RESEARCH ARTICLE OPEN ACCESS

Extraction of Non Proliferative Diabetic retinopathy using new designed wavelet and classification using KNN classifier

Deepali D. Rathod[1], Ramesh R. Manza [2], Yogesh M. Rajput[3], Manoj Saswade[4], Neha Deshpande[5]
[1]*Dept of CS and IT, Dr. B. A. M. University, Aurangabad MS (India)*
[2]*Dept of CS and IT, Dr. B. A. M. University, Aurangabad MS (India)*
[3]*Dept of CS and IT, Dr. B A. M. University, Aurangabad MS (India)*
[4]*Director, Saswade Eye Clinic, Aurangabad MS (India)*
[5]*Director, Guruprasad Netra Rugnalaya pvt. ltd, Aurangabad MS (India)*

ABSTRACT:
Diabetic retinopathy is very serious condition in which increased blood sugar level causes swelling in the blood vessels and it may leak in to the retina. It is the effect of diabetes on the eye. There are four stages of diabetic retinopathy that are Mild non-proliferative diabetic retinopathy, Moderate non-proliferative diabetic retinopathy, severe non-proliferative diabetic retinopathy, Proliferative diabetic retinopathy. In this paper we have done the extraction of non-proliferative diabetic retinopathy. We have extracted microaneurysms and exudates using new designed wavelet (DR), and classification is done using KNN classifier. KNN classifier classifies in to four classes that are mild, moderate, severe, and healthy. For this work we have used three publically available fundus image databases that are DIARETDB0, DIARETDB1 and STARE databases having 130, 89, and 397 fundus images respectively. Using this technique we have got 99.03% accuracy for detection of NPDR.

Date of Submission: 05-12-2017 Date of acceptance: 14-12-2017

I. INTRODUCTION

Diabetic retinopathy is one type of condition in which increased blood sugar level causes swelling in the blood vessels, and it leak in retina. We can say that it is effect of diabetes on the eye [1]. Diabetic retinopathy, occurs when blood vessels in the retina change. Sometimes these vessels swell and leak fluid or even close off completely. In other cases, abnormal new blood vessels grow on the surface of the retina [2]. After 15 years of diabetes, approximately 2% of people become blind, and about 10% develop severe visual impairment [3].

Figure 1: [a] Normal vision [b] Vision due to Diabetic Retinopathy

There are four stages of diabetic retinopathy that are Mild non-proliferative retinopathy, Moderate non-proliferative retinopathy, Severe non-proliferative retinopathy, Proliferative retinopathy [1].

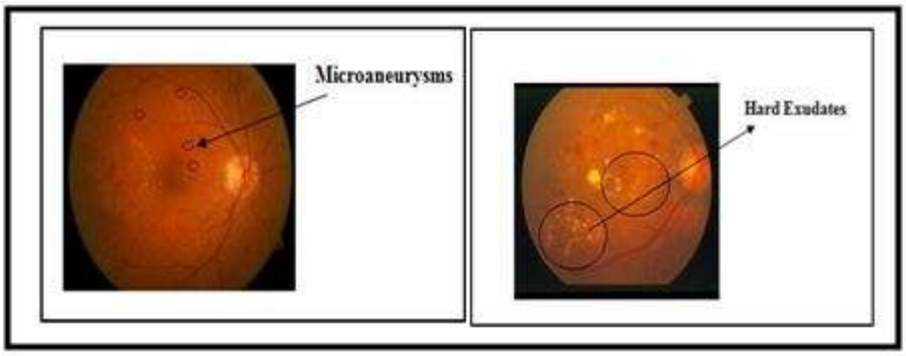


Figure 2: [a]Fundus Image with Microaneurysm [b] Fundus Image with Hard Exudates

a) Microaneurysms:
It is tiny swelling in the wall of blood vessels. Microaneurysm is occurring in the capillaries of retina. It is small round red spot [1]. It is the first clinically detectable sign of diabetic retinopathy.

b) Hard Exudates:
Hard exudates are distinct yellow-white intra-retinal deposits. Exudates are appears in small to large patches which may evolve into rings which is known as circinates (seen as a cluster of microaneurysms). Large confluent plaques can form Hard exudates are largely made up of extracellular lipid which has leaked from abnormal retinal capillaries. Hard exudates are found in the macular region and as the lipids coalesce and extend into the central macula (fovea), vision can be severely compromised [4].

