



Effectual Augmentation of Glaucoma Prediction in Retinal Fundus Images using Hybrid Level Fusion of Image Pre-Processing Techniques

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Abstract

Glaucoma is a condition where the eyes of human beings are infected due to retinal damage which could result in loss of vision. It generally occurs due to prolonged pressure on the eye and affects the optic nerve if not treated at the earliest stage. However, it is hard for even experts to detect it at the earlier stage. Hence numerous image processing techniques were applied to identify Glaucoma in retinal eyes. The profound purpose of the work is to propose a pre-processing console to remove outliers in the Glaucoma retinal Fundus images using Denoising techniques of pre-processing to enhance the prediction using image pre-processing and computer vision techniques. The model was created with three stages including applying the denoising model using the Median Filtering for Edge Preservation, Contrast Limited Adaptive Histogram Equalization (CLAHE) and optimizing by eliminating irrelevant features using the Black Widow Optimization model and finally evaluating the performance of denoising techniques using accuracy-based predictions. The results showed that after performing a combination of denoising and optimizing techniques, the image quality was enhanced with 97% outperforming the existing models.

Keywords: Black Widow Optimization; Denoising Techniques; Glaucoma Prediction; Hybrid Level fusion Models; Image Denoising Optimization; Image Pre-Processing Techniques; Median Filter Technique; Retinal Fundus image;

1. Introduction

Glaucoma being a dreadful ailment, distresses parts of the eye that helps to see, might cause people to lose their vision. It is important to find and treat glaucoma early so that blindness can be prevented. Currently, the discernible cup and disc are separated by hand and their sizes are being tested to measure Cup-to-Disc Ratio (CDR)[1]. However, experts find it difficult and time consuming to analyze and write down information about these places. Another choice might be to use a special computer program called Convolutional Neural Network (CNN) to diagnose glaucoma. To ensure its effectiveness, a substantial number of labeled examples were required during the training phase. In taking care of patients with long-term illnesses like Open-Angle Glaucoma (OAG), doctors use medical tests to determine the stage of the disease. Currently, the patient is at a certain stage in their condition, like regression, stability, or progression (low spread or difference in results), which means that the approval produces consistent and reliable outcomes. If the difference between what the patient has and what is recorded by a test is small, doctors can easily tell the patient's current disease stage without the necessity for advanced methods [2]. However, if the medical tests have a large difference in results, this may not be possible. Determining how quickly glaucoma worsens is difficult because it differs for each person. Other factors make it tricky, like differences in how measurements are taken and the lack of a standard way to define progression. Structural tests like thickness measurements of chunks of the eye can find changes in the eyes of people with glaucoma. It might see these changes happen before any harm is done.

Glaucoma is a problem with the eye that happens when there is too much compression or heaviness inside the eye. This high compression or heaviness affects the nerve optic of the eyes. A significant method to stop this

distress in the eyes is early detection, which is possible only through frequent eye checkups consistently[3]. The chief purpose of the work was designing and developing pre-processing system that removes outliers in the Glaucoma retinal fundus images to enhance the prediction using image pre-processing techniques. The research work's scope has been delimited in the field of medical diagnostics and eye hospitals where Glaucoma diseases have been diagnosed, detected in patients and treated using scientific medical methods. The Research work aimed to use a type of AI called Convolution Neural Networks (CNNs) [4] to quickly detect a condition called Glaucoma. This will help doctors diagnose Glaucoma faster and prevent it from getting worse. CNNs have been successful in finding even small changes caused by glaucoma. This research work encompassed three different models in the current trend where the Glaucoma devices are configured, trained to classify and identify the presence of glaucoma from complex datasets like ORIGA, SCES and G1020 after training the data. The retinal fundus images were examined and the accuracy was found to be 95% based on the experiment with ResNET-50 models and additional optimization with CNN Models. Outcomes of the experiment indicated that the CNN algorithms can become a useful and an efficient tool to analyze groups of people who are at risk of losing their sight from glaucoma.

