PRNet: Progressive Resolution based Network for Radiograph based disease classification

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***Abstract*—COVID-19 and Pneumonia have impacted human life significantly. The number of infected people and deaths are increasing every day due to COVID. Rapid COVID detection is important to control and stop the spread of the disease. Considering that AI can play a significant role in accurate and fast detection of such diseases, EE-RDS conducted a multi-class classification challenge by providing chest X-rays of pneumonia, COVID-19 and normal patients. We proposed PRNet, a novel deep learning pipeline and achieved 96.3% accuracy winning the 2nd position on the test set Leaderboard.**

***Index Terms*—Medical Imaging, Deep Learning, COVID Detection, Pneumonia Detection**

I. Introduction

AI is an emerging field playing an indispensable role in solving real-world challenges. From inception, machine learning has solved innumerable problems in the medical field including disease diagnosis and patient safety prediction. CNN's introduced by Bengio and Lecun (1) shifted the field of medical imaging by improving the performance on various tasks like cancer segmentation (2) and brain tumour prediction. After CNN's, deep learning improved the performance on multiple problems such as planing spine surgery X-ray images (3), video based phenotype detection (4) brain tumour classification from chest X-rays (5) and anomaly detection in Retinal OCT images (6).

COVID-19 has swayed human life to a great extent. According to the World Health Organization, more than 2.37 million people have been diagnosed with COVID-19 (7) and 4.8 million have died due to this disease. Similarly, according to a recent survey, 15% of all children under the age of 5 died of pneumonia in 2017 (8). Early and affordable detection is critical to improve the patient outcomes for these diseases.

The pandemic has reduced the efficacy of the the already overburdened clinicians. Therefore, recent studies have turned to machine/deep learning for accurate and speedy classification of diseases from Radiographs. Madan *et al.* (9) proposed a CNN model called "XCOVNet" which categorizes X-Rays into COVID Positive and COVID Negative with an accuracy of 98.44%. Similarly, Khan *et al.* (10) designed a CNN model using Xception architecture (11) as a backbone followed by 3 fully connected layers. Their dataset comprised of 4 classes i.e., Normal, Pneumonia Viral, Pneumonia Bacterial and COVID-19 and they were able to achieve an overall accuracy of 89.6%. Wand & Xia proposed "ChestNet" (12) in 2018 to classify thoracic diseases on chest Radiographs. They used ChestX-ray14 dataset for the training and evaluation. Their approach consisted of two branches i.e., classification branch and an attention branch. The classification branch is responsible for classifying the x-ray into one of the 14 classes whereas the attention branch is used to exploit the correlation between labels of class and the regions of pathological abnormalities via analyzing the learned feature maps. The architecture used for classification branch was Resnet-152 with pretrained weights on ImageNet. Similarly, Rajpurkar *et al.* predicted pneumonia from chest X-rays better than practicing radiologists using F1 as a metric. They used a 121-layer convolutional neural network to train on ChestX-Ray14 dataset.

A recent challenge to classify Pneumonia, COVID-19 and Normal Patients from chest X-rays was launched by Ethics and Explainability for Responsible Data Science (EE-RDS). In this challenge, they provided 5000+ COVID, 4000+ Pneumonia and 7000+ Normal Patients Chest X-ray Images for training. The validation set consisted of 1432 COVID, 1000 Pneumonia and 1000 normal patients. Similarly the test set without labels was given to ratify the model validity. This dataset is taken from different hospitals and different health professionals with different modalities to help advance the research in the medical field. We scored 96.33% Accuracy with 2nd position on Test Set Leaderboard on the grand-challenge.

II. Methodology

1) Experimental Setup: We used pytorch (13) as the deep learning framework to perform our experiments. In each experiment we used batch size of 16, total epochs 20, early stopping criteria for every 5 epochs. We used gradual warmup-scheduler for 3 epochs and cosine annealing learning rate scheduler for the remaining epochs to adjust the learning rate.

2) Scheduler Adjustments: We used gradual warm-up that increases the learning rate from small to a large value for some epochs. This increase in learning rate from small to large avoids a sudden jump which allows healthy convergence (14).

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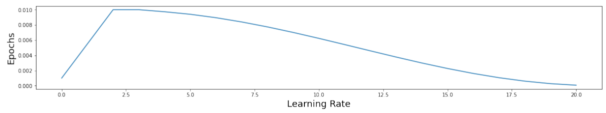

Figure 1: This figure shows the learning rate adjustment using Gradual Warmup Scheduler for 3 epoch and then Cosine Annealing Scheduler for 17 epochs EfficientNet-B0.

We used gradual warm-up for 3 epochs which allows us to train our model with higher learning rate for 3 epoch (Figure 1). After gradual warm-up we adjust our model to Cosine Annealing learning rate scheduler for 17 epochs(15). In our case Cosine Annealing learning rate scheduler starts after the third epoch and decreases the learning rate gradually using Cosine Annealing in each epoch.