II. RELATED WORK

M. Sridevi Mahe swari et al. proposes a novel method for the automated identification of exudates pathologies in retinopathy fundus images based on computational intelligence technique. Approach employs a unique sequential execution of morphological operators to extract fundus image features like vessels, red lesions, and white lesions together with texture feature analysis. Finally features selected are passed into the well-known support vector machine (SVM) classifier which classifies the images into normal and abnormal classes. They got the 93.5% accuracy [5].

Preethi N Patil1 and et al. presents an efficient method to grade the severity of DR in retinal images. Morphological operations are used to detect the pathologies associated with DR, namely, blood vessels, microaneurysms and hard exudates. SVM classifier is used to grade the retinal image under the categories of Non Proliferative DR (NPDR) namely, normal (no DR), mild NPDR, moderate NPDR and severe NPDR. The proposed method successfully classified the subjects into normal, mild NPDR, moderate NPDR and severe NPDR with an accuracy of 100%, 93.33%, 100% and 86.67% respectively. An average sensitivity of 96.08% and an average specificity of 97.92% are reported [6].

Swati Gupta and et al. have detected retinal micro-aneurysms and exudates for automatic screening of DR using classifier. To develop an automated DR screening system detection of dark lesions and bright lesions in digital funds photographs is needed. To detect retinal micro-aneurysms and exudates retinal funds images are taken from Messidor dataset. After pre-processing, morphological operations are performed to find the feature and then features are get extracted such as GLCM and Splat for classification. They achieve the sensitivity and specificity of 87% and 100% respectively with accuracy of 86% [7].

Saiprasad Ravishankar proposes a new constraint for optic disk detection. They first detect the major blood vessels and use the intersection of these to find the approximate location of the optic disk. This is further localized using color properties. They show that many of the features such as the blood vessels, exudates and microaneurysms and hemorrhages can be detected quite accurately using different morphological operations applied appropriately. Extensive evaluation of the algorithm on a database of 516 images with varied contrast, illumination and disease stages yields 97.1% success rate for optic disk localization, a sensitivity and specificity of 95.7% and 94.2% respectively for exudate detection and 95.1% and 90.5% for microaneurysm/hemorrhage detection [8].

