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DEEP LEARNING TECHNIQUES FOR RETINAL IMAGE ENHANCEMENT

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ABSTRACT

Image enhancement is the most important technique used in image research. The purpose of image enhancement is to improve image quality and appearance. One of the most steps in medical image detection and analysis is image enhancement techniques. Retinal image quality complicates clinical diagnosis by computer-aided diagnostic systems and ophthalmologists. Existing methods, such as histogram-based, fusion-based, and Retinex theory-based methods, were more effective for low- and high-illumination images but were ineffective for low-quality fundus images such as blurring and color distortion. To enhance low-quality retinal images, deep learning-based retinal image enhancement was proposed. CLAHE is used to improve the visibility of foggy. To build symmetric networks, we use generative adversarial networks to improve feature extraction. The proposed method is qualitatively and quantitatively analyzed using public and private datasets with key performance indicators such as accuracy. The CycleGAN method is more accurate than the CLAHE method, especially in improving color-distorted retinal images.

Keywords: Retinal Images, Image Enhancement, CLAHE, CycleGAN, Deep Learning.

I. INTRODUCTION

Image enhancement plays a role in image processing functions, where people know to make choices regarding image information. Forms of image enhancement include noise reduction, lateral enhancement, and discriminant enhancement. It can also be a technique to enhance the popularity of electrically saved images by lightening or darkening the image and widening or decreasing the contrast. Image enhancement involves the sensitivity of information in an image to the viewer or presenting enhanced input to other conventional image processing processes. Enhancement procedures have two classes: spatial domain methods and transform domain methods. Spatial domain strategy enhances an image by managing its power and esteem. A large number of systems have focused on the enhancement of gray-level images in spatial space. These techniques incorporate high-pass filtering, low-pass filtering, homomorphism filtering, etc. These procedures have color image enhancement in RGB space. Enhancement frameworks transforming the image power data into a particular area by utilizing strategies, for example, discrete Fourier transform (DFT), discrete cosine transform (DCT), and so forth, and the image is modifying the frequency substance of the image. Most Often, image enhancement algorithms are applied to remotely sensed data to produce a new and improved an image. The improved image is generally easier to comprehend than the original. Remote sensing images collected in multispectral bands, i.e., the same scene scanned in several spectral bands of the EM spectrum. Retinal fundus images provide rich information on pathological changes that may cause arteriosclerosis, diabetes, hypertension, stroke, and cardiovascular disease. These images are for the diagnosis of related diseases. Due to the complicated imaging conditions, the retinal fundus images typically have low contrast, inconsistent lighting, and blurred features. The augmentation of retinal fundus images increase contrast of the retinal vessels. The retinal image enhancement method proposed using deep learning to enhance multiple low-quality retinal images. The retinal image enhancement technique was preventing the creation of artificial boundaries, sharp changes in color saturation, and the loss of image information. To get an image with the essential components of the original image, we first employed normalized convolution with a domain transform. Then, the image containing the basic information was fused with the original image to enhance the vessels and detail of the retinal fundus image. Lastly, these images went through denoising filters to achieve image enhancement. These are for enhancement of low-quality images.

II. LITERATURE SURVEY

[1] Title: A Study an Image Fusion for the Pixel Level and Feature based Techniques

Author: Usha Thakur, Sonal Rai

Description:

The fusion approach is achieved in a multi-decision style use of Laplacian pyramid decomposition to account for the multi-channel residences of the human visible system. For this purpose, metrics defined for contrast, image brightness, and saturation. Quantitative measurements for contrast, brightness, and saturation have been used to examine the performance of the suggested technique. The outcomes demonstrate the method's effectiveness in improving details without distorting the color scheme or adding saturation artifacts, and they also serve as an excellent example of how fusion techniques can be applied to enhance images.

