European Journal of Molecular & Clinical Medicine
ISSN 2515-8260 Volume 7, Issue 4, 2020

PSO-KNN BASED EFFECTIVE OPTIC DISC SEGMENTATION AND CLASSIFICATION IN FUNDUS IMAGES

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ABSTRACT

Glaucoma is the most common sources of the retinal disease that leads to permanent impaired vision worldwide. An automatic Optic Disc (OD) findings in retinal images utilized to diagnosis eye-related diseases like diabetic retinopathy. Numerous methods are offered to detect OD in low-resolution retinal images. This work presents an automatic glaucoma diagnosis using an image processing technique from the digital fundus image. In this work, a novel Particle Swarm Optimization (PSO) optimized KNN used for glaucoma disease classification. PSO is a naturally inspired optimization algorithm, utilized to find optimization parameters of KNN to improve classification accuracy. The proposed algorithm divided into three stages. Preprocessing stage includes noise removal, contrast enhancement using histogram equalization. For OD detection FCM has been used. Finally, PSO-KNN classifier used for categorizing healthy and non-healthy images of Optic Disc. The proposed technique has been coded in MATLAB and tested in the standard database of DRIVE and STARE fundus image. From the result observed that compared to other algorithms proposed approach improves accuracy considerably.

1.INTRODUCTION

Medical imaging is a development of producing images of inner portions of the human body for clinical l diagnosing purpose. The inner parts of the human body can be effortlessly envisaged by the used image processing. Various imaging techniques have been introduced to produce images such as X-ray, CT and MRI techniques. It is used to improve medical science, particularly to Ophthalmology. Ophthalmology [1] is the main part of the medical division used to diagnosis eye-related treatment and disorder. There are various diseases related to retinal, such as cataracts, glaucoma and diabetic retinopathy, etc. From the earlier years, Ophthalmology techniques improved by introducing numerous automatic detection methods but these approaches need further development[2][3].

Glaucoma is a collection of disease-related with the human eye that leads blindness without any indications and cautions. Firstly, glaucoma increases Intraocular Pressure (IOP) and if not identified at an early stage, it spontaneously abolishes the optic nerve and ultimately leads to impaired vision.

Position of Optic Disc (OD) is an important portion of fundus which is used to decide the harshness of glaucoma. It is normally the bright portions in fundus images and optic disc centre is the origin of blood vessels. OD can be classified by shape, the pattern of vessels and sharpness of margins.

By the structure of OD, it can be segmented with shape regression method, template matching [16] and Snake based Contour Refinement. OD can be divided into two parts such as the central bright zone named Optic Cup (OC) and a peripheral region as the neuroretinal rim. Cup identification can be done by threshold level set approach, r-bends information [6], convex hull [8], boundary segmentation method and shape regression method.

The contribution of the proposed method is listed as follows:

• Using an improved pre-processing method - RGB to Grayscale conversion, Green channel separation. Normalization, adaptive median filter, Noise removal and contrast enhancement using histogram equalization.
The optic disc is detected by using FCM, that's Fuzzy C-means clustering approach.

The optic disc is segmented by using the OTSU scheduling approach.
Finally, we used PSO-KNN classifier for categorizing healthy and non-healthy images.

. The structure of this work is as follows. In section 2, presented a related work in the area of glaucoma diagnosis. Section 3 describes the proposed diagnosis system. Section 4 comprises of the implementation. Section 5 presents the conclusion of this work.

2.RELATED WORK

In the literature, many researchers have worked on OD segmentation and classification in their particular application domain.

Jasem Almotiri 2017 et al have presented an automated technique for the segmentation of the OD region in retinal images. The proposed preprocessing technique tested in various data sets of DRIVE, DRISHTI-GS and DiaRetDB1 datasets. Jun Cheng et al 2013 have proposed OD and optic cup segmentation using superpixel classification method. In OD segmentation, histograms, and centre edging statistics are utilized to categorize each superpixel. The proposed method attains higher areas under the curve than other methods. Shijian Lu et al 2011 have presented an OD detection and segmentation technique using circular transformation. Implementation results show that OD detection accuracies of 99.15%, 96.3%, and 97.66% are achieved for the STARE dataset. Ting Yu et al 2015 have presented a fully automatic localization and segmentation of OD in fundus images. The border of the OD is identified by using distance regularized narrowband level set evolution (DRLSE) method. The proposed method achieves a high success rate of 99.52% than the existing one. Junjie Bai et al 2014 have proposed a graph-based optimal segmentation method to concurrently segment multiple star-shaped surfaces. Further, the segmented surfaces are confirmed to be smooth by integrating smoothness limits. Huajun Ying et al have proposed an algorithm to detect OD location in retinal images using simple local histogram analysis. In a high fractal dimension of blood vessel environment, OD can be separated from other bright portions such as hard exudates and artifacts. Compared to other methods, the proposed method has a lower computational cost and is more robust. Canan Çelik et al 2016 have proposed an OD detection method for diagnosing eye diseases. In this work, the red channel is utilized to remove blood vessels in the retina images applied in MESSIDOR database. Then, the Graph Cut algorithm is used for segmentation.

