INDIAN INSTITUTE OF TECHNOLOGY, GUWAHATI

Department of Computer Science and Engineering

Project Report on

OPTIC DISC DETECTION

Based on Image processing with Machine learning

Group No. 18

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Github link - https://github.com/Princeyadav12/Optic_disc_detection/tree/main

Acknowledgement

This project is being submitted as a requirement for course fulfillment of DA526 - Image Processing with machine learning. It is a pleasure to acknowledge our sense of gratitude to Prof. Debanga Raj Neog who guided us throughout the project work. Thank You For Your Guidance and Support for the Entire Course. We thank the Teaching Assistants who were always helpful in clearing doubts.

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SYNOPSIS

An efficient detection of Optic Disc in retinal images is the fundamental step in an automated retinal image analysis system. Optic Disc detection and segmentation helps in identification of diabetic retinopathy and glaucoma in earlier stages. In this project, four different clustering algorithms are used for the detection and segmentation of Optic Disc from retinal images Clustering is a powerful technique that has been achieved in image segmentation.

The cluster analysis is to partition an image data set into a number of disjoint groups or clusters. Input image is first pre-processed using resizing, dilation and blurring on the green color band image. The cluster with maximum intensity is filtered using a connected component to segment out the optic disc. These clustering methods are tested on High Resolution Fundus Dataset which contains 45 retinal images, out of which 15 are healthy, 15 are affected by diabetic retinopathy and 15 are affected by glaucoma. These methods offer a successful detection of Optic Disc which may help in diagnosis of various retinal abnormalities.

CHAPTER 1

PROBLEM STATEMENT

Optic disc detection is a crucial step in the diagnosis of several eye diseases, including glaucoma, diabetic retinopathy, and macular degeneration. However, manual detection of the optic disc is a time-consuming and error-prone process that requires expert knowledge. Thus, there is a need to develop automated optic disc detection methods to assist ophthalmologists in the early detection and diagnosis of such eye diseases.

The challenge in automated optic disc detection lies in accurately localizing the optic disc within retinal images, which can be complicated due to variations in image quality, illumination, and pathological changes in the eye. Additionally, the presence of other anatomical structures, such as blood vessels and lesions, can further complicate the detection process.

Thus, the problem statement for optic disc detection is to develop a robust and accurate algorithm that can automatically detect the optic disc in retinal images with high sensitivity and specificity, while also accounting for image variations and the presence of other structures in the image.

Given a retinal image, we will be segmenting out the optic disc region from it. We will be using a High Resolution Fundus dataset which contains 45 retinal images.
To detect and segment the optic disc region, we will compare and employ various methods. Our approach involves preprocessing the fundus images, followed by the application of different algorithms. In unsupervised learning, we will utilize four clustering algorithms (K means, Fuzzy C mean, Agglomerative, DB Scan) to segment the optic disc region.

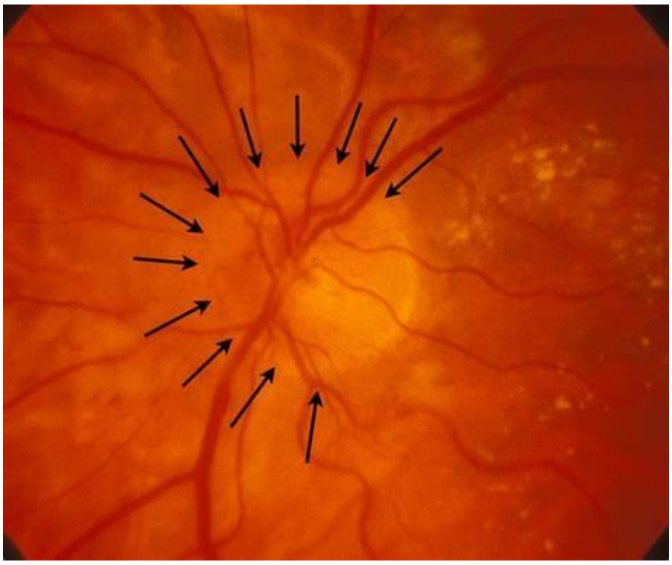


FIG - OPTIC DISC

CHAPTER 2

ABOUT THE DATASET

The public database contains at the moment

- 15 images of healthy patients,
- 15 images of patients with diabetic retinopathy and
- 15 images of glaucomatous patients.

