



INDIAN INSTITUTE OF INFORMATION TECHNOLOGY, ALLAHABAD

V Semester B.Tech in Information Technology

MINI PROJECT - Final Report

Image Based Diabetes detection using eye movement and retinal images

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1. Abstract

Diabetes damages blood vessels all over the body. The damage to your eyes starts when sugar blocks the tiny blood vessels that go to your retina, causing them to leak fluid or bleed. For detection of diabetic eyes firstly detected diabetic retinopathy by screening the eye structure of normal and diabetic patients using ophthalmoscope screening tools. Diabetic retinopathy is a complication of diabetes that affects the blood vessels of the retina. Growth of new blood vessels ,known as proliferative retinopathy, may lead to blindness through hemorrhage and scarring. In this project we are going to develop a model for the classification of diabetic and detect disease (Diabetes) by using Retinal images as our dataset, eye movement and deep neural networks.

2. Introduction & Motivation

A. Introduction

Here we are going to predict diabetic using deep neural networks and image processing. We will have color images of the retina as input data. Vision is the most important human sense. Retinal disease affects millions of people and it may result in loss of vision if proper treatment is not done. One of these diseases is diabetic . Generally , we have ophthalmoscopy for eye disease screening which is the best approach done today . but this approach limits the number of testing per day. So , we are going to make such a model which will help human beings by detecting eye disease called diabetic.

B. Motivation

While surfing on the web, one day one of us came across an advertisement of a child suffering from ASD which took attention to look into the term. On detailed research we analysed The Centers for Disease Control's Autism and Developmental Disabilities Monitoring (ADDM) Network reports that in 2014, approximately 1 in 59 children in the

United States (1 in 37 boys, and 1 in 151 girls), has been identified with an autism spectrum disorder (ASD). The biggest challenge we see coming is to detect the ASD with high accuracy for our testing dataset so as to ensure to get the best output from our project. Thus, we decided to work on the project and propose NGOs to lead it further, maybe our little contribution can create a little effect.

3. Problem Definition & Objectives

A. Problem definition

To Detect Disease (Diabetes) by using Retinal images as our dataset, eye movement and deep neural networks.

B. Objectives:

Primary Objectives :

- Detect the diabetic eye with maximum accuracy.
- Requirements: A good amount of dataset

Secondary Objective:

- To make it cost effective when the project is at its expandable stage so that the project can serve a social cause.

4. Literature Review and Dataset Description

A. Literature Review

Paper Title	Name of the Conference/journal (Year)	Purpose	Methodology	Dataset	Results
Detection of diabetic Retinopathy Images using a fully Convolutional Neural Network	2nd International Conference on Data Science and Business Analytics	The main objective of this paper was to develop a model for the detection of diabetic retinopathy from fundus images of patient	They have used the Image processing, Segmentation, feature Extraction and Classification for their model. For classification, they have used CNN(Convolutional Neural Network) having 6 convolution layers for detection.	They have used an HRF dataset containing a fundus image of a healthy and diabetic person. They have used all three classes for classification to form a 3 class classifier. The dataset was divided into 50% training and 50% testing samples.	Different methods and techniques are used for classifying the fundus images for the same. The proposed convolutional neural network stands as a competitor for the existing models by showing its efficiency. It works well with an accuracy of 91.66%.
Convolutional Neural Networks for Diabetic Retinopathy	International Conference On Medical Imaging Understanding and Analysis, July 2016	The main objective of this paper is to develop a network with CNN architecture and data augmentation on color images for the recognition task of diabetic retinopathy staging.	This paper uses the methodology of Pre-processing technique after that Augmentation process and finally for classification purpose uses the CNN algorithm.	Data set contains over 80,000 images, of approximately 6M pixels per image and scales of retinopathy	It shows that CNN has the potential to be trained to identify the features of diabetic Retinopathy in fundus image.

