SEGMENTATION OF OPTIC DISC FROM FUNDUS IMAGE USING DIFFERENTIAL EVOLUTION

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19Z720 Project Phase 1

Dissertation submitted in partial fulfillment of the requirements for the degree of

BACHELOR OF ENGINEERING
Branch: COMPUTER SCIENCE & ENGINEERING

Of Anna University

November 2022

Department of Computer Science & Engineering
PSG College of Technology

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Head of the Department

CERTIFICATE

Certified that this report titled **"SEGMENTATION OF OPTIC DISC FROM FUNDUS IMAGE USING DIFFERENTIAL EVOLUTION"** for the Project Work I (19Z720) is a bonafide work of **NAVANEETH A B (19Z229), SUDHARSAN V (19Z249), SURIYA PRASAD P (19Z250), THARUN V S (19Z254), VISHWAKJITH I (19Z260)** who have carried out the work under my supervision for the partial fulfillment of the requirements for the award of the degree of Bachelor of Engineering in Computer Science and Engineering. Certified further that to the best of my knowledge and belief, the work reported herein does not form part of any other thesis or dissertation on the basis of which a degree or an award was conferred on an earlier occasion.

Place: Coimbatore
Date: 16/11/2022

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CONTENTS

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ABSTRACT

Glaucoma is a major global health problem, and it is the second leading cause of blindness worldwide, with approximately 6.7 million people being blinded as a result of the disease. Despite increasing public health awareness and the availability of advanced-technology diagnostic tests in developed countries, a high proportion of glaucoma cases remain undiagnosed in the community.

Improved strategies for achieving earlier and more accurate diagnosis of glaucoma will facilitate the prompt implementation of effective treatment options, and subsequently will minimize the anticipated rising burden of the disease in the near future. To achieve such strategies and tackle the problem of undiagnosed Glaucoma, an effective facility to disable the requirement of a clinical professional is key. So a reliable solution to automate the process of detecting Glaucoma with utmost precision and speed is necessary.

A fundus image of a patient has to be processed, to detect an Optic Disc and an Optic Cup and compute the ratio of both its areas. And the derived value would determine whether the patient is affected by Glaucoma or not. And there are a lot of existing solutions from traditional methods to machine learning and deep learning techniques. Since we perceived this problem as an optimization problem, in other words, a search problem to find the center of the optic disc. Hence to derive a solution using an optimization algorithm. A variant of Evolutionary Algorithm called Differential Evolution(DE). With DE, unlike traditional methods, we rely on a random population of pixels and work towards deriving the optimal solution.

CHAPTER - 1

INTRODUCTION

Glaucoma is an eye disease that inflicts damage to the optic nerve. And the optic nerve is a vital component in feeding the brain with visual information from the eyes. Glaucoma is typically the result of irregular high pressure inside one's eye, and overtime, the pressure will possibly erode the optic nerve tissue. And this may cause vision loss or even blindness. If this can be diagnosed early, we may be able to prevent further vision loss. Every year, over 10 million lives are diagnosed with Glaucoma world-wide. Glaucoma is incurable, but early disclosure followed by suitable treatment can greatly diminish decline in vision of affected individuals and thus allow them to relish a greater quality of life. Thereby, it is evident that early diagnosis is vital.

There are multiple types of glaucoma that can occur, such as: open-angle glaucoma, angle-closure glaucoma, normal-tension glaucoma, and pigmentary glaucoma. There are also different kinds of tests to determine the presence of glaucoma along with the precise type of glaucoma, such as: eye pressure test, gonioscopy, visual field test, optic nerve assessment and more. Though, for accurately and conclusively determining the presence of glaucoma, without determining its type, is to identify the cup to disc ratio in the fundus images of the eye.

Therefore, studies have expressed the importance of using fundus images to detect glaucoma with great sensitivity. Consequently, study with fundus imaging has been advocated as a key means for diagnosing and observing disease progression. These studies concentrate in classifying OD and computing CDR to determine the existence of glaucoma predominantly using deep learning and machine learning models like CNN, SVM and Naive Bayes classifier. As a result, this project strives to automate the procedure of removing the challenges in calculating cup to disc ratio from the given input of fundus images by precisely segmenting the optic disk region from the fundus image. And the derived results will be compared with the ground truth and discuss it's further scalability.

To cater to the necessity of importance in arriving with a reliable, precise and efficient approach, we treat this issue as an optimization problem. So to tackle this problem we have explored the approach of using a variant of the Evolutionary Algorithm, called Differential Evolution(DE). Evolutionary Algorithm is a family of algorithms for global optimization inspired by biological evolution, and the subfield of artificial intelligence. DE optimizes a problem by maintaining a population of candidate solutions and creating new candidate solutions by combining existing ones according to its simple formulae, and then keeping whichever candidate solution has the best score or fitness on the optimization problem at hand. A vital aspect of DE is that it initializes the population randomly and also picks new populations randomly.

Using DE, we search for the center of the Optic Disc. The center of the Optic Disc is concurrent with the center of the Optic Cup. Once we have arrived with the most optimal solution, have the derived point as a center, and a circular region is segmented from the input fundus image. This obtained circular region holds the optic disc and optic cup.

CHAPTER - 2

LITERATURE SURVEY

[1] Diabetic Retinal Fundus Images: Preprocessing and Feature Extraction for Early Detection of Diabetic Retinopathy

Dilip Singh Sisodia, Shruti Nair and Pooja Khobragade in this research paper focuses on the increasing risk of Diabetic Retinopathy, an eye ailment. And this can be detected using the retinal fundus images in clinics. But the raw retinal fundus images are hard to process by machine learning algorithms. So this paper discusses the pre-processing of raw retinal fundus images. Some techniques used are: extraction of green channel, histogram equalization, image enhancement and resizing techniques. The retinal images are usually low contrast images. The green channel is neither under illuminated nor over saturated like the other two. Histogram equalization improves the contrast of the image. It reduces the highs and increases the lows. Resizing techniques are used to eliminate the unnecessary regions of the images to improve processing time. All these techniques are performed on the Kaggle Diabetic Retinopathy dataset, and the performance is calculated by considering the mean value and standard deviation. Both mean and standard deviation shows 0 for a normal eye and, 1029.7 and 12.246 respectively for the affected eye. Since their result yielded exudate area as the best-ranked feature, it is very important for us to employ their pre-processing techniques and understand how it would benefit our project.

[2] Image Preprocessing in Classification and Identification of Diabetic Eye Diseases

Rubina Sarki, Khandakar Ahmed, Hua Wang, Yanchun Zhang, Jiangang Ma and Kate Wang, the authors of this research paper that uses the retina fundus images for early detection of Diabetic Eye Disease (DED). This paper offers a methodical study on the importance of image processing for DED classification. The proposed automated classification framework for DED was achieved using several image processing techniques like: image quality enhancement, image segmentation (region of interest), image augmentation (geometric transformation), and classification. Image Enhancement includes CLAHE, Median Filtering and Illumination Correction. CLAHE (Contrast Limited Adaptive Histogram Equalization) is to improve the visibility of the image. It is a useful technique in biomedical image processing because it is very effective at making the normally important salient sections more accessible. It takes care of over-amplification of the contrast. And it doesn't apply equalization for the entire image, instead it breaks down the image into tiles and equalization happens individually to these tiles. The optimal results were obtained using traditional image processing methods with a new build convolution neural network (CNN) architecture. And they have achieved an accuracy of 94.92%.

