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Glaucoma Detection and Its Classification Using Fuzzy-C Means and K-Means Segmentation

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Abstract: - **Glaucoma, the most common cause of blindness is the disease of the optic nerve of the eye and can lead to ultimate blindness if not treated at an early stage. Raised intraocular pressure, increase in cup to disk ratio and visual field test are some of the measures for such a disease. The main objective of this paper is to find an automated tool to detect glaucoma at an early stage and to classify this disease based on its severity and damage of the optic fiber. The objective of this study is pre-processing of retinal fundus image for enhancing the quality which is required for further processing and to design a novel algorithm to measure the cup to disc ratio of retinal fundus image from the online database and classify the disease according to its severity using fuzzy classification toolbox in MATLAB. This paper presents Evaluation K-mean and Fuzzy c-mean image segmentation based Clustering classifier. It was followed by thresholding and level set segmentation stages to provide accurate region segment. The performance and evaluation of the given image segmentation approach were evaluated by comparing K-mean and Fuzzy c-mean algorithms in case of accuracy, processing time, Clustering classifier, and Features and accurate performance results. The database consists Glaucoma affected images executed by K-mean and Fuzzy c-mean image segmentation based Clustering classifier. The experimental results confirm the effectiveness of the proposed Fuzzy c-mean image segmentation based Clustering classifier. The statistical significance Measures of mean values of Peak signal-to-noise ratio (PSNR) and Mean Square Error (MSE) and discrepancy are used for Performance Evaluation of K-mean and Fuzzy c-mean image segmentation. The algorithm's higher accuracy can be found by the increasing number of classified clusters and with Fuzzy c-mean image segmentation.**

I. INTRODUCTION

Diabetic Retinopathy (DR) and Glaucoma are the two major causes for retinal disorder which leads to vision loss if not treated at an early stage. Early screening is very essential so that the patient is out of danger. The ophthalmologists are going to either take fundus images or OCT images for detection and diagnosis of the disease. The detection of glaucoma from a fundus photograph is much easier than that from an OCT image. In our paper we have concentrated mainly on fundus image of the retina. We have detected the cup-to-disc ratio (CDR) to identify the disease at the early stage and used fuzzy classification to classify the severity of the disease. The measure of Intra ocular pressure is also equally important in detecting glaucoma at an early stage. Other methods to detect glaucoma are finding the ratio of the distance between optic disc centre and optic nerve head to optic disc diameter [1]. Typical fundus photo of given retina looks as shown in Fig.1

Figure 1 Normal Fundus Image

Histogram Equalization:

There is a need to enhance the image for getting a better quality of the image. There are many enhancement schemes used for image enhancement which basically include gray scale handling, image filtering and image histogram equalization. Histogram equalization is very commonly used image enhancement technique and is easy to apply. It also helps in retaining the input brightness and generating a quality output image.[2]. The main reason behind using this technique is to enhance the contrast by re-mapping the grey levels in the input image. We use this technique on the retinal fundus image captured by ophthalmologist. In order to enhance the fundus image captured by ophthalmologist, we must first extract the green channel of the fundus image. In the second step, we are interested in its histogram equalization. [3] shown in fig.2

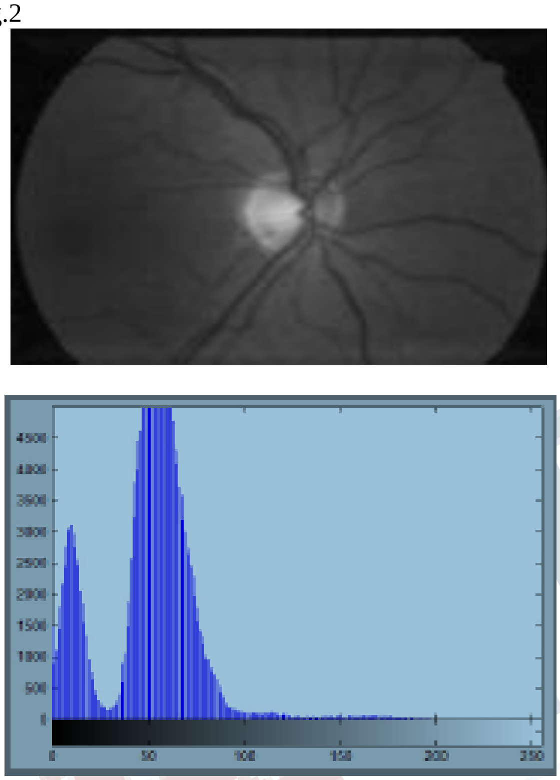

Figure2 Fundusimage and its Histogram equalization

The formula that we are applying is

$$h(v) = \text{round}\left(\frac{cdf(v) - cdf_{min}}{(M \times N) - cdf_{min}} \times (L-1)\right)$$

