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# CLASSIFICATION OF RETINAL IMAGES USING IMPROVED ADAPTIVE FUZZY C-MEANS CLUSTERING ALGORITHM

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***Abstract*-Diabetic Macular Edema (DME) caused due to diabetes in a high risk complication which can cause irreversible loss of vision. Diabetics can also cause other retinal complications all of which are collectively termed as Diabetic Retinopathy (DR). The existing system uses the various algorithms based segmentation are dependent on the intensity of the single pixel and the shape of the gain field is not always effective. In this paper Improved Adaptive Fuzzy C-Means Algorithm (IAFCM) is proposed. It improves the segmentation and the classification accuracy.**

***Index Terms*-Diabetic Retinopathy (DR), Diabetic Macular Edema (DME), Diabetes, Improved Adaptive Fuzzy C-Means Clustering Algorithm (IAFCM), Gain field.**

## 1. INTRODUCTION

The retina is the nerve layer that lines the back of the eye, senses light, and creates impulses that travel through the optic nerve to the brain. There is a small area, called the macula, in the retina that contains special light-sensitive cells. The macula allows us to see fine details clearly.

Fuzzy c-means (FCM) is a data clustering technique in which a dataset is grouped into n clusters with every data point in the dataset belonging to every cluster to a certain degree [1]. For example, a certain data point that lies close to the center of a cluster will have a high degree of belonging or membership to that cluster and another data point that lies far away from the center of a cluster will have a low degree of belonging or membership to that cluster[12]. clustering algorithm (FCM) Fuzzy C-means clustering algorithm (FCM) is also known as Fuzzy ISODATA.

Fuzzy C-means Segmentation is Fuzzy pixel classification .In this clustering technique one piece of data belongs to two or more clusters. Fuzzy C-means clustering algorithm (FCM) allows data points or pixels to belong to multiple classes with varying degree of membership function between 0 to 1[1].

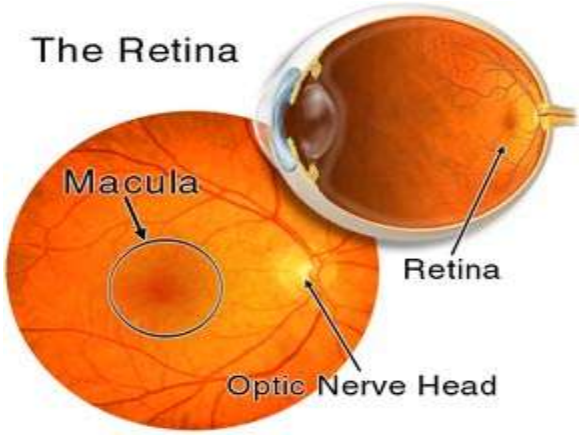


**Figure 1 Retinal Image**

(FCM) computes cluster centers or centroids by minimizing the dissimilarity function with the help of iterative approach. By updating the cluster centers and the membership grades for individual pixel. Fuzzy C-means clustering algorithm (FCM) shifts the cluster centers to the "right" location within set of pixels.

Adaptive Fuzzy C-means Clustering Algorithm (AFCM) uses the gain field to modify the Centers of each cluster and to compensate the slowly changing in homogeneities effects[1]. When the gain field is too sharp it fails to compensate the slow changes. When the gain field is too smooth, it fails to compensate the local changes [3].

## II.METHODOLOGY

In our proposed system we use the Improved Adaptive Fuzzy C-means Clustering Algorithm (IAFCM) to improve the sensitivity, segmentation and classification accuracy in the existing system. The concept of Improved Adaptive Fuzzy C-means Clustering Algorithm(IAFCM) is it uses a new objective function with a different regulation term, which appears to be more effective in controlling the shape of the gain field. Improved Adaptive Fuzzy C-means Clustering

Algorithm(IAFCM) avoids solving large differential equation and gives much faster computational speed[1]. Improved Adaptive Fuzzy C-means Clustering Algorithm(IAFCM) with a new objective function yields better background compensation and results in improved segmentation and classification[11]-[14].

## III.DIABETIC RETINOPATHY

Body does not use and store sugar properly when there is the diabetes mellitus .High blood-sugar levels can damage blood vessels in the retina, the nerve layer at the back of the eye that senses light and helps to send images to the brain. The damage to retinal vessels is referred to as diabetic retinopathy.There are two types of diabetic retinopathy: nonproliferative diabetic retinopathy (NPDR**)** and proliferative diabetic retinopathy (PDR).

