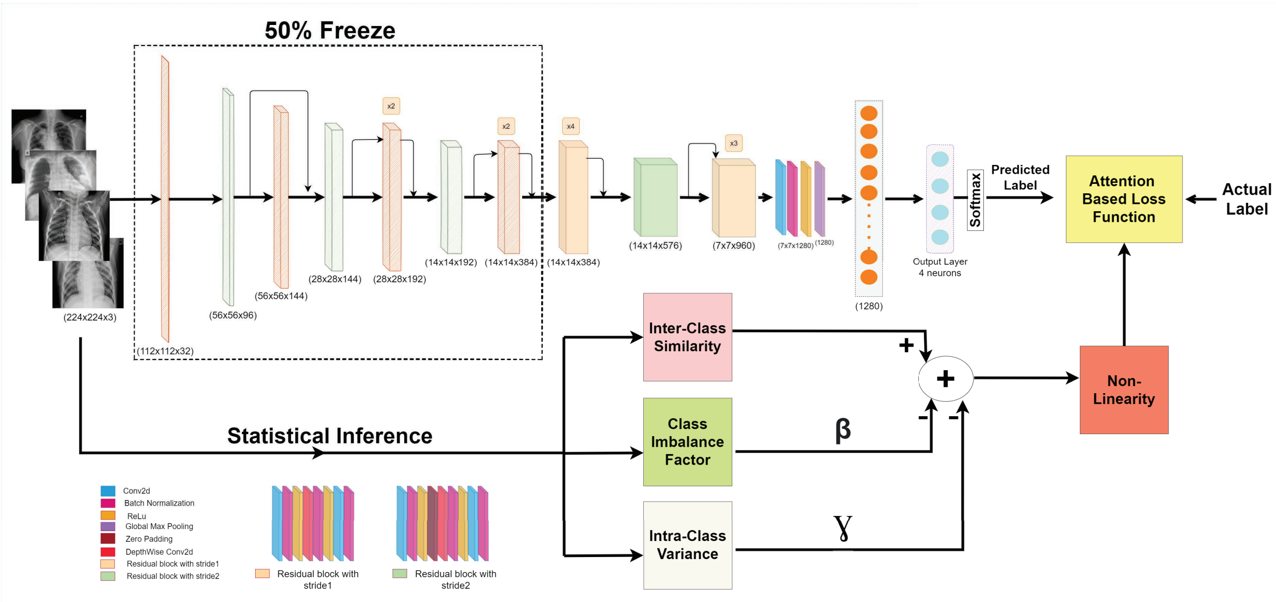

Figure 1: Block Diagram of proposed Framework: Mobile Freeze-Net + Attention-based Loss Function

3 METHODOLOGY AND IMPLEMENTATION

In this section, we have introduced the proposed framework, as well as its training methodology.

3.1 Mobile Freeze-Net with Attention Based Loss function

In this paper, we have utilized a 50% freezing pretrained Mobile Net-V2 architecture called as 'Mobile Freeze Net'. We have observed that the last few layers of CNN model are the most responsible for the final prediction task, thus, we freeze only the first 50% of layers empirically (unlike randomly freezing) and train the remaining last 50% layers of Mobile-Net V2 model. Moreover, we have observed that due to freezing 50% of layers of Mobile Net-V2, it reduces its complexity and automatically resolves the class imbalance problem. For justification, we have compared Mobile Freeze-Net performance (given in Table-1) with stochastic freezing Mobile-Net V2 model in which 50% layers are frozen randomly.