LINK - https://www5.cs.fau.de/research/data/fundus-images/

CHAPTER 3

LITERATURE REVIEW AND RELATED WORK

As the world's population has drastically increased, the number of people suffering from glaucoma, or those suspected to have glaucoma, has increased too. Glaucoma is the second leading cause of blindness after cataract, with ~60 million cases reported worldwide in 2010. It is estimated that by 2020, about 80 million people were registered. Glaucoma is a chronic eye disease, in which the optic nerve is gradually damaged. If glaucoma is left untreated loss of vision occurs gradually, potentially leading to blindness. Therefore, diagnosing glaucoma at early stages is extremely important for proper management and successful treatment and control of the disease. The detection and diagnosis of glaucoma are related to tracing the changes in the optic cup which is a portion of optic disc (OD). The optic disc is a point in the eye where the optic nerve fibers leave the retina. It is a vertical oval with an average dimension of 1.76 mm horizontally and 1.92 mm vertically. Segmenting the optic disc (OD) is an important and essential step in creating a frame of reference for diagnosing glaucoma. Segmentation can be defined as the classification of all the picture elements or pixels in an image into different clusters that exhibit similar features. It involves partitioning an image into groups of pixels which are homogeneous with respect to some criterion.

The groups are called segments. The main components of the retina are blood vessels, optic disc and optic cup. The blood vessels, disc and cup merge in the image, making the segmentation more demanding. Determining the cup–disc ratio (CDR) is essential for detecting the disease for which segmentation of disc and cup from the retinal images is necessary. Generally, there is no unique method or approach for image segmentation. Clustering is a powerful technique that has been achieved in image segmentation. Cluster analysis is to partition an image data set into a number of disjoint groups or clusters. The clustering methods such as K means, Fuzzy c mean (FCM), Density Based spatial clustering of applications with noise (DBSCAN) and Agglomerative hierarchical methods have been proposed. Segmentation of optic disc and cup from the fundus retinal image helps in the detection of glaucoma. In addition to the visual field test and intraocular pressure measurement, precise measurement of the disc and cup areas as well as the cup to disc ratios is important for accurate diagnosis of glaucoma. The evaluation of the appearance of optic disc is central to the diagnosis and treatment of glaucoma. Glaucoma, which is in most cases associated with an increase in intraocular pressure, often produces additional pathological cupping of the optic disc. As glaucoma advances, the cup enlarges until it occupies most of the disc area. The cup to-disc (CDR) ratio is a measurement used in ophthalmology to assess the progression of glaucoma. The optic disc can be flat or it can have a certain amount of normal cupping. The CDR compares the diameter of the cup portion of the optic disc with the total diameter of the optic disc. The normal CDR is 0.3. A large CDR ratio may imply glaucoma or other pathology. In the normal eye horizontal CDR is greater than vertical CDR and in glaucomatous vertical CDR is greater than horizontal CDR.

There have been many works related to optic disc detection in the past few years. In this response, we will discuss some of the significant related works.

- Optic Disc Detection Using Convolutional Neural Networks (CNNs): CNNs have been widely used for optic disc detection due to their ability to automatically learn features from images. For example, Li et al. (2019) proposed a CNN-based method for optic disc detection that incorporated multi-scale features.
- Optic Disc Detection Using Deep Learning-Based Object Detection: Object detection algorithms, such as Faster R-CNN, have also been utilized for optic disc detection. For example, Li et al. (2020) proposed a Faster R-CNN based method for optic disc detection.
- Optic Disc Detection Using Ensemble Learning: Ensemble learning has been used to improve the performance of optic disc detection algorithms. For example, Zhang et al. (2020) proposed an ensemble learning-based method that combined multiple CNN models.
- Optic Disc Detection Using Morphological Operations: Morphological operations, such as opening and closing, have been used for optic disc detection. For example, Wu et al. (2019) proposed a method that combined morphological operations with a deep learning-based model..
- Optic Disc Detection Using Template Matching: Template matching has been used for optic disc detection due to its simplicity and efficiency. For example, Roychowdhury et al. (2019) proposed a template matching-based method.