2. Related Work

Glaucoma is a common eye disease that damages the eye due to strain interior of the eye. Glaucoma varies from person to person. Hence different methods are predominantly used in the current scenario that are studied and presented in the literature works. [5] presented a new method to detect glaucoma by using computer models. The researchers have used different ways to teach the models and then judged how good the models were by comparing them to the decisions made by eye doctors. It used methods that combined labeled and unlabeled data makes learning better. First, it used a computer model that learned information from data that was not about medicine. Later on, it made small adjustments to this model using the information given. After which, a semi-guided system was developed and taught using a mix of labeled and unlabeled information with two different self-teaching methods. The experiment had two sets of data called RIM-ONE and RIGA. The results showed that using deep learning models was successful in identifying glaucoma. This is good news because it can help find people with glaucoma, at the early stage using a computerized test. Two eye doctors compared their observations with the results of models testing glaucoma diagnosis. It discovered that all the models were better at diagnosing glaucoma than they were. This proves that artificial intelligence is very good at diagnosing glaucoma and can be trusted. [6] created a model that can prophesy glaucoma and how serious it is. The severity of glaucoma can be determined by employing a unique U-Net model to classify the blood vessels that have been separated. Ensuring that, the Optic Disc (OD) and the Optic Cup (OC) are distinct to calculate the CDR. The hybrid PolyNet is used to determine how serious someone's glaucoma disease is. It is important to catch glaucoma early to prevent it from getting worse. Blood vessels are separated with U-Net model providing 97% of sensitivity and 88% of specificity respectively. The accuracy was found to be 96% and the F1 score was 98%. So, it made a novel model using deep learning called hybrid PolyNet models. It had the structure separately for OD and OC to get the right outcome. The subject of this work revolves around images that capture the intramural workings of the eye. This work is about pictures of the inside of the eye. It has achieved a high level of accuracy when analyzing these pictures, with a score of 96.21% in a particular dataset. It was also able to correctly identify health issues with 97.32% accuracy and correctly identify healthy cases with 94.26%. [7] introduced a plan for dealing with the Glaucoma situation. This framework brought together the results of hybridized filters with machine learning models. The chief aim of hybridization was identifying potential patients affected with Glaucoma. It achieved this by considering both fast and slow periods of change, and by adjusting to any changes that happen over time. Determining whether a patient diagnosed with OAG will involve expeditious development within the next two or three years is achieved through the use of the system. The model's performance improved by around 7%. This means that the model's accuracy increased from 75% to 82% after hybridizing the models.

If glaucoma is not treated, it can cause sight loss by harming the part of the eye called the cranial Nerve II Head. This can be identified only when doctor insights into the deep side of eyes to identify Glaucoma. This method takes longer to do it by hand. So, this problem can be worked out by using a computer program that can automatically detect Glaucoma using advanced methods called deep learning. One specific method called Convolutional Neural Networks (CNNs) is suitable for solving this problem because it can analyze different aspects of an image and distinguish between normal and Glaucoma-related images. [8] suggested a new way to fragment the Cranial Cup and Cranial Disc to calculate the CDR in patients with Glaucoma. In simple terms, doctors can meticulously disclose Glaucoma using advanced computer technology called Deep Learning with a special type of computer network known as CNN that separate to divide the two discs of the eyes improving its performance.

Clinical records are documents that have lots of information about a person's health. Clinical notes are usually difficult to understand, and there are many varieties of medical codes, so it is hard to assign the correct code to the clinical text. The traditional way of manual coding could cause bad things to happen. The Deep Neural Network model is being used a lot in medical care because of advancements in Machine Learning and Computer Hardware. However, some problems need to be fixed as soon as possible. These problems include too much noise in long documents, complicated code connections, and an uneven distribution of classes. [9] suggested significant model Note-code Interaction Denoising Network (NIDN) to utilize self-attention technique to find the most important information about the medical code in the clinical document utilizing observing tag technique to learn a specific way of representing text related to code. It uses the connection between labels in making predictions, to make it easier to understand long texts and improve how well predict medical codes, and created a denoising module. This module helps to decrease the impact of any noise or errors in the predictions. The results of the experiment prove that the new model is better than other similar models when tested on a real-life MIMIC-III dataset. In this study, [10] uses advanced machine learning to predict how glaucoma will worsen from time to time. The Optical Coherence Tomography Angiography (OCTA) scan of the Glaucoma patient was estimated from their past measurements in threes and twos. The predicted images looked very similar to the real images. Also, the findings indicate that getting OCT scans from just two previous appointments may be enough to forecast the next OCT scan of the patient in six months. [11] aims to investigate the connection between measurements taken with a non-invasive picturing technique and changes in the visual field of people who have normal tension glaucoma. A study was done for almost five years, starting in January 2017 and ending in October 2021. The OCTA metrics were studied in two different areas of the eye: the region around the optic nerve (Peripapillary zone) and the central area of the retina (Macular region). The test was conducted in every six months using a computerized test to measure peripheral vision. The Cox model helped to understand how OCTA measurements at the beginning of the study were related to the chances of NTG getting worse as time passed. The group consisted of 164 patients with Normal Tension Glaucoma (NTG) for 270 eyes. These patients were monitored for a minimum of 2 years. During this monitoring for an average period of 48.58 ± 798 months, 42 out of 270 eyes with NTG (15.56%) experienced worsening of their visual field. In simple words: After considering some risk factors at the start, a lower superotemporal cpVD metric in the OCTA test was linked to worsening vision in the Peripapillary region. [12] suggested a model that can help diagnose glaucoma using pictures of the back of the eye. This app is made with methods that involve analyzing images, using advanced techniques in artificial intelligence. The hybrid architecture models were capable of attaining 99% of efficiency by identifying the brightest spots of the images. The brightest spot algorithm could efficiently extract the Region of interest and give an outcome of 98.67% indicating the reliability and efficiency of the platform.

