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AUTOMATIC GLAUCOMA SEGMENTATION ON HYBRID METHOD USING CSO AND HMM

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Abstract:

The most challenging part of processing and analysing medical images is detecting glaucoma. A neuropsychiatric condition called glaucoma is characterized by dynamic neurodegeneration of the optic nerve, which impairs vision. Glaucoma is an eye condition that, if not identified and treated right away, can cause blindness. It might lead to irreversible vision loss. In this paper, we proposed a novel method for glaucoma detection by retinal disc segmentation. In our method we used a novel method for image segmentation with hybrid method combining HMM (Hidden Morkov Model) and CSO (Cuckoo Search Optimization) .Our proposed method using shows better performance on segmentation results. So our proposed method shows better result than existing works.

Keyword: Glaucoma Detection, HMM, CSO.

1. INTRODUCTION

High intraocular pressure damages the optic nerve head, resulting in the chronic eye disease glaucoma (IOP). By 2020, it is projected to have an impact on about 80 million individuals worldwide. In the early stages of the syndrome, patients do not show any evidence of visual loss, but as the illness worsens, patients begin to lose peripheral vision. Patients with glaucoma who are in its advanced stages are totally blind. Glaucoma progression can be stopped with early detection and treatment. Reliance on medical technology to identify and detect the condition may become unworkable given the rising number of glaucoma patients. The aforementioned issue of glaucoma early diagnosis is the subject of much research employing several image processing techniques [1]. Person with a dilated cornea or who is quickly developing a cataract, both of which may be impacted by a chronic (long-term) increase in intraocular pressure, is reportedly described by the term "glaucoma," which is derived from an ancient Greek word that means "clouded or blue-green tint." A set of diseases known as glaucoma cause irreversible vision loss by harming the optic nerve. This injury is typically brought on by a significant rise in intraocular pressure. The posterior chamber, which is the area between the iris and the lens, is where the eye generates aqueous humor, a vitreous fluid that is discharged by the ciliary body and drains via the trabecular mesh structure. In a healthy eye, the rate of outflow balances the rate of secretion. The condition known as glaucoma arises from the partial or complete obstruction of a drainage canal, which raises intraocular pressure and damages the optic nerve, which sends signals to the brain where visual information can be processed. Total blindness may follow if the injury is not repaired. Therefore, it's crucial to detect glaucoma early [2]. A variety of progressive diseases known as glaucoma cause the eye's

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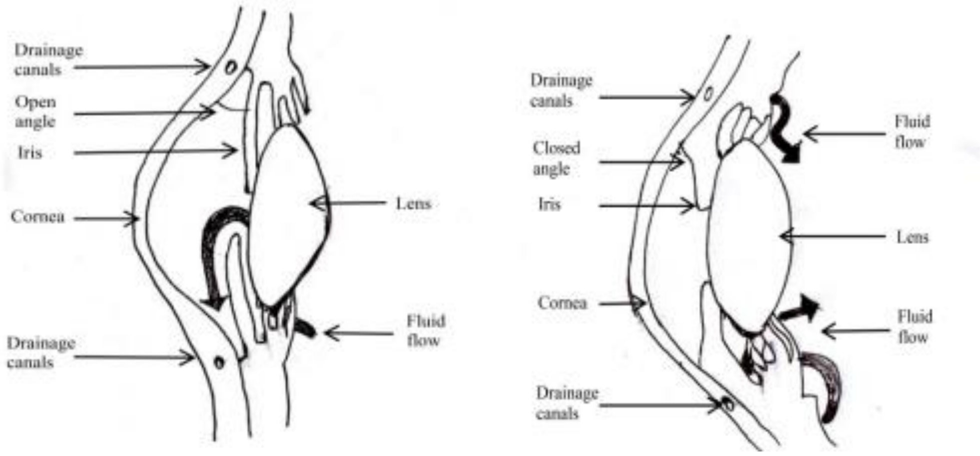
intraocular pressure (IOP) to rise, narrowing the opening through which the optic nerve enters the eye. The optic nerve is under more pressure as a result of this aperture narrowing. Optic nerve damage results from this pressure [3]. The most complex, delicate, and sensitive organs in our bodies are the eyes, which provide us the ability to see the outside world. They make up one-fifth of the data that enters our brain. A group of eye conditions known as glaucoma irreversibly harm the optic nerve, which transmits visual signals to the brain and results in progressive vision loss. The fluid inside the eye, known as aqueous, has a constant pressure called intraocular pressure (IOP). To keep the IOP steady, this fluid is continuously produced inside the eye and drained out at the same time. IOP increases as a result of the typical outflow channel being blocked. This situation leads to damage to the eye's optic nerve. The development of glaucoma is frequently linked to this rise in IOP; however other factors may also be at play. In some cases, glaucoma can occur even when there is normal eye pressure. It is believed that insufficient blood flow regulation to the optic nerve is what causes this particular type of glaucoma. The term "glaucoma" refers to a group of visual illnesses that cause the loss of retinal nerve fibbers, which impairs vision. Thus, glaucoma is an illness of the optic nerve, which carries the visual data from the eye to the brain [4] and connects the two.