In conclusion, there have been several works related to optic disc detection, including deep learning-based methods, object detection-based methods, ensemble learning-based methods, morphological operation-based methods, and template matching-based methods. Each of these approaches has its strengths and weaknesses, and further research in this area can lead to more accurate and efficient optic disc detection algorithms.

CHAPTER 4

METHODOLOGY

4.1 INTRODUCTION TO CLUSTERING

Clustering is the task of dividing the population or data points into a number of groups such that data points in the same groups are more similar to other data points in the same group and dissimilar to the data points in other groups. It is basically a collection of objects on the basis of similarity and dissimilarity between them. Clustering is a type of unsupervised learning method. An unsupervised learning is a method in which we draw references from datasets consisting of input data without labeled responses. Clustering is very important as it determines the intrinsic grouping among the unlabeled data present. There are no criteria for a good clustering. It depends on the user, what are the criteria they may use which satisfy their need.

CLUSTERING METHODS

1. Density based methods: density based methods have played a vital role in finding nonlinear shapes based on density. These methods consider the clusters as the dense region having some similarity and different from the lower dense region. These methods have good accuracy. Density- Based Spatial Clustering of Applications with Noise (DBSCAN) is the most widely used density based algorithm.
2. Hierarchical method: Hierarchical clustering involves creating clusters that have a predetermined ordering. The clusters formed in this method form a tree type structure based on the hierarchy. New clusters are formed using the previously formed one. There are two types of hierarchical clustering: Agglomerative (bottom up) Divisive(top up) 8
3. Partition methods: The main objective of partition clustering algorithm is to divide the data points into K partitions. Each partition reflects one cluster. For example K-means, CLARANS (Clustering Large Applications based upon randomized Search) etc. 4. Grid-based methods: In this method the data space is formulated into a finite number of cells that form a grid-like structure. All the clustering operations done on these grids are fast and independent of the number of data objects, for example STING (Statistical Information Grid), wave cluster, CLIQUE (Clustering In Quest) etc.

4.1.1. DBSCAN CLUSTERING

Density-based spatial clustering of applications with noise (DBSCAN) is a density based clustering algorithm. This algorithm finds core samples of high density and expands clusters from them. It is good for data which contains clusters of similar density.

Algorithm :

- Arbitrary select a point P.
- Retrieve all points density-reachable from P with respect to Eps and MinPts.
- If P is a core point, a cluster is formed.
- If P is a border point, no points are density-reachable from P and DBSCAN visits the next point of the database. Continue the process until all of the points have been processed.

4.1.2. AGGLOMERATIVE CLUSTERING

Agglomerative clustering is a hierarchical clustering technique in which initially each data point is considered as an individual cluster. At each iteration, the similar clusters merge with other clusters until one cluster or K clusters are formed.

Algorithm:

- Compute the proximity matrix.
- Assign each data point as a cluster .
- Merge the two closest clusters and update the proximity matrix.
- Repeat step 3 until k clusters are formed.

4.1.3. K means

K Means algorithm is an iterative algorithm that tries to partition a dataset into K predefined distinct non-overlapping subgroups (clusters) where each data point belongs to only one group. It tries to make the inter-cluster data points as similar as possible while also keeping the clusters as different (far) as possible. It assigns data points to a cluster such that the sum of the squared distance between the data points and the cluster's centroid (arithmetic mean of all the data points that belong to that cluster) is at the minimum.

Algorithm :

- Specify number of clusters K.
- Initialize centroids by first shuffling the dataset and then randomly selecting K data points for the centroids without replacement.
- Keep iterating until there is no change to the centroids. i.e assignment of data points to clusters isn't changing.
    - Compute the sum of the squared distance between data points and all centroids.
    - Assign each data point to the closest cluster (centroid).
    - Compute the centroids for the clusters by taking the average of the all data points that belong to each cluster

4.1.4. Fuzzy C-Means

In fuzzy clustering, every point has a degree of belonging to clusters, as in fuzzy logic, rather than completely belonging to just one cluster. Thus, points on the edge of a cluster may be in the cluster to a lesser degree than points in the center of the cluster. The fuzzy c-means algorithm attempts to partition a finite collection of elements X, into a collection of c fuzzy clusters with respect to some given criterion.