[3] Comparison of Image Preprocessing Techniques on Fundus Images for Early Diagnosis of Glaucoma

The authors of this paper are comparing the pre-processing algorithms which are specifically used on Fundus Images for Early Diagnosis of Glaucoma. Their performance is calculated based on PSNR(Peak Signal to Noise Ratio) and MSE(Mean Square Error) values. Some of the pre-processing techniques for eye fundus images are: Contrast adjustment, Adaptive Histogram Equalization, Average Filtering, Median Filtering and Homomorphic Filtering. To test the accuracy of pre-processing techniques, first, an eye fundus image is taken as input. Second, pre-processing technique is applied to the fundus image. And finally, the MSE and PSNR value is calculated for different pre-processing techniques. After following all the steps with each algorithm, the authors have concluded that Median Filtering and Average Filtering give suitable results. Median filtering is found to be better with high PSNR and low MSE values.

[4] Comparison Of Different Image Preprocessing: Methods Used For Retinal Fundus Images

The authors of this research paper experiment with different preprocessing techniques to understand the performance of each method. Implementation of the computer intelligence techniques to a raw fundus image is an ineffective method to draw conclusions. Hence few of the prominently used techniques to preprocess fundus image are compared in this paper. These methods are: Adaptive histogram equalization(AHE), Wiener Filter, Median Filter, Adaptive median Filter and Gaussian Filter. Adaptive histogram equalization is used to make better contrast of retinal images. The Wiener filtering is a type of restoration technique. A median filter is a type of nonlinear filter. It is mainly used to remove salt and pepper noise. And gaussian smoothing executes the average value of neighboring pixels based on the Gaussian function. And the performance evaluations are compared by their MSE(Mean Square Error) and PSNR(Peak Signal to Noise Ratio). And the paper concludes that the preprocessing technique adaptive median filter is found to be better compared to other preprocessing methods because it has higher PSNR value and lower MSE value.

[5] Differential Evolution Algorithm For Segmentation Of Wound Images

The authors of the study explain the use of differential evolution algorithms for segmentation of wounds in the image of the skin. The capabilities of differential evolution optimization algorithms are explored with simple and effective operations and we can derive a convergence to global optimum which is reflected in wound image segmentation. The system does not exercise the drawbacks of the classical systems such as the K-means clustering algorithm and the outcomes obtained from different wound images have been discussed. DE is easy to implement, requires little parameter tuning, and can find the global optimum regardless of the initial parameter values and exhibits fast convergence. The future of this work will be to study a modified Differential Evolution that cares for the pixel neighborhood relations. The inference from the experiment outcomes are that the proposed approach is flexible and is able to produce a satisfactory segmentation result automatically.

[6] Automatic Tissue Segmentation in Medical Images using Differential Evolution

The authors of this paper discuss the segmentation of medical images and preprocessing steps in medical diagnosis. Evolutionary techniques such as Genetic Algorithms have been established to be efficient in medical image segmentation. Almost all Genetic Algorithms are semi-automatic, demanding either some parameters or domain knowledge like number of clusters, texture, shape etc. Differential Evolution (DE) is a simple and powerful evolutionary technique and Automatic Clustering using Differential Evolution (ACDE) is an enhanced version of DE. There aren't any studies on medical image segmentation using ACDE. And the purpose of this study is to attempt an extraction of the shape of tissues from the medical images automatically using ACDE. Almost all present clustering algorithms for medical image segmentation demand domain knowledge and some parameters in advance. The automatic clustering using differential evolution depends on real valued data sets. The authors have employed the ACDE on medical images and the experiment outcomes have proved that ACDE accurately determines the shape of the tissues in medical images.

[7] Segmentation of Retinal Area by Adaptive SLIC Superpixel

In this paper, the authors have presented the necessary preprocessing and consequently, superpixel segmentation. Preprocessing has been employed with the Gamma Normalization which evaluates the gamma values with no knowledge of the imaging device. Preprocessing is a requirement for the enhancement of the images, the experiment outcomes indicate that the discussed method is beneficial for image quality, detail of the images and improves the existing dynamic range. Superpixel segmentation is a beneficial step for the application of computer vision like medical image segmentation and object class recognition. Superpixel is used to decrease the difficulty of image processing tasks and supply suitable primitive image patterns. It segments an image into regions by considering similarity measures defined using similar features. The motivation is to obtain regions that represent meaningful descriptions with far less data than is the case when using all the pixels in an image. The discussed method is faster, enhances segmentation performance, memory effectiveness etc. So this paper provides the Retinal Area Segmentation enforced by adaptive SLIC.

[8] SLIC Superpixels Compared to State-of-the-Art Superpixel Methods

The authors of this paper discuss the applications of computer vision have come to rely increasingly on superpixels in recent years. Which raises the more important question of what constitutes a good superpixel algorithm. So they draw a comparison to understand the benefits and drawbacks of existing methods. The authors have experimentally compared five state-of-the-art superpixel algorithms for their capability to adhere to image boundaries, speed, memory effectiveness, and their impact on image segmentation performance. The authors then introduced a sixth superpixel algorithm, simple linear iterative clustering (SLIC), which builds on k-means clustering approach to effectively generate superpixels. Despite its fundamental approach, the results of the experiments showed that SLIC had outperformed existing superpixel methods in nearly every respect. It is faster and more memory efficient, and improves segmentation performance etc.

CHAPTER - 3

METHODOLOGY

The proposed approach consists of the following steps: First, a set of preprocessing techniques are implemented on the input fundus image. Second, using Differential Evolution, we are trying to identify the most optimized pixel to be our Optic Disc center.. Third, using the derived result, we will draw a radius around the pixel and segment the part from the image. Finally, we compare the derived results with the existing groundtruth results.

