IoT based BFOA-CNN Model for Automatic Glaucoma Detection

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Abstract

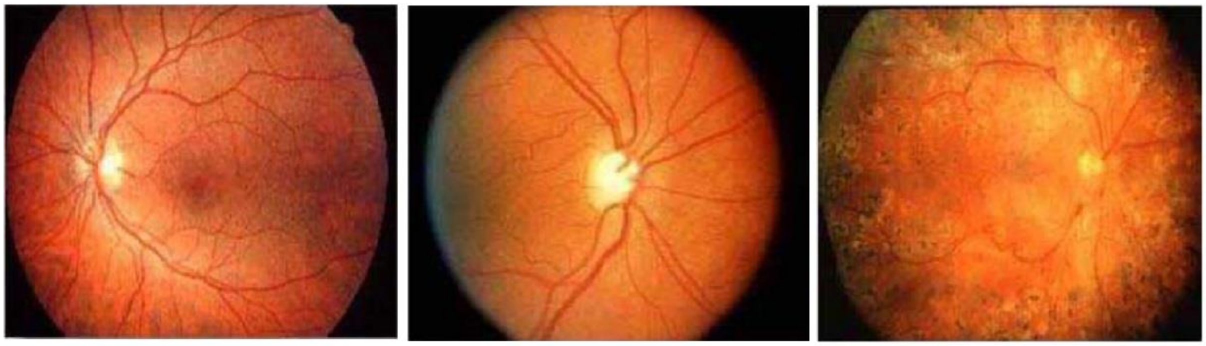
Internet of Things (IoT) and cloud computing are two related domains that depends on each other through which the physicians monitor and support the remote patients. Effective treatment of diseases need a model designed with IoT equipments to identify the diseases. This paper proposes a novel automated glaucoma recognition method for identifying the lesion region present in the given fundus image. The proposed BFOA-CNN model executes in five steps, viz., i) calibrate the image, ii) preprocess the image, iii) segment the image, iv) extract the features and v) classify the image. The image given as input is first calibrated and involved into preprocessing stage so as to make the image suitable to process further for successful classification. Next, optic disc is removed by the entropy method and CRF (Conditional Random Fields) based segmentation process is used for detecting the presence of lesion region in the given fundus image. Further the extraction of shape features is executed and it is followed by the classification using Random Forest classification model. BFOA-CNN model performance is investigated with a set of 101 retinal fundus image and the results proved the best efficiency of the model.

Accuracy: Internet of Things, BFOA-CNN, Retinal fundus image, Glaucoma Recognition, Conditional Random Fields (CRF).

1. Introduction

The considerable advancement of devices in IoT (Internet of Things) such as smart phone, wearable gadgets, and virtual reality facility to networked sensors covered the attention of the medical experts to use these in the monitoring and consulting the remote patients. Particularly the medical imaging process uses techniques like X-ray, CT scan, MRI, Radio-active pharmaceutical process, Endoscopy etc., for acquiring and communicating the information needed for assessing the present condition of the disease either to diagnose or to treat the patient. Yet the computational power of these devices have resource constraint and hence the analysis of the data collected need to be done rapidly. Edge computation is the significant solution for solve the limitation as it introduces the number of IoT equipments to analyse the data, connect the devices, transfer the data, and solve the queries of local databases. The increased number of IoT devices used in health care setup demands the need to ensure the validity of given data. Hence this paper focuses to explore the efficient ways to verify that the physicians receive only real time data [1] .

Application of IoT in healthcare industry ensures the enhancement of its care quality, reduction of medical expenses and optimization of the resources. IoT applied in the medical image processing helps in the identification and suggestion of real time corrective measures by the automated analysis of the images received from the imaging equipments. Digitalization of this medical technology provides easy monitoring and this reduces the waiting time and mental stress of the patients and doctors. Glaucoma – sight deterioration disease is found to one of the disease that could not be cured. It is reported as the second leading factor for blindness all over the globe. It is expected that the number of patients affected by glaucoma will increase till 2020[2]. Glaucoma refers to the number of ocular disorders that includes multi-factorial aetiology, IOP (Intraocular Pressure that is related to the field of optic neuropathy. Glaucoma causes permanent vision loss in the affected eye in case of not treating at the right time. The image details are carried from the light receptors to the brain by the optical nerves and those nerves are damaged by the glaucoma disease and it leads to vision loss. Report states that more than 4 million Americans were affected this disease and unfortunately half of this count is unaware of the reason behind their blindness [3]. This disease has the only remedy of early diagnosis and prevention. Various techniques are designed for detecting this glaucoma disease. Optical Disk (OD) is the exact position in the eye ball from where the ganglion cell axons exit from eye forming the optical nerves. Identifying this OD is the significant task to compute the diagnosing index of glaucoma. Many researchers assume that both the Iris center and image center will be close and hence they set up a radius according to the image size.



