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Automated Optic Disc Segmentation and Classification Model using Optimal Convolutional Neural Network for Glaucoma Diagnosis System

Narmatha Venugopal, Kamarasan Mari

Abstract In present days, Glaucoma is an important disease which affects the retinal portion of the eye. The identification of Glaucoma in a color fundus image is a difficult process and it needs high experience and knowledge. The earlier identification glaucoma could save the patient from blindness. An important way to diagnose the glaucoma is to detect and segment the optic disc (OD) area. The region of OD area finds useful to help the automated identification of abnormal functions occurs in the case of any injury or damage. This paper presented an automated OD segmentation and classification model for the detection of glaucoma. The presented model involves feature extraction using median filter, segmentation using morphological operation and classification using convolution neural network (CNN). Here, optimal parameter settings of the CNN are automatically tuned by the use of particle swarm optimization (PSO) algorithm. The presented model is validated using DRISHTI-GS dataset and a detailed quantitative analysis is made to ensure the goodness of the presented model. In addition, the extensive simulation outcome pointed out that the presented model showed outperforming results with the maximum accuracy of 97.02% in the classification of OD.

Keywords—Feature extraction; Glaucoma; Optic disk; Segmentation; particle swarm optimization..

I. INTRODUCTION

Glaucoma and diabetic retinopathy are considered as one of the crucial eye disease which could leads to complete blindness. Glaucoma is reported as the second cause of blindness all over the globe. The identification of glaucoma at the earlier stage is mandatory for preventing the blindness [1]. The persons affected by glaucoma and diabetic retinopathy gets increased annually and higher than 50% of them become blind. It is a significant challenge faced by ophthalmologists. They will examine the retinal fundus images acquired from the fundus camera to identify several retinal related diseases like glaucoma through the appearance of major symptoms denoted from the optic disc (OD) region and the existence of pathologies like exudates and cotton wool spots. OD is a brightness region in retinal as entry and outlet spot of blood vessel and retinal nerve fibers. OD acts as a viral role in the design of automatic approach of diagnosing glaucoma. At the same time, the identification of OD area will minimize the number of false positives when it is investigated the identification process on bright abnormalities like exudates produced by resemblance features among them. Numerous research works has been made related to the identification of the OD and diabetic retinopathy. [1] undergo segmentation of OD region utilizing the low pas filtering and thresholding. It follows the series of processes namely exudates identification, extracting blood vessels extraction and microaneurysms segmentation for classifying the class of glaucoma and diabetic retinopathy.

Kavitha and Malathi [2] employed the incorporation of gabor filtering and K-Means clustering for segmenting the OD region to diagnose glaucoma. The OD region which undergoes segmentation will be processed through the morphological operations for attaining effective performance. [3] utilized genetic algorithm (GA) in blue channel of the image for improving the identification performance and the removal of OD region. It could easily identify the OD area at a faster rate and attained better detection rate. Weighted error rate (WER) is utilized for validating the outcome. [4] integrated the morphological operations and Kirsch's template for removing optic disk as well as retina blood vessels which will be helpful for detecting exudates. [5] identified the OD region through the maximum variance model using morphology. It takes place on the green channel for obtaining candidate OD pixel (ODP). Then, the segmentation of the boundaries of the OD takes place by the use of Circular Hough Transformation. It takes place on the red as well as green channel, and the optimal outcome is chosen. Blood vessel is avoided by the rotating linear structuring component for improving the segmentation outcome of OD. The simulation takes place on the applied MESSIDOR dataset and it localized the region with the maximum performance. Another OD localization model is presented in [6]. Threshold estimation is employed depending upon the green channel histogram.

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* Correspondence Author
Narmatha Venugopal* ,Department of Computer and Information Science, Annamalai University, Chidambaram, Tamilnadu. Email:balaji.narmatha8@gmail.com
Kamarasan Mari, Department of Computer and Information Science, Annamalai University, Chidambaram, Tamilnadu. Email: smkrasan@yahoo.com

This process takes place to identify every bright region termed as cluster. Next, a set of two parameters namely area criterion and density criterion are employed on the cluster.