Where, cdfmin calculates the minimum value of the cumulative distribution function,

M x N gives the number of pixels in the image. L is the count of grey levels. After the histogram equalization, we can enhance the fundus image and extract the optic disc, optic cup and calculate the CDR ratio.

Optic Disc and Optic Cup Extraction:

In order to calculate Cup-Disc Ratio (CDR), we first need to extract the optic disc and optic cup. Typical steps involved in finding CDR is shown in Fig 4.

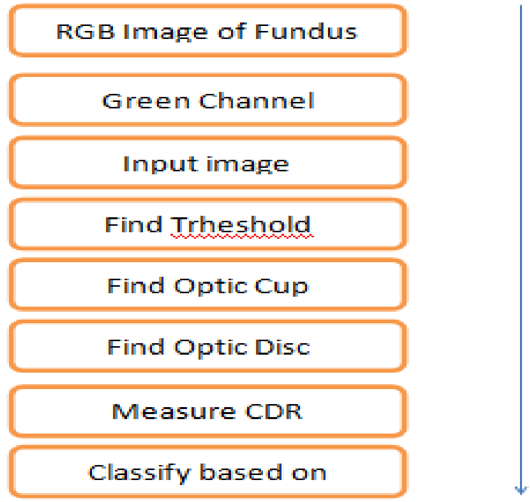

Figure 4. Typical steps involved in Glaucoma

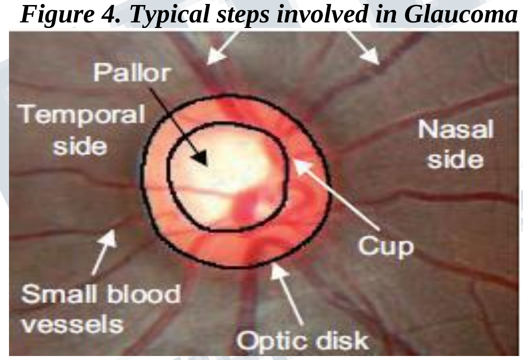

Figure 6. Optic cup and disk boundary

Ophthalmologist can manually detect optic disc boundary and optic Cup boundary. Typical disk boundary is shown above. But it becomes cumbersome if there are thousands of images. The boundary selection implementation results as shown below in Fig 7.

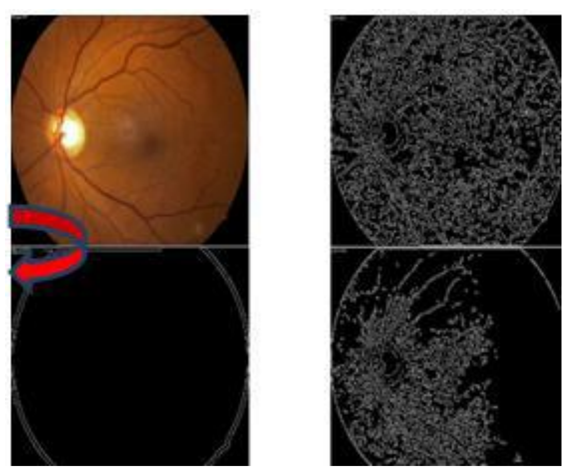

Figure 7. Boundary detection in MATLAB

Cup Disc Ratio:
Then optic cup and disk are extracted as shown in figure 8. Once the optic cup and optic disc are extracted, then comes the measurements of the Cup Disc ratio (CDR). It is calculated as shown in Fig 8