B. Dataset Description-

Dataset (Name/Description)	Characteristics of dataset	Publicly available (if yes then mention URL)
Standard Diabetic Retinopathy Database	The database consists of 200 colour fundus images of which 184 contain at least mild nonproliferative signs of the diabetic retinopathy, and 16 are considered as normal which do not contain any signs of the diabetic retinopathy.	http://www2.it.lut.fi/project/imageret/diaretdb1/

We will be using this ([Dataset](#)) as our dataset. The database consists of 200 colour fundus images. The 200 images were manually assigned into categories representing the progressive states of retinopathy: normal, mild, moderate and severe non-proliferative, and proliferative. Using the categories, the images were divided into the representative training (28 images) and test sets (61 images). Images were captured using the same 50 degree field-of-view digital fundus camera with varying imaging settings.

The dataset descriptions is as follows:-

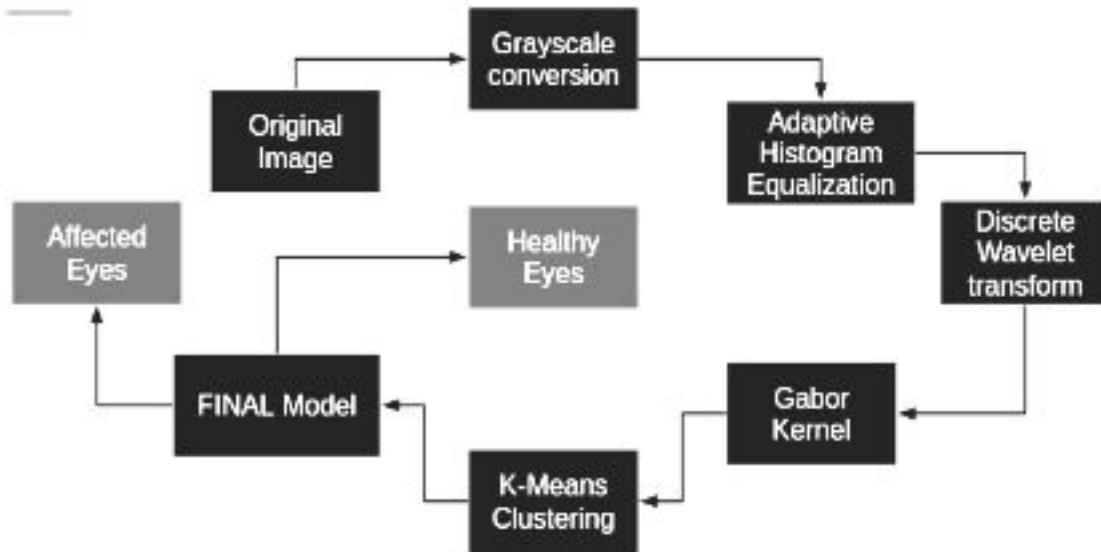
- Train Datasets: Train dataset images used to prepare our model, to train it.
- Test Datasets: Test dataset images used to test our model and then we measure performance of our model.

Testing and Training dataset contain hard exudates, soft exudates, microaneurysms, and hemorrhages type images.

Dataset described above is in the public domain, and can be easily downloaded. We have done worked from

https://drive.google.com/drive/folders/1DfvoLYX3ZdeMmb_LY2syewKiJBz10ili?usp=sharing

5. Algorithm



- **Grayscale Conversion:**

An RGB Image consists of 3 layers R,G,B as it is clearly seen through its name. It's a 3 dimensional matrix , where the grayscale image is of only 2 dimensions, and the values range between 0–255 (8-bit unsigned integers).

```
gray = cv2.cvtColor(image, cv2.COLOR_BGR2GRAY)
```

- **Adaptive Histogram Equalization :**

A computer image processing technique used to improve contrast in images. Ordinary histogram transforms using the single complete image histogram which does not work when the image contains regions that are significantly lighter or darker than most of the image Here, adaptive histogram equalization comes to the rescue by creating transforms using the neighbourhood pixels that means taking the small part of image for each transformation.