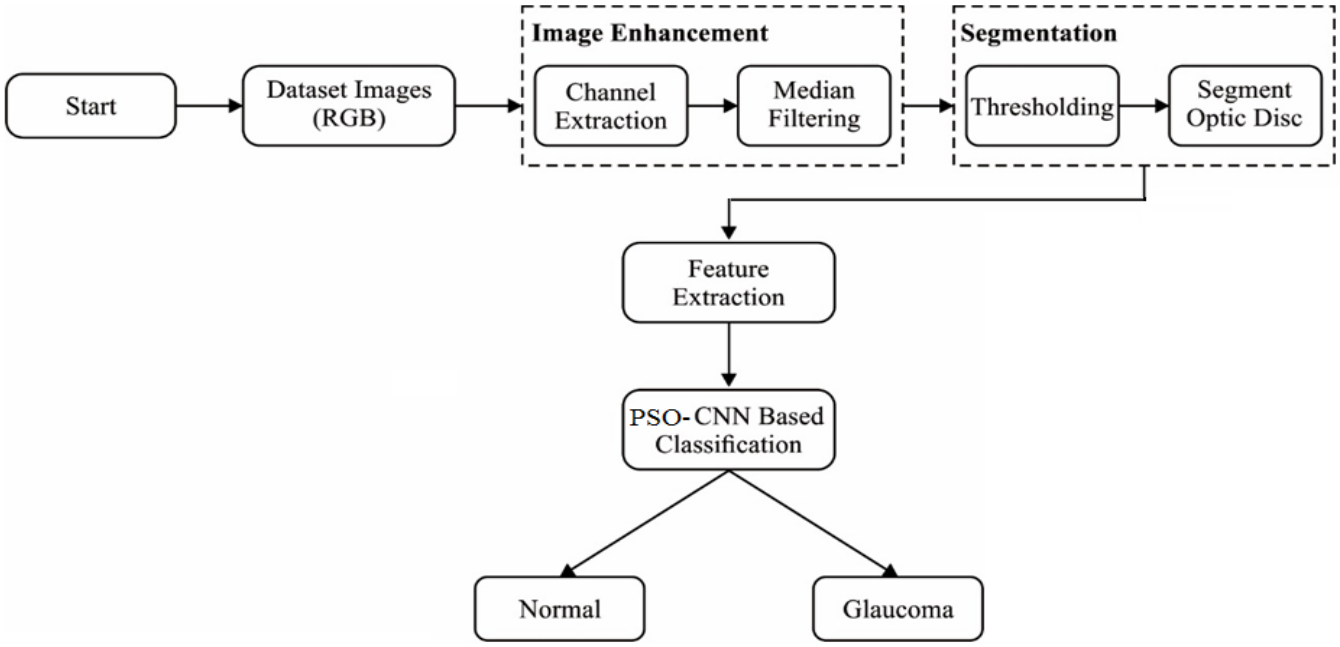


Fig.1. Overall Process of Proposed Method

[7] treated maximum entropy for candidate OD region and the Sobel operator is applied for detecting edges. [8] found the middle of the OD using the computation of ration between two channels such as red and green channel. Then, [9] introduced a preprocessing level on the actual fundus image using the application of average filter for varying intensity levels. The preprocessed method called Contrast stretching details are applied for separating brighter region from background. The preprocessed image undergoes transformation through negative transform for obtaining a predefined threshold as a variable. At the end, watershed model is applied to differentiate OD, exudates and cotton wool spots from background image. [10] avoided the OD using the thresholding model and ilblack's approach is utilized for attaining binary image.