Figure 8 Extraction of optic disk and optic cup

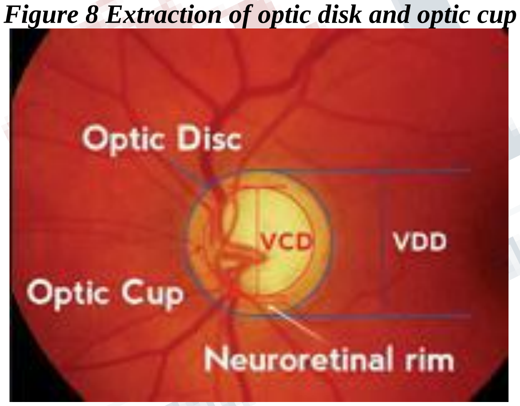

Figure 9.1 Measuring cup disc ratio.

Typical optical cup region and optical disk region is shown in fig 9.Once the cup and disc boundaries are obtained, we will follow clinical method of detecting Cup-Disc Ratio which is an indicator for the detection of the presence of glaucoma disease in the patient.
CDR = Area of the Cup / Area of the Disc
When the cup-disc ratio increases over a threshold value, we consider that the patient is suffering from glaucoma or we can say that the patient is glaucomatous. A tool used for screen automates measuring cup-to-disc ratios to provide earlier intervention and treatment.

Classification of Glaucoma:
It is very important to know whether the input image is glaucomatous or not. Once we identify that the fundus image is glaucomatous based on the CDR, we further classify for its severity like mild, moderate and severe.
Glaucoma can be classified as either Open Angle Glaucoma or Closed Angle Closure.

 Primary Open Angle Glaucoma
Primary open angle glaucoma is affected mainly due to clogging of eye's drainage canals [5] where the inner IOP raises , as proper amount of fluid inside the eye cannot drain. It is very important to diagnose such patients at an early stage as it can affect the vision of patient.

 Closed angle Glaucoma
This type of glaucoma is also called as acute glaucoma or narrow angle glaucoma. It happens due to continual production of fluid within the eye and drains out of, the normal eye. This causes blockage of the drainage angle of the eye. The major difference in primary glaucoma and secondary glaucoma is shown in fig.11. (a) and (b).
Typical classification of glaucoma disease in any patient can be broadly classified as shown in Fig .10

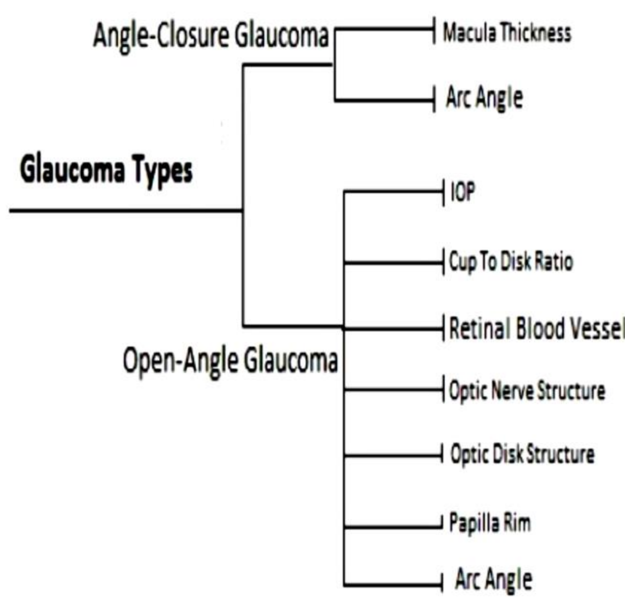

Figure 10. Typical Glaucoma Classification based on severity.