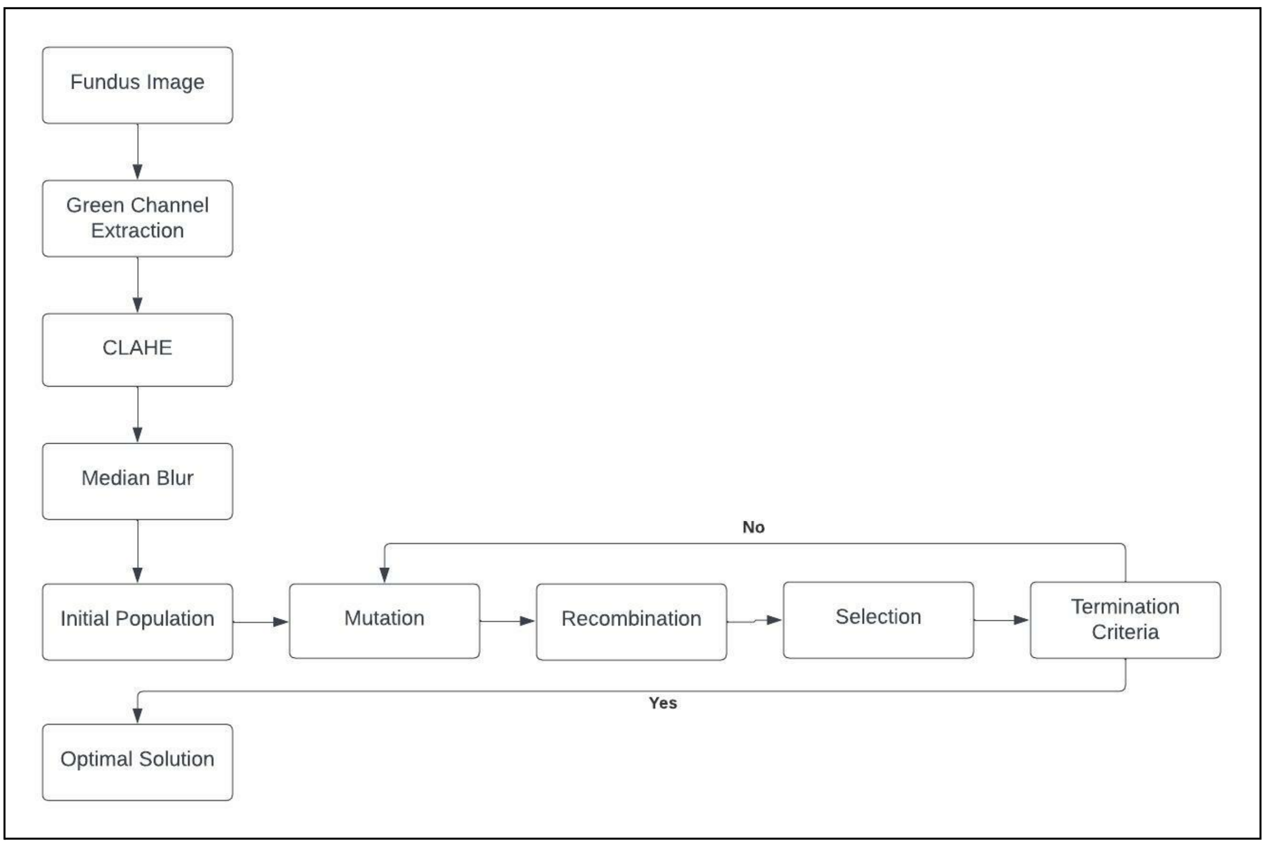

Figure 3.1: The complete flow of the proposed method

3.1 PREPROCESSING

For the early detection of Glaucoma the necessary region in the input fundus image is the optic disc section. But normally, an average fundus image will hold a lot more unnecessary information and obstruction to obtain the desired results, So it is crucial that the input fundus image has to be modified to our advantage, so we can optimize the process of detecting the fundus image.

Preprocessing is essential in ensuring that the dataset remains consistent and exhibits only relevant features. This step is required to facilitate an ease in workload of the following processes. The following preprocessing techniques were used to obtain an ideal image for processing.

3.1.1 Green Channel Extraction

In preprocessing, first the green channel of the image is extracted. The retinal images are usually low contrast images. Among the three color channels in the image (Red, Green, and Blue), the contrast between the blood vessels, exudates and hemorrhages is best seen in the green channel and this channel is neither under illuminated nor over saturated like the other two. Hence, we have extracted only the green channel for analysis and processing. In figure 3.2 the extracted channels from the input image, namely, red, green and blue channels are shown.

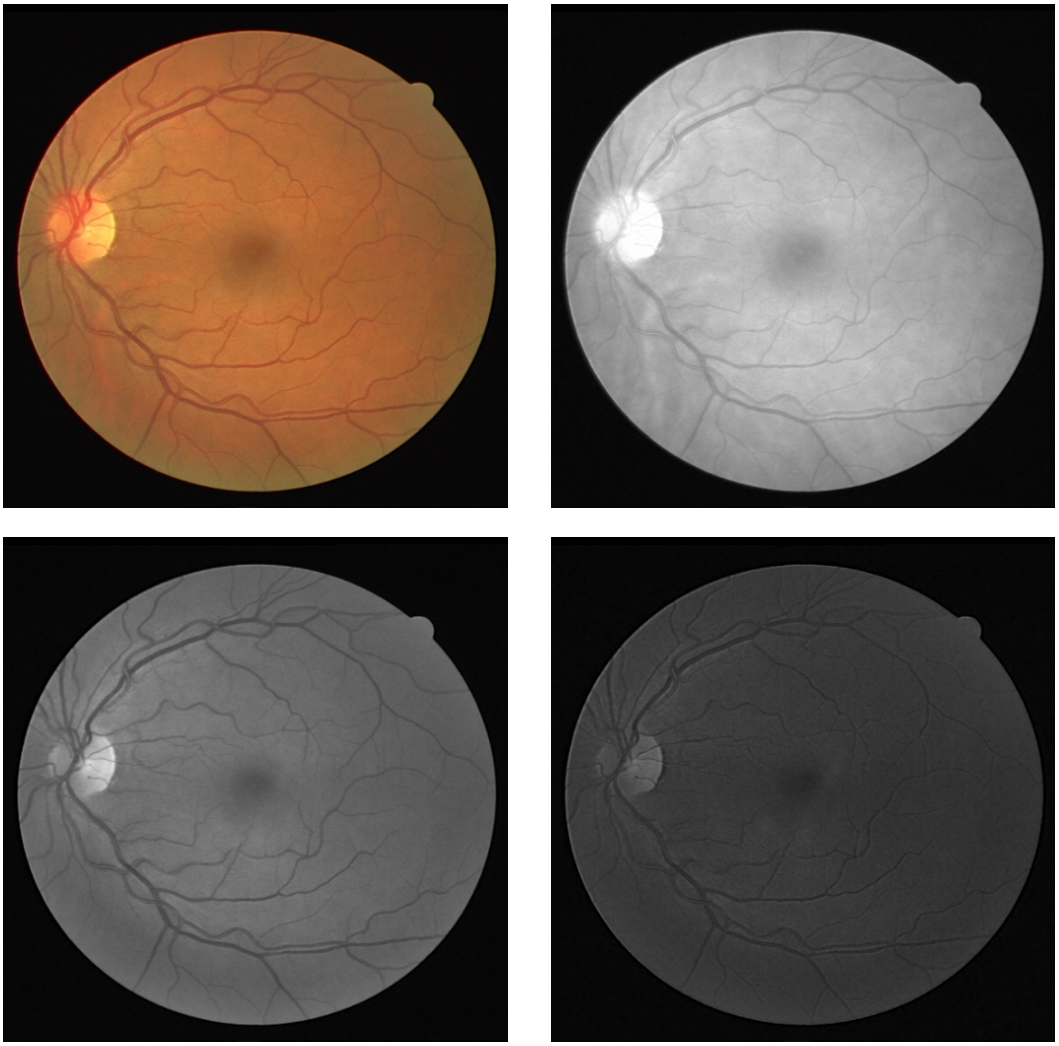

Figure 3.2: The four fundus image show difference in the extraction channel; original image(top-left); red channel extraction(top-right); green channel extraction(bottom-left); and blue channel extraction