- **Discrete Wavelet transform :**

The Discrete Wavelet Transform (DWT), which is based on sub band coding, is found to yield a fast computation of Wavelet Transform. It is easy to implement and reduces the

computation time and resources required. It captures both frequency and location information (location in time)

- **Gabor Kernel :**

When a Gabor filter is applied to an image, it gives the highest response at edges and at points where texture changes. Moreover, it's assumed that it shows a lot of similarity with the human eye visual system.



- **K-Means Clustering :**

A method of clustering that allows one piece of data to belong to two or more clusters. Here, the k value decides the number of clusters to be formed. It forms k number of centroids and assigns a cluster to each centroid.

6. Methodology

1. Import the necessary libraries and python modules.
2. Input images: First, we will take the input images from the dataset in the drive. There will be a total 200 images of size 1152x1500.
3. Then, we will do the preprocessing of images loaded above which will include the following:
 - a. Gray scale Conversion
 - b. Adaptive Histogram Equalization
 - c. Discrete Wavelet Transform

- d. Gabor Kernel
 - e. K-Means Clustering for segmentation
4. Now, we will train the model using the following classifier and will compare their results.
- a. Support Vector Machine
 - b. K- nearest neighbor
5. We will calculate and predict the results by using each of above classifier and visualize the results by following:
- a. Accuracy
 - b. Classification Report
 - c. Confusion Matrix

7. Software and Hardware Requirements:

A. Software Requirements

- Google Collab

Languages

- Python 3
- Matlab

Tools:

- Keras
- Tensorflow
- PIL

Libraries :

- Numpy
- Pandas
- Matplotlib
- SKlearn
- Optimizer

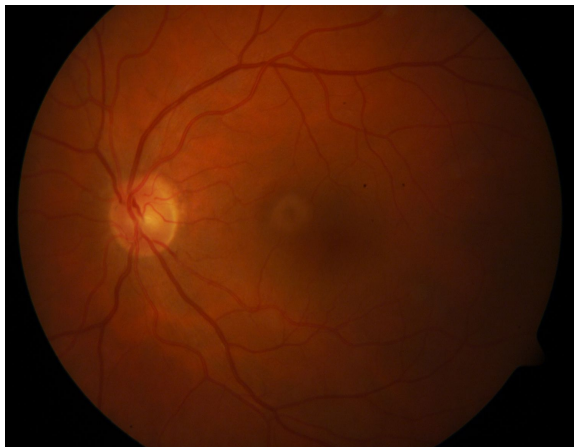
- Layers
- Seaborn
- Os
- VGG16
- Model

B. Hardware Requirements

- Laptop
- 8 GB RAM, GPU
- System with fast processor and a graphics card.

8. Implementation

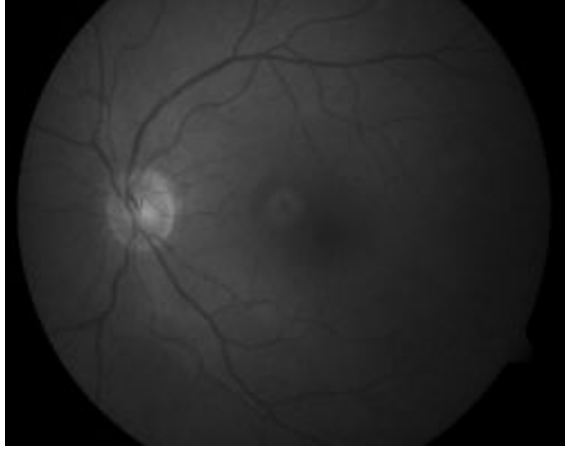
1. We will mount the drive so as to access the dataset.
2. Import the libraries and python modules from the local environment.
3. Now, we will load all the 200 images of size 1152x1500 from the drive.



Original Colored Image

4. Now, we will convert all the images to grayscale so as to get them easily processed.

Therefore, some algorithms can only be applied on 2-D images rather than 3-D, hence we convert an RGB image into a grayscale image, for instance



Conversion to grayscale

5. Then, we will do Adaptive Histogram Equalization of all the images to improve contrast of images.

As a result of this adaptive histogram equalization, the dark area in the input eye image that was badly illuminated has become brighter in the output eye image while the side that was highly illuminated remains or reduces so that the whole illumination of the eye image is the same.