III. METHODOLOGY

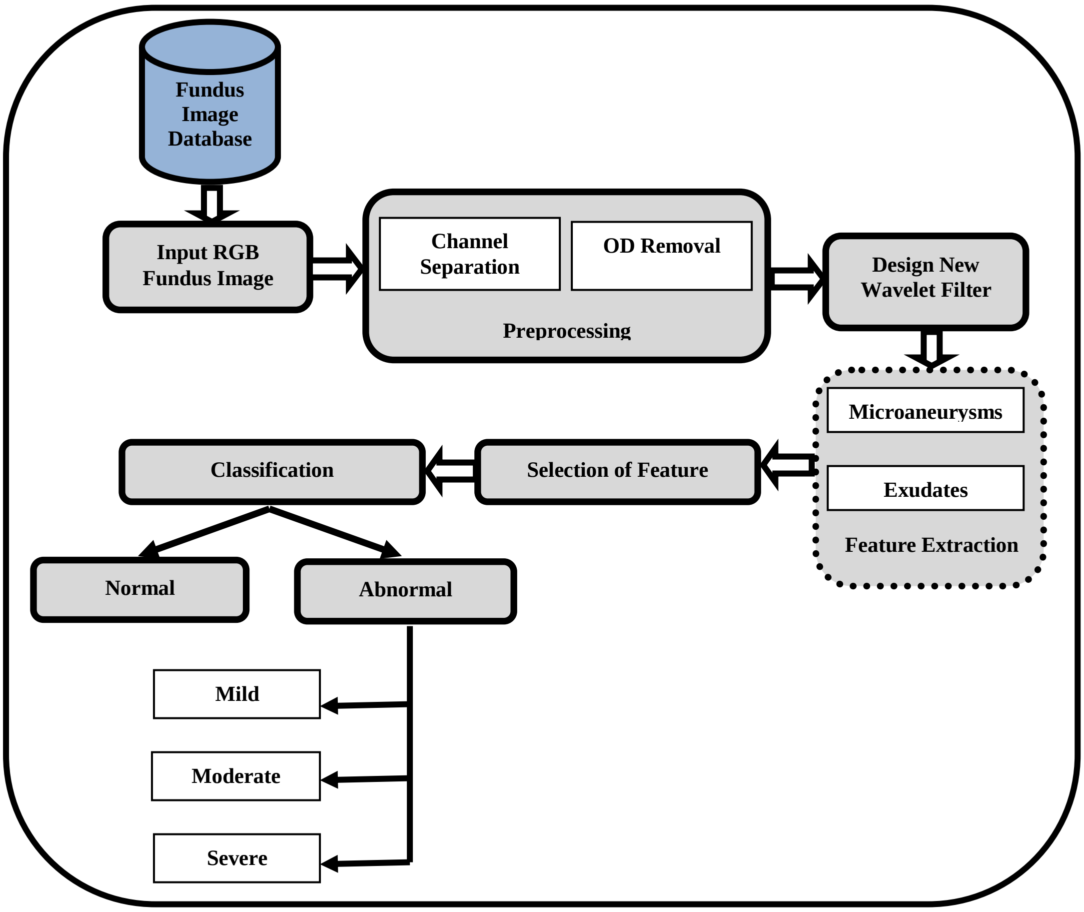


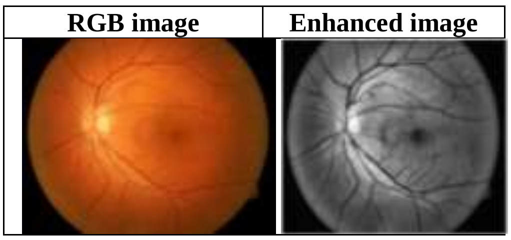
Figure 3: Flow of Extraction of Diabetic retinopathy using new designed wavelet

1) Database Collection:
For this research work we have used various databases like STARE, DIARETDB0 and DIARETDB1.

Table 1: Fundus Image Database

Sr. No	Name of Database	Image Dimension	Field of View (FOV)	Total Images
1	STARE	605 * 700	35	397
2	DIARETDB0	1150 * 1153	50	130
3	DIARETDB1	1150 * 1153	50	89
Total				**616**

2) Preprocessing:



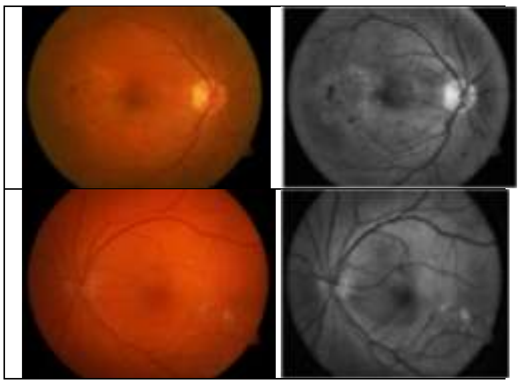


Figure 4: Enhanced Fundus Image

For detection of NPDR we have done the preprocessing of the RGB image. The dimension of all the databases is different therefore we have resized all the images first. Then green channel extraction is done. We are using green channel because intensity of green channel is more as compare to red and blue channel [12].