NPDR commonly known as background retinopathy is an early stage of diabetic retinopathy. In this stage, tiny blood vessels within the retina leak blood or fluid. The leaking fluid causes the retina to swell or to form deposits called exudates. Many people with diabetes have mild NPDR, which usually does not affect their vision. When vision is affected it is the result of macular edema and/or macular ischemia. PDR is present when abnormal new vessels (neovascularization) begin growing on the surface of the retina or optic nerve. The main cause of PDR is widespread closure of retinal blood vessels, preventing adequate blood flow. The retina responds by growing new blood vessels in an attempt to supply blood to the area where original vessels closed Unfortunately, the new, abnormal blood vessels do not resupply the retina with normal blood flow. The new vessels are often accompanied by scar tissue that may cause wrinkling or detachment of the retina.PDR may cause more severe vision loss than NPDR because it can affect both central and peripheral vision

The severity of PDR can be classified as to the presence or absence of high-risk characteristics. Diabetes can also cause other retinal complications which are collectively termed as Diabetic Retinopathy (DR)[2]. The best treatment is to prevent the development of retinopathy as much as possible. Strict control of your blood sugar will significantly reduce the long-term risk of vision loss from diabetic retinopathy. If high blood pressure and kidney problems are present, they need to be treated.

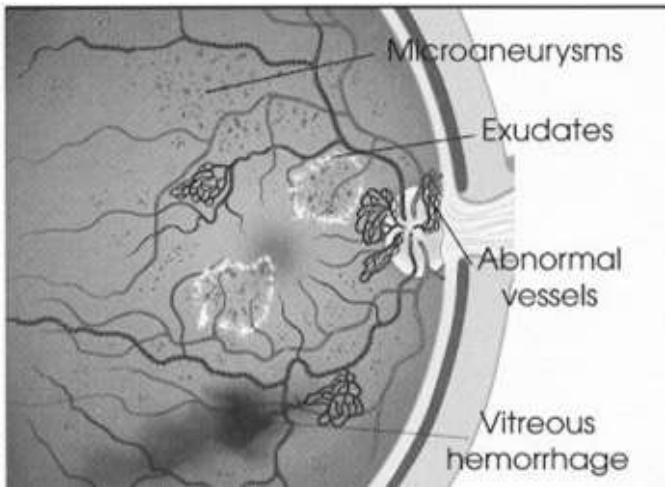


**Figure 2: Close Up of Retina with Diabetic Retinopathy**

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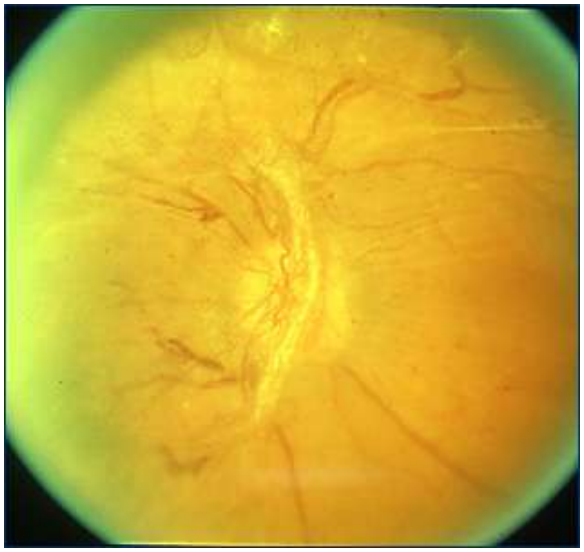

**Figure 3: Photo of Proliferative Retinopathy**

A. Diabetic Macular Edema

Macular edema is swelling, or thickening, of the macula, a small area in the center of the retina that allows us to see fine details clearly[2]. The swelling is caused by fluid leaking from retinal blood vessels. It is the most common cause of visual loss in diabetes. Vision loss may be mild to severe, but even in the worst cases, peripheral vision continues to function. Macular edema may be present at all the stages of diabetic retinopathy and is the most common cause of vision loss in nonproliferative diabetic retinopathy. Because of the increased vascular permeability and breakdown of the blood-retinal barrier, fluid and lipids leak into the retina and cause it to swell. This causes photoreceptor dysfunction, leading to vision loss when the center of

the macula, the fovea, is affected. In the ETDRS, diabetic macular edema (DME) was characterized as "clinically significant" if any of the following were noted: retinal thickening within 500 microns of the fovea, hard exudates within 500 microns of the fovea if associated with adjacent retinal thickening, or an area of retinal thickening 1 disc diameter or larger if any part of it is located within 1 disc diameter of the fovea.