- Consider a running sub image W of $N \times N$ pixels centered on a pixel $P(i,j)$, the image is filtered to produce another sub image P of $(N \times N)$ pixels according to the equation below:

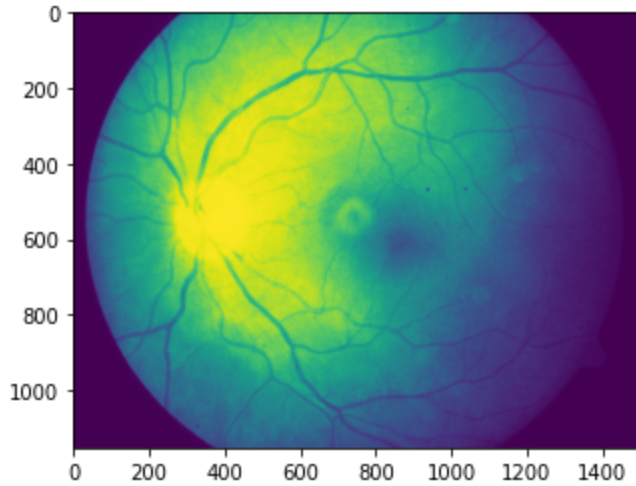
$$P_n = 255 \left(\frac{[\varphi_w(p) - \varphi_w(\text{Min})]}{[\varphi_w(\text{Max}) - \varphi_w(\text{Min})]} \right) \quad (1)$$

Where

$$\varphi_w(p) = \left[1 + \exp\left(\frac{\mu_w - p}{\sigma_w}\right) \right]^{-1} \quad (2)$$

$$\mu_w = \frac{1}{N^2} \sum_{(i,j) \in (k,l)} P(i,j)$$

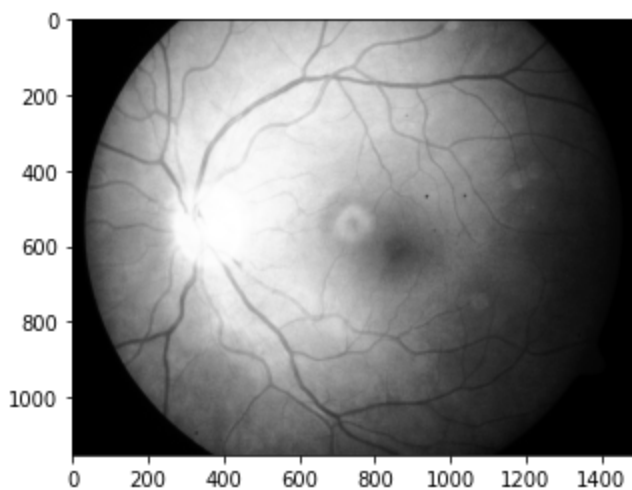
$$\sigma_w = \sqrt{\frac{1}{N^2} \sum_{(i,j) \in (k,l)} (P(i,j) - \mu_w)^2}$$



After applying Adaptive Histogram Equalization

6. We will now apply the Discrete Wavelet Transform on all the images.
 - As resolution of image increases, it requires a lot of disk space.
 - DWT is used to reduce the size of an image without compromising on quality and hence resolution increases.
 - Wavelets are obtained from a single prototype wavelet $\psi(t)$ called mother wavelet by dilations and shifting:

$$\Psi_{a,b}(t) = \frac{1}{\sqrt{a}} \Psi\left(\frac{t-b}{a}\right)$$

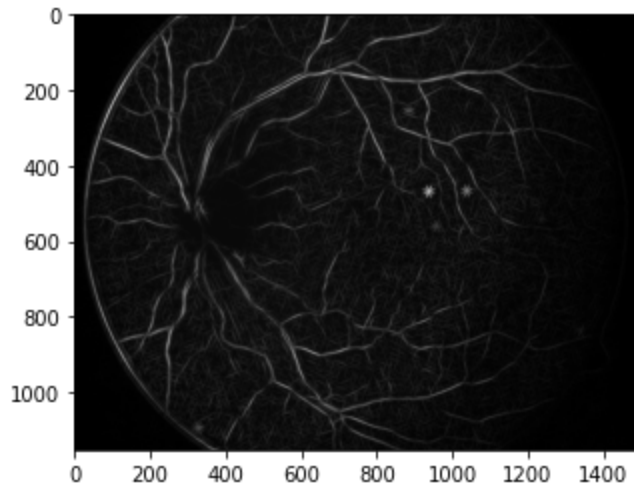


Discrete Wavelet Transform

7. Now we will apply Gabor Kernel filters by finding a suitable filter for it.
This is applied to enhance blood vessels and retinal pores in the image.

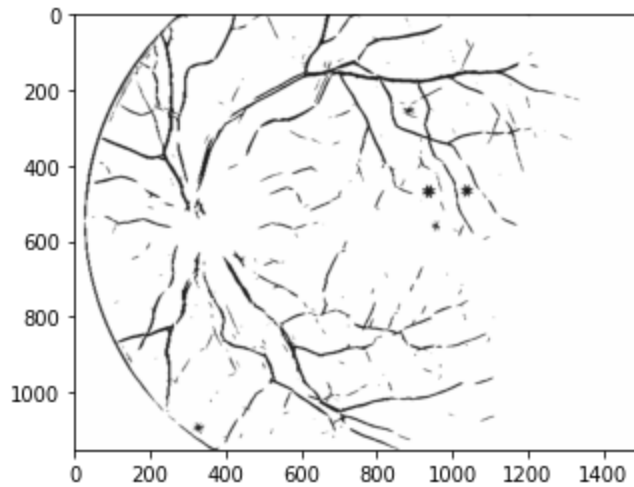
$$\varphi(t) = \exp(-\alpha^2 t^2) \exp(j2\pi f_0 t)$$

$$\Phi(f) = \sqrt{\frac{\pi}{\alpha^2}} \exp\left(-\frac{\pi^2}{\alpha^2 (f - f_0)^2}\right)$$



Applying some necessary filters (Gabor Kernel)

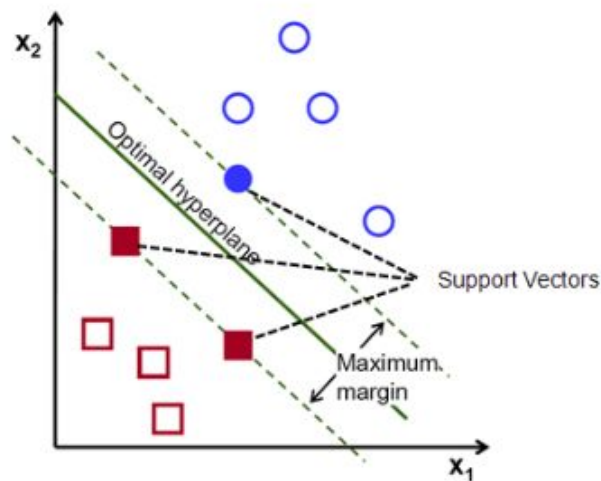
8. We will then apply the K-means clustering algorithm on all the data.



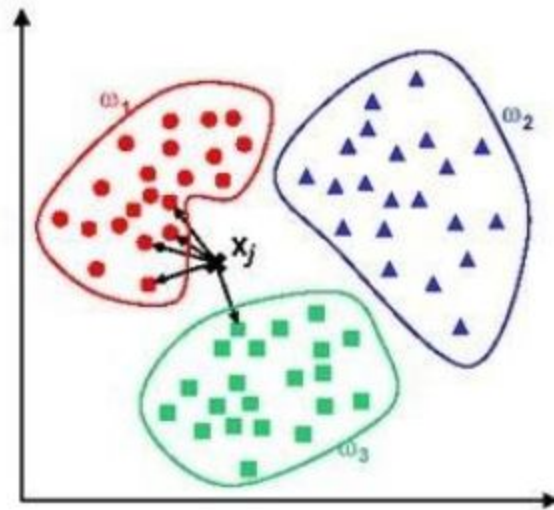
After K- means Clustering

9. After the data is pre processed, then the data is ready to be fit and predicted by the different classifiers. In our project we have used SVM and KNN to predict the results.