Fig.1: a) Open angle glaucoma and b) Angle closure glaucoma



(a) (b)

There are two main types of glaucoma: primary open angle and primary angle closure as shown in figure1. The first is chronic glaucoma, another name for the illness. Most cases of glaucoma are due to blocked drainage pathways, making this type of the disease extremely common. If not treated quickly, it can lead to irreversible blindness. There are a several different types of glaucoma, but the rarest is called angle closure glaucoma. There are currently multiple methods available for detecting glaucoma in the eye. Some of these methods include focusing on the optic nerve head (ONH), analyzing anatomic and geometric alterations in the optic cup and disc, considering a patient's family medical history (genetics), and performing a thorough eye examination [5]. Since most people do not have symptoms in the early stages of the disorder, early detection of glaucoma is essential to prevent the disease from progressing slowly. The

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damage to the ONH is severe when the disease is discovered. This necessitates the use of automatic glaucoma detection. Recently, a study on the development of automatic glaucoma detection was conducted [6]. Thanks to improvements in surgical and preventive medicine, like the mean trabeculectomy, laser surgery, and drainage implants [7], much of this discomfort can be avoided. A recent and rapidly developing technology for diagnosing medical images is computer aided diagnosis (CAD). Computer-aided detection (CAD) has been touted as a more effective method for detecting or diagnosing glaucoma than traditional methods, which do not make use of modern technology. When compared to other options, CAD-based ones are more reliable, economical, and quick to implement. The use of CAD to screen for glaucoma hence becomes a more efficient and cost-effective method. Methods for diagnosing glaucoma from fundus images include power spectral and FDs characteristics, the FFT, the FFT with PCA, the CWT, the DWT, the WPD, and the EWT [8]. In this study, we created a novel glaucoma detection method. In our approach, the DWT and PCA were employed for feature extraction. We used SVM classification to increase accuracy.

2. LITERATURE SURVEY

Detecting glaucoma in the eye can now be done in a variety of ways. Evaluation of the optic nerve head, eye inspection procedures, structural and geometrical changes in the optic cup and disc, family medical history (genetics), and other processes are all a part of this (ONH). Here are a few methods for identifying glaucoma. Li Xionget al. [9] suggested a method for quickly and automatically detecting glaucoma. Accurate OD localisation is necessary for the diagnosis of glaucoma. Thresholding and distance transformation are combined to locate the optic disc. To detect glaucoma, the authors propose a novel method that combines principal component analysis with a Bayesian decision-making approach. Our ability to determine the eigenvectors space of two classes is based on our analysis of two sets of training photos. After that, a test image is displayed on each of these screens. The degree to which each projection deviates from the template is determined. The Bayesian classifier makes the final call. This approach is less complicated and has more encouraging results than one based on calculating OD parameters.

Rajendra Acharya U. et al. [10] suggested that Glaucoma has the potential to permanently harm the ONH, causing vision loss. By using computer-aided diagnosis tools to screen a large number of individuals for glaucoma, the disease may be automatically detected. They attained an average accuracy of 93.10 percent, sensitivity of 89.75 percent, and specificity of 96.20 percent using 510 fundus photographs. Small changes in fundus images can be detected using this Gabor transform coefficient. They got the best outcomes as a result. Additionally, we offered a GRI in this study to categorize the two classes using a single number. Professionals will be helped in validating their diagnosis by this. The proposed method's extremely high specificity suggests that the proportion of false positives is rather low.

Krisana Chinnasarnet al. [11] illustrated that in the field of medical image processing research, early phase glaucoma diagnosis is challenging due to its unclear characteristics and limited number of lesions. In this experiment, it was suggested that early-stage glaucoma may be identified. There were five different image processing methods used. Blood vessel

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segmentation was performed using adaptive tophat filtering. After the vessel was dissected, it was used as a template for skeletonization. Conjunctions and terminals ranked below middle. Forth, elliptical features were defined using principal component analysis. The area of the curve was identified by applying the aforementioned criteria. Using wavelet features from the segmented optic disc, Anushikha Singh et al. [12] suggested a method based on automatic image analysis for diagnosing glaucoma from digital fundus pictures. The features were extracted from the clean image. According to the experimental findings, glaucoma images were classified with a 94.7 percent accuracy using segmented and blood vessel in-painted optic disc images and first level wavelet features, exceeding prior studies. The performance of five supervised classifiers for the categorization of glaucoma images was assessed. It is found that the accuracy of all five classifiers is more than 85%.