[2] Title: A histogram-based approach for object-based query-by-shape-and-color in image and video databases

Author: Ediz S¸ aykol, Ugur Gudukbay, O zgur Ulusoy

Description:

The Histogram equalization approach uses three specialized histograms (i.e., distance, angle, and color histograms) to store information based on extracted characteristics of objects. Images and video frames can have objects retrieved from them. The feature-driven query subsystem of a video database management system has implemented the recommended histogram-based technique. Color and shape information is processed together to enrich query capabilities for content-based retrieval. The evaluation of the recovery efficiency and robustness of the proposed method is presented through performance experiments.

[3] Title: Retinex theory for color image enhancement: A systematic review

Author: Ruaa Riyadh Hussein, Yaser Issam Hamodi, Rooa Adnan Sabri

Description:

The Retinex theory aims to explain human perception of color. Furthermore, his research on the modification of reflective components has introduced approaches to enhance the contrast of images. The classical theory of Retinex and Retinex techniques that have been advanced and improved in the literature were discussed in this review. Therefore, a powerful framework for modifying the reflectance component of Retinex theory can be developed to improve the overall quality of color images.

III. METHODOLOGY

The proposed methodology uses the retina images as input data, and data is preprocessed and removes the blur and color deformation on images using the CycleGAN. CLAHE and CycleGAN styles methods for enhancing the pictures and also give high-quality images as an affair. These styles are used to enhance retinal images and compare CLAHE and CycleGAN. CycleGAN is an image-to-image restatement model. A deep convolutional neural network can be trained for image-to-image restatement tasks using the Cycle Generative Adversarial Network, or CycleGAN. The Network learns a mapping between input and affair images using an unmatched dataset.

To enhance low-quality retinal images, deep learning-based retinal image enhancement was proposed. Retinal image enhancement techniques aim to prevent artificial borders, sudden changes in color levels, and loss of visual information. To get an image with the essential components of the original image, we first employed normalized convolution with a domain transform. The vessels and details of the retinal fundus were then enhanced using the basic information image and the original image. Finally, the combined images were passed through a noise reduction filter to achieve image enhancement, and this enhances the low-quality pictures.

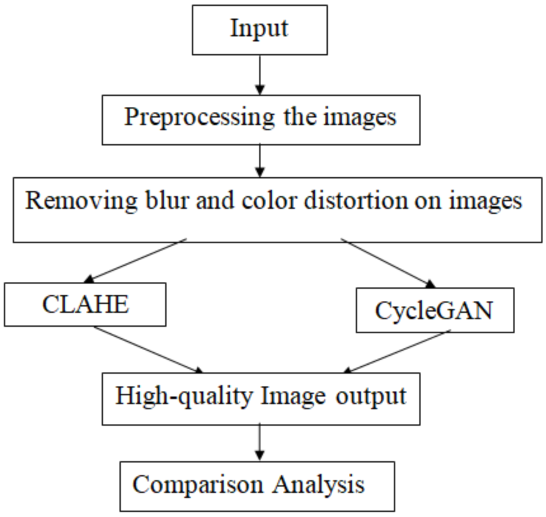

Figure 1: Flow chart of proposed methodology

IV. MODELING AND ANALYSIS

Deep learning-based techniques help achieve this as they are very good at capturing complex patterns and can approximate mathematical functions with very high accuracy. Neural networks are mathematical models of the human brain which used to implement pattern recognition algorithms. The major purpose of using these mathematical models is to locate these complex patterns and predict the outcome of an event. They learn weights for inference by being trained on previously collected data. The retinal image enhancement method is proposed on deep learning to improve many low-quality retinal images. Besides blur, there are many other types of causes of poor-quality images that reduce the feasibility of retinal image processing.

General adversarial networks (GANs) proposed by using neural networks to generate images. However, the user cannot control the GAN or create specific images. Based on the GAN, the cycle-constrained adversarial network (CycleGAN) used cyclic consistency to successfully separate the image content and style, thus preserving the image content while changing the style of the image. The main contributions of this paper study can be summarized as follows: The ability to convert image patterns prompted us to consider using CycleGAN to improve retinal imaging. This method uses deep learning techniques for feature extraction to achieve image enhancement tasks.