We performed our experiments with state-of-the-art EfficientNet backbones (16). We started with Image size of 512x512 and trained EfficientNet-B0 but observed underfitting in multiple circumstances. We then focused on training a deeper model and trained EfficientNet-B5 which resulted in 96.00% Accuracy on test set. To improve this model we designed a training pipeline that achieved 2nd position on Test Leaderboard.

A. Progressive Resolution Training

We designed an improved pipeline of training to focus on global level to local level features progressively. Our training pipeline was designed in 5 steps to improve learning of the model. Figure 2 represents training pipeline with each step.

In first step, we started by training a deeper model (EfficientNet-B5) on 256x256 sized images until its convergence. In the second step, we increased image size to 380x380 and trained the same model with previously trained weights (256x256) until convergence. In the third step, we increased the image size to 460x460 and fine-tuned same model with previously trained weights (380x380) until convergence. In the fourth step, we increased the image size to 512x512 and fine-tuned the same model with previously trained weights (460x460) until convergence. In the fifth step, We increased the image size to 640x640 and fine-tuned same model with previously trained weights (512x512) until convergence. To improve our final model we introduce a probability adjustment approach that achieved 2nd position on Test Leaderboard.

B. Bias-Adjustable Softmax

We introduced a novel way to adjust the skew of the probabilities for each class to adjust the bias at inference level. We modified the Standard Softmax by adjusting a parameter p.

$$\text{Bias Adjustable Softmax} = \left(\frac{\exp(x_i)}{\sum_{j=1}^{J}\exp(x_j)}\right)^p \quad (1)$$

where x is the input logits to softmax, J is the number of classes. The p value is dependent on class weights and its value adjusts the skew of class probabilities. We used this bias adjustable algorithm to win 3rd position in Diabetic Foot Ulcer Challenge 2021 in MICCAI 2021 (17).

1) Bias Adjustable Softmax Heuristic: A heuristic to find value of p for Softmax is shown in Algorithm 1. We start by initializing number of classes C and maximum search space M. We iterate for each class C to search for its p value. We sub-iterate from 0 to M with a step size of 0.01 to search p value as i. In each sub-iteration, we set i as the exponent of Softmax and check the ratio of classes among the complete data. If the ratio is approximately the same as in training dataset, then we select this i as p and move to the next class.

Algorithm 1 Heuristic to find p

```
Initialize C                       ▷ C : Number of Classes
Initialize M    ▷ M : Max search space (Default Value 5)
Initialize j = 0
while j < C do
    X = C_j                         ▷ X : Selected Class
    PD     ▷ X : Probability Distribution of Selected Class
    TD   ▷ X : Training Set Distribution of Selected Class
    Initialize i = 0
    while i < M do
        if PD^i ≈ TD then
            P_j = i
            break
        end if
        i = i + 0.1
    end while
    j = j + 1
end while
```

We use Algorithm 1 to find p value based on distribution of training dataset. At inference, p value ensures that there will be approx the same distribution of minority classes as in the training dataset. We believe such heuristic can help a model to adjust probability curve in case of highly imbalanced classes.

C. Data Augmentation

As the dataset contained limited images for each class and the distribution of the images was imbalanced, it was important to use data augmentation to generalize the model. We used albumentations (18) with pytorch to add augmentations. We used the following augmentations while training to generalize the model: Horizontal Flip, Random Brightness, Random Contrast, Blur, Median Blur, Gaussian Blur, Motion Blur, Optical Distortion, Grid Distortion, Hue Saturation, and Shift Scale Rotate. Figure 3 shows a batch with and without these augmentations.

D. Inference Pipeline

Our inference pipeline is designed by combining the Final Stage model (EfficientNet-B5) of Progressive Resolution Training and Bias Adjustable Softmax. Bias Adjustable Heuristic converged with values 1.0, 0.4, and 1.6 respectively for classes COVID, Pneumonia, and Normal. Our Inference pipeline is shown in 4.