This work is focused on the design of an automated OD segmentation and classification model for the detection of glaucoma. The presented model involves feature extraction using median filter, segmentation using morphological operation and classification using convolution neural network (CNN). This study concentrates on the concept of recognizing the OD region by the use of red channel of retinal fundus images. It is due to the fact that poor contrast is present on the blue channel and green channel will be good for detecting blood vessels. In addition, filtering technique is employed to make the OD region visibly. Here, optimal parameter settings of the CNN are automatically tuned by the use of particle swarm optimization (PSO) algorithm. The presented model is validated using DRISHTI-GS dataset and a detailed quantitative analysis is made to ensure the goodness of the presented model. In addition, the extensive simulation outcome pointed out that the presented model showed outperforming results with the maximum accuracy of 97.02% in segmenting the OD.

II. Proposed Model

The entire working procedure of the presented model is shown in Fig. 1. It involves a set of processes namely channel extraction, filtering, segmentation, feature extraction and classification. Initially, the actual color fundus image has a set of three diverse channels namely red, green and blue. These channels will be extracted and the red one is applied as the input image to the subsequent processes. Then, median filtering is employed as a preprocessing stage for removing the noise and obtaining the OD region visibly. For the segmentation of OD region, Ostu thresholding method is applied. To further segment the region, morphological operations takes place. Next, feature extraction takes place to identify the important features which can represent the OD region. Finally, classification is done by the use of CNN model.

Preprocessing

At this stage, extraction of channels takes place to attain the red channel as the input image. The noise which appears in the provided image is eliminated through median filtering. The median filter operates on the principle of replacing the pixel values with the median level intensity values of neighboring pixels. The pixel value in point (i, j) is provided to the determination of median. It can be mathematically defined as follows:

$$f(i,j) = \underset{(s,t)\in(S_{ij})}{\text{median}}\{g(s,t)\} \qquad (1)$$

Segmentation

The process of thresholding is the middle point of segmentation. Here, the values of pixels lower than the threshold value are considered as background whereas the rest of them are treated as object points.

The threshold process resulted to the binary images which contains a set of two gray level images namely black and white. It can be mathematically represented as follows:

$$b(i,j) = \begin{cases} 1, & if\ f(i,j) \geq T \\ 0, & if\ f(i,j) < T \end{cases} \quad (2)$$

Where T is threshold intensity. Here, Otsu method is employed for the automatic selection of threshold values.

Feature Extraction

Here, feature extraction of segmented OD region takes place for identifying the important features namely texture, color and form feature. Texture feature is extracted utilizing texture computation of second order with assumed relativity with the nearby pixels known as gray level co-occurrence matrix (GLCM). It utilized a set of four directions $0^0, 45^0, 90^0\ and\ 135^0$. Then, the color features are attained from the statistical computation of mean, deviation, skewness and kurtosis.

Classification

CNN is inspired from specific characteristics of the visual cortex and is mainly applied for classifying images. The process involved in the image classification by CNN takes place using a sequence to layers namely convolutional, nonlinear, pooling layers and fully connected layers.

The input image is initially provided to the convolution layer. The pixel values are read from the top left corner of the image. Then, the software chooses a small matrix known as filter which provides the convolution. The process of filter is to perform multiplication of its values with the actual pixel values. Once every position is passed to the filter, a matrix is attained; however, a smaller one than an input matrix is obtained. The CNN holds a set of convolutional networks integrated with nonlinear and pooling layers. Nonlinear layer is included after the inclusion of every convolution function. It holds an activation function that provides a feature of nonlinearity.

The non-linear layer is followed by a pooling layer which is applied to perform the downsampling operation. As a result, the volume of the image gets reduced. It indicated that when few features have been recognized in the earlier convolution operation, then a detailed image is not required to carry out further computation. Once the sequence of convolutional, nonlinear and pooling layers gets completed, it is needed to link it to a fully connected layer. This layer receives the output data from the convolutional networks.