Kwokleung Chan et al. [13] compared various machine classifiers to the STATPAC indicators frequently employed for the diagnosis of glaucoma using SAP data. Machine classifiers offer statistically substantial gains over STATPAC indices generally, as measured by the area under the ROC curve. They exhibit potential for clinical application in conjunction with the STATPAC indices for the diagnosis of glaucoma. Using backward exclusion and forward selection, the visual-field locations were ranked. There have been some significant sites for glaucoma diagnosis found. Our SAP data was used to study the characteristics, benefits, and drawbacks of generative and discriminative machine classifiers. Tehmina Khalil et al.[14] proposed flexible CAD system can be utilized to counter the risk of glaucoma because it outperforms its current automated counterparts in many ways. Only a few methods have used features together with classification in existing systems that mostly rely on CDR to diagnose glaucoma. These methods have low sensitivity because noise and other changes are present. The results were remarkable, and they used texture analysis on the red channel to capture intensity changes brought on by glaucoma. The suggested method also included a third judgment category, suspicious, which helped to completely eliminate glaucoma patients because not a single case of glaucoma was referred to as normal. The proposed technique can therefore be used to diagnose glaucoma in distant areas with a shortage of ophthalmologists, with only genuine cases being sent to the expert for additional testing. Optic coherence tomography (OCT) pictures are used to examine the optic nerve in depth; fundus scans do not achieve this. A model based on deep picture features that Law Kumar Singh et al. [15] presented enables medical professionals to diagnose glaucoma more accurately and quickly. Since it has been determined that the retrieved features are reliant on one another and must be integrated, a parametric-based examination for glaucoma in the retinal fundus must be constructed. The deep image characteristics retrieved by the suggested method were used for training and testing using support vector machine (SVM), K-nearest neighbor (KNN), Nave Bayes classifier (NBC), and artificial neural networks (ANNs) (ANN). The results of the experiment showed that the accuracy of the SVM, KNN, Nave Bayes, and suggested neural network-based model for deep image analysis ranged from 97.61 to 98.60 percent. It has been discovered that the recommended model beats other current models in cutting-edge approaches in terms of sensitivity, specificity, and computation speed.

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Stalin David D. et al.[16] identified an early Glaucoma detection in order to prevent permanent vision loss. Computer-aided solutions can help with affordable, precise glaucoma screening and diagnosis because existing imaging technologies are expensive and need interpretation by highly skilled specialists. The system described in this research is effective and was built by merging various image technology techniques. In our method, colour photos are converted to grayscale images using adaptive histogram equalization before being used to identify important features with a hybrid colour and structure descriptor. In terms of overall classification accuracy, our suggested classifier method fared better than other leading neural network-based classifier algorithms. Over 97 percent accuracy was reached by their categorization method for all classifications. A deep learning-based segmentation technique for OC and OD segmentation in glaucoma detection analysis was put out by Raja J. et al. [17]. The healthy and glaucoma eyes were distinguished using an SVM classifier based on the morphometric data. The projected technique for separation and classification is made more robust by the adaptive convolution, and it also yields acceptable results for the DRISHTI-GS dataset. Through the use of deep learning-based VGG-19 network segmentation, the OC and OD can be separated with 92% segmentation accuracy, 86% sensitivity, and 93% specificity. If proven accurate, the proposed approach might also be used to determine the specific glaucoma stage. There has also been an analysis of the classifier's efficiency. When compared to the VGG 19 RF classifier, the VGG 19 SVM classifier displays a 2% increase in classification accuracy. Bock R. et al. [18] presented a glaucoma classification technique with the help of glaucoma-specific pre-processing and the right mix of generic features, we are able to successfully apply the general data-driven technique to this medical classification challenge. The proposed two-stage classification method streamlines the process of fusing classifiers from several image sources. According to the study, this assembly increases classification certainty and strengthens the final conclusion. Established approaches restrict the feature dimensionality early using parametric models or structural measures. On the other hand, they distill all visual information into distinct traits. Overall, the low-cost digital color fundus camera performs at a level that is comparable to medically important glaucoma parameters, yielding a competitive, trustworthy, and probabilistic glaucoma risk index. This illustrates that glaucoma features may be extracted using data-driven GRI. Future versions may offer a basic, inexpensive glaucoma indication and simply refer patients to more involved clinical trials when absolutely necessary. Kishore Balasubramanian et al. [19] mentioned that detecting glaucoma disease is one of the most significant research issues in a computer-aided health monitoring system. The experiment's objective is to develop a useful segmentation and feature extraction method for classifying the normality and abnormality of glaucoma disease using the HRF and RIMONE datasets. The optic discs were segmented using correlation-based template matching segmentation in this situation. Then, in order to exclude the unnecessary feature vectors, hybrid feature extraction (homogeneity and correlation) was used in conjunction with the PCA scheme to achieve optimal feature subsets. KNN classification algorithm was used to classify the acquired feature values. The suggested methodology demonstrated a 3–30% improvement over existing approaches.

