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# Automatic Detection of Diabetic Retinopathy using Retinal Fundus Images Implementing Machine Learning Algorithms

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**Abstract**

Diabetic retinopathy is one of the leading causes of loss of vision that has affected approximately 93 million people. An analysis considering 35 studies, all across the world, estimated that the global figure of DR among diabetes patients is in the range of 7.62%–47.1%. If Diabetic retinopathy is not identified in an initial stage, it can cause serious vision problems such as vitreous hemorrhage, retinal detachment, glaucoma, and even permanent total blindness. Currently, it is detected by trained ophthalmologists and examining and evaluating the fundus photographs require a lot of time. This leads to delayed follow-ups and hence delayed treatment. Since we are aware that the population increases every day and so does the number of diabetic patients, the current infrastructure and manual method are insufficient. Thus there is a requirement for automatic and effective diabetic retinopathy detection. There have been previous attempts made at this and have even provided good progress with the classification and pattern recognition in the image and machine learning, we still require a method that can have potential as close as to the realistic clinical examination method. So in this paper, we have proposed a prompt method to detect diabetic retinopathy using retinal fundus images. Our model makes the prediction whether a person has diabetic retinopathy using Support Vector Machine with radial basis function (SVM-rbf) and also with the help of K-Nearest Neighbors (KNN) which are machine learning algorithms and we received an accuracy of about 96.62% and 94.38% using SVM-rbf and KNN respectively.

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## 1. Introduction

Diabetic Retinopathy is a classified as a medical condition that damages the retina of the eye due to complications of diabetes mellitus. About 80% of the people that get affected by Diabetic Retinopathy are the ones who have had diabetes for over 20 years. A person suffering from diabetes has high blood sugar which damages the blood vessels in our body.

As seen in first stage, called the non-proliferative diabetic retinopathy, there aren't any specific symptoms. In this stage microaneurysms (microscopic blood-filled bulges in the artery walls) are formed in the retina. This happens because the blood vessels in the retina are fragile and they get blocked by the sugar. In the second stage, neovascularization (formation of abnormal new blood vessels) occurs as part of proliferative diabetic retinopathy. These

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vessels are fragile and they don't function well. They become leaky, burst and bleed causing vitreous hemorrhage. This causes blurry vision and leaves specks of blood and spot on the retina. Regular bleeding forms scars and may differentiate the retina and eye leading to a separated retina. In later stages, about 50% or more people suffering from diabetic retinopathy get diabetic macular edema ( DME) in which the blood vessels leaking fluid in the retina cause swelling in the macula. It even leads to Neovascular Glaucoma (NVG) in which abnormal blood vessels develop on the retina and prevent the fluid from coming out of the eye. In extreme cases, Diabetic Retinopathy can also lead to complete vision loss.

About 12 % of new cases of blindness are caused by Diabetic Retinopathy and it is also a major cause for blindness for people in the age group of 20-64. Anyone suffering from any type of diabetes for a longer duration can get diabetic retinopathy. Hence it is essential for diabetes patients to get an eye examination done on a regular basis. Currently detecting diabetic retinopathy manually is a gradual process that requires a trained clinician or ophthalmologist to examine and evaluate the digital colored fundus images of the retina. If the results are delayed, it might lead to lost follow up, miscommunication and hence late treatment. In rural areas, there are no eye specialists available.

There is a need for an automated detection method that gives accurate results. Therefore we have developed a model that can detect diabetic retinopathy using retinal fundus images as input with the help of image processing algorithms. For our machine learning model, we have used a publicly available dataset consisting of fundus photographs from Kaggle. In the model, we have worked with 90 images out of which 5 are infected with Diabetic Retinopathy and rest 85 are used to test our model. We converted the images to greyscale using adaptive histogram equalization and then created a 2D array of images on which we performed Discrete-Wavelet transformation. We then used Gaussian filtering and K-Means clustering on the image. For training our Machine Learning model we used Support Vector Machine with radial basis function (SVM-rbf) and K-Nearest Neighbors (KNN) algorithms that gave an accuracy of 96.62% and 94.38%.