Particle Swarm Optimization (PSO)

Here, PSO algorithm is applied for the parameter optimization of CNN. It makes use of diverse particle and every particle intends to identify the optimum solution via the communication with other particles. Consider the particle count as P and the parameter set of the pth particle after the rth round as as $x^p(r) = (x_1^p(k), \dots, x_N^p(k))^T$ where N indicates the parameter count involved in optimization. The initial parameter set $x^p(0)$ is selected in an arbitrary way. Then , the jth element of the inertia term $v^p(rand)$ can be represented by

$$v_j^p(r+1) = wv_j^p(r) + c_1 r_{1_j}^p(r)\left(x_j^{p-best}(r) - x_j^p(r)\right) + c_2 r_{2_j}^p(r)\left(x_j^{g-best}(r) - x_j^p(r)\right)$$

$$x^{p-best}(r) = \arg_{x^p(k)} \min\{f(x^p(j)) | j = 0, \dots, r\}, \quad (3)$$

$$x^{g-best}(r) = \arg_{x^{p-best}(r)} \min\left\{f\left(x^{p-best}(r)\right) | p = 1, \dots, P\right\},$$

Where $rand_{1_j}^p$ and $rand_{2_j}^p$ indicates the arbitrary values in $[0, 1]$ and w, c_1 and c_2 represents the weights. The p-best represent the optimal parameters which are derived after r rounds and g-best represents the optimal parameters between every particle. The $v^p(r+1)$ is always capped by the following equation for preventing it from becomes very high.

$$v_j^p(r+1) = \begin{cases} v_{max}, & \text{if } v_j^p(r+1) > v_{max} \\ -v_{max}, & \text{if } v_j^p(r+1) < -v_{max} \end{cases} \quad (4)$$

Consequently, the subsequent search point of the pth particle can be represented as

$$x^p(r+1) = x^p(r) + v^p(r+1) \quad (5)$$

Fig. 2 shows the visualization of Eq. (5). The evolutionary algorithms are found necessary for optimizing the CNN parameters due to the fact that it does not compute the derivates and hence, gradient-based method could not be employed.

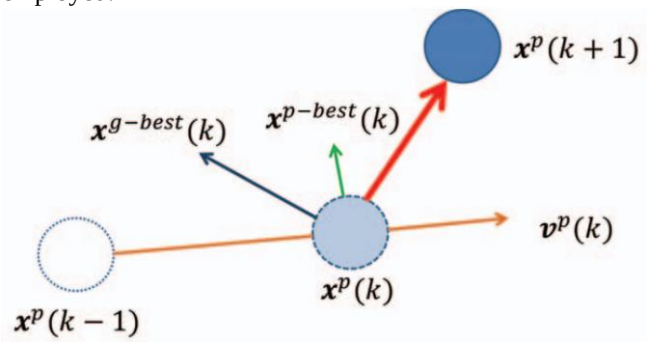


Fig. 2. PSO based parameter optimization process

Parameters for Optimization.

It is assumed that the structure of the network is previously provided and attempted for optimizing the relevant parameters namely kernel size, padding, feature map count and pooling kinds. Due to the fact that integer parameters exist, searching of parameters initially takes place by the use of floating-point values. When the parameter exceeds the dynamic range, a reflection takes place to their adaptive range. It is uncapped for ensuring that it should not stuck in the low or high value. The stride will not undergo optimization for ensuring that maximum search space is available and makes the issue resolvable through CNN. When the stride undergoes optimization using PSO, the image sizes becomes tiny and CNN could not be employed.

Optimization of CNN Using PSO

The work process of the PSO-CNN is depicted in Fig. 3. At the beginning, P particles undergo random generation and are provided to the identical training samples and passed into identical iteration count utilizing back propagation.