(a) Normal **(b) Glaucoma** **(c) Diabetic Retinopathy**

Fig. 1.1. Images of distince fundus abnormalities

Glaucoma disease is a kind of disease in which the optic nerves are affected leading to night blindness or loss of vision and it could be prevented through early detection and treatment. IOP known as Intraocular Pressure is an important risk that leads to failure of optical nerves. For developing closer tissues, a clear fluid is sent to the inner and outer chamber of anterior chamber (an empty space) that exists before the eyeball. The liquid is collected by the cornea and iris and sent out of the chamber if the angle is open. From there it passes through soft meshwork of nerves like drain and comes out of the eye. The liquid is passed with very minimum force by the meshwork drain and angle is opened. Optical nerves are damaged by the increased pressure of the liquid in the eyes and it leads to vision loss. Hence the maintenance of IOP is more important and failure of which might lead to collapse in retina and optical nerve [4].

Early diagnosis of glaucoma alone helps in avoiding vision loss whereas it is a medical challenge and on the other hand misdiagnosis leads to significant later functional loss [5]. Further glaucoma diagnosing in myopic eye and brain tumor affected patients is much more difficult due to the change in optical disc shape and visual defects. Hence doctors demand an effective machine learning method that detects glaucoma efficiently.

2. Literature Survey

Various image processing algorithms were proposed to detect glaucoma. Studies were found in the localizing and segmenting optical discs for detecting glaucoma [6]. Several algorithms were found that extracts image features or transforms image for training the classifiers used. Compared to clinical observations, this feature extraction method identifies and provides relevant information with excellent classification. Few methods used for detecting glaucoma are ; i) extraction of probabilistic combination of previous compressed feature from the pixel intensity values, FT (Fourier Transform) and B-splines coefficient [7], ii) analysis of higher order spectrum along with texture-based feature extraction from preprocessed image with SVM (Support Vector Machine) classifiers [8], iii) similar higher order spectrum extracted features with discrete wavelet transform and Support Vector Machine classifiers, iv) applying an empirical wavelet transform and least-square Support vector machines [9], v) using an adaptive histogram equalization along with various filter bank executed for creating local configuration pattern for feeding kNN (k-nearest neighbor) classifier [10]. All these approaches identify the features in the image for training the classifier to match the features extracted either from the original image or transformed image. Each algorithm explores distinct features and transformation of ONH for determining the matching patterns to detect the existence of glaucoma. Similarly, this paper applies a approach known as CNN (Convolutional Neural Networks) for detecting glaucoma disease.

CNNs are found to be efficient in detecting eye diseases using CAD (Computer Aided Detection) systems. Since 2015 various researches were taken for segmenting retinal vessels using CNN, assessing quality of images, optical disc and its cup segmentation [11], detecting retinopathy caused by diabetics, detecting age-macular degeneration detection of hemorrhages in other patients. Architecture of CNN makes it an efficient tool for glaucoma detection as it explores both the images features of local and global. There are studies where CNN is also used to handle color fundus image problems. In [12], the researcher applies architecture with 6 layers for optic disc patch which is segmented already. In [13], glaucoma is detected by extracting features using CNN and trained SVM classifier. Recent by Fu et. al. [14] proposed new group of network that worked based on distinct CNNs to classify global fundus image and various regions of optical disc. Another work [15-17] included the deep learning algorithm embedded with transfer learning and its results proved the highest level of accuracy, specificity and sensitivity. Lastly, in OCT, many investigations were observed in the performance of application of CNN to detect glaucoma, and layer segmentation.

3. Proposed Methodology

The methodology of BFOA-CNN technique to detect lesions and classify fundus images is shown in Fig. 4.1. First step is that the given images undergo image calibration processing. In this step the adjustment of un-calibrated image happens. Next step is the pre-processing of calibrated image. Successively, entropy approach is executed to determine the OD center position. Next the vessel is segmented using CRF model and it is followed by the extraction of shape features for discovering the presence of lesion in the given image. Finally, based on the presence of red lesions, the disease is categorised using classification process based on RF.

3.1 Calibrating the Images

DR screening is done with FoV by 45º, where d is the diameter for fixing different size of filters. Equations 3.1,3.2 and 3.3 give p1,p2 and p3 which are the measures of parameters respectively. And x=10, y=360 and z=28.

p1 – radius of the OD is given as

$$p1 = \frac{d}{x} \tag{3.1}$$

p2 – size of minimum micro-aneurysm is obtained from

$$p2 = \frac{d}{y}$$ 3.2

p3, size of higher haemorrhage is calculated from

$$p3 = \frac{d}{z}$$ 3.3

3.2 Segmentation based on CRF

Noise present in the image is removed using FP (False Positive) red lesion. Exact OD center position is explored using entropy model. Generally, OD part comprises highest intensity region where the retinal vessel constrains with minimum intensity. This segmenting of vessels is termed as reduction of energy in CRF method. Original classification of CRF is executed in which the relative images are kept as it is with no modifications for explicating the image samples. Each node is called as a pixel and the edges of neighbour nodes are connected based on the connectivity rule. Actually in CRF, the images undergo mapping with graph where the pixels are referred as nodes and the edge of each node is connected to other node edge based on rule of connectivity. Every node is linked with four pixel adjacent connectivity in local neighbourhood CRF while in FC node, the nodes are connected with every image's alternate pixels.