Huazhu Fu et al 2018 have proposed a deep learning architecture based OD segmentation named M-Net, which consider the OD and OC segmentation concurrently. The proposed M-Net contains input and output layers with U-shape convolutional network. The U-shape network is used to learn the complex hierarchical.

Ana Salazar-Gonzalez et al 2014 have presented a Markov random field (MRF) image reconstruction method based segmentation for blood vessels and optic disk in the fundus retinal images. The first step of extraction of the retina vascular tree using the graph cut technique. Then, blood vessel data is then utilized to calculate the location of the OD. The proposed technique is validated on three public datasets, DIARETDB1, DRIVE, and STARE.

Feng Pan et al 2020 have used the GrabCut technique to create the coarse foreground segmentation in retinal images. The proposed method train the network based on an improved U-net model with the produced foreground map. Validation performed on the RIM-ONE benchmarks to show the effectiveness of our algorithm.

3. **PROPOSED METHODOLOGY**

The proposed system mainly consists of the following steps,

Step1: Image Acquisition: Fundus image mainly collected from datasets DRIVE and STARE. For prime research taken 40 from each dataset (40 healthy, 40 non-healthy).
Step 2: Pre-processing: Main steps are the following,

1. RGB to gray
2. Green channel separation.
3. ROI extracted using morphological operations.
4. A used adaptive median filter for noise reduction. For contrast enhancement used histogram equalization.

Step3: Healthy image's consists of the optic disc, Fovea, Macula and blood vessels. In this work, an algorithm only detected and localized an optic disc.
Step 4: Optic disc is detected by using FCM, that's Fuzzy C-means clustering approach[14].
FCM works by allocating membership values to each pixel corresponding to each cluster centre on the basis of the distance between the cluster centre and the pixel. More the pixel is close to the cluster center more is its membership towards the specific cluster centre.
Step 5: Optic disc is segmented by using the OTSU scheduling approach[15].
Otsu method was introduced by Scholar Otsu in 1979. Which is extensively used because it is simple and effective. The Otsu method needs computing a grey level histogram before running
Step 6: Finally we used PSO-KNN classifier for categorizing healthy and non-healthy images. If (Number of classes==2), we received comparatively good accuracy than more than two classes.
Step 7: Calculated Accuracy in terms of usually used measures.

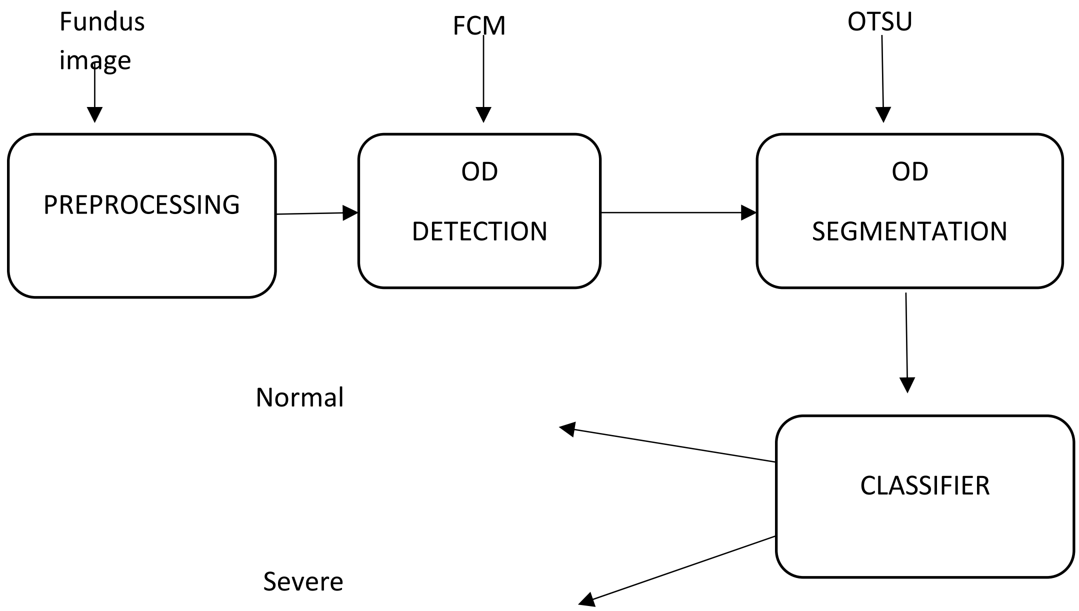


Figure 1: Proposed System

The overall accuracy and efficiency of KNN based on the method used to find K nearest neighbours. The identification of K nearest neighbours and the similarity metric of KNN classifier considered as an optimization problem. In this work Particle Swarm Optimization (PSO) utilized to find optimization parameters of KNN like attribute selection, voting power of neighbours, value for K. weight vector and instance selection.