A novel method was introduced by [13] for a computer to learn about eye images in glaucoma cases. EyeLearn is a novel method that can learn even if there are mistakes or problems in the images. EyeLearn has a tool called artifact correction. This tool helps learn how to make the best predictions of images without any errors or defects. Furthermore, EyeLearn uses a method called clustering-guided contrastive learning to specifically understand the similarities and differences among images. During training, pictures are grouped based on their similarities or differences. This helps in learning about pictures that are either close or different, depending on which group it belongs to. To test EyeLearn, it uses what it has learned to forecast the ocular field and detect Glaucoma using real pictures of patients with Glaucoma. Many tests and comparisons with the best methods show that EyeLearn is very good at learning the best way to represent ophthalmic images. [14] attempted to create a computer program using deep learning that can detect Glaucoma early by looking at pictures of the back of the eye. The program looks for problems in a specific layer of the eye and uses a special type of imaging to measure its thickness. The fundus images were analyzed from a total of 560 images where classification and evaluation were performed and found to be convincing to identify the presence of Glaucoma. The hybridization of SSIM and PSNR along with the RNFL distribution measured and compared the differences between images created by the model and the original images. It made a new computer program that can take thickness information from eye images. It tested this program and found it to be reliable. This program can use the thickness information to make images of the diameter of a part of the eye called the RNFL. The quality of the images was measured using PSNR (a measure of image quality) which was 19.31 decibels, and SSIM (another measure of image similarity) was 0.44. The inference output was like the original images produced by OCT when it came to predicting the distribution of RNFL thickness. Based on the literature study, some of the research gaps were identified and are listed as follows:

- The models were not capable of identifying the strains of the image due to lack of pre-processing methods in different layers,
- Image Quality enhancement has been a concern in augmenting the prediction of Glaucoma at the earliest stage possible,

- The thickness map created was good enough to detect glaucoma in a medical setting, and the images created were same as to the actual ones,
- Many Frameworks and models like EyeLearn [13], Note-code Interaction Denoising Network (NIDN) [9] could bring prediction to Glaucoma but couldn't handle the pre-processing methods, especially the denoising methods to enhance the results,

Images of the eyes, including maps that measure the thickness of certain parts, are very important in finding and tracking eye diseases like glaucoma. To help diagnose eye diseases using computers, it needs to find important details in eye images that can show signs of vision problems. These details are called biomarkers, such as thinning patterns in the retina nerve fiber layer. However, it is difficult to learn from ophthalmic images how defilement to the retina is connected to vision loss in humans. This is mainly because there are significant differences in the anatomy of the eyes among different patients. This problem becomes harder because of issues with image quality and automated image analysis.

3. Methodological Design

The proposed model involves the preprocessing model with machine learning and a neural network technique called denoising, that is aimed to remove noisy data as well as unwanted information from image datasets. The preprocessing steps involve Denoising and Edge preservation by Median filtering and CLAHE. This process smoothens the Retinal fundus images of Glaucoma dataset. The smoothed image undergoes optimization by Black Widow Optimization. The process of the denoising technique continues with training the model based on noisy data identifying the patterns of information based on the created models and testing the glaucoma images thereby eliminating the noisy data indicated in Figure 1.