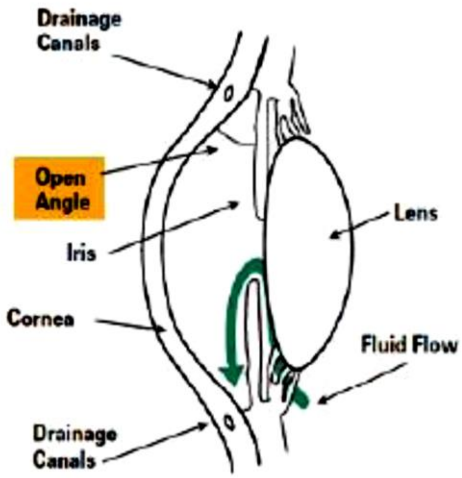

Figure 11 a. Open Angle

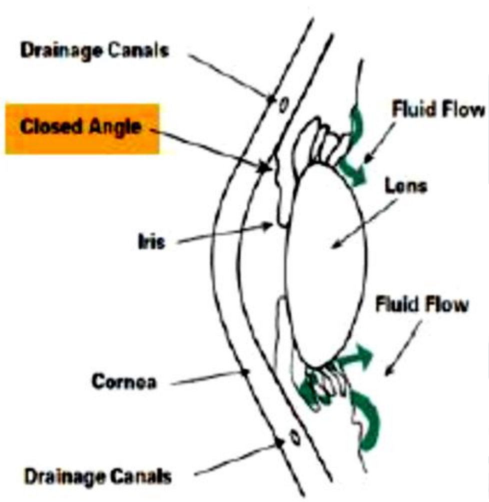

Figure 11b. Closed Angle

K-means and Fuzzy C means

K-means (or alternatively Hard C-means after introduction of soft Fuzzy C-means clustering) is a well-known clustering algorithm that partitions a given dataset into □ (or □) clusters. It needs a parameter c representing the number of clusters which should be known or determined as a fixed apriori value before going to cluster analysis. KM is reported fast, robust and simple to implement. As reported in many studies it gives comparatively good results if clusters in datasets are distinct or well separated. It was also examined that KM is relatively efficient in computational time complexity with its cost of □(□□□□) in Lloyd algorithm (where t: number of iterations, c: number of clusters, n: number of objects, p: number of dimensions or number of features). Despite its above mentioned advantages, KM has several disadvantages too regarding the form and scattering of clusters in datasets. First of all, KM may not be successful to find overlapping clusters, and it is not invariant to non-linear transformations of data. For that reason, representations of a certain dataset with Cartesian coordinates and polar coordinates may give different clustering results. KM also fails to cluster noisy data and non-linear datasets.

In order to overcome some of the problems faced with KM, Bezdek (1981) introduced Fuzzy C-means (FCM) which is based on Dunn's study (Dunn 1973) as an extension of KM. As reviewed by Suganya & Shanthi (2012) and Ali et al. (2008), a dozen of the algorithms have been developed in order to improve the efficiency and accuracy of FCM. However, the basic FCM algorithm has frequently been used in a wide area of applications from engineering to economics. FCM is a soft algorithm clustering fuzzy data in which an object is not only a member of a cluster but member of many clusters in varying degree of membership as well. In this way, objects located on boundaries of clusters are not forced to fully belong to a certain cluster, but rather they can be member of many clusters with a partial membership degree between 0 and 1. In spite of its relatively higher cost with □(□□2□□), when compared to KM, FCM has also been used in many clustering applications because of its above mentioned advantages in agriculture and forestry area (di Martino et al. 2007; 2009).

Although FCM is believed to be more efficient to analyze fuzzy data, it does not have a constant superiority in all cases of data structures according to the research findings. However, the recent studies generally have focused on comparison of KM and FCM by using some well-known test datasets such as Iris and Wine in R environment (Jipkate & Gohokar 2012; Panda et al. 2012; Ghosh & Dubey 2013; Bora & Gupta 2014). Thus, it would be helpful to examine these hard-and-soft C-means partitioning algorithms for the data structures following different patterns and shapes of clusters. For that reason, in this paper we compared the efficiency of KM and FCM algorithms on synthetically generated datasets consisting of different shaped clusters scattering with regular and non-regular patterns in two dimensional space.

2.1. K-means algorithm

FCM algorithm minimizes the objective function in Equation (3).