3.1.2 CLAHE

CLAHE is a variant of Adaptive histogram equalization (AHE) which takes care of over-amplification of the contrast. CLAHE operates on small regions in the image, called tiles, rather than the entire image. The neighboring tiles are then combined using bilinear interpolation to remove the artificial boundaries. This algorithm can be applied to improve the contrast of images. Though we have extracted the green channel, CLAHE is another technique to improve the contrast so we can have a distinct optic region.

Bright regions would turn brighter and dull regions would turn darker. This would help the optic disc region to stand out from the rest of the image. The important parameters that are to be considered while using CLAHE are:

- Clip Limit – This parameter sets the threshold for contrast limiting. The default value is 40.
- Tile Grid Size – This sets the number of tiles in the row and column. By default this is 8×8. It is used while the image is divided into tiles for applying CLAHE.

In the figure 3.3 below you can see two histograms: one is before applying CLAHE and latter is after applying CLAHE.

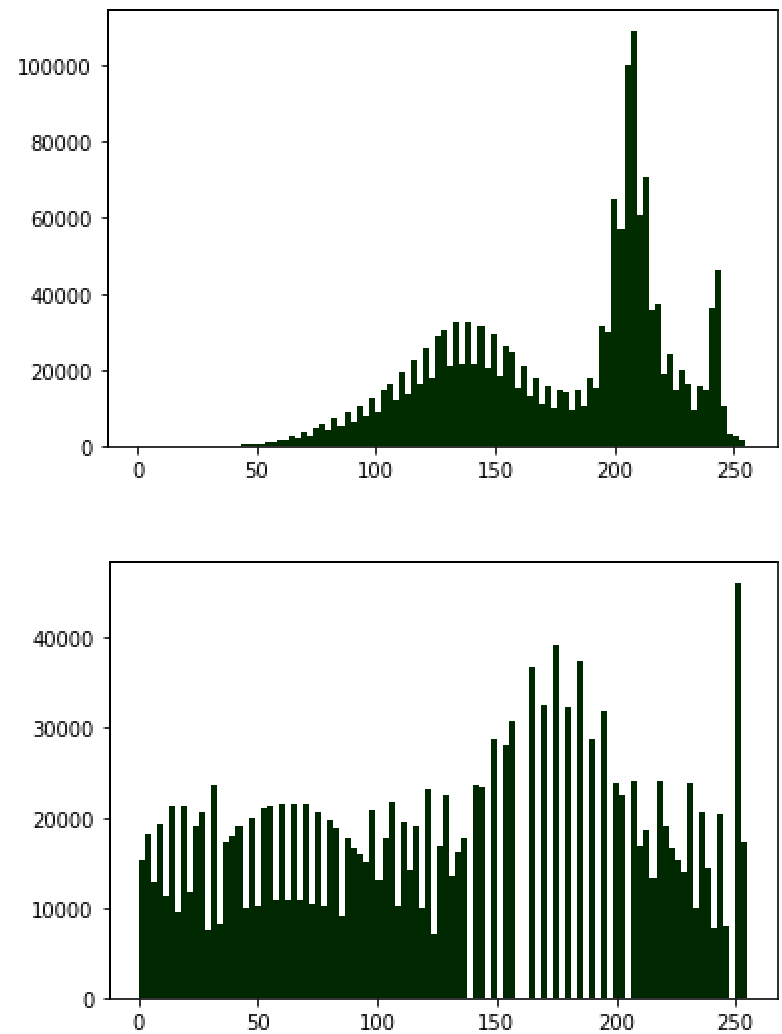

Figure 3.3: The histogram of the green channel: before CLAHE(to the top) and after CLAHE

In the figure 3.4 below you can see the difference of before and after using CLAHE on the fundus image.

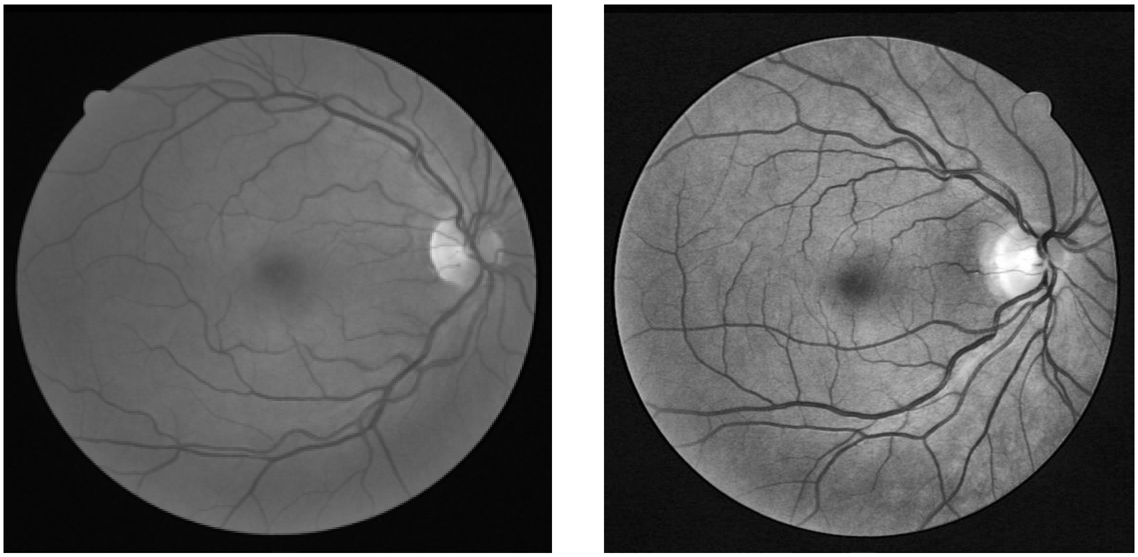

Figure 3.4: Applying CLAHE to fundus image; before applying CLAHE(to the left) and after applying CLAHE

3.1.3 Median Blur

A median filter is a type of nonlinear filter. It is mainly used to remove salt and pepper noise. It is better than the mean filter, median is the middle value of the neighborhood pixel. Median filters keep the sharpness of image edges while removing noise. So this helps to preserve important edges in an image that can be vital for further processing. Median filter is useful in non-linear smoothing. In image processing initially it is necessary to perform noise removal in an image before further processing steps. Disadvantages of the median filtering is its removal of both noises and details. Median filter can’t understand exact details from noises.