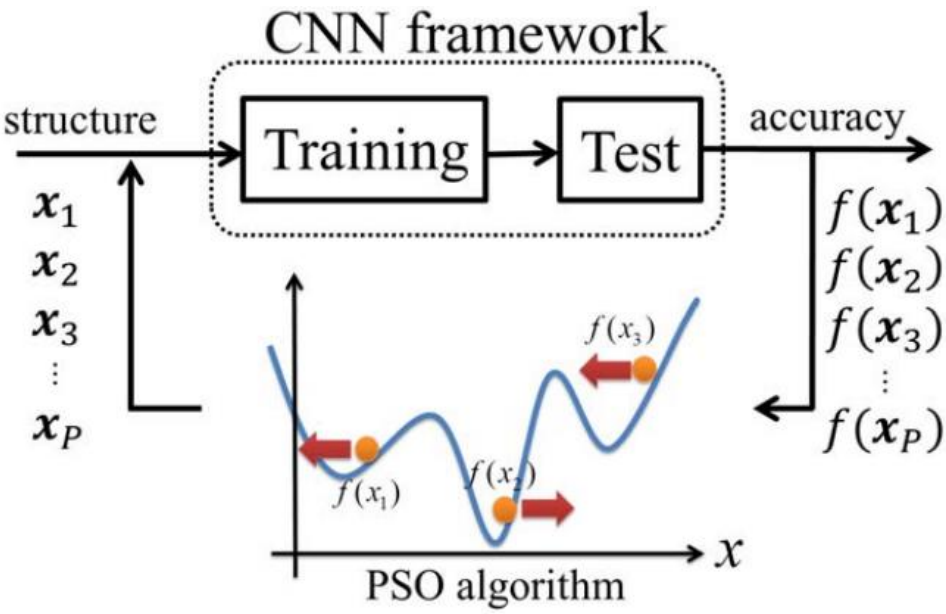


Fig. 3. Flow of proposed optimization

Next, the results of every particle, i.e. the classifier undergo evaluation by the use of validation dataset. The parameters are altered based on Eq. (3). It is earlier verified that the PSO offers maximum possibility of identifying the parameters over the arbitrary arrangement of parameters.

Efficient Optimization

Preferably, the effectiveness of every particle needs to be validation under identical conditions in the last training level. But, it is unrealistic due to the fact that when the particle count is M and iteration count is k, a total of Mk times the computation time is required. It is noted that a set of two models are applied for reducing the epoch count during the maintenance of above said effectiveness.

Ranking correlation model:

The conversion rate is based on the function of epochs and is depends upon the dataset. When the dataset is identified, it is probable to identify the epoch count required for training the network. Initially, the training of CNN takes place with maximum epoch count and determines the Spearman's ranking correlation:

$$\rho = 1 - \frac{6\sum_{j=1}^{k}(d_j)^2}{n_0} \qquad (6)$$

$$d_j = \sigma(p_j) - \sigma(q_j), k_0 = k^3 - k \qquad (7)$$

The epoch count is determined that exceed the fixed threshold value E for correlation and utilize E epochs to again process the PSO algorithm.

Volatility based model:

Though the previous model is precise, it requires high epoch count for training the network which is generally expensive. So, volatility based model is applied. Based on the epoch count, the classifier performance becomes more stable. At the beginning level, the results show low stability due to the arbitrary nature of back propagation (BP). At the same time, since the training continues, the network results to exhibits its implicit results. So, the stability of the network can be defined using volatility:

$$CV = \frac{\mu}{\sigma} \qquad (8)$$

Where

$$\mu = \frac{\sum_{j}^{N} accuracy^{r}[j]}{N} \qquad (9)$$

$$\sigma = \sqrt{\frac{\sum_{j}^{N}(accuracy^{r}[j] - \mu)^2}{N}} \qquad (10)$$

where $accuracy^{r}[j]$ indicates the classifier accuracy of the jth particle at the rth round. Once the CV becomes constant, it indicates that the network becomes more stable and allows the comparison of the results between the network.

III. Performance Validation

Dataset

The presented model is tested against DRISHTI-GS dataset [11] which comprises a total of 101 retinal fundus images to segment and classify OD region. The images are gathered from a hospital in Madurai, India. The physicians initially identify the Glaucoma patients using the practical investigations. These images are captured form the patients under the age of 40-80 years old. The information related to the dataset is provided in Table 1 and some sample images are shown in Fig. 4. From the existing 101 images in the dataset, a set of 31 images falls under the normal class and a set of 70 images comes under the Glaucoma class.