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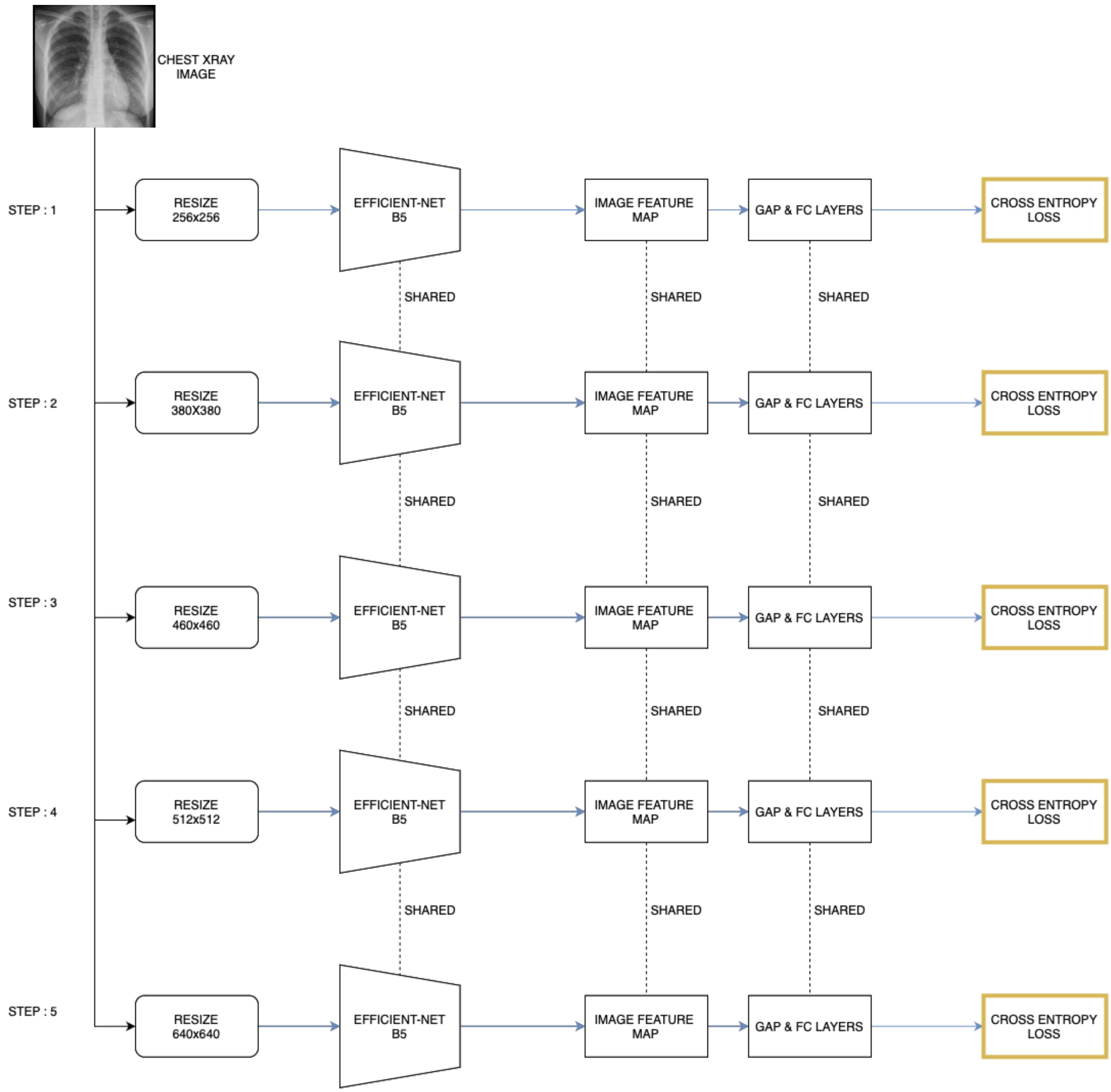

Figure 2: This figure represents our progressive training pipeline step-by-step. In each step, we increase the image size and fine-tune the model. Model after step 5 achieved 96.17% Accuracy on Test Leaderboard.

III. Results and Discussion

We compared the performance of light convolutional neural network EfficientNet-B0 and deeper convolutional neural network EfficientNet-B5 with Constant Resolution and Progressive Resolution. We also compared the performance of these pipelines using Bias-Adjustable Softmax.

Table I represents the comparison of Progressive Resolution based and Constant Resolution based training. Moreover, it shows the comparison of Bias-Adjustable Softmax and Standard Softmax on these training pipelines. EfficientNet-B5 with Progressive Learning and Bias-Adjustable Softmax achieved Accuracy of 96.33% on Test Set Leaderboard.

We observe that, training a model on small images and increasing image size gradually allows the model to learn features from bird-eye view and then gradually learn the detailed features as Image size increases in the training. This Progressive Resolution training can be used in multiple image classification problems in the future.