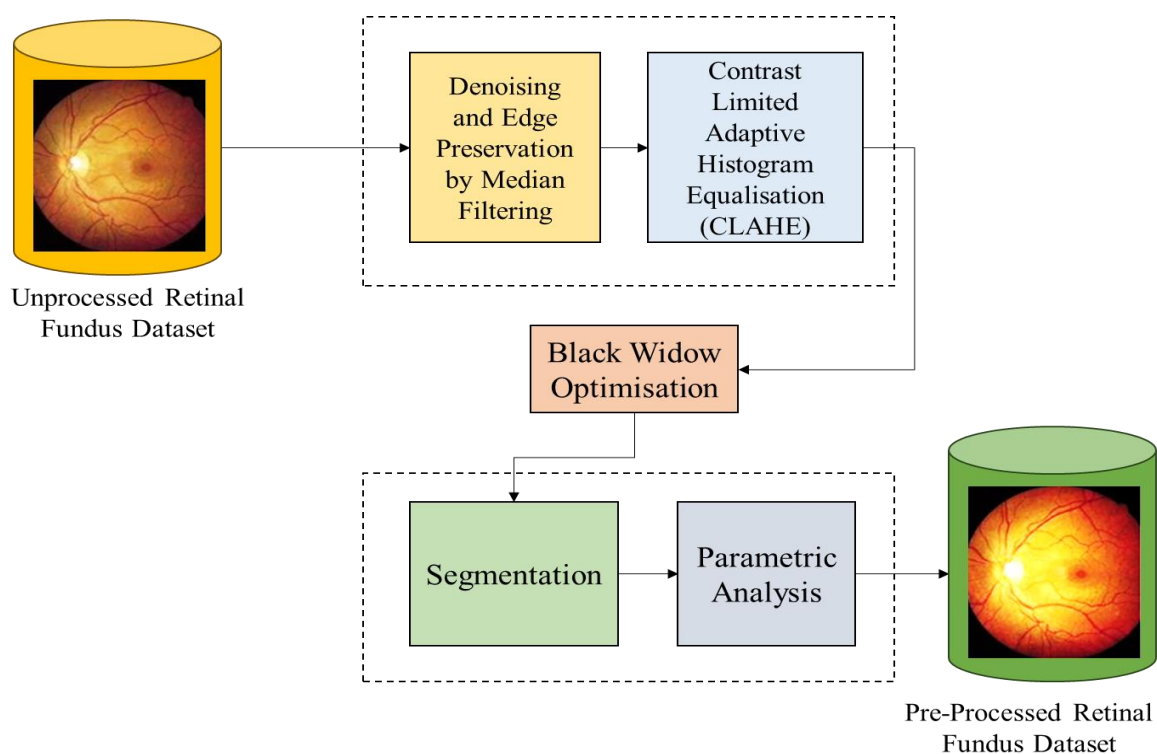


Figure 1: Architecture of Optimal Pre-processing of Retinal Fundus Images

3.1 Preprocessing of Glaucoma Image Dataset

The Preprocessing of Retinal Fundus Images comprised of Median Filtering for Edge Preservation and CLAHE.

3.1.1 Median Filtering for Edge Preservation

Noise removal in the glaucoma images is non-linearly utilized for edge preservation. The Median filter algorithm reduces the salt and pepper noises of image filtering [16]. It works on each image pixel by pixel and it replaces every value with the median value's neighboring pixels. Every value from the neighbor's pixel is rearranged in the numerical order and the considered pixel, the median pixel is replaced by the rearranged

values. In this method, image sharpness is not reduced in the median filter. If $X_1, X_2, X_3, \dots, X_n$ is the sequence for the nearest pixel value considered and its mathematical form is represented in Equation (1) and (2) as follows:

$$MF = \text{median}(X_i) = \frac{\sum_{i=1}^n X_i(n+1)}{2}, \text{ when } n \text{ is odd} \quad (1)$$

$$MF = \text{median}(X_i) = \sum_{i=1}^n X_i \left(\frac{n}{2} \right) + 1, \text{ when } n \text{ is even} \quad (2)$$

Where $i = 1, 2, 3, \dots, n$ and median are premeditated on the basis of summation and mean of the pixels of the image.

3.1.2 CLAHE Enhancement for Glaucoma Images

CLAHE is suitable for biomedical images like Glaucoma. Image quality is increased by the noise removal. Components of image are extracted by this algorithm; and it is utilized for image pre-processing that is containing the shape of interest. The human interpretations of Glaucoma images are complicated. Thus, this approach [17] is efficient for the Glaucoma image's detection. Various eye abnormalities with various shapes are made clear by using the noise removal techniques. This process is efficient to proceed with the process of segmentation for ROI extraction, calcification and identification of tissue disorder. Dilation, Erosion, opening and closing through reconstruction is used for the reduction of noise. At first, image enhancement is improved; histogram for every region is computed depending on the contrast expansion limitation, and the limitation of chip for clipping histograms. In Glaucoma, holes or gaps are filled by means of Erosion. Erosion calculation of the binary image A is structured by Element B in Equation (3):

$$A \ominus B = \{z \in E | B_z \subseteq A\} \quad (3)$$

Dilated gradient mask is shown by means of Dilation. In the Glaucoma region, few holes are found inside it. A 's dilation is followed by structured B in the Equation (4):