$$\mathrm{r} = \frac{\mathrm{R}}{(\mathrm{R}+\mathrm{G}+\mathrm{B})} \ldots\ldots\ldots\ldots\ldots\ldots.. \ (1)$$

After green channel extraction we have apply median filter for noise removal, the median filter replaces a pixel by the median, instead of the average, of all pixels in a neighborhood ω

$$y[m,n] = median\{x[i,j],(i,j)\epsilon\omega\} \ldots\ldots\ldots (2)$$

Where ω represents a neighborhood defined by the user, centered around location [m,n] in the image [13].

After that we have done the enhancement using Contrast limited adaptive histogram equalization (CLAHE).

$$g = [g_{max} - g_{min}\ ] * P(f) + g_{min} \ \ldots\ldots\ldots.(3)$$

Where g_{max} = Maximum pixel value

g_{min} = Minimum pixel value

g = computed pixel value

$P(f)$= CPD (Cumulative probability distribution)

By using this contrast limited adaptive histogram equalization function we have enhance the quality of image. The CLAHE algorithm partitions the images into contextual regions and applies the histogram equalization to each one. This evens out the distribution of used grey values and thus makes hidden features of the image more visible [14].

3) Optic Disc (OD) Removal:

Step1: Preprocessing.

Step 2: Morphological opening is done on the image. Using disk shaped morphological structuring element (SE) having radius of size 15.

Step 3: Thresholding is performed on the output image. We have considered the value for thresholding is 0.44 because this value gives the best result.

Step 4: Thresholded image is subtracted from Morphological opening image.

Step 5: OD removed [15].

RGB image	**OD Removal**

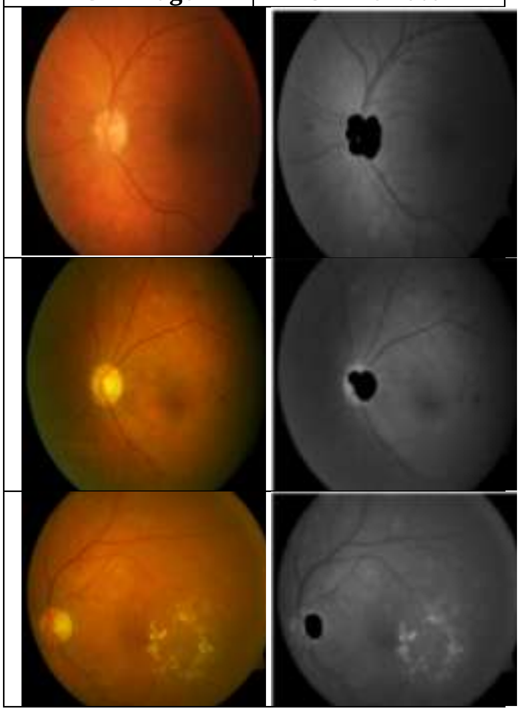


Figure 5: Optic Disc Removal Fundus Image

4) Designed New Wavelet:

We have design new wavelet filter (named as DR) for the extraction of NPDR lesion.

Step1: Create orthogonal wavelet of type 1

Step2: Create a filter

a=3;

sq =a*a;……(4)

DR = [(2+sq) (4+sq)(4-sq)(2-sq)]/16 ;…..(5)

Step3: Add the new wavelet family to the stack of wavelet families.