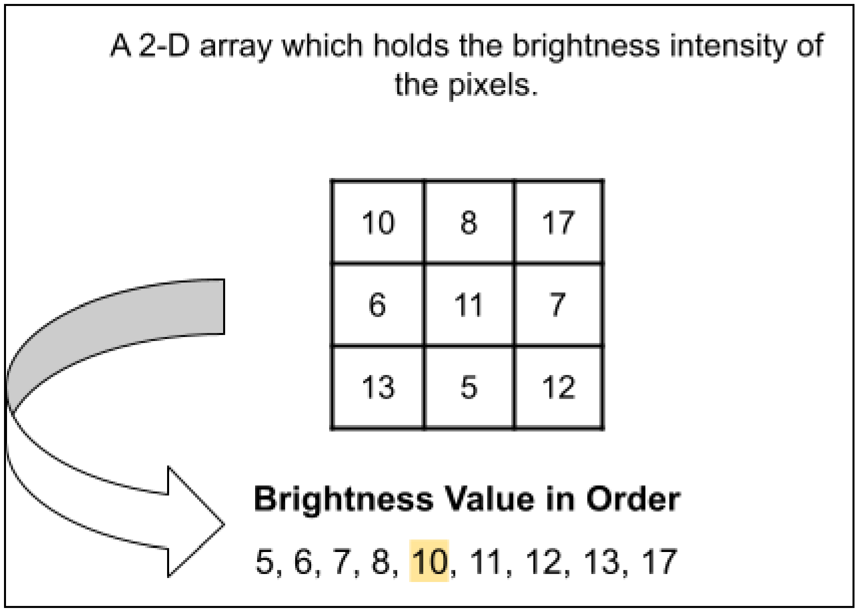

Figure 3.5: Working of the median filter

In the figure 3.5 above, we can see how the 2-D array of elements are sorted into a 1-D array. The median is derived by sorting all the values from low to high, and then taking the value in the center. If there are two values in the center, the average of these two is taken. And all the pixels in the neighborhood will obtain the median value.

$$I'(u,v) \leftarrow \text{median}\left\{I(u+i,v+j) \mid (i,j) \in R\right\}.$$

In the figure 3.6 below you can see the difference of before and after using the median filter on the fundus image.

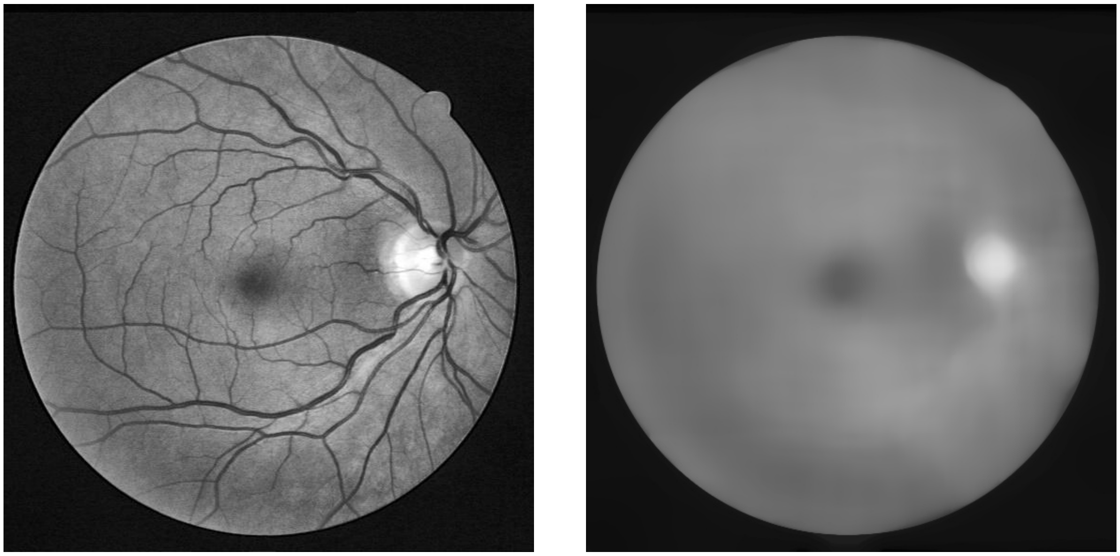

Figure 3.6: Depicts the effect of median blur on fundus image: before applying medina blur(to the left) and after applying median blur

3.2 DIFFERENTIAL EVOLUTION

Differential Evolution(DE) belongs to the EA family and is a population-based method that is widely used to solve various types of optimization problems. It generates new offspring by recombining solutions under certain conditions, unlike other EAs that produce offspring by perturbing the solutions with scaled difference vectors. The current individual solution will be replaced if it is outperformed by the new offspring solution. DE is considered a robust and simple algorithm because its search process is governed by few algorithm-specific parameters, such as scaling factor and crossover rate. Similar to other EAs, DE can produce new offspring solutions through three mechanisms: mutation, crossover and selection.

The algorithmic framework of a basic DE consists of four phases, namely, initialisation, mutation, crossover and selection, as shown in figure. 3.7. Initialisation is a one-time process, while the remaining three mechanisms are repeated in the search process of DE in a D-dimensional solution space until the termination criteria are satisfied.

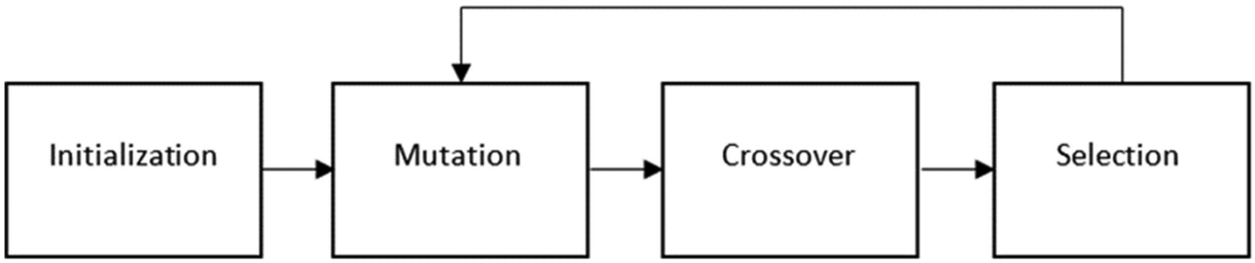

Figure 3.7: The four phases of Differential Evolution

3.2.1 Initial Population

Initialisation is the first process that occurs in DE to search for a global optimum solution located in a D-dimensional real parameter space. In our case, the parameter space is a retinal fundus image so we will be representing it as a 2-dimensional space. The initial solutions for a given optimization problem consist of NP real-valued parameter vectors, where NP represents the population size of DE. During the t-th iteration, each i-th individual solution of DE can be represented as a 2-dimensional vector as,

$$X_i^t = (X_{i,1}, X_{i,2})$$

Where i = 1,2,3,......,NP.