Implementation

- Public and Private datasets
- Image Preprocessing
- Using CLAHE Method
- Using CycleGAN Method

Public and Private Datasets

To train the retinal image improvement network proposed in this study, we use the EyePacs dataset and a personal dataset. The training set of the EyePacs dataset includes 3000 color retinal images, of which 2000 are low-quality, and 1000 are high-quality. We aimlessly elect 1600 low-quality and 600 high-quality images to construct the dataset for the image improvement network. The named images suffer a double-eyeless review of the image quality evaluation by three retinal ophthalmologists. The training set consists of 1000 low-quality and 400 high-quality images: the remaining 600 low-quality and 200 high-quality images from the test set. The private dataset is from the L V Prasad Eye Hospital and consists of 50 retinal images with moderate glaucoma and 50 retinal images without glaucoma.

Image Preprocessing

Image processing is for applying various procedures to an image to improve it or extract relevant information from it. It's a type of signal processing in which the input is an image, and the affair may be an image or characteristics features associated with that Image.

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- Using Image preprocessing, the image path is read from the dataset is divided into testing and training.
- Those images are stored in the cargo images brochure containing in arrays.

Contrast Limited Adaptive Histogram Equalization (CLAHE) Method

Adaptive histogram equalization (AHE) is an image preprocessing approach to enhance differences between the images. These are used to calculate multiple histograms involving specific sections of the photo to redistribute the brightness of an Image. It's hence able to perfect the original difference and enhance the descriptions of edges in each region of an image. However, AHE tends to over-amplify noise in the kind of homogeneous regions of an Image. By limiting the modification, a variety of adaptive histogram equalization known as difference-limited adaptive histogram equalization (CLAHE) avoids this effect.

The main three components of the CLAHE method are bilinear interpolation, histogram equalization, and generation. There are portions in the photographs. A tile is the name of each part. There are four parts in the input image that is displayed. Histogram equalization is also performed on each tile using a predefined clip limit. Histogram equalization consists of five varieties histogram computation, excess calculation, excess distribution, excess redistribution, and scaling and mapping using an additive distribution function (CDF). The histogram is a set of cases for each tile. The clip limit improvement in histogram bin values is compounded and distributed to other bins. CDF was calculated for the histogram values. CDF values of each tile are measured and designed using the input image pixel values. The affecting tiles are kept together using bilinear interpolation to create an output image with a bettered difference.

CycleGAN

CycleGAN allows us to use unpaired training data. This method implies that we do not require exact correspondences between specific images in domains A and B to teach it to translate Images between them. Even when there are no photographs of a zebra in precisely the same posture as a horse, with the same background, etc., humans can translate between images of horses and zebras. With no need to match training pairs, CycleGAN enables learning a mapping from one domain A (for example, photos of horses) to another domain B (for example, images of zebras). Here is a list of the distinctions between paired and unpaired data:

- Paired training data: {(a (i), b (i))} N i=1
- Un-paired training data:

– Source set: {a (i)} N i=1 with each x (i) ∈ A

– Target set: {b (j)} M j=1 with each y (j) ∈ B

– For example, A is the set of horse pictures, and B is the set of zebra pictures, where there are no direct correspondences between images in A and B.

Algorithm CycleGAN Training Loop

1: procedure TRAINCYCLEGAN

2: Draw a mini batch of samples$\{a^{(1)},\ldots,a^{(m)}\}$ from domain A

3: Draw a mini batch of samples $\{b^{(1)},\ldots,b^{(n)}\}$ from domain B

4: Compute the discriminator loss on real images:

$$\mathcal{J}_{real}^{(D)}=\frac{1}{m}\sum_{i=1}^{m}(D_A(a^{(i)})-1)^2+\frac{1}{n}\sum_{j=1}^{n}(D_B\,(b^{(j)}-1))^2$$

5: Compute the discriminator loss on fake images:

$$\mathcal{J}_{fake}^{(D)}=\frac{1}{m}\sum_{i=1}^{m}(D_B(G_{A\to B}(a^{(i)})))^2+\frac{1}{n}\sum_{j=1}^{n}(D_A(G_{B\to A}(b^{(j)})))^2$$