$JFCM(\boldsymbol{X};\boldsymbol{U},\boldsymbol{V}) = \Sigma\Sigma uijmnj{=}1ci{=}1Dij\boldsymbol{A}2$ (3)

This function differs from classical KM with the use of weighted squared errors instead of using squared errors only. In the objective function in Equation (3), $\boldsymbol{U}$ is a fuzzy partition matrix that is computed from dataset $\boldsymbol{X}$:

U$=[uij]\in MFCM$ (4)

The fuzzy clustering of $\boldsymbol{X}$ is represented with $\boldsymbol{U}$ membership matrix in $c\times n$ dimension.The element uij is the membership value of ith object to jth cluster. In this case, the jth column of $\boldsymbol{U}$ matrix is formed with membership values of n objects to jth cluster. $\boldsymbol{V}$ is a prototype vector of cluster prototypes (centroids):
$\boldsymbol{V}$=[$\mathbf{v}$1,$\mathbf{v}$2,…,$\mathbf{v}c$],$\mathbf{v}i\in\mathbb{R}p$ (5)
$Dij\boldsymbol{A}2$ is the distances between ith features vector and the centroid of jth cluster. They are computed as a squared inner-product distance norm in Equation (6):
$Dij\boldsymbol{A}2=\|\mathbf{x}j-\mathbf{v}i\|\boldsymbol{A}2=(\mathbf{x}j-\mathbf{v}i)T\boldsymbol{A}(\mathbf{x}j-\mathbf{v}i)$
FCM is an iterative process and stops when the number of iterations is reached to maximum, or when the difference between two consecutive values of objective function is less than a predefined convergence value (ε). The steps involved in FCM are:

1) Initialize $\boldsymbol{U}(0)$ membership matrix randomly.

2) Calculate prototype vectors: $\mathbf{v}i=\Sigma uijm\boldsymbol{x}jnj=1\Sigma uijmnj=1$; $1\leq i\leq c$ (10)

3) Calculate membership values with:

$uij=1\Sigma(Dij\boldsymbol{A}/Dkj\boldsymbol{A})2/(m-1)ck=1$; $1\leq i\leq c$,$1\leq j\leq n$ (11)

4) Compare $\boldsymbol{U}(t+1)$ with $\boldsymbol{U}(t)$, where t is the iteration number.

5) If $\|\boldsymbol{U}(t+1)-\boldsymbol{U}(t)\|<\varepsilon$ then stop else return to the step 2.

THE PROPOSED METHOD

The database for paper contain glaucoma images applied for all the K-mean and Fuzzy c-mean image segmentation based Clustering classifier.
In this section, the results are presented which obtained by applying and evaluation K-mean and Fuzzy c-mean image segmentation.
The statistical significance Measures of mean values of Peak signal-to-noise ratio (PSNR) and Mean Square Error (MSE) and discrepancy use to Performance Evaluation of K-mean and Fuzzy c-mean image segmentation based Clustering classifier Peak signal-to-noise ratio, often-abbreviated PSNR, is an engineering term for the ratio between the maximum possible power of a signal and the power of corrupting noise that affects the fidelity of its representation. Because many signals have a very wide dynamic range, PSNR usually expressed regarding the logarithmic decibel scale. The psnr function implements the following equation to calculate the Peak Signal-to-Noise Ratio (PSNR):

where peakval is either specified by the user or taken from the range of the image datatype (e.g. for uint8 image it is 255). MSE is the mean square error, i.e. MSE between A and ref.

Mean Squared Error (MSE) of an estimator measures the average of the squares of the "errors", that is, the difference between the estimator and what estimate. MSE is a risk function, corresponding to the expected value of the squared error loss or quadratic loss [11]. Suppose that we measure the quality of t, as a measure of the center of the distribution, regarding the mean square error MSE(t) is a weighted average of the squares of the distances between t and the class marks with the relative frequencies as the weight factors. Thus, the best measure of the center, about this measure of error, is the value of t that minimizes MSE[10].

II.CONCLUSION

Glaucoma, being the second major cause of blindness can be effectively predicted using the basic fundus photographs which are used for prediction of symptoms of glaucoma at an early stage for the better good of the patient. We have proposed an algorithm for Performance Evaluation of K-mean and Fuzzy c-mean image segmentation based Clustering classifier. The paper concludes that all of K-means and Fuzzy C-means approximately generate the same number of regions in all selected cluster, from another side, we note K-means create a percentage of error (MSE) with high PSNR Compared with the Fuzzy C-Means which generate small low percentage of error with low PSNR. The algorithm's higher accuracy can be found by the increasing number of clustering classifier with Fuzzy c-mean image segmentation.