By looking at the miss-classified images, by Mobile Freeze-net Model, we have visualized that many images from LO class have been miss-classified due to higher inter-class similarity with respect to Normal class and vice versa. Therefore, little bit more attention should be given to those classes which have higher inter-class similarity. Proposed attention based loss function is the modification of WCCE, in which attention weights for each class is assigned by the following formulas (1-3). The final proposed framework can be observed in Figure.1

$$L_{AttCCE}(y,p) = -\frac{1}{N_c}\sum_{i=1}^{N_c}\sum_{c=1}^{K}\alpha_c * log(p_{i,c}) \tag{1}$$

$$\alpha^1{}_c = r_{inter}(c_1,c_2) + \beta * class_{im}(c) + \gamma * \sigma_{intra}(c) \tag{2}$$

$$\alpha_c = n/(1-(\alpha^1{}_c)^q) \tag{3}$$

Here, in equation (1), $p_{i,c}$ is the probability that the i^{th} sample belongs to class c, here α_c is the attention weight, N_c is the total number of samples in a particular class, K is total number of class in the dataset. In equation (2), we extract some statistical inferences (inter-class similarity, intra-class variance etc.) from the dataset itself by Monte Carlo method. From equation (2), this can also be observed that, attention weight $\alpha^1{}_c$ is directly proportional to inter-class similarity. Moreover, $class_{im}$ and σ_{intra} components are deployed in equation (2), as a balancing factor which cancels out some values of the main r_{inter} a little bit. These two balancing components are multiplied by β and γ, which are chosen 0.05 and 0.1 empirically, in order to ensure that they have a very little influence on the final statistical inference. A depth explanation of computing attention weights α_c can be found in a GitHub link, which is shared later. The final α_c is obtained by further incorporating some non-linearity and normalization factor n, given in equation (3). The normalization factor n is empirically chosen as 0.001 and q determines the degree of non-linearity incorporated in the equation (3) which is chosen 0.25.

3.2 Training methodology

Tesla P100 GPU, provided by Google Colab Pro service, was used to train all the models given in Table-1. Standard CNN models Inception-V3, Mobile-Net V2 have been pre-trained from the Image-Net dataset. Whereas, existing models Covid-Net, Covid-Lite, CW-BCCE + ResNet-18 are trained from the scratch. For training all the models, the batch size 8 is deployed. Adams-optimizer is employed as the preferred choice of optimizer for all the experiments with a learning rate of $1e^{-4}$. A patience of 5 epochs for validation loss (call back criteria) is employed in order to prevent the overfitting in those models. For both Mobile Freeze-Net and proposed model (i.e. Mobile Freeze-Net+ Attention based loss function), only one

Table 1: Performance comparisons of various existing models with proposed model on CXR Dataset (Macro-Average) of Testing

Methodology	F1Score	Accuracy	Precision	Recall	AUC
Covid-Net (Train from scratch) [7]	0.87	0.87	0.88	0.86	0.88
Covid-Lite (Train from scratch) [5]	0.86	0.85	0.86	0.87	0.88
Inception-V3 (100% fine tuning)	0.78	0.80	0.77	0.79	0.80
ResNet-18+ CWBCCE Loss (Train from scratch) [6]	0.93	0.92	0.93	0.94	0.98
Mobile-NetV2 (100% fine tuning)	0.91	0.89	0.91	0.91	0.95
Mobile Freeze-Net (50% freeze)	0.94	0.93	0.93	0.94	0.98
Mobile-NetV2 (50% stochastic fine tuning)	0.93	0.92	0.94	0.92	0.98
Proposed Framework	**0.95**	**0.95**	**0.96**	**0.95**	**0.99**

classification layer (head) is used at the end, shown in Figure 1. For 10 fold cross-validation experiment, all 10 folds are randomly chosen from the dataset, thereafter, any 8 folds are chosen for training, 1 fold for validation and 1 fold for testing.

4 OBSERVATIONS AND ANALYSIS:

Table-1 represents evaluation metrics (Macro-Average) comparison of various existing CNN models with the proposed model. This can be observed from Table-1 that, the performance of Mobile Net-V2 model has been considerably boosted after freezing its first 50% of layers. Total there is 3-4% improvement after freezing first 50% layers in Mobile Freeze-Net. Moreover, this can be observed from the Table-1 that after incorporating attention-based loss function, Mobile Freeze-Net performance has increased 1-2%. Overall, our proposed framework has outperformed all the existing models, shown in Table-1. In order to prove the validity of our proposed model, we have conducted 10 fold cross validation experiments on both of the models Mobile Freeze-Net and proposed model (i.e. Mobile Freeze-Net + Attention-based loss function). This can be further observed from Table-2. **Each fold's result along with the validation and training graph, its confusion matrix and calculation of attention weights can be further found in GitHub website (https://github.com/RahulKhurana-16/MobileFreezeNet)**.

