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Quadruplet loss and SqueezeNets for Covid-19 detection from Chest-X rays

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Abstract

The Coronavirus Pandemic triggered by SARS-CoV-2 has wreaked havoc on the planet and is expanding exponentially. While scanning methods, including CT scans and chest X-rays, are commonly used, artificial intelligence implementations are also deployed for COVID-based pneumonia detection. Due to image biases in X-ray data, bilateral filtration and Histogram Equalization are used followed by lung segmentation by a U-Net, which successfully segmented 83.2% of the collected dataset. The segmented lungs are fed into a Quadruplet Network with SqueezeNet encoders for increased computational efficiency and high-level embeddings generation. The embeddings are computed using a Multi-Layer Perceptron and visualized by T-SNE (T-Distributed Stochastic Neighbor Embedding) scatterplots. The proposed research results in a 94.6% classifying accuracy which is 2% more than the baseline Convolutional Neural Network and a 90.2% decrease in prediction time.

Keywords: COVID-19, Deep Learning applications, Lung Segmentation, X-Rays-based prediction

MSC 2020: 68R10, 68Q25, 05C35, 05C05.

1 Introduction

The rampant increase in Covid-19 caused by Severe Acute Respiratory Syndrome Coronavirus 2 (SARS-CoV-2) [1] has induced world-wide trauma. With conventional and limited testing criteria resulting in false negatives, [2] and repeated testing. This paper proposes a similarity learning implementation to accelerate coronavirus detection.

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The model can be used as a screening platform for RT-PCR tests [3], quickening covid detection and streamlining the process. Image biases caused due to a variety of different X-ray apparatus in the publicly available datasets are avoided by using Histogram Equalization and U-Net-based Chest segmentation [4]. The image biases consist of various insignificant textual data on images along with varying contrast values which can hinder training and feature learning. The sample images which show these imbalances are mentioned below in Figure 1.

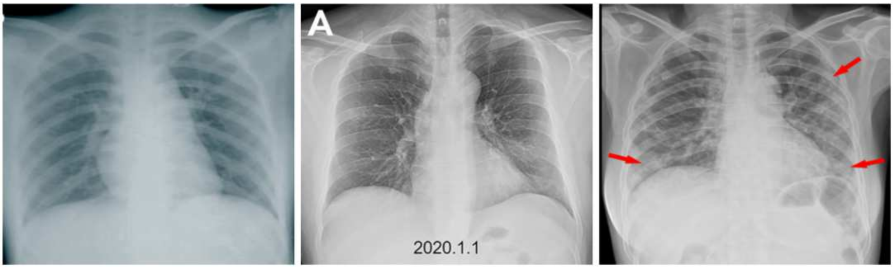

Figure 1. The first image contains a different color balance, the second image illustrates textual data and the third image carries various insignificant symbols that might hinder training

The proposed model is a Siamese Network [5] with SqueezeNet-based [6] vector generators, trained on Quadruplet Loss [7] which is used to procure high-level embeddings. The encoder architecture is kept as a vanilla SqueezeNet due to the lightweight nature, minimal weight sizes, and significantly faster prediction rates when compared to AlexNet or similar mainstream deep architectures [6]. The embeddings are further computed using an MLP (Multi-layered Perceptron) [8] and visualized by the T-SNE algorithm (T-distributed Stochastic Neighborhood Embedding) [9]. The proposed method outperformed a baseline CNN (Convolutional Neural Network) [10] in classifying segmented lung images into three groups (COVID-19 pneumonia, Normal Cases, Other Viral and Bacterial pneumonia) with an overall classifying accuracy of 94.6%, and gave superlative computational results like an 89.8% decrease in prediction time.

