Ensemble of Contrast Limiting Adaptive Histogram Equalization and Cyclic Generative Adversarial Network: A Novel Data Augmentation Approach to Improve Deep Learning-based Medical Diagnosis based on X-ray Images.

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***Abstract*—In spite of abundance of research done in the neural network architecture for medical diagnosis, the data augmentation method hasn't been studied as much even though the data augmentation is equally important as the quality of model architecture especially in the field of medical diagnosis based on X-Ray images. [6] Lung X-ray samples of COVID-19 patients weren't enough to train deep neural network for detection of COVID-19 at the beginning of pandemic. The novel research done by Moris et al. [1] applied Cyclic Generative Adversarial Network to generate the additional X-ray images of COVID-19 infected lung from X-ray images of normal lungs. This research targeted to improve the existing X-ray image augmentation method of Cyclic Generative Adversarial Network (CycleGAN) by collaborating it with Contrast Limiting Adaptive Histogram Equalization (CLAHE), an algorithm to reduce the noise and improve the contrast in the image. Pre-trained residual network with ensemble of CycleGAN and CLAHE as data augmentation method achieved 99.38% validation accuracy, outperforming 92.81% of pre-trained residual network with CycleGAN alone. To further improve ensemble of CycleGAN and CLAHE, normalization in X-ray images can be applied to optimize the convergence in training CycleGAN.**

I. Introduction

While there has been floods of studies in model architecture for medical diagnosis based on X-ray images, there has not been many studies in X-ray images augmentation. In any machine learning problem, data augmentation is important as the efficiency of model architecture. For example, the samples of X-ray of those who are infected by brand-new diseases may not be sufficient to train deep neural detection model at the beginning of pandemic. To address insufficiency of X-ray images of COVID-19 infected lungs in training set, Moris et al. generated additional COVID-19 samples from non-COVID-19 samples using Cyclic Generative Adversarial Network (CycleGAN), one of image-to-image translation methods, and achieved the test accuracy of 98.61% in detecting COVID-19 samples [1].

As seen above, CycleGAN could allow COVID-19 detection model to learn increased number of samples, thereby increasing detection accuracy. However, CycleGAN might have to be trained with noise-less X-ray samples to generate generalized X-ray images. To reduce the noise, CLAHE (Contrast Limited Adaptive Histogram Equalization) can be used. CLAHE increases the contrast in X-ray images but also limit the contrast caused by noises. [2] The regulated contrast created by CLAHE may both help CycleGAN and diagnosis model to better catch the mapping difference between diseased and non-diseased samples. The purpose of this study was to test whether ensemble of CLAHE and CycleGAN is better at increasing diagnosis accuracy than CycleGAN alone.

II. Methods

The dataset used for this research consisted of normal X-ray lung samples and bacterial pneumonia patient's X-ray lung samples from Kaggle. Before training CycleGAN, training set was first augmented by CLAHE. There are two degrees of freedom in CLAHE Algorithm: clip limit and tile size. CLAHE works by moving the tile across the image and set the contrast in the area within the tile equal to or below the clip limit. [3] The clip limit was set to 2.6, and the tile size was set to 8 pixels by 8 pixels.

CycleGAN used both the samples from diseased and non-diseased patients to train both the generator that creates diseased samples from non-diseased and the generator that creates non-diseased samples from diseased. Discriminator was used to test whether generated samples are identical to actual samples. Generators will be trained by following loss function:

$$L_{Adv}(N) = E[\log(D_N(N))] + E[\log(1 - D_N(G_N(BP))] \quad (1)$$

$$L_{Adv}(BP) = E[\log D_{BP}(BP)] + E[\log(1 - D_{BP}(G_{BP}(N))] \quad (2)$$

$$Lcyc(G_N, G_{BP}) = E[\|G_{BP}(G_N(BP)) - BP\|] + E[\|G_N(G_{BP}(N)) - N\|] \quad (3)$$

$$L_{Total} = 5L_{Adv}(N) + 5L_{Adv}(BP) + 10L_{cyc}(G_N, G_{BP}) \quad (4)$$

N and BP each refers to normal X-ray images and bacterial pneumonia X-ray images. Total loss L_{total} (4) includes adversarial loss L_{Adv} and cyclic loss L_{cyc}. Adversarial loss $L_{Adv}(N)$ (1) penalizes the generator G_N if normal X-ray images generated from bacterial pneumonia X-ray images isn't classified to be normal according to discriminator D_N. Adversarial loss $L_{Adv}(BP)$ (2) penalizes generator G_{BP} in exactly same way if X-ray images of lung infected by bacterial pneumonia generated from normal X-ray images isn't classified to be in bacterial pneumonia class according to discriminator D_{BP}. Cyclic loss penalizes the inconsistency within samples created by generators G_N and G_{BP} [4]. The architecture of generator was U-Net with residual blocks in the middle. The combination of long skip connection of U-Net and short skip connection of residual block will enable the generator to converge faster [5].