## 2. Literature Survey

The work presented in [1] focuses on automatic detection of Diabetic Retinopathy. Algorithm's like Support Vector Machine (SVM), Logistic Regression, K- Nearest Neighbor and Decision Trees have been used to reach the goal. The paper concludes that SVM performed way better than the other algorithms which are considered. Paper [2] provides and elaborate methodology that first involves comparison of the green channel image and the greyscale image of the original colored images of retina. The greyscale image then goes through fuzzy filtering and fuzzy histogram equalization which is supposed to make the image contrast better. Further on Circular Hough Transform (CHT) is applied to locate optic disk. Top hat transformation leads to the macula detection. In the next stage Thresholding and Fuzzy C means (FCM) procedures are used to examine the presence of exudates. In the end four different classification methods namely, k-nearest neighbors (KNN), Polynomial Kernel SVM, SVM RBF and Naive Bayes are implemented and their results are compared. The work presented here [3] introduces a new way to identify fovea and macula from the images provided. The localization of macula is done by identifying the blood vessels and then a region is selected where the macula is present and after that fovea is spotted in the region by performing segmentation. They first converted the images into black and white and then used CLAHE and later applied discrete wavelet transform (DWT). This method could not identify the dark spot in some of the image because of the presence of uncharacteristic features surrounding the macula.In paper [4] the features of the fundus images are extracted using the Machine Learning Bagging Ensemble Classifier (ML-BEC). In the first step features like blood vessels, optic disc, neural tissue are extracted from the fundus image using t-Distributed Stochastic Neighbor Embedding(t-SNE). Then the ensemble classifier is used to analyze the fundus image and the predictionsare made.25% of the fundus images are used to train the model.. The author has used Hue saturation value (HSV) space to modify the luminosity of the retinal images in [5].Multi-channel histogram analysis, Morphological Top-hat transform and CLAHE (Contrast Limited Adaptive Histogram Equalization) algorithms were also used in this model to detect exudates. The drawback that could be inferred from this paper was that about 28% of the images were not classified by this modelIn paper [6] the automatic detection of Diabetic retinopathy is achieved using the Naïve Bayes classifier. The training set contains the information about the deformity and disease in the retinal images. The classifier gathers information from the training set and makes the prediction. A dataset of 102 images are used. The AUC (Area Under Receiver Operating Characteristic curve) used in this paper resulted in an accuracy of 98.3%.In this paper [7] they have presented the use of different text features of diabetic retinopathy, i.e. Local Ternary Pattern (LTP) and Local Energy-based Shape Histogram (LESH). Support Vector Machines (SVM) are used for segregation. They performed the experiments on MESSIDORdataset that was publicly available. In accordance with the result we can interpret that LESH using SVMrbf is more accurate. The proposed system [8] introduces a way to automatically segregate the images into defected and normal by recognizing the presence of exudates in it. Several other features are also taken into consideration for identification.

Morphological operations and top hat transformation techniques are used. After the above processing is done the images are given to the SVM classifier which in result will segregate the images automatically. The proposed method [9] introduces a three stage method for the detection of microaneurysms. They performed initial processing on the images and performed segmentation of blood vessels. Decision tree is used to categorize the images. This method helps in early stage identification of retinopathy. Image processing was used [10] for the detection of microaneurysms from color fundus images. The color fundus image was uploaded on the web page. This image was converted to grey scale and resized during pre-processing. To detect the edges of the image canny edge detection was used. Morphological operations mainly include opening and closing operations. The image which was detected by blob was overlapped on the original image to get the output. The fuzzy c means method is used in [11]. In order to segregate into dark and bright lesion, here they use SVM and naïve bayes to segregate them. Once all the processing and detection of features is done they are passed on to the classifier. This approach for large data sets needs a standardized classifier for better results. Discrete wavelet transform was used [12] to detect the presence of exudates from color retina image. Identification of human retina as normal or diabetic was implemented using feature extraction method. Preprocessing involved grey scale conversion of image, noise removal and image enhancement. To detect the blood vessels in the retina image wavelet transform and mathematical morphology were used. Area thresholding was used to remove optic disks from exudates which were detected by using morphological closing operator. By this exudates were clearly visible in the segmented retina image. In paper [13] the retinal images are first preprocessed that involves transformation to grayscale and then sharpened using 2-D filter. CLAHE is used and then blood vessels are identified by improving image contrast. Otsu’s thresholding is then performed on the obtained image. The presence of exudates is ensured by performing Image Subtraction. Paper [14] distinguishes between different stages of Diabetic Retinopathy ranging from healthy to severe. Image is converted to CMY and then binarized to find the presence of prominent features that denote DR. Support Vector Machine (SVM) is then implemented on the dataset and a confusion matrix is constructed to calculate the accuracy of the model. Paper [15] first converts RGB image to HSI. The fundus images are then divided using k-Means Clustering. The author has then implemented Gray Level Co-occurrence Matrix (GLCM) to identify the features that will distinguish a non-diabetic retinopathy affected retina from an affected one. A classification model is then built using Support Vector Machine (SVM).