PSO is a well-improved optimization model created by Kennedy and Eberhart [13]. A Particle Swarm Optimization (PSO) is an occupant based stochastic optimization calculation model by the recreation of the regular conduct of bird gatherings. Swarm Intelligence (SI) is a novel scattered intellectual model for working out of optimization inconveniences that at absolute originally took its brainwave from the biological delineations by swarming, gathering and coordinating occasions invertebrates. PSO incorporates swarming deeds which are seen in herds of birds, trains of fish, or runs of honey bees, and furthermore in human shared conduct, from which the proposition is developed. Consequently, the PSO is a populace based optimization approach, which could be utilized and furthermore applied easily to determine an assortment of optimization challenges.

The proposed PSO strategy characterizes each particle as an expected key to an emergency in D-dimensional space. Every last one of the particles knows about its best an incentive up to now (pbest) and its spot. Moreover, every particle knows the best expense as of recently in the gathering (gbest) among pbests. This data is the connection of information for how the further particles in the district have been performed. Every single particle attempts to modify its area and destinations utilizing the accompanying in succession:

- The separation among both present position and pbest
- The separation among both position and gbest

This change can be represented by the idea of speed velocity. This speed Velocity of every single arbiter can be adjusted by the underneath condition (1) in the Inactivity Weight Approach (IWA).

$$VK+1 = W * VK + C1 * Rand1 * (PK – XK) + C2 * Rand2 * (GK – XK) \quad (1)$$

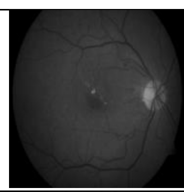
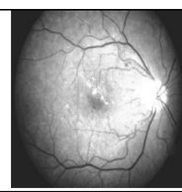
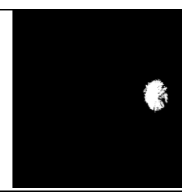
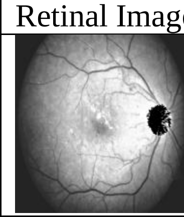
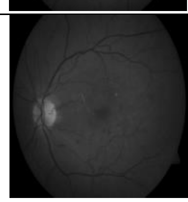
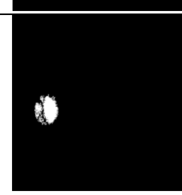
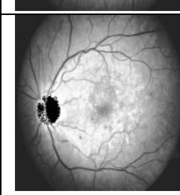
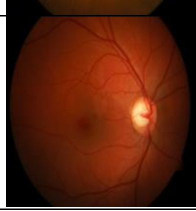
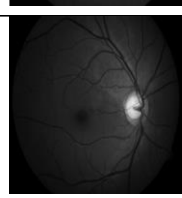
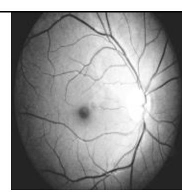
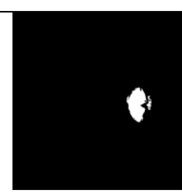
where, W – non-negative inactivity factor, VK – speed velocity of article, XK - present situation of particle, C1 - the psychological segment for relative impact, C2-decide the public segment for relative impact of the, PK - pbest of particle , GK - gbest of the particle, Rand1 , Rand2 - arbitrary numbers which are utilized to save the scope of the populace, and are reliably appropriated in the stretch [0,1].From the condition (1), a particle settles on a choice where to move straightaway, thinking about its own insight, which is the remembering memory of its best point of reference position, and the ability of its most triumphant particle in the swarm. In the particle swarm strategy, the particle searches for the arrangements in the emergency opening with a range [−s, s]. Every thing refreshes its area as indicated by condition (2).