3.3 BFOA-CNN Model

BFOA-CNN technique work flow model is shown in Fig. 3.1. It shows the preprocessing process of the image for removing the noise. Followed by the execution of BFOA-CNN model and finally the classification is done with RF model.

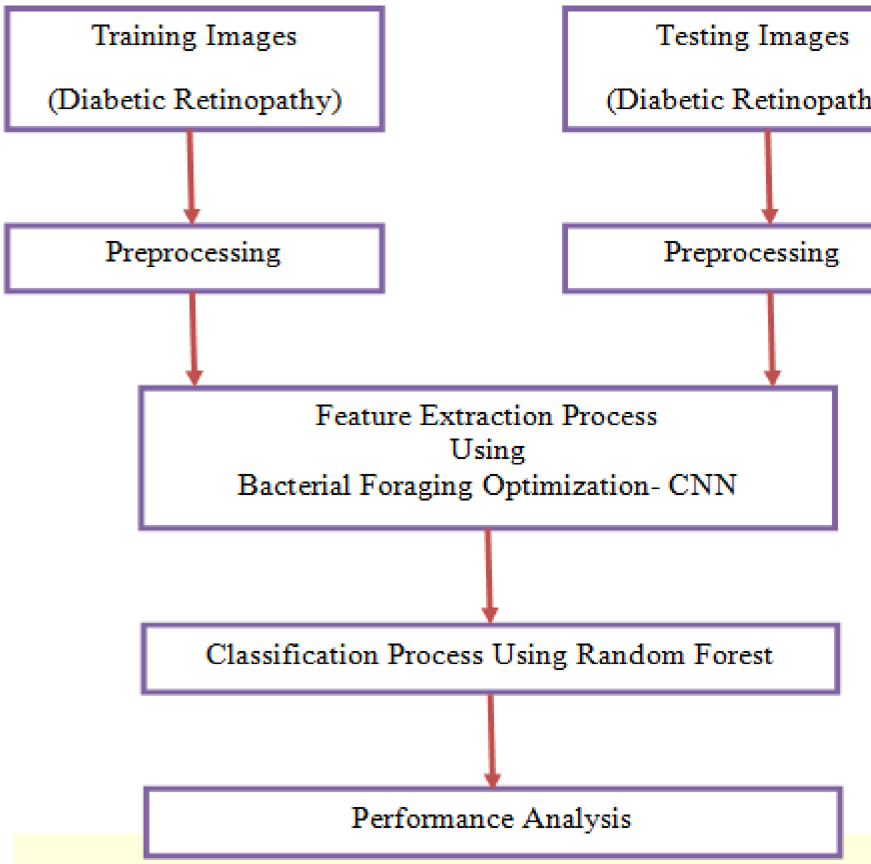


Fig. 3.1. Work flow of the entire process

3.3.1 Preprocessing and Augmentation

This phase is vital for removing the noises present in the image. The proposed model has general diabetic retinopathy images. CNN gives better accuracy while a large dataset is used. Also, the CNN function minimizes the small dataset because of the presence of over fitting problem. Execution of proposed model exhibits data augmentation for enhancing the dataset and restricts the over fitting problem. Data augmentation improving in turn increases the quantity of samples through the implementation of geometric transformation of the dataset using dedicated image processing techniques.

3.3.2 Features extraction based on CNN

In an AI platform, DL is meant to be a subset of ML method. CNN technique that used in this proposed work enables the simplification, production and exploration of various tough tasks through conventional methods. At the same time, the presence of multi-level abstraction enables multi-layer approach to recognize the data representation [18]. CNN is a supervised technique that depends on DL and gives better enhancement in feature extraction.

Major layers of CNN are:

- Pooling
- Convolutional
- Fully connected (FC)

Input image is complex for generating different maps of features from a convolution layer. It is solved by using kernels. Reduction of parameters and adjacent pixel association is observed in this approach. A CNN approach uses two levels of training. Induction of input images were done at feed forward level. In the mean time, every neuron is given a dot product of input vector and calculation of parameter vector is made. Successively the result is determined and the loss function is compared. Error rate is estimated based on the error. Chain rule is used to calculate the parameter gradient for tailoring the entire parameters. The average performance is measured with maximum number of iterative processes [19].

3.3.2.1 Initializing the weight

Speed of the convergence of the network is appropriate on the initialization of right weight. Various techniques exist for weight initialization. On the observation of the performance of several initializers "He" initializer is noted with best performance.