Since we know the probability of a diabetic person to develop diabetic retinopathy is quite high and this medical condition can lead to dangerous sequences such as complete blindness, regular monitoring and examination of the retina is required. Due to the lack of availability of experienced doctors in rural areas and villages, these regular examinations and correct diagnosis of the condition go unfulfilled. Apart from this, even when ophthalmologists detect diabetic retinopathy by examining the fundus photographs, the manual diagnosis takes time. Waiting for reports and follow ups are delayed. Moreover manual techniques have a risk of being erroneous or non-accurate. Thus to overcome these drawbacks of the current situation, we've tried to provide a more accurate and time-saving solution by using machine learning. We propose an automatic detection of Diabetic retinopathy using retinal fundus image that processes the images and gives the result if the retina is affected or not.

## 3. Methodology

The proposed method of automatic detection of diabetic retinopathy uses several techniques to classify between healthy eye and infected eye. At first we perform pre-processing of the images to remove the noises and then enhance its features in order to use Machine Learning algorithms on them and predict the possibility of diabetic retinopathy. Here for pre-processing we are performing the following techniques which is shown in figure.1.

## 4. Materials

The database used is a publicly available Kaggle dataset. We used a small part of the dataset consisting of 90 colored fundus images. These images are taken by a fundus camera that is a specialized camera containing an intricate microscope attached to flash to carry out fundus photography. Out of those 90 images there are 5 images that show signs of diabetic retinopathy which is used for training. Rest 85 are used for testing the model. The images are of resolution 1500x1000 pixels in jpeg format.

## 5. Preprocessing Of Images

Preprocessing is a method to improve the visual look of the image, stabilize it and enhance the image data in order to make if efficient for the computation process. For detecting features in fundus images that result in diabetic retinopathy, the images have to undergo pre-processing. This stage ensures that the image is free from impurities and uneven illumination so that proper features extraction can take place.

The techniques for pre-processing used in this model include Grayscale conversion, Adaptive Histogram Equalization (AHE), Discrete Wavelet Transform (DWT), Gabo retr Kernel and K-Means Clustering for segmentation of blood vessels as presented in figure.1 As an input, a set of 90 fundus images is fed into each algorithm.

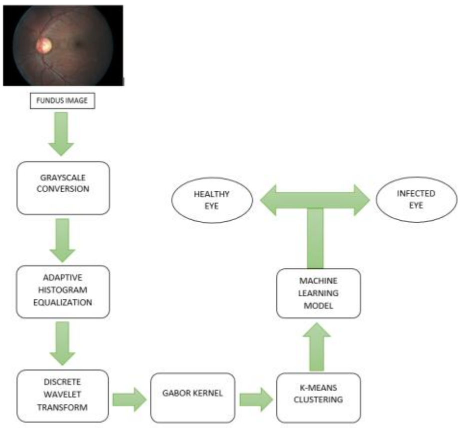
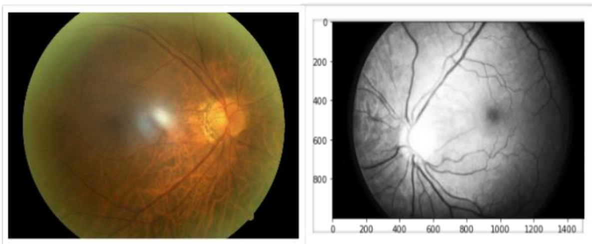



Figure 1: flowchart for Diabetic retinopathy detection

### Grayscale Conversion

In order to detect diabetic retinopathy in a given fundus image, specific features have to be signalized in the fundus image. The images of resolution 1500 x 1000 from the dataset is fed into the algorithm for conversion of colored images into greyscale images. For this proposed method we use opencv function.