2 Related Work

Many attempts have been made for accurate classification of COVID-19 Pneumonia from body scans, mainly using Computerized Tomography (CT) scans and Chest X-rays [4]. The paper [11] used a DeTraC (Decompose, Transfer, and Compose) Deep Convolutional Neural Network on Chest X-rays and achieved a classification accuracy of 93.1%. The paper [12] used a CNN-based architecture called CovXNet resulting in a multiclass percentage accuracy of 90.2 and a 97.4% accuracy for COVID19/Normal binary classification. The paper [13] used a GAN (Generative Adversarial Network) for image augmentation and Light-CovidNet architecture for X-ray classification resulting in a 96.97% mean accuracy. The paper [14] used a Truncated Inception Net on a COVID-19 X-ray dataset and obtained an accuracy of 99.92% with an AUC of 1. The paper [15] designed a fuzzy strategy known as output Neuron Holding, which modifies the twice Transfer Learning technique. They used Layer-wise Relevance Propagation (LRP) to produce heat maps to help us understand how the models work. The paper [4] pointed out the complication of image biases caused due to a diversity of X-ray machines across the globe. The networks trained on publicly available datasets learned the image biases as a classification feature instead of COVID-based Pneumonia features causing fallacious real-time results. Hence, Lung segmentation is recommended and used.

3 Methodology

Total 2697 X-rays images are obtained by subsetting two databases, for COVID-19-based pneumonia [16] and for normal and other pneumonia [17]. The X-rays images of lungs undergo U-Net-based lung segmentation for image bias avoidance and are further classified using a SqueezeNet-based quadruplet loss model and an MLP. The proposed model and baselines are trained by identical 80:20 train-test splits, for an unbiased comparison. The Grayscale Images undergo bilateral filtration to enhance image quality and histogram equalization to nullify contrast-based biases. Preprocessed images have an array shape of 256x256 and are fed into a U-Net for lung segmentation purposes.

The segmentation model is trained on the famous JSRT [18] and Montgomery dataset [19] which contains non-pneumonia chest X-rays and the ground truth Lung masks. Due to the dataset constraint for COVID-19 X-rays, unavailability of a COVID-based segmentation dataset, and image clarity uncertainties, only 83.2% of images are successfully segmented. The entire process of Lung segmentation and image preprocessing is shown below in Figure 2.

Figure 2. Sample flow of X-ray preprocessing for a segmented output

The segmented lung set is used to generate random quadruplets containing an anchor image of a particular class, a positive image with the same class, and two negative images depicting different classes. The quadruplets are fed into a Siamese network with Quadruplet Loss and four SqueezeNets, which have shared weights and are implemented for vector generation. The loss function follows the original paper [7] with the hyperparameters 'alpha' and 'beta', fine-tuned as 0.2. The model pipeline for computing Quadruplet Loss and similarity learning is mentioned below in Figure 3.

The SqueezeNets contain multiple Fire Modules and Pooling layers along with a Squeeze Ratio [6] of 0.125, which, when trained for similarity learning, generates a memory-efficient embedding space, which can be further used for pneumonia classification. The softmax layer is removed and a dense layer is added for embedding generation and similarity learning. The embeddings obtained from the SqueezeNet have a dimensionality of 256. They are further fed into a three-layered perceptron, which classifies the embeddings by computing a probabilistic distribution of the four pneumonia classes.