Algorithm:

- Assign an initial random centroid to each cluster (Group).
- Compute the distance between each point and the cluster center using a simple algorithm.
- Based on distance between each point and the cluster center, re-compute the membership function.
- Based on the new membership function, re-compute the centroid. 5. If the difference between the original centroid and the next one is below a certain threshold value, say, €, then the algorithm stops, else it continues till this condition is true.

CHAPTER 5

SYSTEM IMPLEMENTATION

5.1 SYSTEM DESIGN

The block diagram of the proposed system, which explains step by step implementation, is shown in the figure below. The input retinal images are taken from High Resolution Fundus (HRF) image dataset.

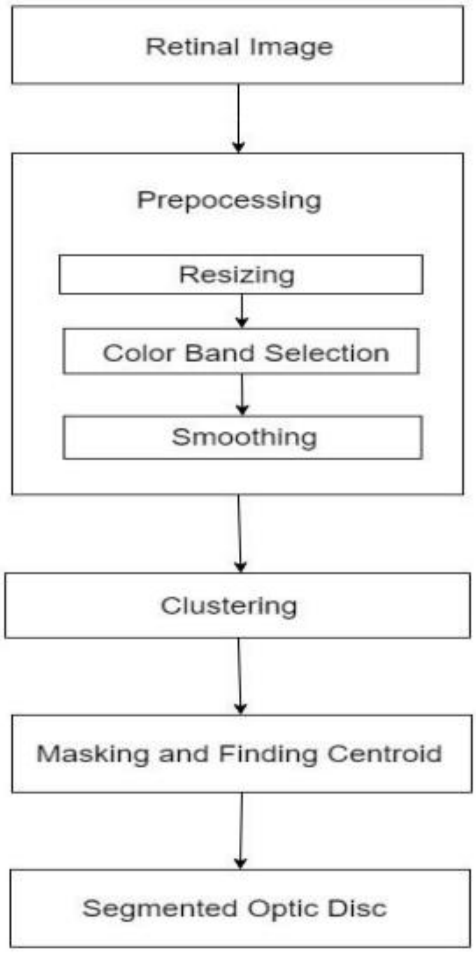


Fig: Block diagram of the implemented system

5.1.1 PRE-PROCESSING

The retinal images provided as input may contain variations of brightness or color information known as noise. To cope with such degraded images, the images are enhanced which improves visibility and perceptibility of image. The goal of preprocessing includes: removing the noise, enhancing contrast, sharpening or smoothing, elimination or retaining certain features in an image.

- Working with the original size of the retinal images could use high computational power and may not fit into certain spaces on a screen. So resizing is done to alter the size of the original image without cutting anything out. img = cv2.resize(img,(350,233)) This function resizes the original image.
- Each pixel of the retinal images contains three color values, R, G, and B. They can be any numeric value between 0 and 255. It is not advisable to process with the colored image as such because it requires large

computational power and it does not own distinct facts about anatomical and pathological structure in the retinal images. So the initial step is to separate the color bands from the retinal images.

- The green color band is better for the segmentation of OD as compared to the red and blue color band. In the green color band, the image is of good contrast, so it is used for further processing. _, g,_ = cv2.split(img) This function splits the image and stores the green color band image.

5.1.2 CLUSTERING FOR SEGMENTATION OF THE OPTIC DISC

After pre-processing the input retinal image, clustering is done for detecting the optic disc. Clustering divides the number of pixels into groups based on their similarities. Since the optic disc is the brightest region of the input retinal image, so all the pixels forming the optic disc will possess similar properties and hence will fall in the same cluster. And this cluster is later segmented as the optic disc. For clustering four algorithms are used –

- Agglomerative (Hierarchical clustering)
- K means (Partition clustering)
- Fuzzy C Means (partition clustering)
- DBSCAN (Density based clustering)

5.1.3 MASKING

After clustering, the optic disc must be in the brightest region of the clustered image, so we mask out all other pixels of the image except the brightest pixels. Now, we find the centroid of the masked image using the function cv2.moments(). Using this centroid we draw a circle of fixed radius in the original image to segment out the optic disc.