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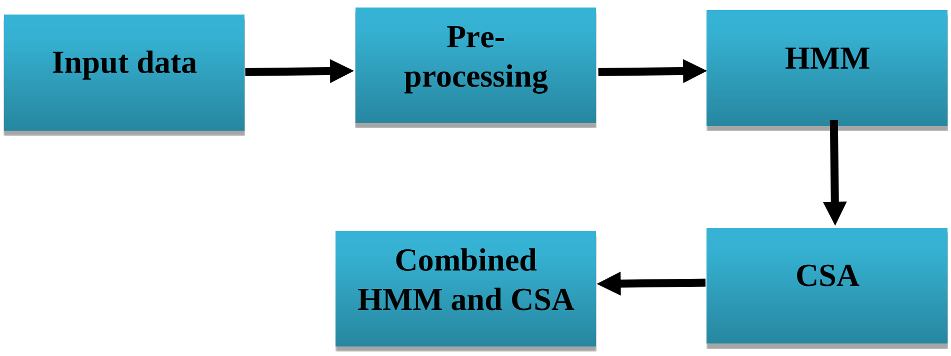
Summary:

- To address the aforementioned problem of early glaucoma diagnosis, extensive research is being done employing various image processing techniques.
- Various viewpoints must be used to analyze the differences between some studies that were generated in a different way, including the usage of features, segmentation techniques, feature extraction methods, and classification methods.
- Research on medical image processing is especially in need of some early glaucoma detection.
- The ability to stop or reduce the progression of a disease depends on early detection.

3. PROPOSED METHOD

This research proposes a model for diagnosing glaucoma in retinal fundus images utilizing several feature extraction and SVM classifier techniques. The images of the retinal fundus served as the input for subsequent processing that carried out a thorough analysis of those images using 20 features [15]. Both healthy and glaucoma-infected results of the aforementioned glaucoma detection for each input data set, namely fundus images, are possible. As shown in Fig.2 the proposed technique is separated into many stages: input data, pre-processing, feature extraction, Dimensionality Reduction, and classification.

Fig.2: Proposed method block diagram



i) Input Data

Images for input are acquired from the RIM-1 public picture collection. The proposed approach was tested on 505 photographs. There are 250 glaucoma photos and 255 normal images among the 505 images [8]. Figure 3 depicts the pictures of normal and glaucoma.

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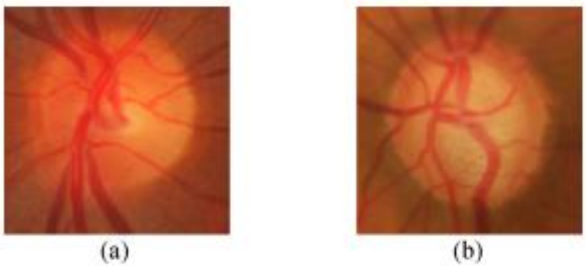
Fig 3: Sample input images (a) normal (b) glaucoma



ii) Image preprocessing

To collect glaucoma characteristics, the suggested appearance-based technique examines the full input image data. In a pre-processing stage, glaucoma-unrelated alterations are taken out of the images in order to highlight these desired qualities in the input data. This includes variations in image capture such uneven lighting or different optic nerve head positions as well as retinal structures unrelated to glaucoma like the vascular tree.

Regardless of whether or not the data variance is relevant to the classification goal, appearance-based methods preserve it in the low-dimensional representation. Remove light in homogeneities, a variable unrelated to glaucoma, from imaging data before analyzing it.

It is common for fundus images to have an oversaturated red channel (particularly in the central, optic nerve head region) and an under saturated or noisy blue channel due to the reflecting qualities of the eye ground. We decided to just use the green channel for accurate picture processing because it showed continuous saturation. [18].

Fig4: Pre-processing steps in proposed system

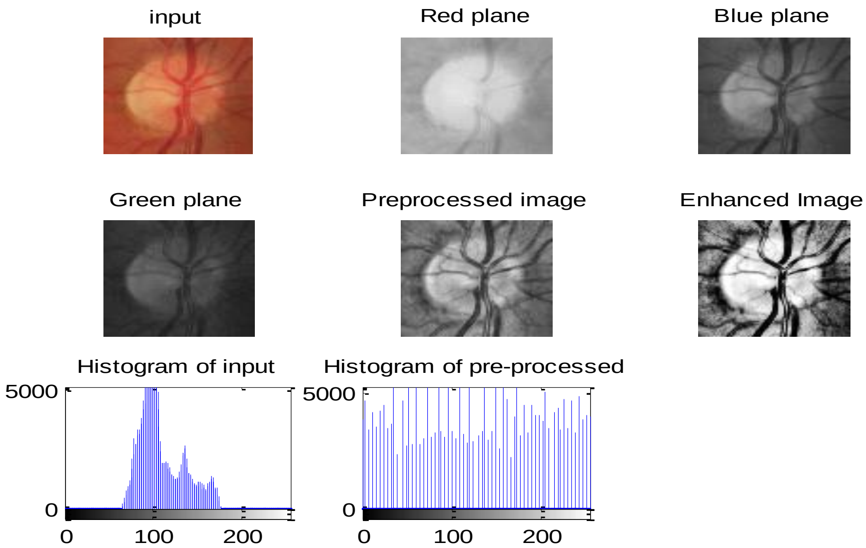


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Figure 4a employs a red, green, and blue (RGB) color scheme to depict fundus pictures, which are traditionally composed of three channels. If such photos are found to have several colors, carrying out different operations on them becomes difficult. As a result, in that case, it should be extracted across a single channel, which is critical for optimizing the output. The green channel image is presented in Fig. 4b, which is utilized to portray the sensitive region of the human eye and conveys the majority of the information. Initially, the gray/green channel component of the input fundus images is transformed [15]. The weighted sum of the RGB components is calculated using Equation 1 to convert RGB to gray/green channel.