$$A \oplus B = \{Z \in E | (B^s)_z \cap A \neq \emptyset\} \quad (4)$$

Morphological reconstruction follows the erosion calculation, A 's erosion is obtained by the opening B and the resulting image dilation is obtained through B as presented in Equation (5):

$$A \circ B = (A \ominus B) \oplus B \quad (5)$$

Morphological reconstruction follows the dilation calculation and it is used for reconstruction with closing, where B is used for closing of A 's dilation by B and it is provided in Equation (6):

$$A \cdot B = (A \oplus B) \ominus B \quad (6)$$

For the image enhancement, CLAHE uses contrast enhancement and morphological reconstruction and it is effective in obtaining the region of glaucoma to decrease the existence of unwanted noise in the image. Thus, these hybrid combinations performances are better.

Image quality is enhanced by the pre-processing method and it can be proved by PSNR [18] with time series. In order to check the quality of image, the standard criteria of measurement are performed by PSNR. The value of PSNR is obtained by Equation (7):

$$PSNR = 10 \log_{10} \left(\frac{R^2}{MSE} \right) \quad (7)$$

Linear Combination of partition result's mapping region are mapped with every pixel in every technique. After the noise removal, image quality is removed by this enhancement technique and the enhanced glaucoma images are obtained. The next process is to segment the glaucoma region in the image with image segmentation method.

3.1.3 Black Widow Optimization

The optimization called Black Widow Optimization(BWO) algorithm selects the parameters optimally by RCNN design. A unique characteristic of mating is followed by black widow spiders. Cannibalism is the exclusive stage in the BWO algorithm [19]. Arthropods for breathing air in spiders comprise 8 legs and venomous fangs. Arachnids are this species with larger order in the 7th rank in complete diversity of species. This algorithm begins with initial population of spider and every spider demonstrated the solution. New generation is generated by a pair of spiders. Female black widow grubs the male after mating in this algorithm. After mating, sperm is stored in female black widow and the sack of eggs was produced. Egg sacs will be created after 11 days.

Computation of RCNN parameters is obtained using this algorithm. BWO's characteristics are presented as, minimization of learning error rate by selecting RCNN parameters. Problem variable's parameters are needed in design to find the solution. For these problems, black widow spider algorithm produces optimal answers. Every black widow spider takes the parameters for the problem. Formula for BWO's initial population is presented in Equation (8) as described below:

$$P_i = [D_1, D_2, \dots, D_N] \quad (8)$$

Where the parameter of RCNN's dimension is described by D_N , floating point numbers are denoted by D_1, D_2 in which the fitness function is achieved. Formula for the fitness function is given in Equation (9) is described as,

$$F(P_i) = F[D_1, D_2, \dots, D_N] \quad (9)$$

The matrix for candidate widow matrix is created for imitating this algorithm according to the spider's initial population. Later to this, the process of breeding is operated by the random selection of parents, in which the female spider eats the male spider after mating.

These pair selection is independent in this algorithm that initiates the mate to create the new generation and also mate distinctly. In each and every process of mating, 1000 eggs are generated in the real word applications. Finally, very strong spider babies were produced. Long widow array in random manner is generated. Depending on the offspring operation, the formula for procreate in Equation (10) as follows,

$$\begin{cases} O_1 = \alpha \times D_1 + (1 - \alpha) \times D_2 \\ O_2 = \alpha \times D_2 + (1 - \alpha) \times D_1 \end{cases} \quad (10)$$

Reproduced array is called α , widow array is produced by the arbitrary numbers [20] incorporates the creation of offspring by the employment of α through the succeeding equation, in which the parents are represented by D_1 and D_2 and the offspring are represented by O_1 and O_2 .

By repeating the process for $DN/2$ times through random number selection will not be duplicated. Lastly, sorting of this array is depended on the rate of cannibalism and fitness parameter. In addition, collection of best individuals creates new population generation. The fitness parameter is evaluated in Equation (10).

The results are obtained by applying the ANFIS rule. If α ratio is lower than 1, D parameter is lowered. If α is lower than threshold t , D parameter is lowered. When the α ratio is equal to 1, then the D parameter possesses mid value. When α ratio is higher than the t threshold, then the D parameter is high, where threshold is represented as t , the threshold value is taken as the fitness value.

Three various cannibalism rates are presented in this black widow optimization. They are as follows: Sexual cannibalism, muscular cannibalism and mother cannibalism [21]. In this process, sexual cannibalism is taken in which the male spider has been eaten by the female ones after mating. Mute pop is selected automatically with population. Every solution will be randomly chosen that changes two elements in the structure of an array. The rate of mutation is calculated depending on the mute pop. The condition of termination depends on the following steps; attaining the accuracy at particular level, no changes in the fitness value and number of iterations. The obtained optimal solutions are gathered with termination check. The Algorithm for performing the Black widow Optimisation model is given in Table 1.