Although the cause of the micro vascular changes in diabetes is not fully understood, the deficient oxygenation of the retina may induce an over expression of vascular endothelial growth factor (VEGF), with a consequent increase in vascular leakage and retinal edema. Besides ischemia, inflammation may also play a role in the development of macular edema in Diabetic Retinopathy.

Five different morphologic patterns of DME have been identified with the help of the OCT. Most of the patients with DME have diffuse retinal thickening or cystoid macular edema (presence of intraretinal cystoid-like spaces). In some patients, DME may be associated with posterior hyaloidal traction, serous retinal detachment or traction retinal detachment. Cystoid macular edema and posterior hyaloid traction are significantly associated with worse visual acuity.

Diabetic macular edema is believed to result from fluid and lipid transudation from microaneurysms and telangiectatic capillaries. Focal laser photocoagulation is used to heat and close the microaneurysms, causing them to stop leaking. Macular edema often improves following this form of treatment. Some clinicians apply laser burns in a grid pattern overlying areas of retinal edema without directing treatment to specific microaneurysms; this method can also be effective in reducing retinal thickening. The mechanism by which grid laser treatment achieves these results is not known.

When you are first diagnosed with diabetes, you should have your eyes checked:

- Within five years of the diagnosis if you are 30 years or younger;
- Within a few months of the diagnosis if you are older than 30 years.
- Diabetic retinopathy;
- Computer-aided diagnosis;
- Digital imaging;

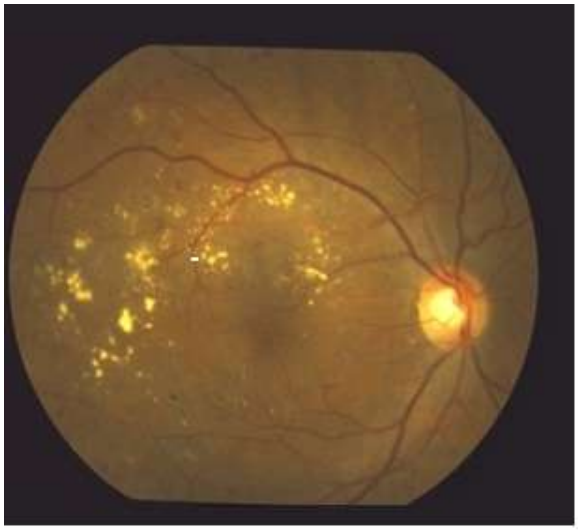

**Figure 4: Diabetic Macular Edema with Swelling and Exudation**

B.Severe Macular Edema

For years, the standard treatment for diabetic macular edema (DME) has been laser. The goal of laser treatment is prevention of severe vision loss. In patients who have already lost vision, laser improves vision in only 20-30% of cases. Retina specialists have used intraocular injections of steroids and anti-VEGF drugs to try and reduce swelling further and improve vision. Lucentis injections, often in combination with laser treatment, improved vision at 1 year in almost 50% of patients.

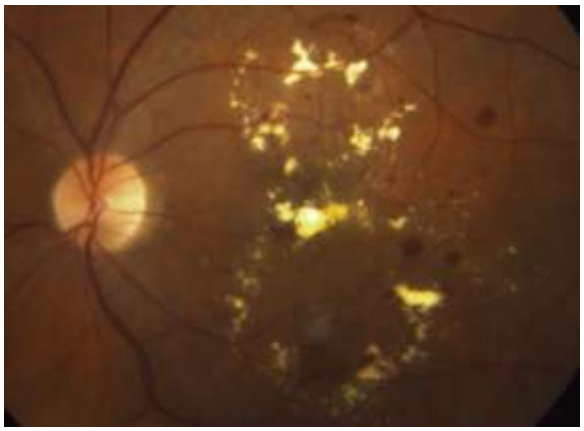

**Figure 5:Severe Macular Edema**

Laser treatment alone improved vision in 28% of patients. In patients with a history of cataract surgery, those treated with steroids showed a similar improvement to those treated with Lucentis.