$$G = R * 0.2989 + G * 0.5870 + B * 0.1140 \qquad (1)$$

Fundus pictures' red, green, and blue components are represented here by R, G, and B, respectively.

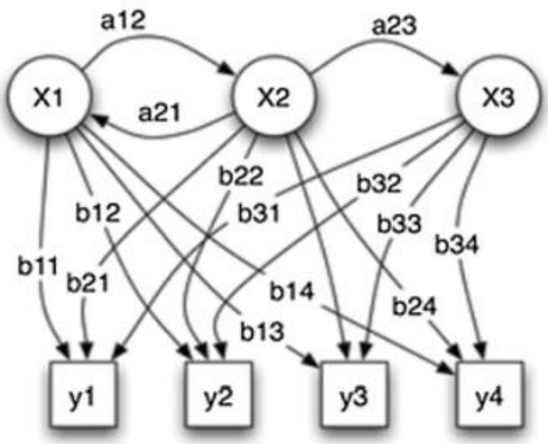
iii)Segmentation

a) HMM

The status is clearly visible to the observations in simpler Markov models and thus the probabilities of state change are the only parameters while the status in the HMM is not seen directly, but the output is obvious according to the state. Each state has a probability distribution over possible output tokens. Therefore the tokens provided by HMM provide some information about the status sequence, also known as the model theory. Since these parameters are known precisely, the model is also called a HMM. HMM are particularly well known for their use in enhancement learning, and for the identification of temporal patterns such as voice, handwriting, gestures, voice component, musical score, partial discards and bioinformatics [20].

Probabilistic parameters of a hidden Markov model explained as follows [21]: x and s = represents the states; y = represents the possible observations; a = represents the state transition probabilities; b = represents the output probabilities.

Fig 5: Architecture of a Hidden Markov model



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The Fig. 4 represents the hidden Markov model general architecture. In this architecture, each random variable represented as oval shape, where each random variable consists of list of values.

$$x(t) \in \{x1, x2, x3\} \quad (1)$$

$$y(t) \in \{y1, y2, y3\} \quad (2)$$

Where x (t) = represents the hidden state at time t, y (t) = represents the observation at state at time t, Arrows represents the conditional dependencies.

The hidden Markov model general architecture state that value of the hidden variable x (t - 1) is used to model the hidden variable x (t). This definition is also named as Markov property. In addition, the value of the hidden variable x (t) is also used to model the observed variable y (t).

Observed sequence and its probability is modelled as

$$Y = y(0), y(1), \ldots . y(L-1) \quad (3)$$

$$X = x(0), x(1), \ldots . x(L-1) \quad (4)$$

Where L = Length, Y = Observed sequence, Probability of an observed sequence. The total number of cycles in all the hidden node sequences is modelled as in equation 4.

b) CSO

Yang and Deb proposed a biological inspired optimization technique called cuckoo search optimization (CSO) based on brood parasites of bird cuckoo. Usually cuckoo does not construct nests but lay their eggs in some host bird nests. If it identifies that the eggs are not their own, host bird either rebuild their nest or they will abandon their eggs. Egg contained in a nest is considered as a solution and cuckoo egg considered as a new solution [22]. Cuckoo search optimization algorithm is used here for finding the optimum scalar values for wavelet transform. Range of scalar values is obtained using trial and error values. In CSO, each solution is considered as each nest. In our application, we generated 50 nests within the range. Random cuckoo selecting a nest for laying eggs is performed based on Levy fight. After nest selection evaluated the fitness of nest, based on the fitness value cuckoo updates the rank of nests [23].

In cuckoo search, generation of new solutions x (t+1) is performed using levy fight.

$$xi^{t+1} = xi^{t} + amlevy(\lambda) \quad (5)$$

In Eq. (5) step size (a) is related to the scales of the problem of interests. The product m represents entry wise multiplications. The Levy flight essentially provides a random walk while the random step length is drawn from a Levy distribution.

$$levy \sim u = t^{-\lambda}, (1 < \lambda \leq 3) \quad (6)$$

The above equation is essentially the stochastic equation for random walk. In general, our calculation standard formula is using for Levy distribution which has an infinite variance with an infinite mean; the steps in equation 6.