The initial population condition starts at t = 0. The initial candidate solutions can be generated during the initialisation stage on the basis of the lower and upper limit boundaries of the solution search space represented respectively, as follows:

$$X_{min} = (X_{min,1}, X_{min,2})$$

$$X_{max} = (X_{max,1}, X_{max,2})$$

For each i-th DE solution, the j-th dimensional component can be initialized by randomly generating a value in between the upper limit of Xmax,j and lower limit of Xmin,j as,

$$X_{i,j}^{(0)} = X_{min,j} + rand_{i,j}[0,1]\left(X_{max,j} - X_{min,j}\right)$$

Where rand is a uniform distribution of real values between 0 and 1.

3.2.2 Mutation

In biological terms, mutation is defined as an instant change of characteristic observed from a chromosome gene. In the context of evolutionary computation, mutation is a random perturbation process performed on selected decision variables. In DE philosophy, a mutant or donor vector denoted as Y_i^t is constructed from a mutation process on the basis of a given target vector of X_i^t

$$Y_i^t = X_{r_1}^t + F(X_{r_2}^t - X_{r_3}^t)$$

r1 ≠ r2 ≠ r3 ≠ i where r1, r2, r3 ∈ [1, NP] that are the individuals who are chosen randomly from the current generation.

F is a scaling factor that is used to control the mutation. By altering the value of F the exploration for the solution can be manipulated as it has the ability to find new individuals.

F lies in the continuous range of [0,1].

3.2.3 Crossover

In this phase, both the mutant and target vectors cross their components together in a probabilistic manner to produce a trial vector (offspring). This crossover process allows the target solution to inherit the attributes of the donor solution or mutant. Two commonly used crossover operators are known as uniform crossover and exponential crossover. In our proposed approach we have implemented the uniform crossover operator. The uniform crossover scheme is controlled by a crossover rate (CR) that has a value between [0,1]. The trial solution generated by uniform crossover can be defined as follows:

$$Z_i^t = \begin{cases} Y_{i,j}^t & if\ rand_{i,j}[0,1] \leq CR\ \ or\ \ j = k \\ X_{i,j}^t & Otherwise \end{cases}$$

k ∈ {1, 2} is a randomly selected dimension index to ensure at least one dimensional component of the trial solution is inherited from the donor vector.

3.2.4 Selection

The selection process enables DE to determine the survival of a target (parent) or a trial (offspring) solution in the next iteration of the search process while retaining the population size of DE in every generation. Once the new population is formed in the next generation, the iterative processes of mutation, crossover and selection are performed continuously until the termination criteria are satisfied, which usually is the number of generations. Two types of selection exist, namely, local and global. The selection process of DE is mathematically described as follows:

$$X_i^{t+1} = \begin{cases} Z_i^t & \text{if } f(Z_i^t) \leq f(X_i^t) \\ X_i^t & \text{Otherwise} \end{cases}$$

where $f : \mathbb{R}^n \rightarrow \mathbb{R}$ is the fitness function which must be minimized. The function takes a candidate solution as an argument in the form of a vector of real numbers and produces a real number as output which indicates the fitness of the given candidate solution. The gradient of ‘f’ is not known. If the latest trial vector of Z_i^t produces a better objective function value, then the current target vector X_i^t i will be replaced by Z_i^t in the next iteration.

3.2.5 Fitness Function

A fitness function is a specific type of objective function that is used to condense, as a single figure of merit, how close a specified design solution is to fulfilling the described objectives. Fitness functions are employed in genetic programming and genetic algorithms to guide simulations towards optimal design solutions. It takes a candidate solution to the problem as input and produces as output how “fit” or how “good” the solution is with respect to the problem in consideration.

The fitness function varies for each problem and it doesn't take a generic form. It is designed uniquely for the needs of the problem.

$$f(x_i) = (\sum_{l=-p}^{p} x_{i,1} + l) + (\sum_{l=-p}^{p} x_{i,2} + l)$$

where *p* represents the number of pixels from the given point.

3.3 PERFORMANCE METRICS

For the datasets of Fundus images we have used, we have also obtained the ground truth values of the center of the optic disc, which were manually plotted by a clinical professional. And using these ground truth values, we have employed different metrics to evaluate the efficiency of our Differential Evolution(DE) approach. So the following are the metrics we have used.

3.3.1 Euclidean Distance

The optimal solution that is derived from the algorithm is assumed to be the ideal center of the optic disc. To put that into perspective and evaluate the performance, we calculate the euclidean distance between the derived optimal solution and existing ground truth value.

$$d(p,q) = \sqrt{\sum_{i=1}^{n} (q_i - p_i)^2}$$

p, q = *two points in Euclidean n-space*

q_i , p_i = *Euclidean vectors, starting from the origin of the space (initial point)*

n = *number of coordinates*

3.3.2 Confusion Matrix

	D Positive	**D Negative**	**Total**
A Positive	*TruePositive(TP)*	*FalseNegative(FN)*	*TP + FN*
A Negative	*FalsePositive(FP)*	*TrueNegative(TN)*	*FP + TN*
Total	*Sensitivity*	*Specificity*	

The above confusion matrix: ‘A positive’ = actual positive, ‘A negative’ = actual negative, ‘D positive’ = derived positive, ‘D negative’ = derived negative.

It is very important for us to understand what would constitute True Positive, True Negative, False Positive and False Negative. Using the ground truth value as the center, we draw a circular region which would be the ideal segmentation of the optic disc. This circular region would be the actual positive and everything outside this region will be considered actual negative. Next, using the derived optimal solution as the center, we draw a circular region with the same radius. The area inside this circular region will be considered as the derived positive and the area outside will be considered derived negative.

Refer to Figure 3.8 below and you will find two circles covering the optic disc. The black circle is drawn using the ground truth value which is the actual positive and the red circle is drawn using the optimal solution derived from the algorithm and that is the derived positive. And accordingly we will have our four possible outcomes.