Step 4: Display the two pairs of scaling and wavelet functions

Step 5: We can now use this new orthogonal wavelet to analyze a signal or image

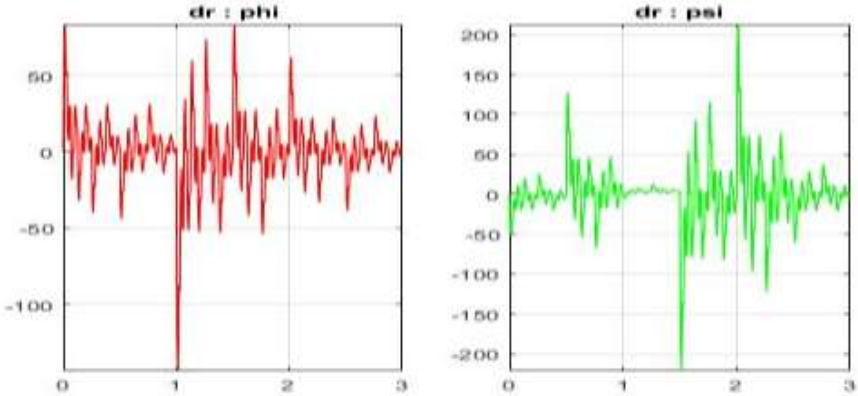


Figure 6: New Designed Wavelet (DR)

5) Lesion Detection:

For detection of NPDR we have extracted two lesions microaneurysms and exudates. The steps performed for the detection is given as follows:

a) Microaneurysms (MA) detection

Step 1: Input RGB Image
Step 2: Preprocessing
Step 3: Optic Disc (OD) removal
Step 4: Image intensity adjustment.
Step 5: Thresholding is applied.
Step 6: Morphological opening is done on the output image.
Step 7: Discrete wavelet transform using new designed wavelet DR
Step 8: Morphological operations are done.
Step 9: Extraction of MA.

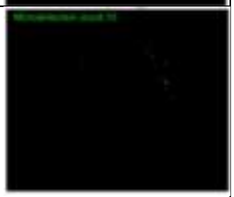
RGB Image	MA extraction
	
	
	

Figure 7: Extraction of Microaneurysms

b) Exudates detection:

Step 1: Input RGB Image
Step 2: Preprocessing
Step 3: Optic Disc (OD) removal
Step 4: Contrast Limited Adaptive Histogram equalization is done.
Step 5: Image intensity value is adjusted.
Step 6: Image thresholding is done.
Step 7: Morphological opening is performed on thresholded image.
Step 8: Output of morphological opening image is subtracted from thresholded image for extraction of Exudates.
Step 9: Discrete wavelet transform using new designed wavelet.
Step 10: Extraction of Exudates.

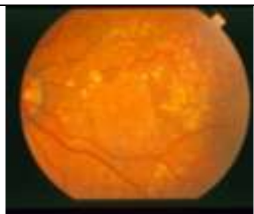
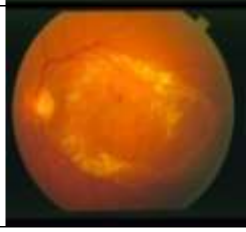
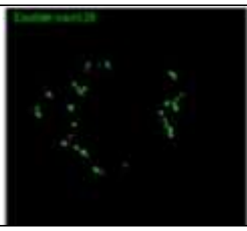
RGB Image	Extraction of Exudates
	
	
	

Figure 8: Extraction of Exudates

6) Feature Data:

a) Area and total count of MA: After extraction of Microanurysms the area of white pixels are calculated and total number of white pixels are calculated.

b) Area and total count of Exudates: After extraction of Exudates the area of white pixels are calculated and total number of white pixels are calculated.

Image	MA area(DR)	MA count(DR)	Exudate area(DR)	Exudate count(DR)
image001	11	11	6	1
image002	0	0	179	10
image003	0	0	72	2
image004	9	6	30	3
image005	4	4	9	1
image005	6	5	749	48
image006	22	7	118	8
image007	21	17	39	3
image008	15	13	224	11
image009	6	5	32	2
image010	1	1	33	2
im0001	70	41	40	2
im0002	5	4	538	29
im0003	96	44	949	66
im0004	5	5	92	7
im0005	26	21	673	44

7) Classification output:

After calculating the features of MA and Exudates we have applied KNN algorithm for the classification. KNN classifier directly predict using training dataset. Predictions are made for a new instance (x) by searching through the entire training set for the K most similar instances (the neighbors) and summarizing the output variable for those K instances. To determine which of the K instances in the training dataset are most similar to a new input a distance measure is used. For real-valued input variables, the most popular distance measure is Euclidean distance .Euclidean distance is calculated as the square root of the sum of the squared differences between a new point (x) and an existing point (xi) across all input attributes j [16].

$$(x, xi) = \text{sqrt}\big(\text{sum}(\,(xj - xij)^2)\big) \dots\dots..(6)$$

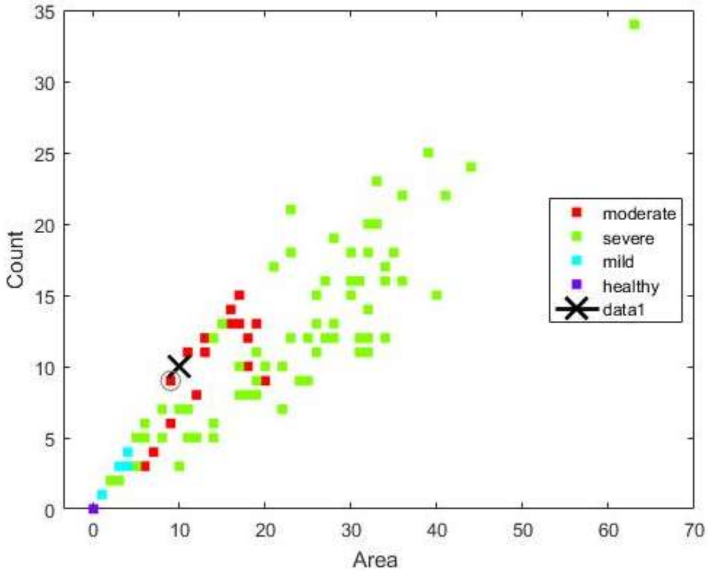


Figure 9: Scatter plot Output for KNN classifier

We have drawn the confusion matrix using result of KNN classifier and we got 99.03% accuracy.

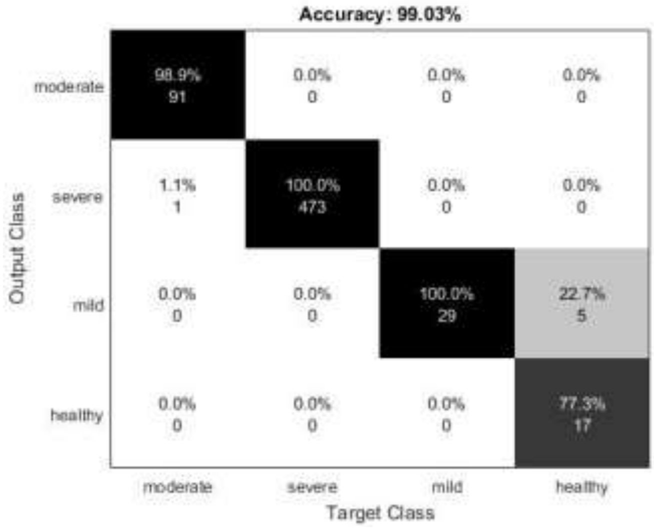


Figure 10: Confusion Matrix

IV. CONCLUSION:

In this paper we have done the extraction of NPDR using new designed wavelet (DR). Firstly we have done the preprocessing. On the preprocessed image we have applied new designed wavelet filter and extracted the lesion MA and Exudates. After lesion extraction feature selection is done we have calculated the area of MA and Exudates and also calculated the total number of MA and Exudates. And apply KNN classification for the grading of NPDR. For Accuracy of KNN classifier confusion matrix is drawn and we got 99.03 %.