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The objective of this technique is to replace the not so good egg by the new solution. In the conventional form, each nest has one egg. Nevertheless, the simplest algorithm can be extended to multiple solution applications [23].

c) Combined HMM and CSO

HMM is only dependent on every state and its corresponding observed object: The sequence labelling, in addition to having a relationship with individual words, also relates to such aspects as the observed sequence length, word context and others. To overcome flaws in HMM we are optimizing the same with Cuckoo search optimization. This optimizer performs better on continuous non-linear optimization.

Algorithm1. Combined HMM and CSO Algorithm

1. Compute IMi=HMM (lb) where IMi is multidirectional sub-image of Ib .
2. Initialize HMM parameter from equation (1) and (2)
3. For each row on image matrix IMi
4. For each column image matrix IMi repeat step 1-3
5. Refine HMM parameters by Eq. (3) and (4)
6. IF vessel discontinuity THEN
7. HMM predicts the pixel state
8. IMF is final image.
9. Initialize a population of n host nests at random
10. while stopping criteria not met do
11. Obtain a cuckoo Xi at random by Levy flights
12. Choose a nest Xj randomly
13. if F(Xi) better than F(Xj) then
14. Replace j by the new solution
15. end
16. Abandon a fraction of the worse nests and create new ones using Levy flights
17. End

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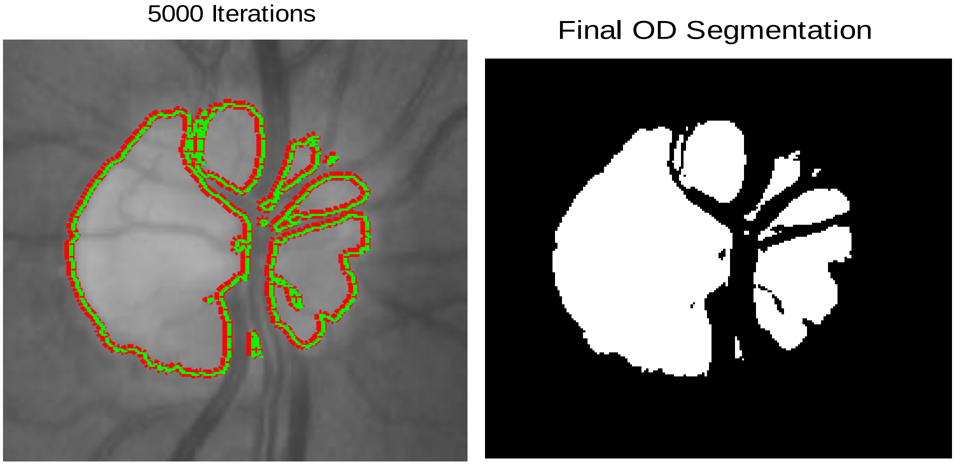
Fig 6: Proposed Segmented image



d) SVM Classification

The various forms of data are combined in the final processing stage using a probabilistic two-stage classifier method to produce a single glaucoma prediction [18].

One of the most popular supervised classification techniques in machine learning is support vector machines (SVMs). A hard margin classifier examines the most basic form of SVM by resolving an optimization problem to determine the linear classification rule with the largest geometric margin. In the case of linearly separable data, the hard margin SVM constructs the hyper plane that correctly classes all data while maximizing the distance to the closest training data points. The SVM optimization problem needs to be adjusted because it is unusual for datasets to be linearly separable. In order to strike a balance between improving geometric margin using the soft margin method and decreasing classification error on training data points, this modification is required. The construction of a soft margin hyper plane maximizes the distance to the nearest examples of cleanly separated data while allowing misclassification of challenging or noisy cases [1].

The SVM is a relatively new method for addressing problems in classification and regression. Locating the decision plane with the biggest margin from the closest training patterns is the fundamental tenet of SVM [13]. The kernel function used to categorize the input into different classes determines the complexity parameter and accuracy of the SVM classifier. Multiple kernel functions are measured for the SVM classifier's performance, and the best kernel function with the highest accuracy is ultimately selected for classification [12]. We used a supervised learning model called the support vector machine (SVM) classifier to distinguish between healthy and glaucoma-affected ocular fund i. The goal of SVM is to forecast the target values of the test data based solely on the attributes of the test data. Test data are the modified input image matrices from the PCA and pre-processing processes that came before [3].

For the supervised classification of discrete classes, SVM is a useful machine learning technique. The method uses the fitting of a hyper plane across the feature space to make a linear

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classification decision between two classes. In reality, it is impossible to linearly separate the vast bulk of data in existence. Kernel functions are the greatest method for separating them. To map feature points to higher dimensions, utilize the kernel function [10].

The decision function u(x) for the SVM has the following generic form:

$$u(x) = \sum_{i}^{N} aiyik(x, xi) + b \qquad (5)$$

The SVM trains to produce the kernel function, which is denoted as k(x, xi), while adhering to the restrictions aiyi=0 and 0=ai=A. The penalty period set by the user Performance in generalization is governed by the parameter A in a support vector machine. As a result of the training, only a small fraction of s will be non-zero. Figure 5 depicts the structure of the classification SVM. Using SVMs, optical character recognition, face recognition, and text categorization have all demonstrated good generalization performance. Additionally, gene expression, DNA, and protein data have all been analyzed using it.