IV. Acknowledgements

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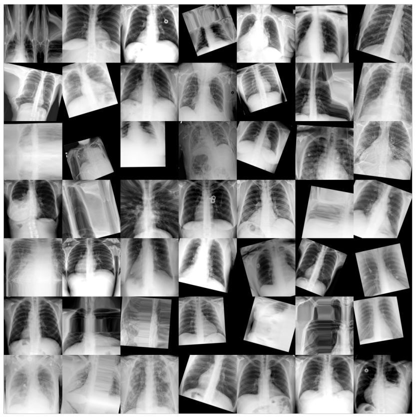
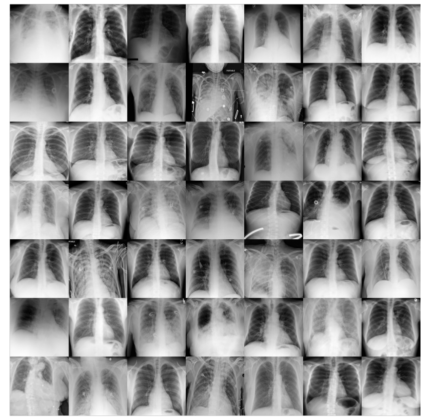


(a) Training Batch with Augmentations



(b) Training Batch with No Augmentations

Figure 3: Comparison of Chest XRay Images with and without augmentations

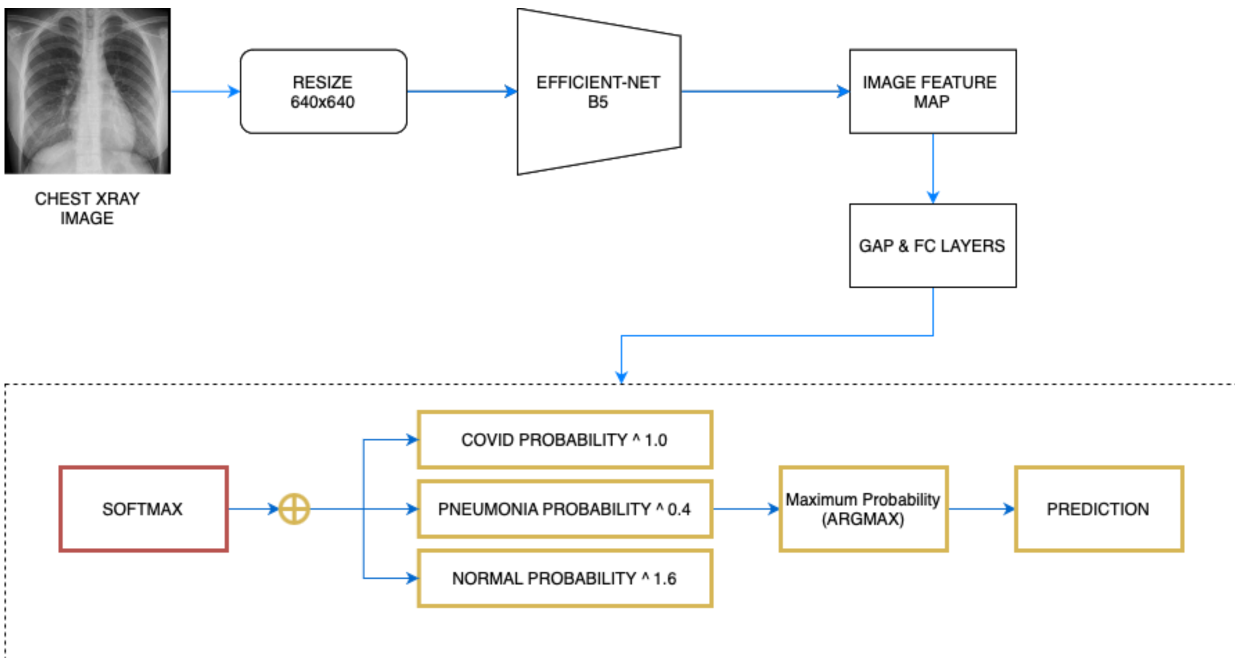


Figure 4: This figure represents inference pipeline of our progressively trained model with Bias Adjustable Softmax. We applied Bias Adjustable Softmax with p values of 1.0, 0.4, and 1.6 respectively for classes COVID, Pneumonia, and Normal.

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Backbone	Image Size	Progressive Resolution	Bias Adjustable Softmax	5-Fold Accuracy	Validation Accuracy	Test Accuracy
EfficientNet-B0	512x512	No	No	96.73%	96.02%	95.66%
EfficientNet-B0	512x512	No	Yes	97.77%	96.41%	96.00%
EfficientNet-B0	640x640	Yes	No	97.13%	96.75%	95.80%
EfficientNet-B0	640x640	Yes	Yes	97.83%	97.28%	96.00%
EfficientNet-B5	512x512	No	No	97.40%	97.11%	96.00%
EfficientNet-B5	512x512	No	Yes	97.91%	97.55%	96.03%
EfficientNet-B5	640x640	Yes	No	97.58%	97.49%	96.17%
EfficientNet-B5	640x640	Yes	Yes	97.99%	97.73%	96.33%

Table I: A comparison of state-of-the-art Image Classification backbones with Bias-Adjustable Softmax and Standard Softmax

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