To test combination of CLAHE and CycleGAN as a data augmentation method, one of pre-trained residual networks from Keras module, ResNet50, was used as a bacterial pneumonia detection model. Three data augmentation scenarios were tested with ResNet50: no data augmentation, CycleGAN alone, and ensemble of CLAHE and CycleGAN. CycleGAN generated 15 normal X-ray images from 15 bacterial pneumonia X-ray images, and vice versa. In the scenario of ensemble of CLAHE and CycleGAN, the training set for ResNet50 were first augmented by CLAHE. Then, the generator from CycleGAN generated 15 normal X-ray images from augmented 15 bacterial pneumonia X-ray images, and vice versa.

III. Results and Discussion

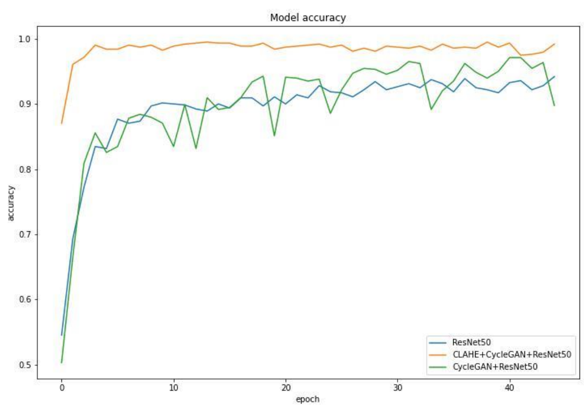

Figure 1. Graph comparison of training accuracy for ResNet50 with different data augmentation scenarios.

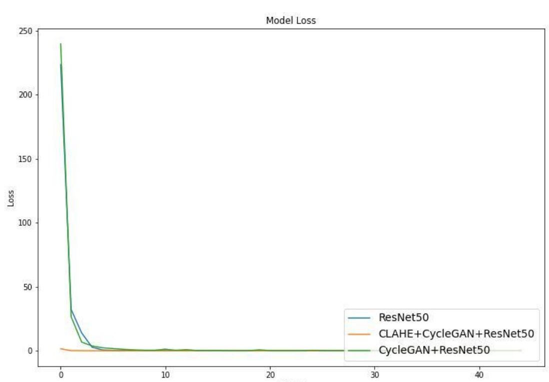

Figure 2. Graph comparison of training loss over epoch for ResNet50 with different data augmentation scenarios.

Models	***Data Augmentation***	***Performance on validation set***	
		Accuracy	***Binary Cross Entropy Loss***
ResNet50	*CLAHE+CycleGAN*	**99.38%**	**0.0155**
ResNet50	*CycleGAN*	92.81%	0.1748
ResNet50	*No Data Augmentation*	93.17%	0.1674

Figure 3. Comparison of validation accuracy and loss for ResNet50 with different data augmentation methods.

As shown in Figure 1, ResNet50 with CLAHE and CycleGAN converged fastest to the highest training accuracy. Without additional generated samples by CycleGAN and CLAHE, ResNet50 converged stably but achieved the lower training accuracy. With additional generated samples but without CLAHE, ResNet50 with CycleGAN achieved the higher training accuracy than ResNet50 with no data augmentation at a few epochs but overall, failed to converge. The reason why ResNet50 with CycleGAN failed to converge might be that CycleGAN produced the low-quality training samples because it poorly mapped the features of X-ray images without CLAHE. With failed convergence in training session, ResNet50, with augmented training dataset by CycleGAN, rather achieved accuracy of 92.81% lower than 93.17% of ResNet50 with no augmentation. On the other hand, CLAHE has enabled CycleGAN to catch the important features of each class and generate the high-quality X-ray and detection model ResNet50 to catch the contrasting features between X-ray images in bacterial pneumonia and normal class, which led ResNet50 with CycleGAN and CLAHE to achieve the highest validation accuracy of 99.38%.

IV. Conclusion

Data augmentation is important as the model architecture especially treating limited number of X-ray images. To solve the issue of limited number of COVID-19 infected lung X-ray images Moris et al. used CycleGAN to generate additional X-ray images of COVID-19 infected lung from normal X-ray images. This research shows that combination of CycleGAN and CLAHE outperformed CycleGAN alone as a data augmentation method. To improve the proposed data augmentation method further, normalization could also be applied before applying CLAHE to X-ray images. Trained by normalized images, CycleGAN would be able to converge faster due to decreased fluctuation in gradients.

V. References

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