Fig7: A visualization of the architecture of SVM in classification

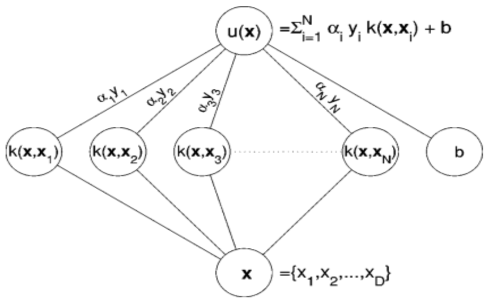

Fig 8: Classification of eye image resulting Normal

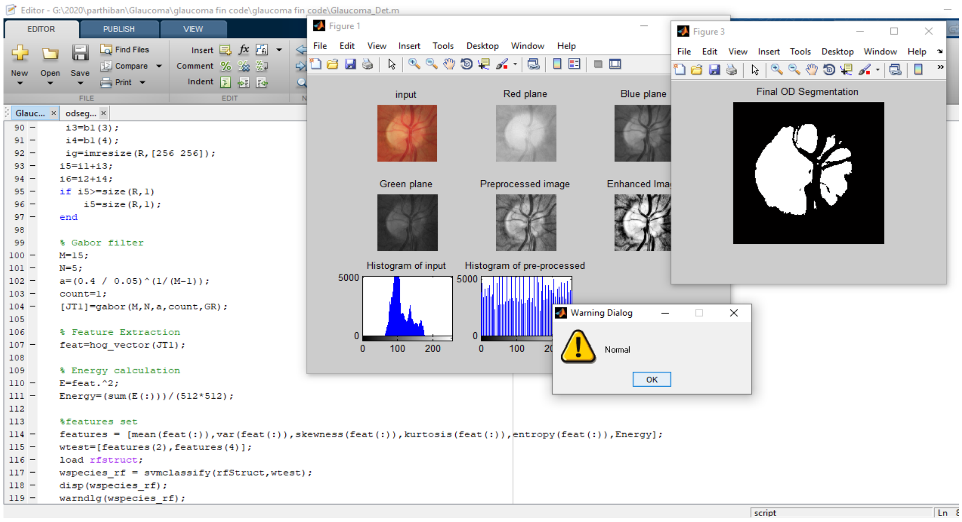

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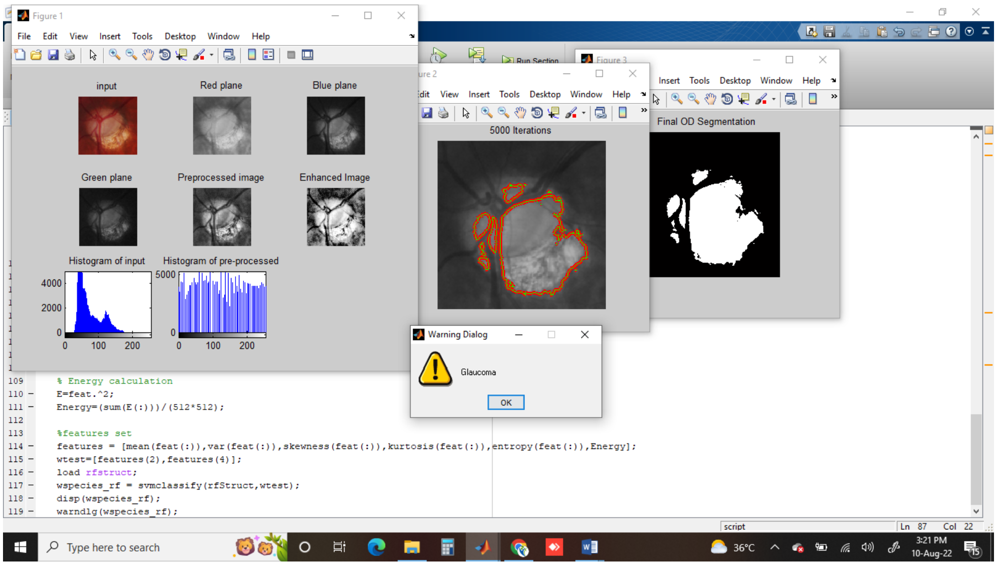
Fig 9: Classification of eye image resulting Abnormal-Glaucoma affected



e) Result

A more accurate approach for detecting glaucoma from fundus pictures employing HMM, CSO, and SVM is proposed in this research. From the RIM-1 public image library, 505 images were taken [8]. All of the images have been resized, altered, and enhanced. Finally, the 14 robust characteristics were given into the SVM classifier.