(a) (b)

Figure 2: (a) Sample input image (b) Grayscale converted fundus image

### Adaptive Histogram Equalization (AHE)

Adaptive histogram equalization plays an important role to in pre-processing of images where this image-processing algorithm helps to enhance the contrast in images for the visibility of details in the images. Grayscale converted fundus images are given as input to the algorithm which uses OpenCV function to apply Adaptive Histogram Equalization. It divides the images into small parts or segments, deciding the maximum intensity to which it will increase, using the occurrence of grey-level parts or segments in the image, further calculating the probability mass function in order to redistributes the lightness values of the images and finally stitches up these small blocks into a full image. So after the application of Adaptive histogram equalization algorithm, the dark region of image becomes brighter and the brighter region remains the same or its brightness is reduced in order to make the whole image is uniformly contrasted. Further stored in 1-D array

### Discrete Wavelet Transform (DWT)

Images has smooth or continuous regions as well as noise, hasty changes and interrupted by edges. As the next step of preprocessing discrete wavelet transform is helpful in eliminating noise to an extent, abrupt changes from the image. In order to apply discrete wavelet transform approximation and detail coefficients are calculated using multilevel wavelet decomposition. It revolves around low pass sub band and high pass sub band. These sub bands that differentiates a signal in such a way that it constitutes a set of basic functions and these basis functions are termed as wavelets. Applying dilations and shifting to a single prototype wavelet called mother wavelet ψ (t), Wavelets are obtained,

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}}\psi\left(\frac{t-b}{a}\right) \quad (1)$$

Where a is the scaling parameter and b is the shifting parameter .The basis function is generated by mother wavelets based on some characteristics related with the function [cA, cH, cV, cD] = dwt2(X,'wname')] where X is taken as input that is fundus image and wname as wavelet returning coefficient matrix of cA and cH, cV, cD (horizontal, vertical, diagonal).In this paper wname is haar wavelet. Above discussed algorithm is applied on fundus image referring to equation (1) which results in figure.3

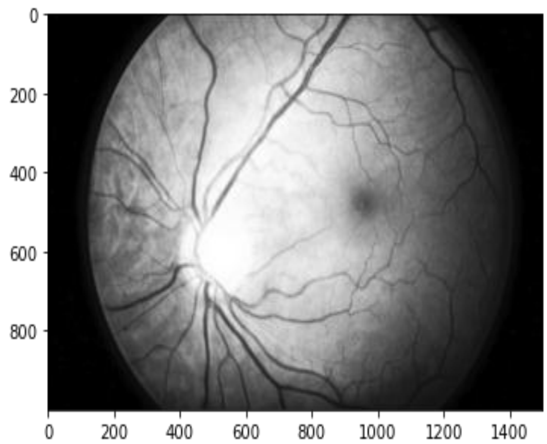



Figure 3: Fundus image results after applying discrete wavelet transform (DWT) with 2D axis represented by pixel values of the image

### Gaussian filter

As we are done with removing all the abrupt edges and noises from images, Gaussian filter is used to highlight the edges of regions. For extraction of retinal vessels first we are supposed to apply First Matched filter with derivative of Gaussian filter on the images

$$k(x,y) = \frac{1}{\sqrt{2\pi\sigma}}\exp\left(\frac{x^2}{2\sigma^2}\right) - \mu \quad (2)$$

Where $\mu$ and $\sigma$ are the scale and mean of matched filter kernel k

$$\mu = \frac{1}{2t\sigma}\left(\int_{-t\sigma}^{t\sigma} \frac{1}{\sqrt{2\pi\sigma}} \exp\left(\frac{-x^2}{2\sigma^2}\right) dx\right) \qquad (3)$$

Using equation (2) and (3), smooth background is removed from the images. Spatial co-ordinates are denoted by (x, y) of the filter which depends on parameter t which is used to maintain the confidence interval of the Gaussian distribution along the x-axis and parameter l is the length of kernel along y axis. By normalizing each pixel in the image according to the filter response Threshold value is computed .It can be observed that the vessel pixel has a lower threshold value and non-retinal pixel has a higher pixel value which can be observed in figure.4 with x-axis, y-axis as pixel values of the image

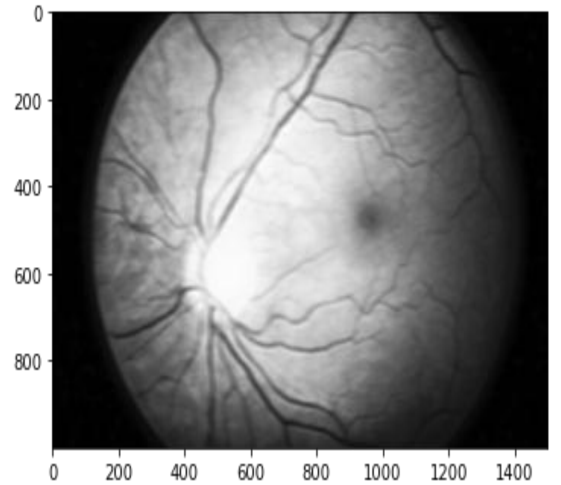



Figure 4: Fundus image result after applying Matched filter with first-order derivative of Gaussian (mf-fdog)