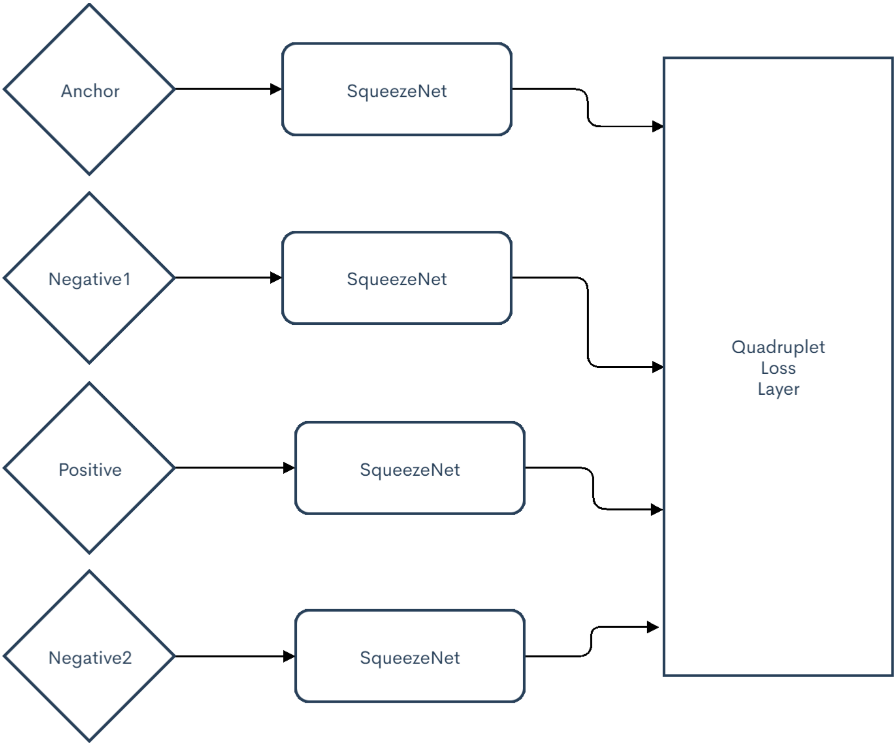

Figure 3. Data flow for the quadruplet loss network

4 Results and Discussion

To justify the use of proposed methodologies, a Convolution Neural Network (CNN) is used as a baseline. The model contains four convolutional blocks, and each block contains a convolutional layer with $2\hat{n}$ filters and a Max-Pooling layer with a pooling window of 2,2. The first block contains 32 filters followed by 64 and 128 convolutional units. The outputs are flattened and fed into a softmax layer for a probabilistic distribution of classes. The model is trained on the Cross-Entropy loss [20] function with a learning rate of 10^{-3}.

All the mentioned approaches are trained and benchmarked on a singular Google Colaboratory GPU accelerated runtime [21]. This ensures a safe and unbiased comparative study. The framework called Keras [22] is used for the deployment of all the mentioned deep learning algorithms. The proposed model gave a classifying accuracy of 94.6%, outperforming the baseline CNN by '2%'. The prediction time for the entire pipeline averaged 0.245 seconds for 449 segmented X-rays, which was 10.2 times faster than the baseline. The use of similarity learning is also deemed successful by observing the T-SNE scatter plots as the intra-class distance is minimized and the inter-class distance is maximized.

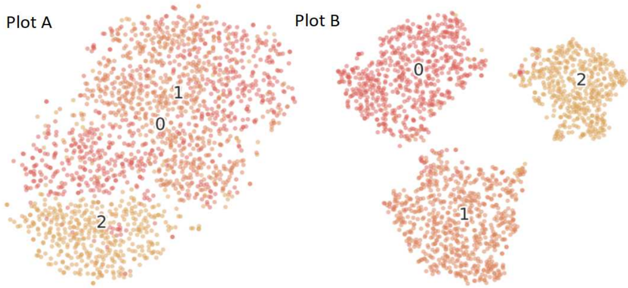

Figure 4. T-SNE Scatter plots, Plot A contains unaltered testing data whereas Plot B contains the high-level embeddings generated by the SqueezeNet Encoder. Here, '0', '1', and '2' represent 'Covid-19 pneumonia', 'other pneumonia' and 'normal cases' respectively

5 Conclusion and Future Work

The paper proposed a Quadruplet Loss approach with SqueezeNet-based vector generation for automated COVID-19 detection from chest X-rays. The said methodologies were able to successfully classify segmented lungs with an accuracy of 94.6% and an extremely low prediction time averaging at 5.45 x (10ˆ-4) seconds per image. The model outperformed a baseline CNN with an increase in classification accuracy of 2% and faster prediction times with a factor of 10.2.

For the upcoming future, we will test the robustness of the algorithm, implement multiple Encoder Architectures and work on a superior lung segmentation method for pneumonia patients which is independent of dataset constraints.

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