$$Xk+1 = Xk + Vk+1 \quad (2)$$

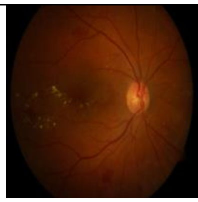
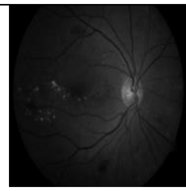
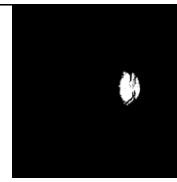
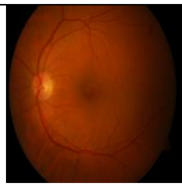
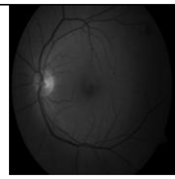
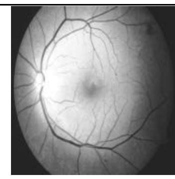
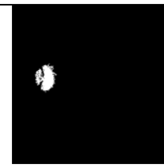
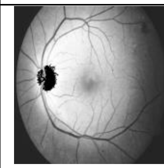
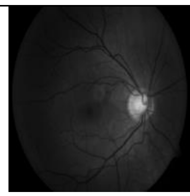
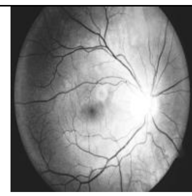
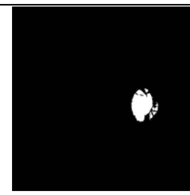
After the PSO fitness applied, the local maximum fitness value is estimated and compared with the global maximum. The cluster points will be changed corresponding to the particle having a global maximum. Otherwise, the next iteration is continued with the same old population. The KNN classification algorithm finds the test sample's category according to the K training samples which are the close neighbors to the test sample, and judge it to that category which has the largest category probability.

4.EXPERIMENTAL RESULTS

The proposed method implemented using MATLAB tool and experiments have been conducted in a database of DRIVE and STARE fundus images and results of the experiments are presented below.
Figure .2 Output images of the proposed method

Image No	Fundus Image	Green Channel	Histogram Equalization	Optic Disc Segmentation	Optic Disc Mapped to Retinal Image
diaretdb1_image001					
diaretdb1_image002					
diaretdb1_image03					

ISSN 2515-8260 Volume 7, Issue 4, 2020

diaretdb1_image04					
diaretdb1_image05					
diaretdb1_image06					

The MATLAB implementation results on datasets is assessed. The pre-processing and final segmentation result is shown in Figure 2.The performance of the PSO-KNN is compared with the standard KNN, SVM and GO (Genetic optimization) algorithms. It must be considered that the overall average classification accuracy of the PSO-KNN is 98.3 %. Figure .3 shows a bar chart demonstration for the comparison of the proposed method with standard classifiers.

Table .1 Accuracy comparison

Method	Accuracy-%
KNN	95
SVM	94.1
GO-KNN	96.7
PSO-KNN	98.3

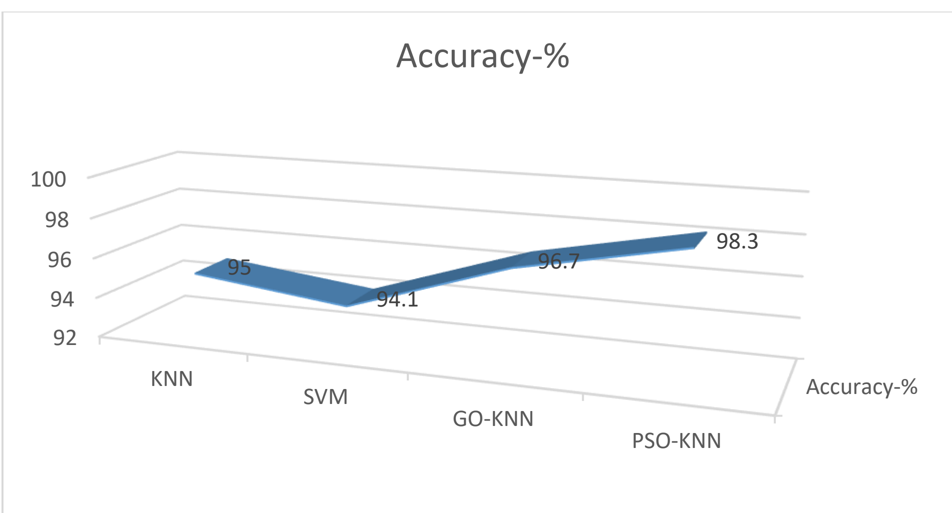


Figure 3 Performance analysis

5.CONCLUSION

Glaucoma is types of eye disease which causes permanent injury to the optic nerve and leads to impairment. In the earlier stage, it experiences no symptoms but finally leads to blindness when untreated. To find the occurrence of glaucoma at the starting stage, this work proposes a new PSO optimized KNN method for automatic classification of glaucoma disease. The proposed PSO-KNN classifier shows higher accuracy compared to other conventional algorithms. Thus the proposed technique automatically classify the glaucoma disease of the human being which supports for medical treatment according to the classification result.

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