**Gabor kernel**

For detection of retinal vessels after the edges have been highlighted, Gabor filters fits the best. Gabor filters are used for texture analysis, edge detection, feature extraction and many more which are orientation sensitive filters.

$$g(x, y; \lambda, \theta, \psi, \sigma, \gamma) = \exp\left(-\frac{x'^2 + \gamma^2 y'^2}{2\sigma^2}\right) \exp\left(i\left(2\pi \frac{x'}{\lambda} + \psi\right)\right) \qquad (4)$$

According to equation (4) It's a function of various parameter's where (x, y) decides the kernel size, $\sigma$ (sigma) denotes standard deviation, where $\theta$ gives choice of angle to your filter, $\lambda$ (lambda) denotes the wavelength, $\gamma$ says about aspect ratio, $\psi$ (phi) denotes phase offset. So as results of applying Gabor filter to images we get figure.6

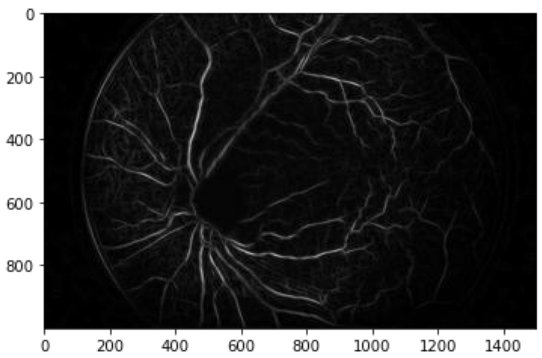



Figure: 5: Fundus image results after applying Gabor filter with 2D axis represented by pixel values of the image

**K-Means Clustering**

This is a machine learning algorithm which aims to segregate n observations into k clusters by assigning every data point to its nearest clusters where cluster is a group of data with similarity Here it is used to create segments in the input fundus image and also to detect blood vessels which can be used to grade theinput fundus images as infected or healthy retina as shown in figure.7.with pixel values aligned on 2D axis

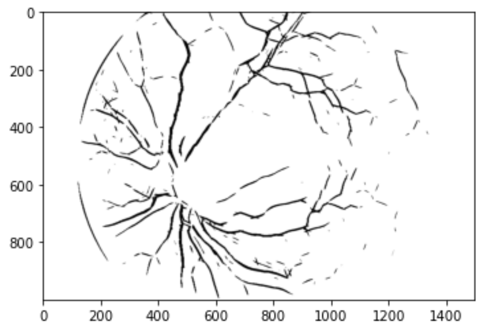



Figure.6: Fundus image results after applying k-means clustering

After the preprocessing is done, the pre-processed images are passed on to the machine learning algorithms to check the accuracy and distinguish between healthy and infected retinas.

Our method is using 2 Machine learning algorithms, those being Support vector machine with radial basis function (SVM-rbf) and K –nearest neighbor

**Support vector machine with radial basis function (SVM-rbf)**

A Support vector machine model is a supervised machine learning model which uses a method called kernel trick to segregate the data and finds a feasible boundary between the possible outputs. But in contrast, when there is no satisfactory support vector classifier to separate the data which is overlapped based on classification parameters, then we can apply Support vector machine with radial basis function

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because it provides infinite dimensions$e^{-\gamma(a-b)^2}$, Here a,b suggest the number of possible data output to be classified into. The difference between them gives us the amount of influence one has on another is a function of squared distance, $\gamma$ is used to calculate the amount of influence 2 observation has on each other. Support vector machine with radial basis function which is a machine learning algorithm is used during training process where the model finds out an efficient method to classify images into their respective classes as normal and infected eye. For classifying the training dataset into classes, SVM-rbf decides the classification parameters. We provide 90 fundus images as input to model. The training process analyses the training set and SVM-rbf is practiced to produce classification parameters with respect to features that have been calculated. The determined classification parameters are used to assort the data.

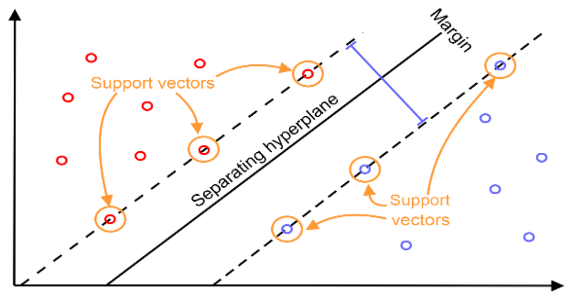


Figure7: A training dataset with 2 classes (red circle and blue circle) distributed in dataspace and the hyperplane separating two classes

As referred to figure.7the image content is classified into categories based on the parameters designed by support vector classifier with radial basis function.