ACKNOWLEDGEMENT

we are thankful to University Grant Commission (UGC) for providing us a financial support for the Major Research Project entitled “Development of Color Image Segmentation and Filtering Techniques for Early Detection of Diabetic Retinopathy” F. No.: 41 – 651/2012 (SR) also we are thankful to DST for providing us a financial support for the major research project entitled “Development of multi resolution analysis techniques for early detection of non-proliferative diabetic retinopathy without using angiography” F.No. SERB/F/2294/2013-14.

REFERENCES

[1]. (Diabetic Retinopathy) www.nei.nih.gov/health/diabetic/retinopathy.asp
[2]. Eye Smart eye health Information from the American Academy of Ophthalmology, The Eye MD Association.
[3]. WHO (According to World Health Organization) media center updated on March 13 http://www.who.int/mediacentre/factsheets/fs312/en/
[4]. (Hard Exudates) http://www.glycosmedia.com/education/diabetic-retinopathy/diabetic-retinopathy-features-of-diabetes-hard-exudates/
[5]. M. Sridevi Mahe swari , Adarsh Punnolil, “A Novel Approach for Retinal Lesion Detection In Diabetic Retinopathy Images”, International Journal of Innovative Research in Science, Engineering and Technology,Volume 3, Special Issue 3, March 2014
[6]. Preethi N Patil, G. G. Rajput, “Detection and Classification Of Non Proliferative Diabetic Retinopathy Stages Using Morphological Operations And Svm Classifier”,IJCET Volume 4, Issue 6, November - December (2013), pp. 01-08
[7]. Swati Gupta* and Karandikar AM, “Diagnosis of Diabetic Retinopathy using Machine Learning”, J Res Development, Volume 3 • Issue 2 • 1000127
[8]. Saiprasad Ravishankar, Arpit Jain, Anurag Mittal, “Automated Feature Extraction for Early Detection of Diabetic Retinopathy in Fundus Images”, 2009 IEEE
[9]. http://www.ces.clemson.edu/~ahoover/stare/
[10]. http://www2.it.lut.fi/project/imageret/diaretdb0/
[11]. http://www2.it.lut.fi/project/imageret/diaretdb1/

[12]. Yogesh M. Rajput, Ramesh R. Manza, Manjiri B. Patwari, Neha Deshpande, " Retinal Optic Disc Detection Using Speed Up Robust Features", National Conference on Computer & Management Science [CMS-13], April 25-26, 2013, Radhai Mahavidyalaya, Auarngabad-431003(MS India).
[13]. (Median filter)http://fourier.eng.hmc.edu/e161/lectures/smooth_sharpen/node2.html
[14]. Rajesh kumar Rai, Puran Gour, Balvant Singh " Underwater Image Segmentation using CLAHE Enhancement and Thresholding", International Journal of Emerging Technology and Advanced Engineering Website: www.ijetae.com (ISSN 2250-2459, Volume 2, Issue 1, and January 2012).
[15]. Amit Ashok Kamthane, "The Lesion Exudate Detection In Retinal Images", International Journal of Advanced Computational Engineering and Networking, ISSN: 2320-2106, Volume-3, Issue-9, Sept.-2015
[16]. (KNNclassifier)https://machinelearningmastery.com/k-nearest-neighbors-for-machine-learning/
[17]. (DR image) https://en.wikipedia.org/wiki/Diabetic_retinopathy

International Journal of Engineering Research and Applications (IJERA) is **UGC approved** Journal with Sl. No. 4525, Journal no. 47088. Indexed in Cross Ref, Index Copernicus (ICV 80.82), NASA, Ads, Researcher Id Thomson Reuters, DOAJ.

Deepali D. Rathod "Extraction of Non Proliferative Diabetic retinopathy using new designed wavelet and classification using KNN classifier." International Journal of Engineering Research and Applications (IJERA) , vol. 7, no. 12, 2017, pp. 06-13.