Table 1: Black Widow Optimization Model to optimize the denoised images

Algorithm Black Widow Optimization Model for Denoised Images (BWOMDI)
Initialize BW, Procreate, Cannibalism_rate, Mutation Rate (MR) and N (Number of Iterations), Max
Def Dim_Arr $P_i := [D_1, D_2, \dots, D_N]$
IterateWhile $P_i = \max$
Select P_i
Decrement P_i
Iterate For $i := 1$ to D_N
Decrement P_i
Select D_1 and D_2
Destroy Father D_1
Obtain O_2
Test if $P_i > 1$ then
Mutate Widow
Obtain $F(P_i)$
Else

```

Compute Cannibalism_Rate
End if
End For
End While
End Black Widow Optimization Model for Denoised Images (BWOMDI)
    
```

As indicated in the Table 1:, the algorithm Black Widow Optimization Model for Denoised Images (BWOMDI) has sufficient model to optimize the images denoised from the existing denoising techniques and to enhance the prediction accuracy.

4. Experimental Implementation and Analysis

Python is used for simulation which is dedicated for some explicit problems and open dataset from Kaggle Secondary Source is taken from Retinal Fundus Images. This dataset contains 650 glaucoma images. The performance evaluation is carried by Compared analysis of BCO-RCNN method with models like CNN, RF-DNN and FCN. The Dataset comprised of class value indicating presence or absence of Glaucoma as shown in Figure 2:

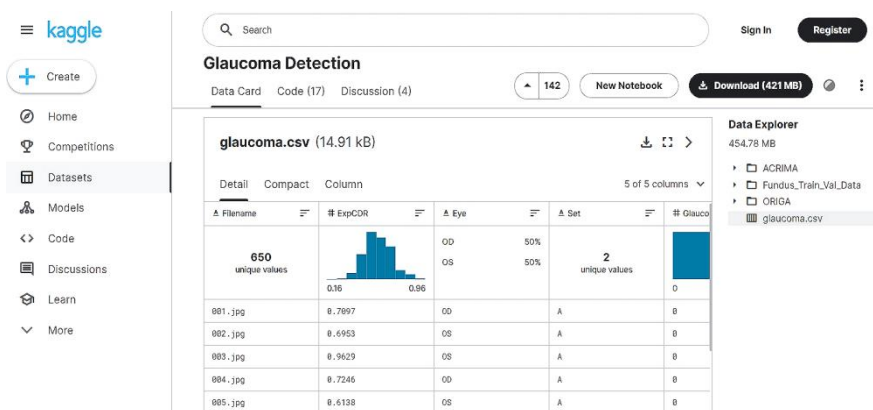


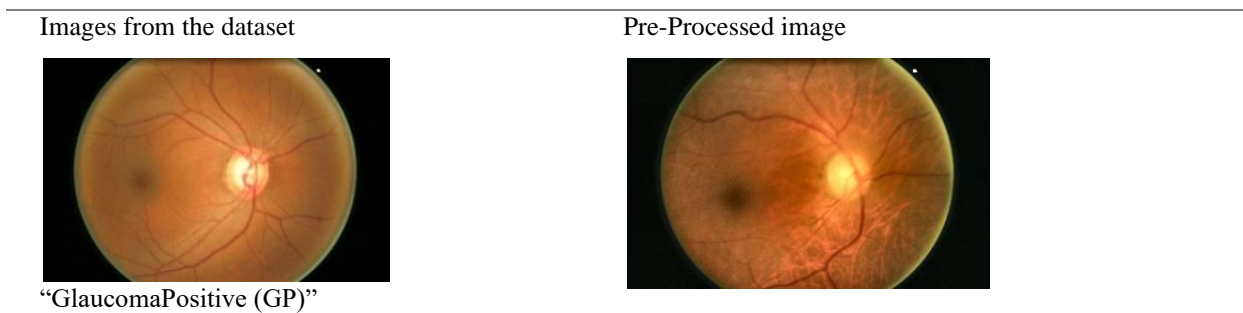
Figure 2: Dataset from Kaggle Retinal Fundus Images

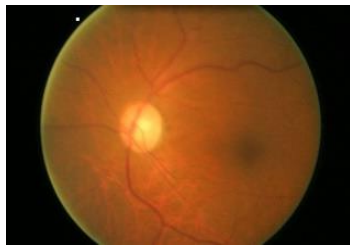
The Glaucoma detection based on hybridized models produced the confusion matrix where GN represents Glaucoma Negative and GP represents Glaucoma Positive. The Glaucoma detection in this experiment has been predicted based on the four evaluation parameters as given in Equation (11).