6: Update the discriminators

7: Compute the B→A generator loss:

$$\mathcal{J}^{(G_{A\to B})}=\frac{1}{n}\sum_{j=1}^{n}(D_A\left(G_{B\to A}(b^{(i)})\right)-1)^2+\mathcal{J}_{cycle}^{(B\to A\to B)}$$

8: Compute the A→ B generator loss:

$$\mathcal{J}^{(G_{A\to B})} = \frac{1}{m}\sum_{i=1}^{m}(D_B\left(G_{A\to B}\left(a^{(i)}\right)\right) - 1)^2 + \mathcal{J}_{cycle}^{(A\to B\to A)}$$

9: Update the generators

Using CYCLEGAN

- This approach makes use of both generators and discriminators.
- One generator produces images for the second domain using input from the first domain.
- The second generator produces images for the first domain using images as input from the second domain.
- Following that, the generator models are adjusted by the results of discriminator models, which evaluate how plausible the generated images are.
- To distinguish between the images' style and substance, this method makes use of cycle consistency.

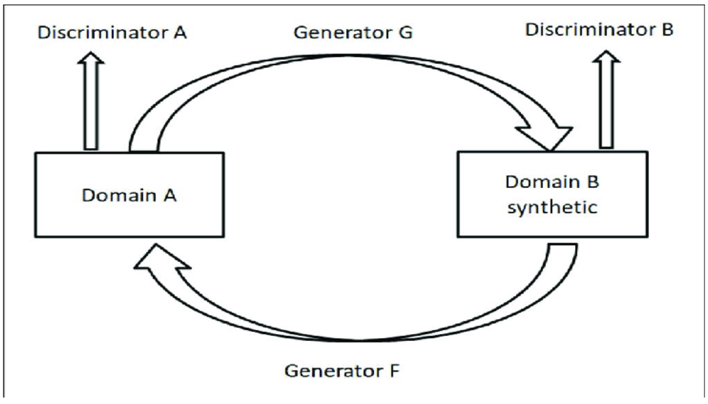

Figure 2: CYCLEGAN Architecture

- It consists of mapping function (G and F) that acts as generators and their corresponding Discriminators (DA and DB)
- 2 Generators are G: AtoB, F: BtoA

Where A is the input image distribution, and B is the desired output distribution.

The two discriminators are

DA: distinguish G (A) (Generated Output) from B (Real Output)

DB: distinguish F (B) (Generated Inverse Output) from A (Input distribution)

The main aim behind CycleGAN is to introduce a cycle consistency loss to constrain the model. The method is to translate an image from domain A to domain B and then translate the generated image back to domain A. The cycle consistency component of the loss is the mean squared error between the input images and their reconstructions obtained by passing through both generators in sequence (i.e., from domain A to B via the A→B generator and then from domain B back to A via the B →A generator). The cycle consistency loss for the B →A→ B cycle is as follows:

$$\frac{1}{m}\sum_{i=1}^{m}\left(b^{(i)} - G_{A\to B}\left(G_{B\to A}\left(b^{(i)}\right)\right)\right)^2$$

The loss for the A → B→ A cycle is analogous.

V. RESULTS AND DISCUSSION

The below mentioned results are CLAHE and CycleGAN methods.

Results of CLAHE method

- Normalizing the histogram to get a discrete PDF.
- And the CDF is given by calculating the cumulative sum of the PDF data.
- Uses the equalization function to give an equalized image.
- The final step is to un-normalize the CDF to become the equalization function and result in the image.