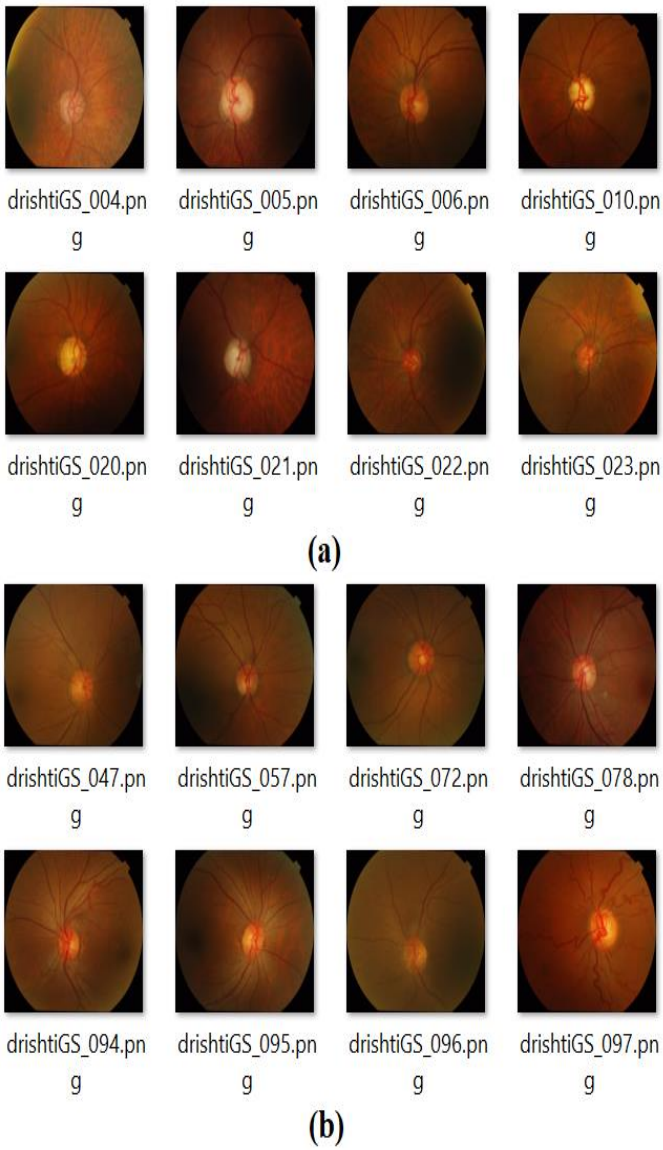


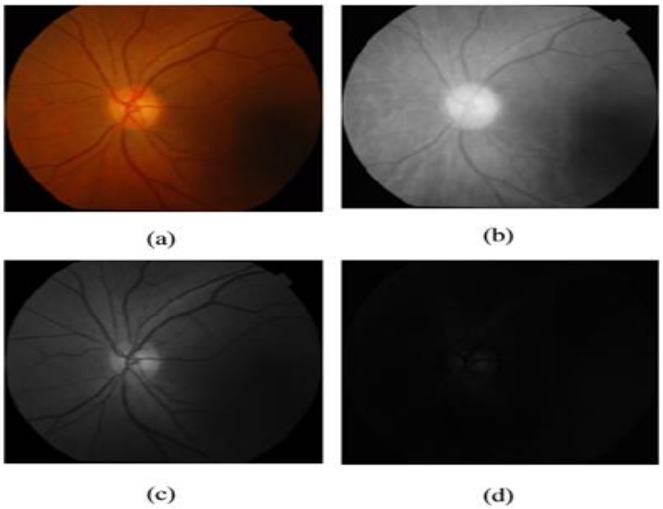
Fig. 4. Sample test images: (a) Glaucoma (b) Normal

TABLE I
DATASET DETAILS

• Description	• Dataset
• Total Number of Images	• 101
• Number of Normal Class	• 31
• Number of Glaucoma Class	• 70

Results Analysis

The selection of red channels from the outcome of the extracted image indicated the contrast among the OD and background is depicted in Fig. 5.