3.3.2.2 Activation function

Normally for the successive convolution in a deep network, a non-linear operator or activation function is used because it enhances the concept. In a DNN, good convolution that involves ReLU (Rectified Linear Unit) activation function increases the training speed. ReLU technique rates the negative towards 0 and is described as:

$$relu(u) = \begin{cases} u & if\ u \geq 0 \\ 0 & if\ u < 0 \end{cases} \tag{3.4}$$

Associated with ReLU, Leaky ReLU is performed in the Equation (3.5). The function is passive and it permits minimum non-zero gradient.

$$leaky_{relu(u)} = \begin{cases} x & if\ u \geq 0 \\ ax & if\ u < 0 \end{cases} \tag{3.5}$$

Here $\alpha = 0.3$. Presently, ELU (Exponential Linear Unit) tends improving accuracy of classifier and the speed of training. Still because of the minimum computation cost of ELU, it obtains higher negative rate that enables to give mean unit activation near to 0 viz., batch normalization.

$$elu(u) = \begin{cases} u & if\ u \geq 0 \\ a(e^u - 1 & if\ u < 0 \end{cases} \tag{3.6}$$

In a SELU (Scaled Exponential Linear Unit) the presence of activation function, analysis of developing network action is shown in Eq. (3.7). At the time of minimal twist of ELU, SELU is presented and equation for computation is as follows:

$$selu(u) = \lambda \begin{cases} u & if\ u \geq 0 \\ ae^u - \alpha & if\ u < 0 \end{cases} \tag{3.7}$$

3.3.2.3 Pooling

Pooling layer is the successive layer of convolution layer. It minimizes the number of parameter and size of feature maps. It leads to the decrease in the cost of computation. Minor modifications are made to pooling layer to assume neighboring pixel calculations. One of the widely used pooling techniques is max-pooling. Normally, in every convolution layer, the max-pooling layer will be of 2×2 and the size of the filter implies 2 strides and reaches maximum nearly 4.

3.3.2.4 Regularization

Critical concern for ML is that it should design a technique that performs efficiently even for new data similar to the training data. Various regularization methods were proposed for DL. Until the regularization of the efficient technique a dropout that performs at low cost is used. During the training phase, this technique randomly eliminates small nodes present in the entire layer and hence over fitting is avoided. Dropout is a collection of techniques that provides distinct training networks simultaneously.

3.3.2.15 Loss function

Another significant feature in designing DNN is the loss function selection. In general the widely used optimal function is Categorical cross-entropy function (H). On discrete variable u, description of 2 distributions (p and q) are:

$$H(p,q) = -\sum_u p(u) \ln(q(u)) \tag{3.8}$$

Here p(u) and q(u) represents the true distribution estimation.

3.4 Bacteria Foraging Optimization algorithm (BFOA)

Passino proposed Bacteria Foraging Optimization algorithm (BFOA), another bio-inspired algorithm for optimization [20]. In the recent decade, various optimization algorithms like Evolutionary Programming (EP) [21], Genetic Algorithm (GA) [22] had proved their performance in efficient optimization. Along with that other bio-inspired algorithms such as Ant Colony Optimization (ACO) [23], and Particle Swarm Optimization (PSO) [24] also prove their best optimization solutions. In that series this BFOA Algorithm which imitates the behavior of E-coli bacteria is also applied for finding the optimal solutions.

E-coli bacteria search rich nutrient in the given searching space with its energy used per unit period of time. Bacteria with common features are formed as single group. They communicate using signals with each other. Equation 4.2 gives the formula for creation of signals. Chemotaxis is referred to the swimming action of the bacteria to search the rich nutrient in the given space. This Chemotatic movement is of two types; (i) bacteria swims in one constant direction (ii) tumble, where the bacteria moves in the random direction based on the presence of nutrients in the given searching space[25]. Most of the recent researches use this Bacteria Foraging Optimization Algorithm. At first it was used to optimize the electrical engineering problems and later with the hybridization of the BFOA with various other algorithms proved its better performance to find the local and global optimum solutions. Biologically, very thin flagellum set present in the E-coli bacteria helps it to either swim or tumble during the chemotaxis. [26]. Cells are pulled by the flagellum while the bacterium rotates clockwise. Bacterium also tumbles randomly for finding the gradient that is rich in nutrient. Anti-clockwise movement of flagella aids the bacteria to swim fast. The growth of the bacterium depends on the amount of food it gets and well grown bacterium reproduces which means that the bacterium divides into two. The sudden changes in the search space will affect the bacteria to find the optimum solution. Hence the process of elimination Dispersal maintains the environment population [27].

3.4.1 Chemotaxis movement

Flagella help the bacterium to search the nutrition through swimming. Swimming of bacterium is in two types (i) constant direction swimming (ii) Tumbling – random direction swimming. Following equation is used to calculate the chemotatic movement of bacterium:

$$P^i(j+1,k,l) = P^i(j,k,l) + c(i)\ \Delta(i) / \mathrm{Sqrt}\ (\Delta(i) * \Delta(i)) \qquad 3.9$$

Here c(i) refers to the basic swimming distance , $P^i(j+1,k,l)$ refers to i^{th} bacterium at J- chemotatic step and k refers to the bacteria reproduction. Elimination dispersal loop is given by 1. Δ(i) denotes vector in the arbitrary direction.