Table 2: 10-fold Cross Validation results for Mobile Freeze-Net (Weighted Average) of Testing

folds	F1Score	Accuracy	Precision	Recall	AUC
Mean ± std dev of Mobile Freeze-Net	0.930 ± 0.006	0.930± 0.006	0.931± 0.005	0.929± 0.006	0.986± 0.002
Mean ± std dev **of proposed Framework**	**0.940** ± 0.004	**0.939**± 0.004	**0.940**± 0.004	**0.939**± 0.004	**0.988**± 0.002

This can be observed from Table-2 that, both of the models Mobile Freeze-Net and proposed model have very stable performances, since their standard deviation is significantly less. Another very important observation can be made from Table-2 is that, overall there is 1% improvement of Mean value of evaluation metrics, after incorporating Attention-based loss function. This is a significant improvement, according to our perception.

5 CONCLUSIONS

A 50% Freezing Mobile-Net V2 model along with attention based loss function was proposed for Covid-19 detection from an imbalanced CXR dataset. Attention weights of WCCE loss function are computed from the statistical inference of the dataset and thereafter, it is incorporated in the Mobile Freeze-Net model. Experimental results suggested that the performance of Mobile Freeze-Net has been improved 1-2% after employing attention based loss function. Moreover, the proposed framework outperformed other existing CNN models for Covid-19 detection from CXR dataset.

ACKNOWLEDGMENTS

This work is not supported or funded by any organization.

REFERENCES

[1] Muhammad EH Chowdhury, Tawsifur Rahman, Amith Khandakar, Rashid Mazhar, Muhammad Abdul Kadir, Zaid Bin Mahbub, Khandakar Reajul Islam, Muhammad Salman Khan, Atif Iqbal, Nasser Al Emadi, et al. 2020. Can AI help in screening viral and COVID-19 pneumonia? *IEEE Access* 8 (2020), 132665–132676.

[2] Janmenjoy Nayak, Bighnaraj Naik, Paidi Dinesh, Kanithi Vakula, B Kameswara Rao, Weiping Ding, and Danilo Pelusi. 2021. Intelligent system for COVID-19 prognosis: A state-of-the-art survey. *Applied Intelligence* 51, 5 (2021), 2908–2938.

[3] Coronaviridae Study Group of the International et al. 2020. The species Severe acute respiratory syndrome-related coronavirus: classifying 2019-nCoV and naming it SARS-CoV-2. *Nature microbiology* 5, 4 (2020), 536.

[4] Santanu Roy, Mrinal Tyagi, Vibhuti Bansal, and Vikas Jain. 2022. SVD-CLAHE boosting and balanced loss function for Covid-19 detection from an imbalanced Chest X-ray dataset. *Computers in Biology and Medicine* (2022), 106092.

[5] Manu Siddhartha and Avik Santra. 2020. COVIDLite: A depth-wise separable deep neural network with white balance and CLAHE for detection of COVID-19. *arXiv preprint arXiv:2006.13873* (2020).

[6] Mrinal Tyagi, Santanu Roy, and Vibhuti Bansal. 2022. Custom Weighted Balanced Loss function for Covid 19 Detection from an Imbalanced CXR Dataset. In *2022 26th International Conference on Pattern Recognition (ICPR)*. IEEE, 2707–2713.

[7] Linda Wang, Zhong Qiu Lin, and Alexander Wong. 2020. Covid-net: A tailored deep convolutional neural network design for detection of covid-19 cases from chest x-ray images. *Scientific Reports* 10, 1 (2020), 1–12.