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IV.BLOCK DIAGRAM OF PROPOSED SYSTEM

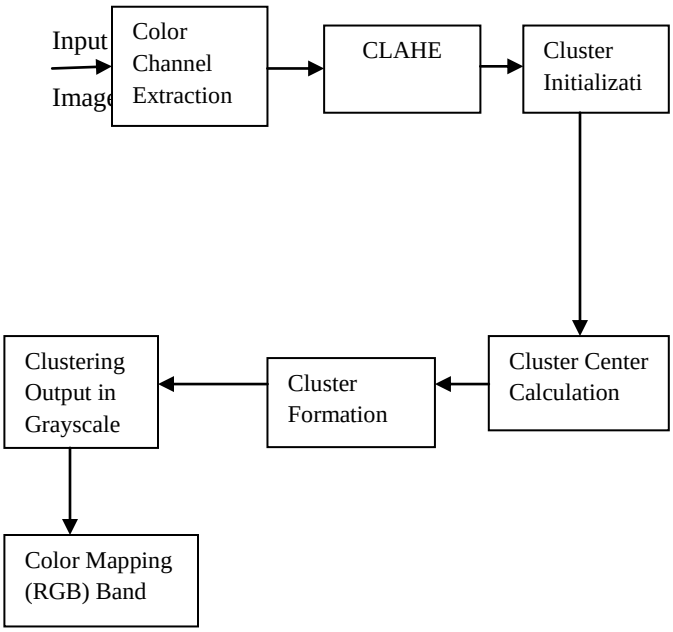


**Figure 6: A Schematic diagram of the proposed scheme**

A. Input Image

Color fundus image is given as an input image. The figure 4 shows the input image.

B.Color Channel Extraction

It will separate the color image into Red, Green, Blue and /or luminance components.

C.CLAHE

CLAHE (Contrast Limiting Adaptive Histogram Equalization) differ from ordinary Adaptive Histogram Equalization in its contrast limiting. CLAHE(Contrast Limiting Adaptive Histogram Equalization) was developed to prevent the over amplification of noise that adaptive histogram equalization can give rise to .This is achieved by limiting the contrast enhancement of AHE(Adaptive Histogram Equalization).Noise can be reduced while maintaining the high spatial frequency content of the image by applying a CLAHE(Contrast Limiting Adaptive Histogram Equalization).

D.Cluster Initialization

Cluster Initialization will determine the numbers to the clusters.

E.Cluster Center Calculation

Calculates the cluster center in order to segment the objects.

F.Cluster Formation

It is the task of assigning a set of objects into groups) so that the objects in the same cluster are more similar (in some sense or another) to each other than to those in other clusters. Clustering is a main task of explorative data mining, and a common technique for statistical data analysis used in many fields, including machine learning, pattern recognition, image analysis, information retrieval, and bioinformatics.

G.Color Mapping

Color mapping is a function that maps (transforms) the colors of one (source) image to the colors of another (target).

H.Histogram

An image histogram is a type of histogram that acts as a graphical representation of the tonal distribution in a digital image. It plots the number of pixels for each tonal value. By looking at the histogram for a specific image a viewer will be able to judge the entire tonal distribution at a glance.

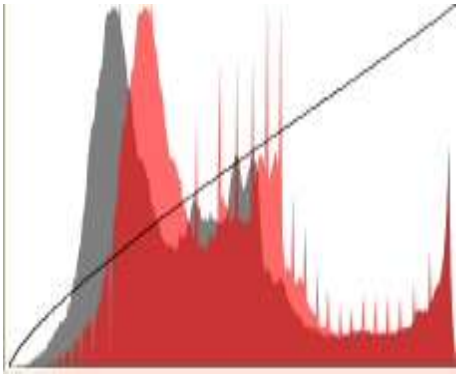

**Figure7: Histogram Image**

Histogram modeling techniques (e.g. histogram equalization) provide a sophisticated method for modifying the dynamic range and contrast of an image. The Figure7 shows the histogram image.

The horizontal axis of the graph represents the tonal variations, while the vertical axis represents the number of pixels in that particular tone. The left side of the horizontal axis represents the black and dark areas, the middle represents medium grey and the right hand side represents light and pure white areas. The vertical axis represents the size of the area that is captured in each one of these zones. Thus, the histogram for a very bright image with few dark areas and/or shadows will have most of its data points on the right side and center of the graph. Conversely, the histogram for a very dark image will have the

majority of its data points on the left side and center of the graph.

Image histograms can be useful tools for thresholding.Because the information contained in the graph is a representation of pixel distribution as a function of tonal variation, image histograms can be analyzed for peaks and/or valleys which can then be used to determine a threshold value. This threshold value can then be used for edge detection, image segmentation, and co-occurrence matrices.