3.4.2 Swarming

Each bacterium present in the group should travel to find the gradient that is rich in nutrient. It has two kinds of characteristics: attractant or repellant. The characteristic of attractant makes the bacteria to swim with high fitness value while swimming towards the gradient of nutrition.

Equation to measure the cell to cell signal:

$$J_{cc}(P(i,j,k,l)) = \sum_{i=1}^{S} P(;,i,j,k,ell) \quad 3.10$$

Here S represents the quantity of bacteria, Jcc(ɵ(i,j,k,l)) refers to i^{th} bacterium at J- chemotatic step and k refers to the bacteria reproduction. Elimination dispersal loop is given by 1.

3.4.3 Reproduction

Health of the bacterium decides the reproduction capability of it and hence after the final movement, the value of bacterial health is estimated using

$$J^{i}_{health} = \sum_{j=1}^{Nc+1} ji(j,k,l) \quad 3.11$$

Where J^{i}_{health} refers to the i^{th} bacterium health after the j^{th} chemotatic movement.. Nc refers to the total chemotatic movements.

Here the bacteria are arranged in ascending order of its health value. The bacterium that has the less health value than the given optimal value is eliminated. Healthy bacteria are reproduced (divided into two). Finally, the reproduced bacteria are let into the search space again for searching the nutrients.

3.4.4 Elimination Dispersal

In BFOA (Bacteria Foraging Optimization Algorithm) certain situations might occur where the elimination happens while there is no reproduction. In this case the identification of local and global optimal solutions will be a problem. Hence, elimination dispersal need to be done to maintain the consistency in the population present in the given search space.

Steps of Bacteria Foraging optimization Algorithm;

Input:

Feature Values – Mean, Standard Deviation of Median of Duration, Latency and Digraph and their combinations.

Output :

Subset Feature Values.

Step 1: Calculate the feature values of x(i) (Duration, Latency and Digraph or combined value or all)

Step 2: Estimate fitness values of every feature value x(i)

Fitness function f(x) = 1/ 1+x_i

Step 3: Initial declarations are:

S- Quantity of bacteria

Nc - Total swarming steps

Ns - Total swimming distance

Nre – Count of Reproduction

Ned - Total Elimination Dispersal Event

Swimming Size = c(i)

Step 4: Iterative processes for NS times

1. For every bacterium selection of a random feature value (x_i) is made
2. Either swimming or tumbling is performed

   Swimming – moving in one constant direction

   Tumbling – moving in random direction
3. Calculate Local best (Lbest) value.

   $$\sum_{i=1}^{s} Xi = P(i,j,k,ell) + c(i)\,\Delta(i) / \mathrm{Sqrt}\,(\Delta(i) * \Delta(i))$$
4. Calculate Pbest value using

   $$\sum_{i=1}^{s} Xi = P(i,j+1,k,ell) + c(i)\,\Delta(i) / \mathrm{Sqrt}\,(\Delta(i) * \Delta(i))$$

   $\Delta(i)$ - Vector in the Random direction.

Step 5. Reproduction

1. Arrange the bacteria based on its health value
2. Eliminate the bacteria that has less value than the optimal value
3. Divide the remaining bacterium into two similar bacteria and leave in the search space.

Step 6: Elimination dispersal event

For maintaining the population quantity, elimination and dispersal of the bacteria is done based on the probability of Ped.

Step 7 Fitness value of each bacteria is calculated after every j^{th} chemotatic step , k^{th} reproduction and the loop is terminated.

Step 8 Finally the Global best (Gbest) value is calculated.

Step 9 Calculated Global best (Gbest) value is considered to be the optimal value.

4. Classification based on RF

RF based on supervised learning method is used for classification in this method. Random forest is developed with large number of trees; similarly RF builds Decision Tree DT based on the data given and predicts the best solution from the selected list. This collection model is best compared to the individual decision tree as here the consolidated result is attained from the individual results. RF is observed as multi-way classification approach as it includes huge quantity of trees and each tree is grown using random tasks. All tree leaf nodes are designed using the calculation of early distribution of all classes of images. Internal nodes comprise of a test that divides the data space. Categorization of images is done through tree transmission and collection of the achieved distribution of leaves. Feeding of randomness is done at two points of training period:O One is at selection phase and the other is during the sub-sampling of training dataset by which each tree is ensured to grow in different subset.

5. Performance Validation

Validation of BFOA-CNN model is done using the Drishti-GS dataset. The programming language for simulation is Python. 101 color fundus images along with right annotations were present. Fig. 5.1 analyses the results of BFOA-CNN on the given dataset. Figs. 5.1a and 5.1c show the given input images and its respective classified (Normal and Abnormal) images are given in Fig. 5.1b and 5.1d.