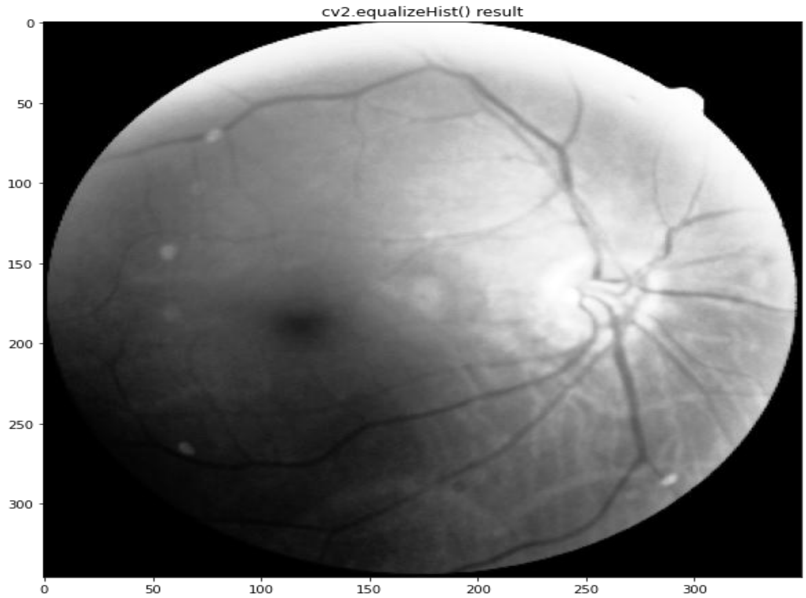

Figure 3: CLAHE Image

Results of CYCLEGAN method

Using the functions, we trained the network for 200 epochs. The outcome is that our network was successful in reducing the poor fundus images. And the generated images are AtoB and BtoA images. By using two datasets, public and private images are generated.

- Below images are generated using Public dataset.