$$CM\{Glaucoma\} = \begin{bmatrix} TP & FP \\ FN & TN \end{bmatrix} \quad (11)$$

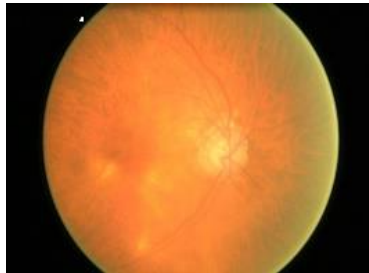
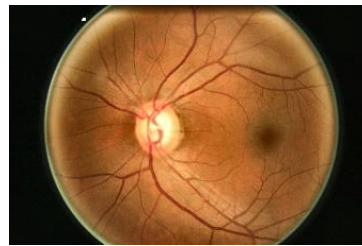
Where TP, is indicated as the positively predicted value along with False Positive which is FN also predicted correctly. In case of negative or error predictions, the TN and FP were wrong based on the fact that the truth has been identified negative as well as False data being predicted as positive values respectively. The Overall results of Glaucoma predictions with retinal fundus images were presented in Table 2:

Table 2: Resulted retinal glaucoma prediction of BWO-RCNN





"GlaucomaNegative (GN)"



"GlaucomaPositive (GP)"



"GlaucomaNegative (GN)"



As indicated in Table 2: the Glaucoma retinal fundus images have shown few enhancements especially in improving the quality of the image thereby augmenting the prediction efficiency. The clarity of the images has also improved from being noisy in the initial stage data.

After completing the implementation process, the results for confusion matrix based on Glaucoma Positive and Glaucoma Negative along with the CM {Glaucoma}, the degree of measurement result, computation, or requirement imitates the standard or correct value indicated as accuracy of Glaucoma prediction which is calculated based on equation (12) and the overall outcomes were summarized in comparison with the existing models as represented in Table 3:

$$\text{Accuracy} = \frac{TP+FP}{TP+TN+FP+FN} \quad (12)$$

Based on calculated results,

Table.3. Evaluation of Accuracy in Prediction and its enhancement with number of samples with different existing and proposed models.

Table 3: Evaluation of Accuracy in Prediction and its Enhancement with Number of Samples with Different Existing and Proposed Models.

Number of Samples	Accuracy (%)			
	Proposed BWO-RCNN	CNN [21]	RF-DNN [22]	FCN[23]
100	93	93	93	91
200	94	93	94	92
300	95	94	95	94
400	96	93	96	95
500	97	93	96	94

As shown in Table 3, the accuracy of prediction has improved from time-to-time based on the number of samples. The accuracy was 93% when the minimum number of samples was 100 and it increased to 94% in 200 samples, 95% in 300 samples, 96% in 400 samples and finally settled with 97% in 500 samples after 5 consequent iterations. In Fig.3, the accuracy comparison is demonstrated with X-axis as number of samples and accuracy in percentage at Y-axis. CNN is represented in blue color, RF-DNN is denoted by green color, FCN is indicated by red color and orange color represents proposed RCNN. From the figure, the proposed RCNN shows that it accomplished improved performance compared to the existing methods. The results showed that there is a