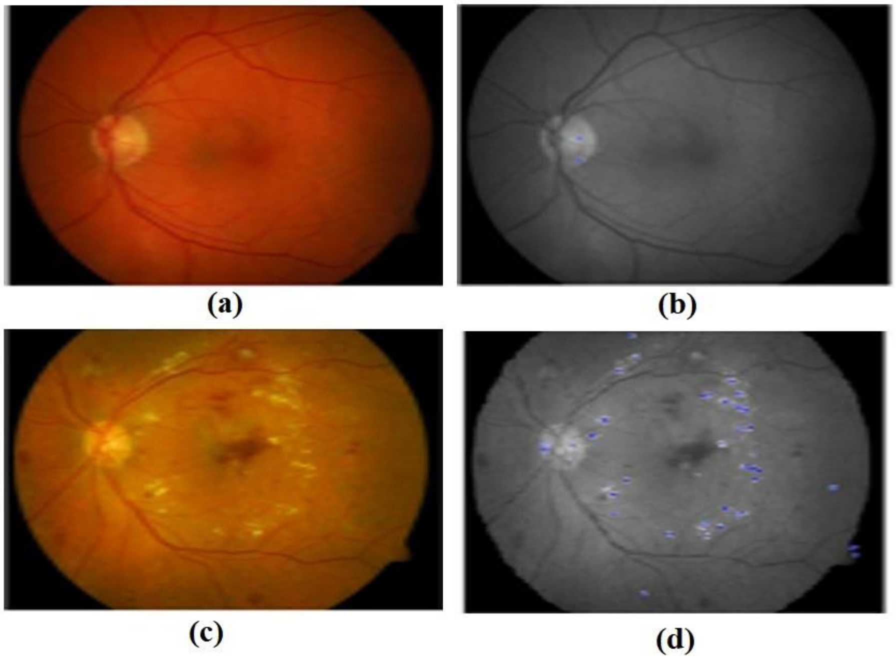


Fig.5.1.(a) and (c) Input Image (b) and (d) Output Normal/Abnormal Image

Fig. 5.2 exhibits sample input image and the image generated while executing the BFOA-CNN model. Fig. 5.2a gives the original fundus image given and its pre-processed versions are shown in Fig. 5.2b. Result of green channel extraction and OD removed image are shown in Fig. 5.2c. Fig. 5.2d gives the exactly segmented image and Fig. 5.2e shows the extraction of selected region. The final classification of the original fundus image is given in 5.2f. Fig. 5.3 depicts the BFOA-CNN model's other quantitative results analysis for abnormal image classification.

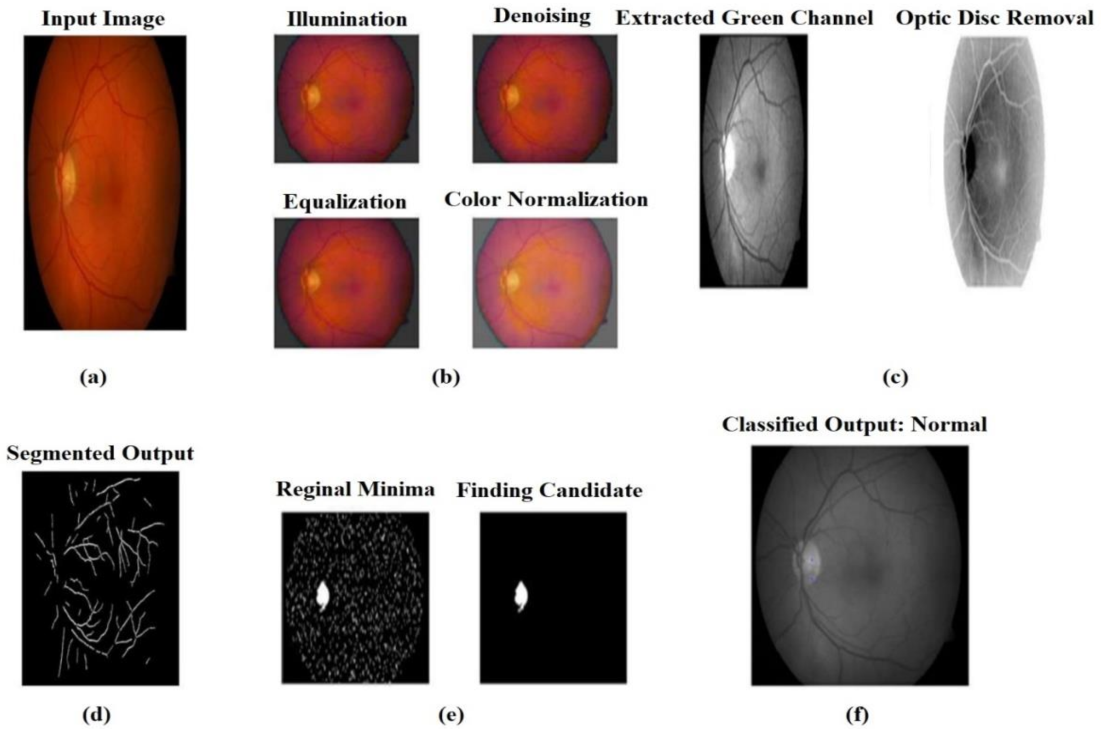


Fig.5.2.Illustration 1 (a) Original (b) Preprocessed (c) OD removed (d) Blood vessel segmented (e) Candidate extractedn (f) Classified images