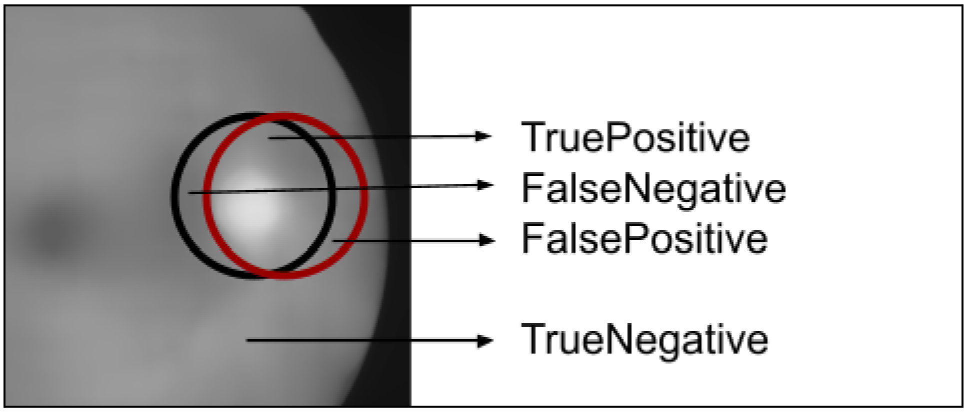

Figure 3.8: Depicts the regions of TP, TN, FP and FN

3.3.3 Accuracy

Accuracy is an essential metric for the evaluation of the results. It is a summary of the true positive and true negatives divided by the confusion of the matrix components' total values. Thus, the elements of the confusion matrix mentioned above will be calculated to evaluate the effectiveness of our proposed approach.

$$Accuracy(\%) = (TP + TN)/(TP + FN + TN + FT)$$

3.3.4 Sensitivity

Sensitivity is measured as the number of accurate positive predictions divided by the sum of positive. The best sensitivity is 1.0, whereas the worst is 0.0. We calculate sensitivity using following equation;

$$Sensitivity = TP\,/\,(TP + FN)$$

3.3.5 Specificity

Specificity is measured as the number of correct negative predictions divided by the sum of negatives. The best specificity is 1.0, whereas the worst is 0.0. We calculate sensitivity using the following equation;

$$Specificity = TN / (TN + FP)$$

CHAPTER - 4

EXPERIMENTS AND RESULTS

4.1 DATASET USED

The proposed methodology is evaluated on three publicly available retinal image databases. They are the following:

4.1.1 DRIVE Dataset

This dataset includes 40 retinal images of sizes 565 × 584 pixels which are used for studying various pathologies related to diabetics. These images were acquired in the Netherlands during a diabetic discussion conclave. The collected fundus images are of patients having a varying range of ages from 25–90 years. The camera used for acquiring the images had a 45 degrees field of view.

4.1.2 Chase Dataset

This dataset includes 28 images of sizes 999 × 960 pixels and are acquired in the event named, Child Heart and Health Study in England (CHASE) where 14 children took part. The captured images have good contrast but suffer from illumination problems.

4.1.3 HRF Dataset

This package is part of the signal-processing and machine learning toolbox Bob. It provides an interface for the HRF Dataset. The dataset contains 45 eye fundus images with a resolution of 3304 x 2336. Which can be downloaded in high resolution from their official website.

4.2 PERFORMANCE EVALUATION

4.2.1 Euclidean Distance

Table 1

A sample comparison of the ground truth coordinates and derived coordinates with the euclidean distance between them.

S.No	Ground Truth		Derived		Distance
	x(Actual)	y(Actual)	x(Determined)	y(Determined)	
1	90	257	99	258	9.06
2	460	275	438	277	22.09
3	93	275	128	270	35.36
4	360	275	359	282	7.07
5	85	260	97	256	12.65

Table 2

Comparing the average euclidean distance of each dataset between preprocessed and original datasets.

Dataset	Preprocessing	Euclidean Distance Average
Chase Dataset	Without Preprocessing	23.36
	Preprocessed	22.07
Drive Dataset	Without Preprocessing	21.10
	Preprocessed	15.78
HRF Dataset	Without Preprocessing	97.05
	Preprocessed	64.29

The preprocessing techniques deliver an enormous impact on the detection of the optic disc center. In the dataset DRIVE and HRF, the difference seems to be significant as they both are low in contrast and captured a large number of blood vessels. Unlike the Chase dataset, which naturally is high in contrast and as it lacks the blood vessels, the preprocessing techniques don't create a similar impact.

4.2.2 Accuracy, Sensitivity & Specificity

Table 3

Comparative study between preprocessed and the original dataset with techniques like Accuracy, Sensitivity & Specificity

Dataset	Preprocessing	Accuracy	Sensitivity	Specificity
Chase Dataset	Without Preprocessing	99.2%	76.97%	99.59%
	Preprocessed	99.34%	81.07%	99.66%
Drive Dataset	Without Preprocessing	99.01%	67.32%	99.49%
	Preprocessed	99.21%	74.01%	99.60%
HRF Dataset	Without Preprocessing	98.97%	58.26%	99.48%
	Preprocessed	99.32%	72.21%	99.65%

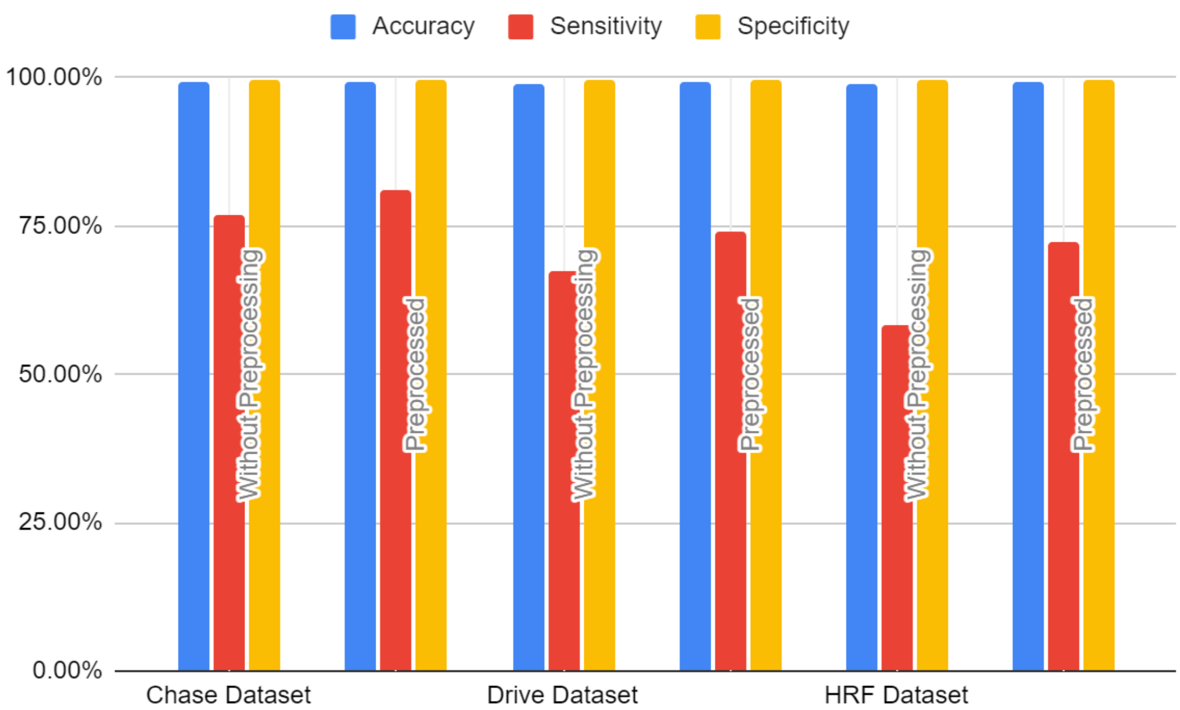

Figure 4.1: A graphical representation of Table 3

Table 4

A comparative study between the proposed approach and the other existing techniques.