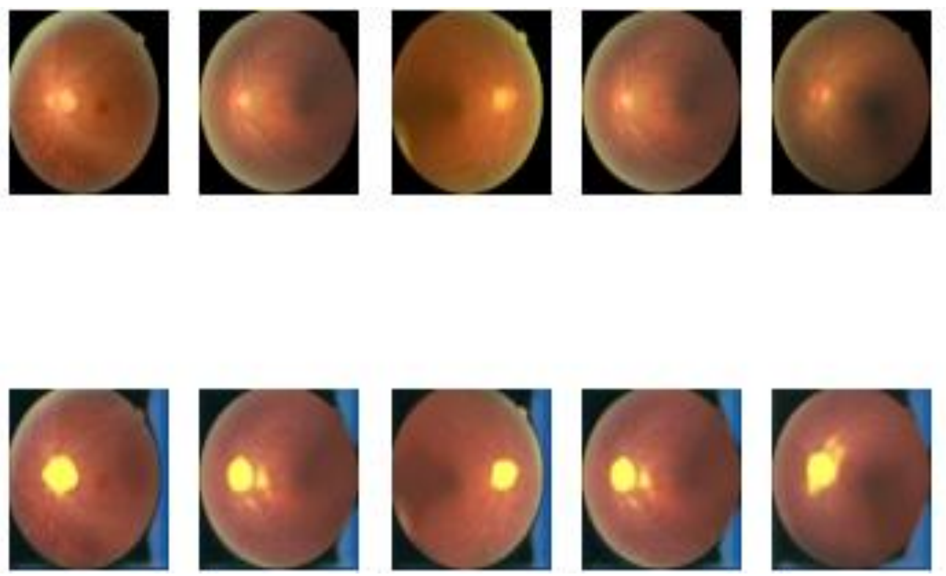

Figure 4: During 100th epoch of generated image

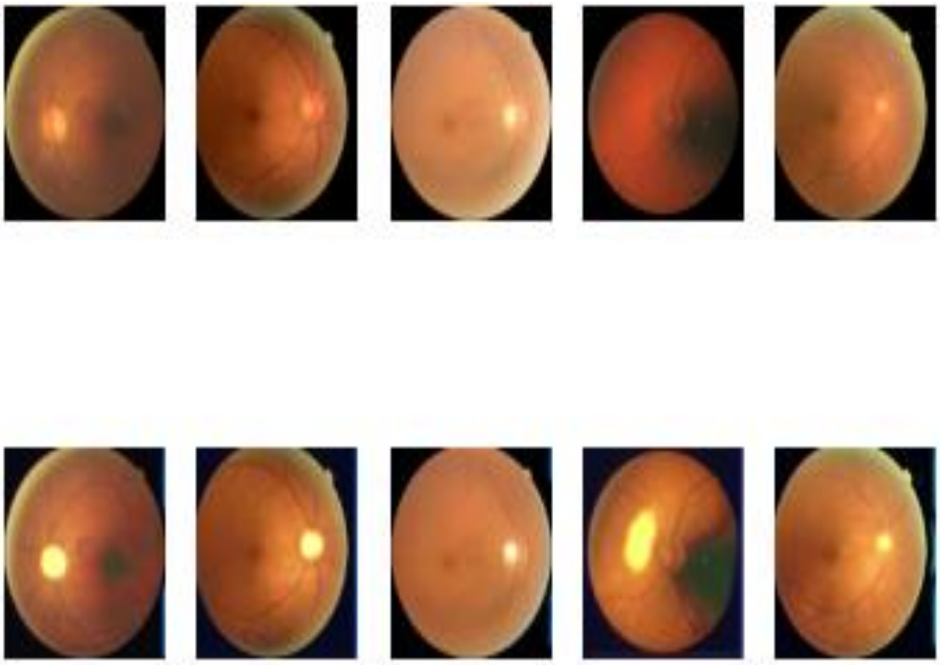

Figure 5: During 200th epoch of generated image

- Below images are generated using Private Dataset.