(a) Input image (b) Red (c) Green and (d) Blue channel
Fig. 5. Feature extraction results

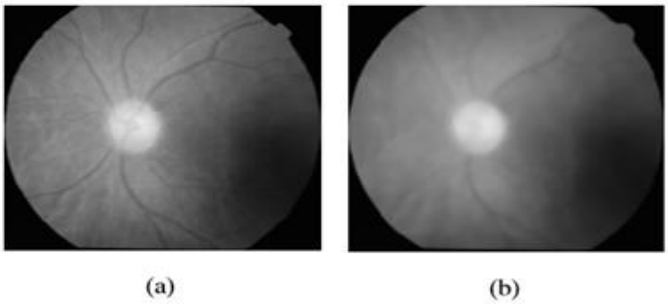


Fig. 6. The result of filtered images (a) Red Channel Image (b) Filtered Image

Next, median filter is employed to the red channel for removing noise present in the image and making the OD region highly visible. In addition, it could minimize the visibility of blood vessels in the OD region. Fig. 6 shows the sample examples of the input red channel image along with its respective filtered image from the outcome of median filter.

Threshold value is attained from the Otsu model which is highly affected while separating the OD region from the background as well as from other images. The segmented threshold image undergo processing by the use of opening function for obtaining effective segmentation of OD region and leads to the generation of the binary image. Then, the generated segmented image will be validated by the use of ground truth image to identify the classification accuracy. The segmented image along with the ground truth image is shown in Fig. 7.

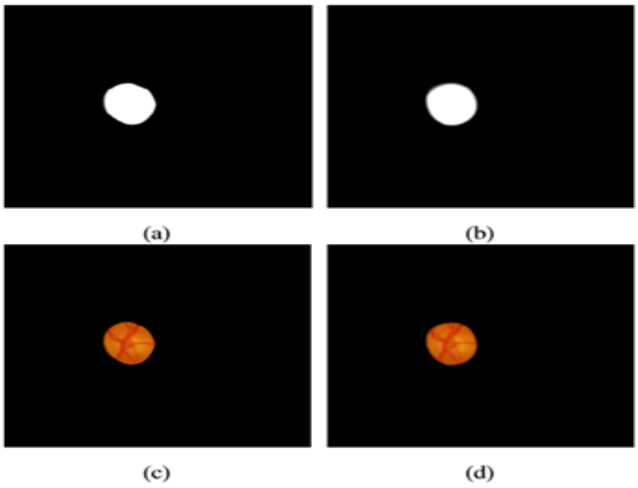


Fig. 7. (a) Segmented binary image. (b) Ground truth (c) SegmentedOD (d) Segmented ground truth

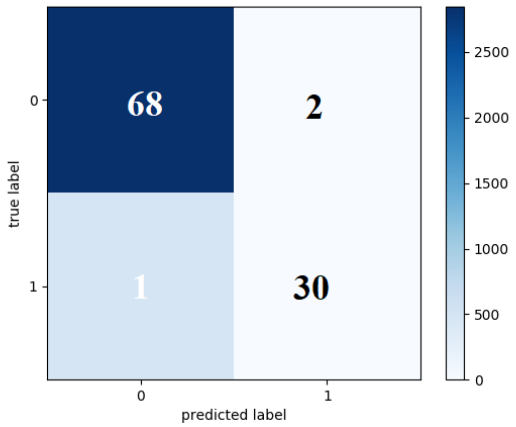


Fig. 8. Confusion matrix for the Glaucoma dataset

TABLE II
AVERAGE TEXTURE FEATURE (CONTRAST)