Dataset	Algorithm	Accuracy	Sensitivity	Specificity
Chase Dataset	Circular Hough Transform	95.79%	83.13%	99.71%
	S. Roychowdhury and Team	99.14%	89.62%	N/A
	Proposed	99.34%	81.07%	99.66%
Drive Dataset	Circular Hough Transform	96.72%	81.87%	99.66%
	M.N. Zahoor, M.M. Fraz	99.80%	83.09%	N/A
	Proposed	99.21%	74.01%	99.60%

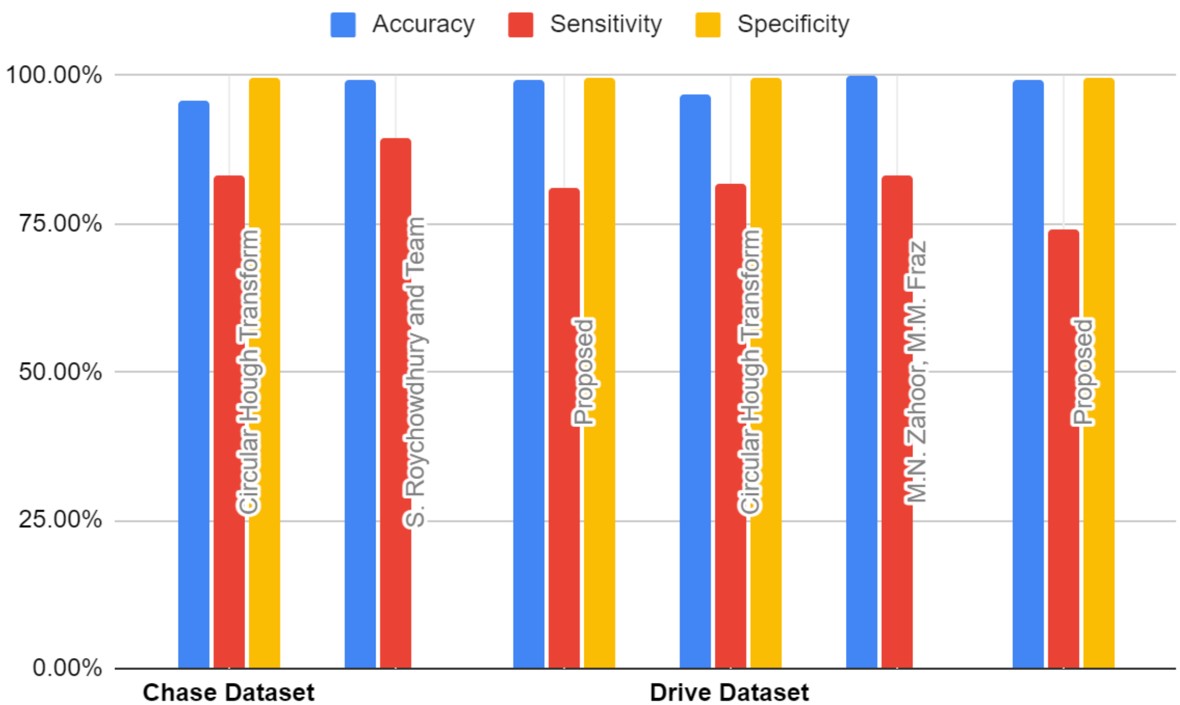

Figure 4.2: A graphical representation of Table 4

CHAPTER 5

CONCLUSION

Early detection of Glaucoma can create an extensive impact and prevent affected patients from vision loss. Effective treatments can be given to remove harm of Glaucoma when detected at early stages. The necessary solution should remove the requirement of a clinical professional to detect the existence of the condition.

This study illustrates the implementation of the Differential Evolution(DE) algorithm to segment the Optic Disc from the input fundus image. The existing solutions predominantly use traditional methods, machine learning and deep learning techniques. To approach this issue as an optimization problem, to find the center of the optic disc so the region around them can be segmented for further processing.

The proposed approach, including the preprocessing techniques along with differential evolution, has been found to deliver promising results in an extremely efficient duration. The framework does lack the sensitivity the other state of the art techniques poses. And the other drawback would be that the proposed approach is tested only on small datasets. And these would be the necessary areas of scope to be improved in the future.

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APPENDICES

CODE

Preprocessing

```
def preprocessing():
        for i in tqdm(range(1,41),desc='Pre-Processing in progress'):
        open_path = openimage(i)
        img = cv2.imread(open_path)

        if img is None:
        print(f"image {i} not found")

        b,g,r = cv2.split(img)
        img = g

        blank = np.zeros(img.shape,dtype='uint8')

        clahe = cv2.createCLAHE(clipLimit=2)
        clahe_image = clahe.apply(img)

        blur = cv2.medianBlur(clahe_image,55)

        save_path = saveimage(i)
        cv2.imwrite(save_path,blur)
```

Initial Population

```
def solution_set(npop,shape):
        height,width = shape[0],shape[1]
        xmin,ymin = 50,200
        xmax,ymax = width-49,height-199
```

```
    b1 = random.sample(range(ymin,ymax), npop)
    b2 = random.sample(range(xmin,xmax), npop)

    return list(zip(b1,b2))
```

Crossover

```
def opticdecross( population, mutant, cross, shape ):
    height, width = shape[0], shape[1]
    xmin, ymin = 50,200
    xmax, ymax = width-50, height-200
    ir = random.randrange(0,2)
    cross_point = [0,0]
    for i in range(2):
    if( random.uniform(0,1) <= cross or i==ir ):
    if i == 0:
        if( mutant[0] <= ymax and mutant[0] >= ymin ):
        cross_point[0] = mutant[0]
        else:
        cross_point[0] = population[0]
    if i == 1:
        if( mutant[1] <= xmax and mutant[1] >= xmin ):
        cross_point[1] = mutant[1]
        else:
        cross_point[1] = population[1]
    return tuple(cross_point)
```

Fitness Function

```
def fitness_value(img,point):
    x,y = point[1],point[0]
    radius = 22
```

```
img = img[y-radius:y+radius+1,x-radius:x+radius+1]
s = img.sum()
y = 1 - (s / 1000)

return y
```

PLAGIARISM REPORT

VeriGuide - Originality Report
Individual Report

Background Information

File Name:	Project_Phase_I_Report.pdf
Report Generated On:	15/11/2022, 08:28:04 PM

Similarity Statistics Overview

Similar Sentence(s) Found By VeriGuide:	1 out of 346 sentences = 0.29%
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Entry	Source	From	Similarity
1	https://pubmed.ncbi.nlm.nih.gov/34423109/	Internet	1 / 346 = 0.29%

Figure 7.1: VeriGuide - Originality Report