10. **Support Vector Machine:** Support vector machine training process is applied to analyze training data to find an optimal way to classify images into their respective classes namely Normal and Diseased. Classification parameters are calculated using support vector machine learning. The training process analyzes training data to find an optimal way to classify images into their respective classes. The training data should be sufficient to be statistically significant. The support vector machine learning algorithm is applied to produce the classification parameters according to calculated features. The derived classification parameters are used to classify the images.



11. **K-NEAREST NEIGHBORS :** KNN is a case-based learning method, which keeps all the training data for classification. There are many existing algorithms such as decision trees or neural networks initially designed to build such a model. One of the evaluation standards for different algorithms is their performance. As KNN is a simple but effective method for classification and it is convincing as one of the most effective methods, it motivates us to build a model for KNN to improve its efficiency whilst preserving its classification accuracy as well.



12. We will first fit the model and then predict the results for each of the above classifiers.

13. Here we will visualize the results of classification as follows:

- a. Accuracy score
- b. Classification Report
- c. Confusion Matrix

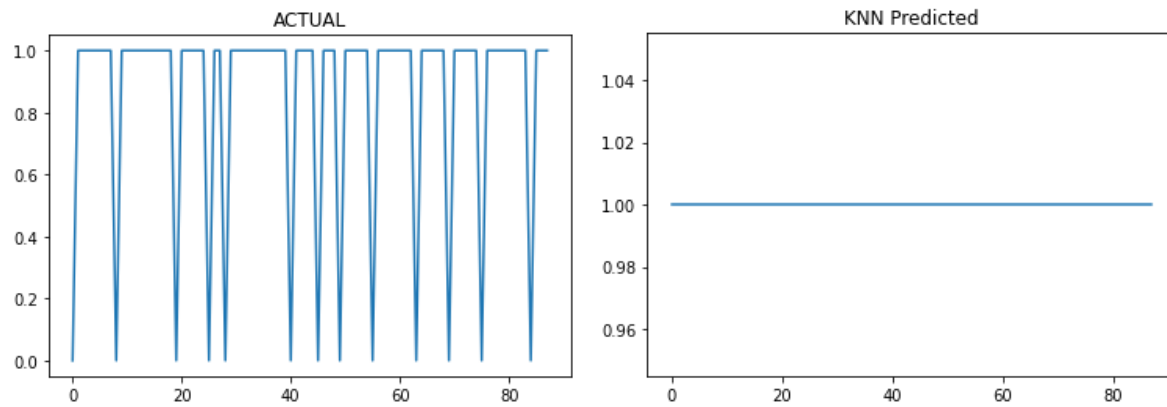
14. Now we will be describing our arrays and parameters used in code :

- a. **imm_kmean** : Numpy array ,which is conversion of all images in the dataset.
- b. **Y**: Array for Results (1 : Diabetic, 0: Non-Diabetic)
- c. **Imm_train** : Numpy Array, Containing Training Dataset
- d. **y_train** : Array Containing results of Training Dataset.