• Channel	• Contrast
• Red	• 11.155
• Green	• 2.708
• Blue	• 0.439

Contrast is generally applied to determine the intensity variation among the images. The red channel leads to maximum contrast with the value of 11.155 implied that its intensity greatly varies from the other ones. However, the green and blue channel showed lower contrast values of 2.708 and 0.439 respectively. At the same time, the OD of the object and the background can be neatly separated on the red channel. Fig. 8 shows the confusion matrix derived by the presented model on the Glaucoma dataset. From this matrix, it is observable that a maximum of 68 images are correctly classified under the class 'Normal' and 30 images are also properly classified under the class 'Glaucoma'.

TABLE III
COMPARISON OF PROPOSED WITH EXISTING METHODS

• Methods	• Sensitivity	• Specificity	• Accuracy
• PSO+CNN	**• 98.55**	**• 93.75**	**• 97.02**
• CNN	• 97.05	• 87.87	• 94.05
• VGG19 TL	• 93.33	• 81.63	• 87.48
• VGG19	• 71.11	• 89.21	• 80.16
• Standard CNN	• 75.76	• 78.72	• 77.14
• GOOGLENET	• 80.00	• 90.96	• 85.48

To further verify the superior results of the applied model, a detailed comparative analysis is made with the available models on the identical dataset. The obtained compared values are given in Table 2 and Fig. 9. The table values pointed out that the CNN model shows maximum classification with the accuracy of 94.05, sensitivity if 97.05 and specificity of 87.87. However, the PSO-CNN model shows extraordinary classification with the sensitivity of 98.55, specificity of 93.75 and accuracy of 97.02. These values are found to the highest values compared to other methods. These values stressed out that the presented segmentation based Glaucoma classification model is the superior one over the compared methods.

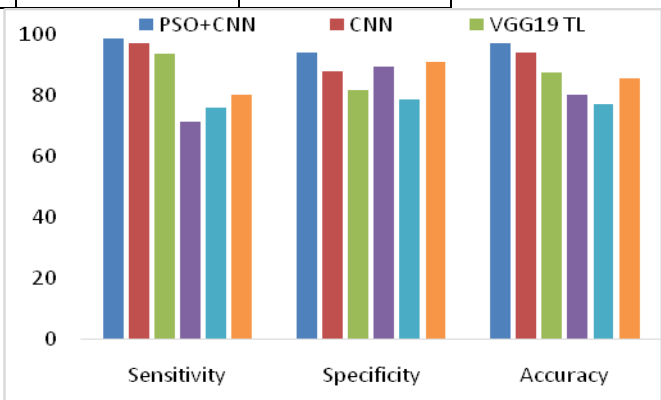


Fig. 9. Classifier results analysis among various methods

IV. CONCLUSION

Presently, Glaucoma is reported as the second cause of blindness all over the globe. Numerous research works has been made related to the identification of the OD.The presented model involves feature extraction using median filter, segmentation using morphological operation and classification using CNN. Then, the optimal parameter settings of the CNN are automatically tuned by the use of PSO algorithm. This study concentrates on the concept of recognizing the OD region by the use of red channel of retinal fundus images. It is due to the fact that poor contrast is present on the blue channel and green channel will be good for detecting blood vessels. In addition, filtering technique is employed to make the OD region visibly.The presented model is validated using DRISHTI-GS dataset and a detailed quantitative analysis is made to ensure the goodness of the presented model. In addition, the extensive simulation outcome pointed out that the presented PSO-CNN model showed outperforming results with the maximum accuracy of 97.02% in segmenting the OD.

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AUTHORS PROFILE

Narmatha Venugopal* ,Department of Computer and Information Science, Annamalai University, Chidambaram, Tamilnadu. Email: balaji.narmatha8@gmail.com
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Kamarasan Mari*, Department of Computer and Information Science, Annamalai University, Chidambaram, Tamilnadu.
Email: smkrasan@yahoo.com
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