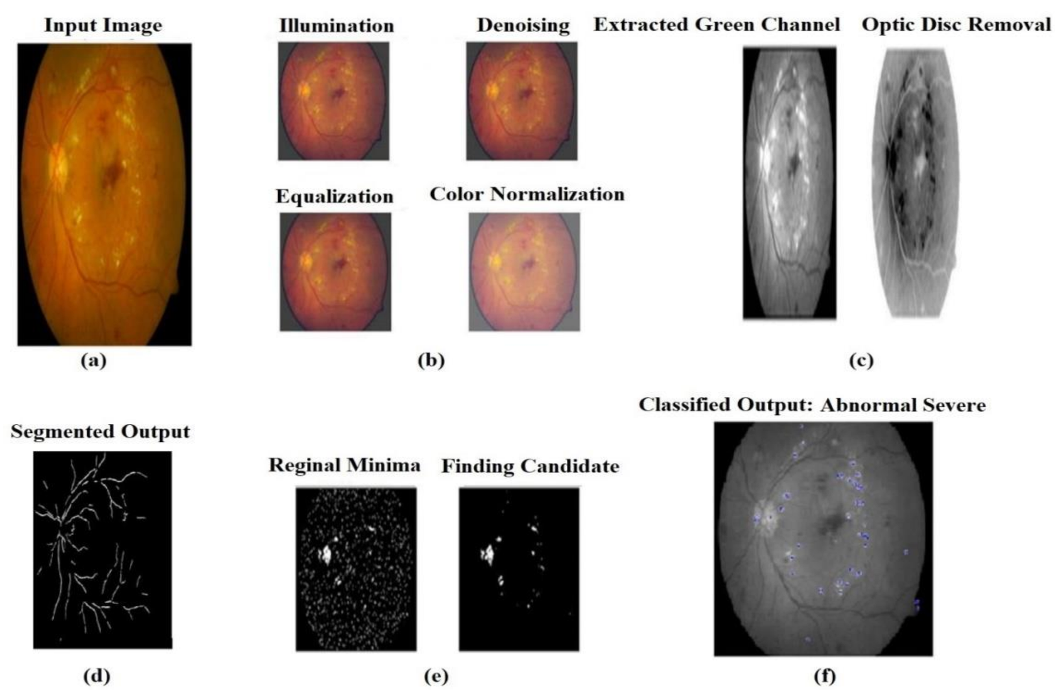


Fig.5.3 Illustration 2 (a) Original (b) Preprocessed (c) OD removed (d) Blood vessel segmented (e) Candidate extractedn (f) Classified images

6. Results analysis

Table 6.1 states various parametric results of BFOA-CNN model using the given dataset. Fig.5.4 shows the proposed method BFOA-CNN achieves 0.954 of sensitivity among all other methods.

Table.6.1 : Comparison of performance analysis

Methods	Sensitivity	Specificity	Accuracy
BFOA-CNN-RF	0.954	0.991	0.972
Naïve Bayes	0.929	0.976	0.928
MLP	0.940	0.930	0.940
SVM	0.929	1.000	0.928
K-NN	0.951	0.953	0.952

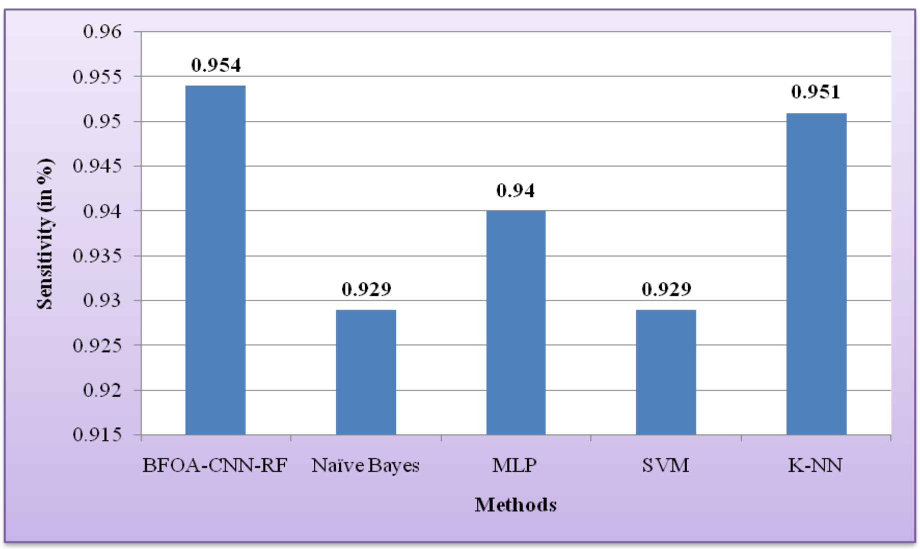


Fig.5.4 : Sensitivity of the Proposed Method BFOA-CNN with other methods.

While validating the results with respect to specificity, the proposed method BFOA-CNN presented model offered a maximum specificity value of 97.2 shown in Fig.5.5.