CHAPTER 6

RESULTS

The dataset used in this project is HRF(High Resolution Fundus) dataset, which contains 15 images of healthy patients, 15 images of patients with diabetic retinopathy and 15 images of glaucomatous patients. Binary gold standard segmentation values are available for each image. Based on these gold standard values, a number of hits and misses were calculated.

The performance of OD detection methods is assessed by comparing the OD center difference between manually labeled coordinates (XOD, YOD) and detected coordinates (XC, YC). The detected OD center considers it a hit if it satisfies the equation given below:

$$\sqrt{(X_{OD}-X_C)^2+(Y_{OD}-Y_C)^2} \leq R_{mean}$$

Where Rmean is the average of all the gold standard radii of the dataset. For the HRF dataset the average radius was 187.5 units in length. If the equation is not satisfied, then it is considered as a miss.

The result of k means, Fuzzy C Means, Agglomerative and DBSCAN clustering is shown below. Fig 1 is the input image and fig 2 is the output image of the respective algorithms. The green circle in fig 2 represents the portion of the optic disc detected by the respective algorithm.

1. K means

FIG 1

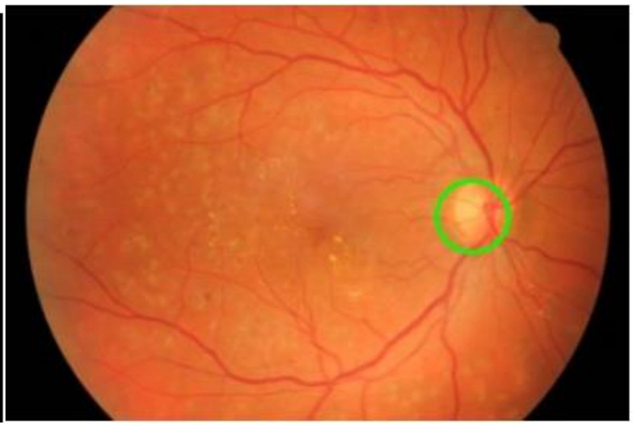


FIG 2

2. Fuzzy C means

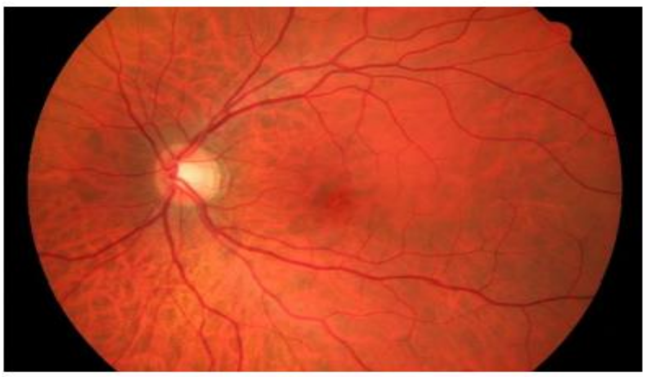


FIG 1

FIG 2

3. Agglomerative

FIG 1

FIG 2

4. DBSCAN

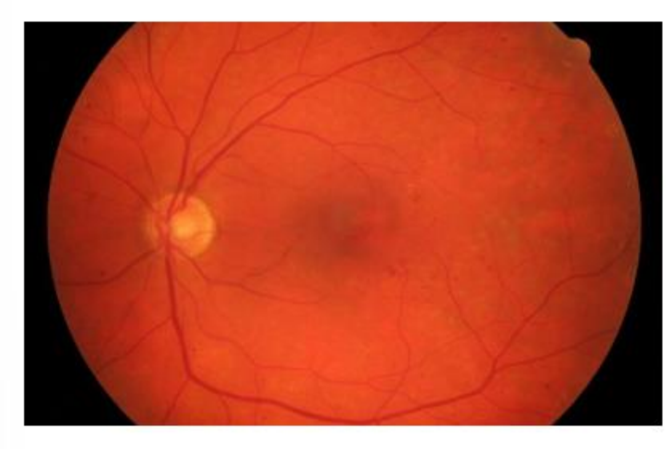


FIG 1

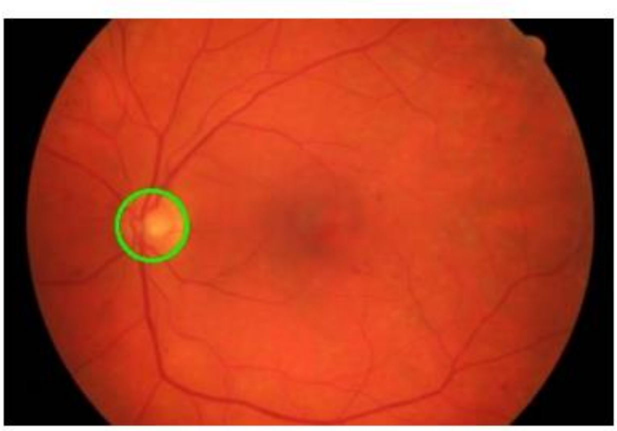
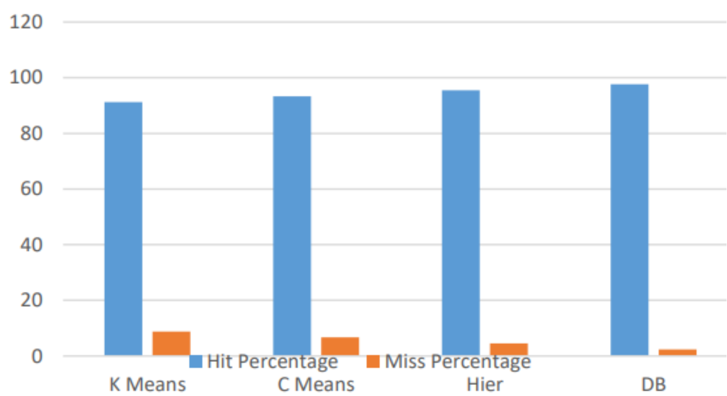


FIG 2

Comparative Analysis of Clustering Algorithms

Hit & Miss Evaluation:

ALGORITHMS	Hit Percentage	Miss Percentage
K Means	91.2	8.8
Fuzzy C Means	93.3	6.7
Agglomerative	95.5	4.5
DBSCAN	97.7	2.3



CHAPTER 7

CONCLUSION