*IAFCM (Improved Adaptive Fuzzy C-Means Clustering) Algorithm:*

Clustering is a way to separate groups of objects. C-means clustering treats each object as having a location in space. C-means clustering requires that you specify the number of clusters to be partitioned and a distance metric to quantify how close two objects are to each other. Color Based Segmentation Using C-Means Clustering.

$$u_{ik}=\frac{||y_i-g_i c_k||^{2q-1}}{\sum_{i=1}^{NC}||y_i-g_i c_k||^{-2/q-1}}$$

$$c_k=\frac{\sum_{i\in D} u_{ik}^q G_i y_i}{\sum_{i\in D} u_{ik}^q G_i^2}$$

$$g_i=(H*g)_i,$$

The solution of the above equation gives the optimum values of ( $u_{ik}$ , $c_k$, $g_i$), which lead to the algorithm described as IAFCM.

1) Initialize $g_i$ with 1(i=1...N) and cluster centers $c_k$ (k=1….NC) with random values within the image intensity, Where NC is the number of clusters.
2) Update the membership function$u_{ik}$.
3) Update the cluster centers $c_k$ .
4) Calculate the gainfield$g_i$.
5) Update the gainfield$g_i$.

Using the above equation the segmentation of retinal images is done. The results are shown below.

## V.RESULTS AND DISCUSSION

Outputs of the above mentioned IAFCM algorithm was simulated using Matlab and severity of the disease is also discussed. Outputs are shown

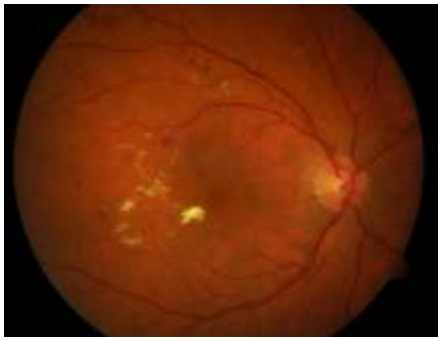

**Figure 8: Input Image**

The figure 8 shows the retinal image of input image and circular region of interest centered on macula. The input image is a color fundus image. It is of default size 576*768. For our convenience, the input image is resized to 512*512.

Color fundus image is given as input image after that preprocessing is done. The preprocessing output is shown in the figure. In this CLAHE (Contrast Limited Adaptive Histogram Equalization) is performed.

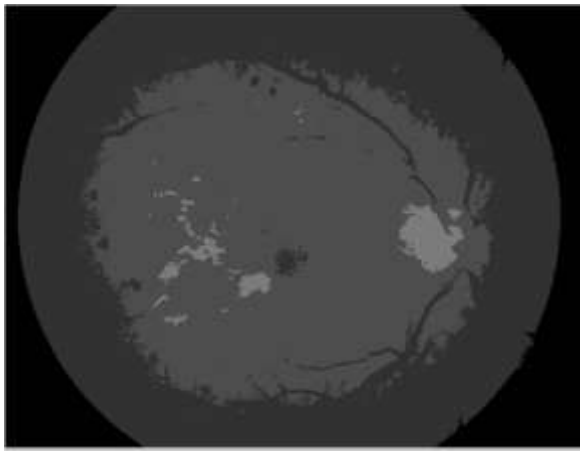

**Figure 9: Preprocessing Output**

The Figure 9 shows the preprocessing output. The color image is converted into gray image after enhances the image and contrast limited histogram equalization.

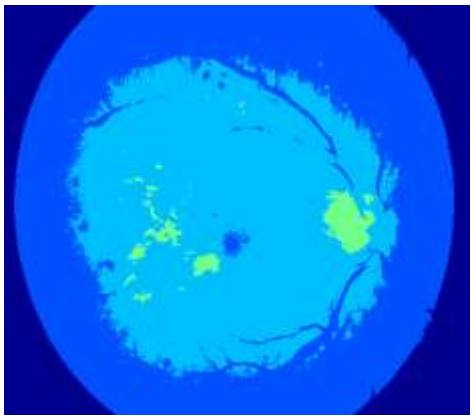

**Figure 10:Segmented Output**

The Figure 10 shows that segmented output which shows the severity of DME.

## VI.CONCLUSION

I proposed a method to reduce the time complexity and increase both the segmentation and classification accuracy. By using this IAFCM algorithm classification ratio is also increased, it gave higher segmentation accuracy than that of region based segmentation. IAFCM algorithm provides the information that how the retina is affected by DME. Severity of the DME is also found using this IAFCM algorithm. In this after preprocessing the segmentation is done. Classification accuracy of FCM, AFCM, IAFCM values is compared.

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