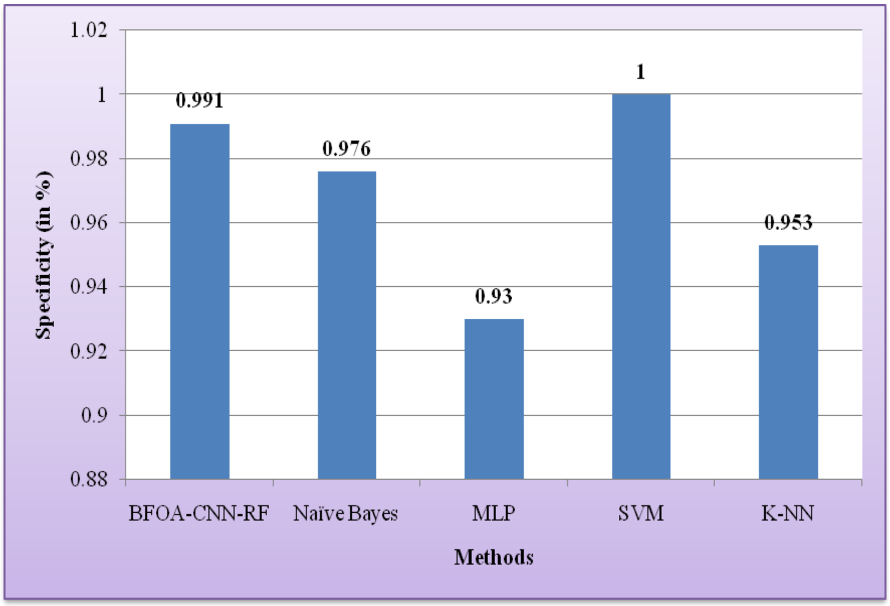


Fig.5.5 : Specificity of the Proposed Method BFOA-CNN with other methods.

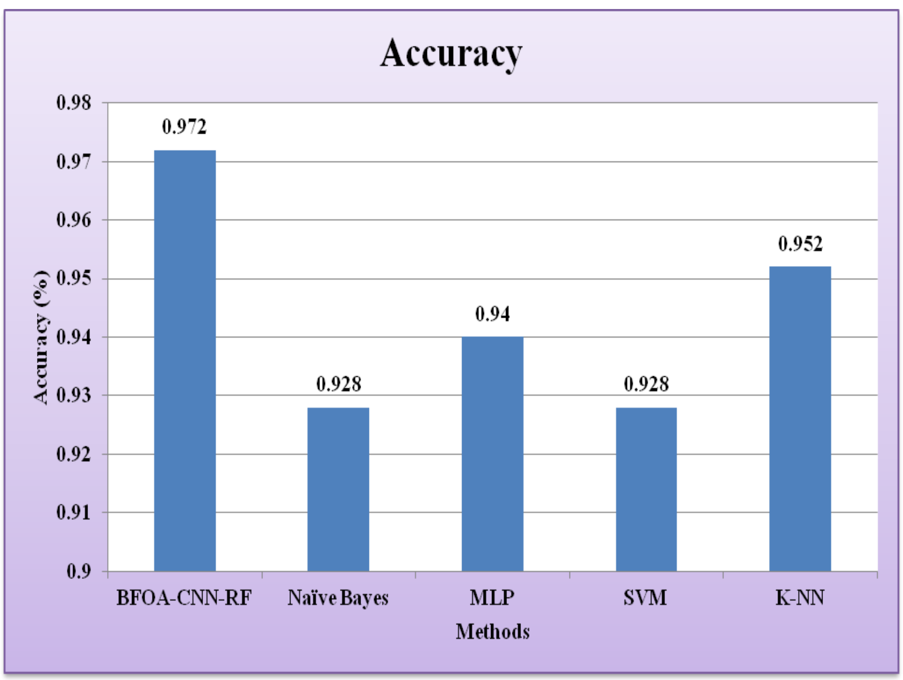


Fig.5.6 : Accuracy of the Proposed Method BFOA-CNN with other methods.

Similarly, on the validation of the performance with respect to the accuracy, it is evident that the proposed model offered maximum classification with the highest accuracy value of 97.20. These values verified the enhanced classifier results of the presented approach over the existing approaches.

7. Conclusion

BFOA-CNN is the novel technique introduced in this paper for detecting the lesions in fundus image. Entropy approach is executed to determine the OD center position. Next the vessel is segmented using CRF model and it is followed by the extraction of shape features for discovering the presence of lesion in the given image. Finally, based on the presence of red lesions, the disease is categorised using classification process based on RF. Simulating the proposed model in Phython programming language and Drishti-GS dataset, it proved to be highly efficient with the sensitivity of 0.954, specificity of 0.991 and accuracy of 0.972. Hence it is clear that BFOA-CNN model outperforms other existing techniques and it is suggested that BFOA-CNN model is proposed to be an optimal tool for diagnosing Diabetic Retinopathy. Further investigations can be undertaken for enhancing BFOA-CNN model with other techniques of segmentation.

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