Criteria for performance definition the efficiency of the suggested method was measured using the three standard performance criteria of specificity, accuracy, and sensitivity. The following are examples of performance indicators [5]:

Specificity: An official TNR. As a percentage, it measures how many correctly identified healthy test photos there were. This is the equation:

$$SPE(\%) = \frac{TN}{TN+FP} x100 \qquad (6)$$

Sensitivity: It's a TPR. It is described as the percentage of all glaucoma test photos that were correctly diagnosed as having glaucoma. The formula is as follows:

$$SEN(\%) = \frac{TP}{TP+FN} x100 \qquad (7)$$

Accuracy: It is the percentage of photos of glaucoma and healthy people that were correctly identified among all test photographs. The formula is as follows:

$$ACC(\%) = \frac{TP+TN}{TP+TN+FP+FN} x100 \qquad (8)$$

Where TP, TN, FP and FN are defined as:

TP: True Positive, Images that are categorized as glaucoma images are those specific images.

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TN: True Negative, Healthy images are those that fall under this category.

FP: False Positive, Shots that have been labelled as glaucoma images are in fact healthy photos.

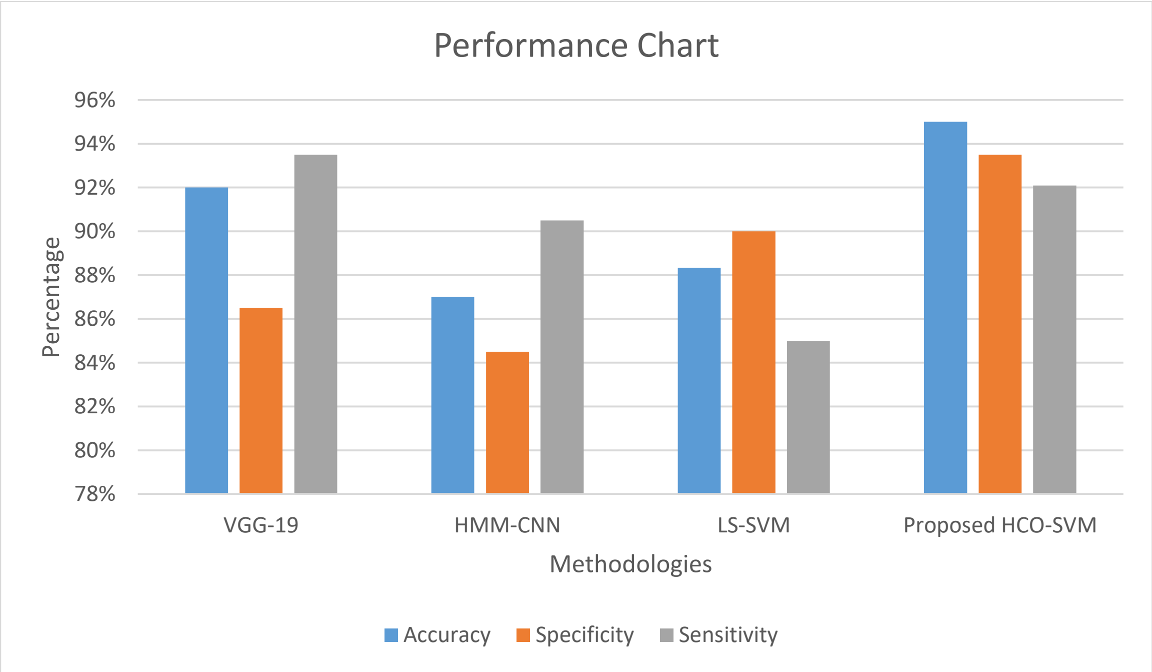
FN: False Negative, Photos of glaucoma is marked as being in good health.

Table 1: Performance of Existing and Proposed Method for Glaucoma Detection

Methods	Accuracy	Specificity	Sensitivity
VGG-19	92%	86.5%	93.5%
HMM-CNN	87%	84.5%	90.5%
LS-SVM	88.33%	90%	85%
Proposed HCO-SVM	95%	93.5%	92.1%

Table 1 and Figure 6 compare the performance of existing and proposed methods for detecting glaucoma. It demonstrates the existing and proposed methods' accuracy, specificity, and sensitivity. When compared to CNN and LS-SVM methodologies, VGG-19 networks have a greater accuracy of 92 percent, while our proposed method employing HMM, CSO, and SVM techniques has a higher accuracy of 95 percent, which is higher than VGG-19. As a result, our proposed strategy outperforms previous works.

Fig 10: Performance of Existing and Proposed Method for Glaucoma Detection



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4. CONCLUSION

In the field of medical image processing research, early phase glaucoma diagnosis is challenging due to its unclear characteristics and limited number of lesions. In this experiment, it was suggested that early-stage glaucoma may be identified. We described a novel retinal disc segmentation algorithm for glaucoma detection technique with. In our approach, we proposed a novel algorithm by combining HMM and CSO model and formed a hybrid segmentation algorithm. As a result, our suggested approach performs better than earlier works. The resultant image has been classified with Support Vector Machine with GLCM features. To increase accuracy and efficiency, future work in this field might make use of various feature selection and categorization strategies.

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