### K-Nearest Neighbors

KNN or K-Nearest Neighbors, is a supervised machine learning algorithm, in which we feed the algorithm with previously classified data, where the algorithm label's the new data points referring to its nearest neighbors that is k. Focusing on how the algorithm works is, it uses Euclidean distance formula to calculate the distance between any two data point. The number of nearest neighbors it has to consider for calculating the category of new data point is decided by k.

The algorithm can work better if we can find some representatives to represent the whole training data for classification, viz. constructing an inductive learning model from the training dataset and then using this model for classification. KNN is a simple machine learning algorithm and is efficient when it comes to classification. Hence KNN was chosen as it has good accuracy as well as efficiency. Figure.6.depicts how it works where $X_1, X_2$the classification parameters.

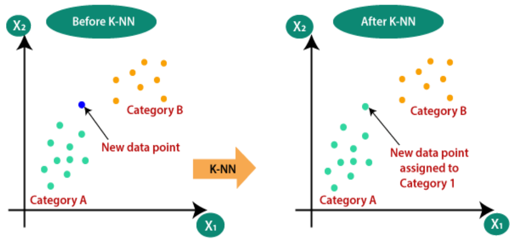


Figure 8: Application of k-nearest neighbor on dataset

## 6. Results and Discussion

In this paper, we have detected Diabetic retinopathy using colored fundus images. The images are first converted to grayscale using Grayscale transformations and then Adaptive Histogram Equalization (AHE), discrete wavelet transform using Haar wavelet, Gabor kernel and K means clustering is applied. In order to make a prediction whether the input fundus image shows symptoms of Diabetic retinopathy we have used two methods namely, Support Vector Machine with Radial Basis Function (SVM RBF) and K-Nearest Neighbors (KNN). We have used an open-source dataset available at Kaggle consisting of retinal fundus images. We have used a small portion of this dataset consisting of 90 images in order to train and henceforth test our model. Out of 90 images, 5 images were infected with diabetic retinopathy and the rest 85 images are used to test our model. We have evaluated our model on the basis of accuracy. To calculate their values we used the following equations:

$$Accuracy = \frac{TN+TP}{TN+FP+TP+FN} \qquad (8)$$

According to equation (8)

TP= True positive TN= True negative
FP= False Positive FN= False Negative

Table 1: Comparison of accuracy with different methods

| paper | method | Accuracy (in %) |
|---|---|---|
| S M Asiful Huda [1] | SVM | 88 |
| A.S. Akshaya [8] | SVM | 83.83 |
| GS Annie Grace[15] | SVM | 96 |
| Rahim [2] | Polynomial kernel SVM:<br>RBF kernel SVM: | 70<br>93 |
| Proposed method | SVM-rbf:<br>KNN: | 96.62<br>94.38 |

From our results, we can conclude that SVM RBF is more efficient than KNN. The SVM RBF provided an accuracy of 96.62 % whereas the KNN method is 94.38 % accurate. Hence through this paper, we are able to build a model for automatic and efficient detection of Diabetic Retinopathy which reduces the manual work and therefore reduces the time consumed.

## 7. Conclusion

Detection of Diabetic retinopathy is achieved using colored fundus images. The images are transformed into black and white images using Grayscale transformations and then applied with Adaptive Histogram Equalization (AHE), Haar transformation, Gabor kernel and K means clustering. For predicting whether a particular fundus image is showing symptoms of Diabetic Retinopathy we have used two methods SVM and KNN. But as it turned out from our results that SVM is more efficient that KNN. The SVM showed 96.62 % accuracy and the KNN method resulted with 94.38 % accuracy. So the work of detection of diabetic retinopathy is achieved using fundus images which at last reduces manual work and time.

## 8. Future Scope

The proposed method for the automatic detection of diabetic retinopathy classifies the input into healthy and infected eyes  In future scope, grading can be applied that is we can classify these input images into mild, moderate and severe conditions of diabetic retinopathy and also provide a diagnosis and precaution for the conditions. We can try differentiating between the hard and the soft exudates for better results and also glaucoma conditions can be detected. For more convenient use of our proposed method, web pages and applications can be implemented

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