In this project the K-means (KM), Fuzzy C-means (FCM), DBSCAN and Agglomerative algorithms were compared for their computing performance and clustering accuracy on High Resolution Fundus images. The essential difference between fuzzy c-means clustering and standard k-means clustering is the partitioning of objects into each group. Rather than the hard partitioning of standard k-means clustering, where objects belong to only a single cluster, fuzzy c-means clustering considers each object a member of every cluster, with a variable degree of “membership”. K-Means is very sensitive to noise in the dataset whereas Hierarchical Clustering Algorithm is less sensitive to noise in the dataset.

From the implementations we can claim that the k-means can be used for its simplicity of implementation and for its convergence speed. K-means also produces relatively high-quality clusters considering the low level of computation required. Fuzzy C-means gives better results for overlapped data sets and comparatively is better than the k-means algorithm. And lastly both hierarchical and DBSCAN produces the best results but it takes a higher computational time. So, it is advisable to use these two.

Each algorithm has its own set of parameters that need to be tuned for optimal performance. K-means requires the number of clusters as an input, which can be challenging to determine in advance. DBSCAN has parameters such as the neighborhood size and minimum number of points, which impact the cluster formation. Hierarchical clustering's linkage criteria and the number of clusters to extract can significantly affect the results. FCM has a fuzziness parameter that determines the degree of overlap between clusters.

It's important to note that the choice of clustering algorithm should be based on the characteristics of the dataset, the specific objectives of the analysis, and the trade-offs between computational efficiency and clustering accuracy.