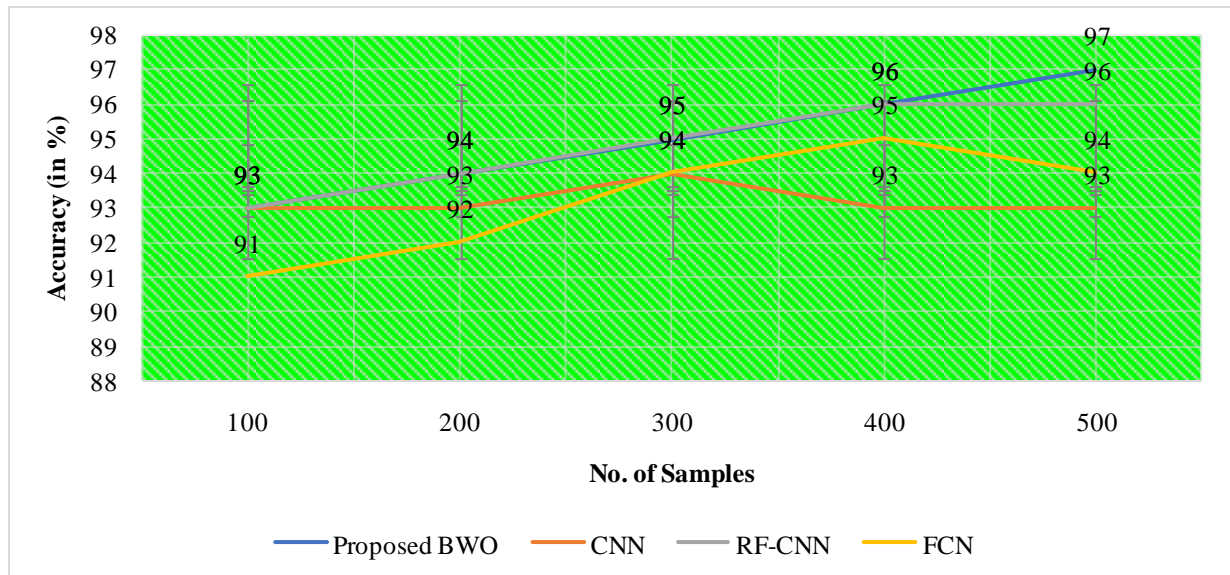


Figure 3: Enhancement of accuracy as the samples increased on a time-to-time basis.

direct relationship between the enhancement of accuracy with the number of samples being selected for prediction. Out of 650 samples, 500 samples were trained and tested to find the accuracy and then compared with the other Image processing models as given in Table.3.

Table 3: Consolidated assessment of the proposed model with the existing techniques like CNN, RF-DNN and FCN

S.No	Model	Accuracy
1	Proposed Combined BWO (%)	97
2	CNN [16] (%)	95
3	RF-DNN [17] (%)	96
4	FCN [18] (%)	96

As shown in Table 3:, the Proposed model which is the combined Denoising and Black Widow Optimization model has outperformed the existing models. The results are presented in graphical form in Figure 4.

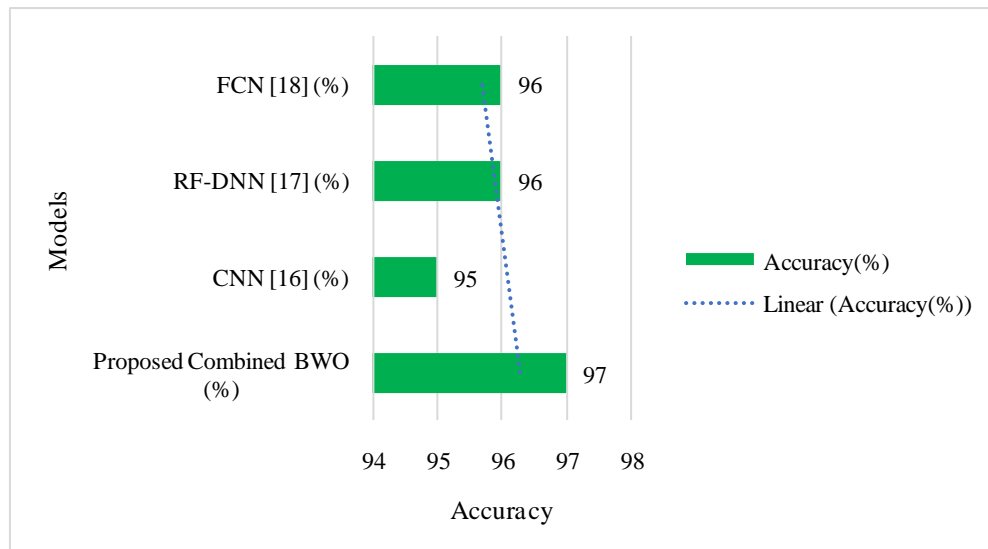


Figure 4: Enhancement of Accuracy of the proposed model outperforming existing models.

From the results in Figure 4, it has been perceived that the proposed approach attains accuracy of 97% outperforming the existing models. Also, there is a linear improvement of augmentation in comparison to the existing models. Therefore, the proposed method is found to be comparatively efficient than the existing methods. The Combine BWO gives a lower sensitivity and achieves high false positive rate region for some glaucomatous cases in Kaggle and it occurred to be small.

5. Conclusion

In this paper, we have a proposed a methodology for identifying Glaucoma in retinal Fundus images using fusion of Denoising techniques like Median Filtering for Edge Preservation, CLAHE and the Optimization techniques like Black Widow Optimization model, and produced an enhancement in the quality of Glaucoma retinal fundus images. As well as augmented the prediction accuracy to 97% outperforming the existing models. The performance of the prediction was found convincing and capable to identify Glaucoma at the earliest stage of its inception as tested from medical testing centers. In future, this research can be propounded using segmentation process and further test its performance for better prediction in the future.

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