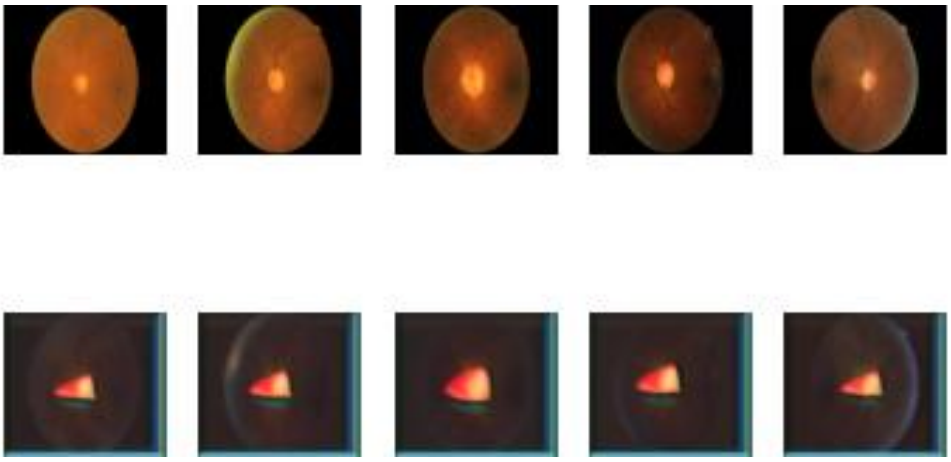

Figure 6: During 100th epoch of generated image

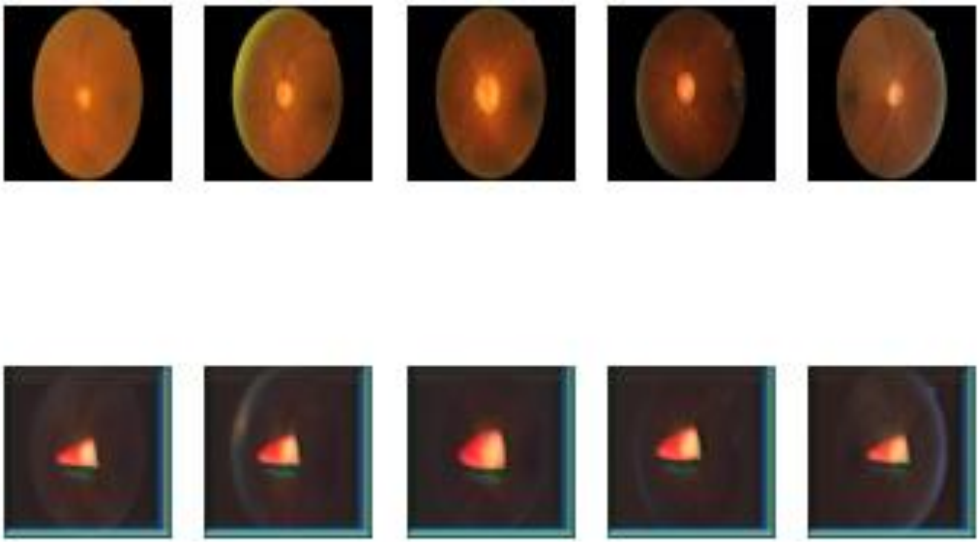

Figure 7: During 200th epoch of generated image

Comparative analysis of CLAHE and CycleGAN methods

CycleGAN produced the best results when enhancing the three different low-quality fundus images blurry, underexposed, and overexposed. The improved fundus images featured sharp optic disc and blood vessel architecture, strong contrast, and vibrant colors. Only the CLAHE algorithm outperformed CycleGAN in terms of image clarity. Images improved by CycleGAN have a higher BRISQUE quality score than those improved using the CLAHE algorithm. CycleGAN outperformed the other algorithms in both metrics. Only slightly slower than CLAHE, CycleGAN enhanced 100 pictures in 35 seconds. CycleGAN-enhanced images had DR diagnostic results that were better than those of the original images.

Table 1. Comparison of CLAHE and CycleGAN methods

Method	Accuracy
CLAHE method	45% Accuracy
CYCLEGAN method using Public dataset	84% Accuracy
CYCLEGAN method using Private dataset	81% Accuracy

From the above results, it is deduced that CycleGAN can effectively enhance low-quality blurry, underexposed, and overexposed fundus images and improve the accuracy of computer-aided DR diagnostic networks. The enlarged fundus image is useful for medical professionals to do pathological examinations and may have significant clinical benefits in ophthalmology diagnosis.

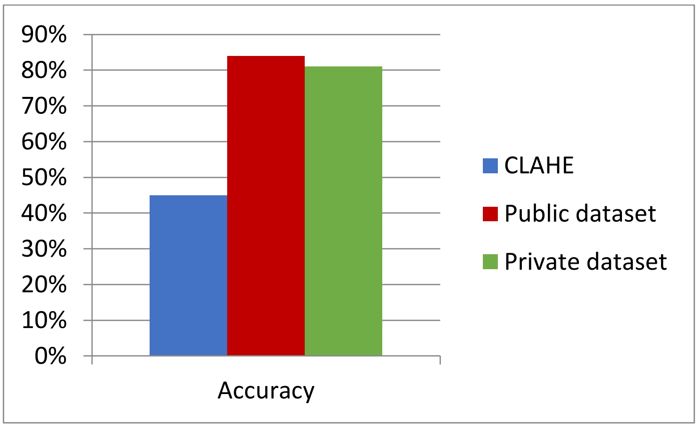

Figure 8: Accuracy Graph

VI. CONCLUSION

The CLAHE method gives an accuracy of 45%. Compared to the CLAHE method, CycleGAN is more accurate in enhancing images. It improves blurriness and generates sharp. CycleGAN uses a generator and discriminator, and both models perform better at their respective tasks. It gives the accurate value of accuracy, i.e., 84% on the public dataset and 81% on the private dataset. A large dataset of matched images that is difficult to create or occasionally doesn't exist is needed for image-to-image translation, which entails the controlled change of an image. Using mismatched collections of images from two separate domains, CycleGAN is a method for training unsupervised image translation models using the GAN architecture. CycleGAN is still a new technology that has limitations and also huge potential. We can now create unseen images using CycleGAN based on an input object with a comparable geometric structure. To raise public awareness of climate change, projects were developed to show how disasters affect housing and create face-swapping videos using CycleGAN.

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