15. We will fit our model using `imm_train` and `y_train` , and then test the model using `imm_kmean` and `Y`.

9. Results

KNN:



➤ Confusion Matrix :

```
[[ 0 13]
```

```
[ 0 75]]
```

- TP - True Negative 0
- FP - False Positive 13
- FN - False Negative 0
- TP - True Positive 75

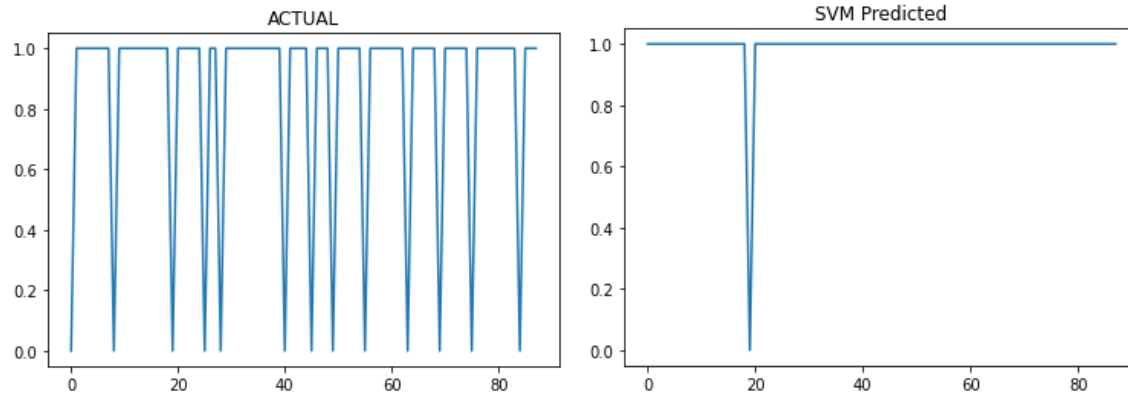
➤ Accuracy Rate: 0.8522727272727273

➤ Misclassification Rate: 0.14772727272727273

➤ Classification Report:

	precision	recall	f1-score	support
0.0	1.000000	0.076923	0.142857	13
1.0	0.862069	1.000000	0.925926	75
accuracy			0.852272	88
macro avg	0.931034	0.538462	0.534392	88
weighted avg	0.882445	0.863636	0.810245	88

SVM:



➤ Confusion Matrix :

```
[[ 1 12]
```

```
[ 0 75]]
```

- TP - True Negative 1
- FP - False Positive 12
- FN - False Negative 0
- TP - True Positive 75
- Accuracy Rate: 0.8636363636363636
- Misclassification Rate: 0.13636363636363635

➤ Classification Report :

	precision	recall	f1-score	support
0.0	1.000000	0.076923	0.142857	12
1.0	0.862069	1.000000	0.925926	75
accuracy			0.863636	88
macro avg	0.931034	0.538462	0.534392	88
weighted avg	0.882445	0.863636	0.810245	88

9. Conclusion

- Diabetic Retinopathy is detected by analyzing coloured eye images.
- The input retinal images are of poor quality. So they were preprocessed using Grayscale conversion, Adaptive Histogram Equalization, Discrete Wavelet Transform, Gabor kernel and k-means clustering.
- As an achievement of this work, we are able to detect if a person has Diabetic Retinopathy or not.
- Both the techniques used for classification were good in performance, but SVM is more efficient than KNN.
- Thus this work has given a successful Diabetic Retinopathy Diagnosing method which helps to diagnose the disease in early stages which mutually reduces the manual work.

10. References

- [1]. Harry Pratt , Frans Coenen , Deborah M Broadbent , Simon P Harding , Yalin Zheng, “Convolutional neural networks for Diabetic Retinopathy”, International Conference on Medical Imaging Understanding and Analysis 2016, MIUA 201616
[Convolutional neural networks for Diabetic Retinopathy](#)
- [2]. Yiyue Lou, Department of Biostatistics, College of Public Health, University of Iowa, Iowa City, Iowa, United States Ali Erginay, Service d' Ophtalmologie, Hôpital Lariboisière, APHP, Paris, France Warren Clarida, IDx LLC, Iowa City, Iowa, United States,
[Improved Automated Detection of Diabetic Retinopathy on a Publicly Available Dataset Through Integration of Deep Learning](#)
- [3]. Manaswini Jena , Samita Prava Mishra , Debahuti Mishra , “Detection of Diabetic Retinopathy Images using A Fully Convolutional Neural Network”, 2nd International Conference on Data Science and Business Analytics.
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