DCCN Based Grading of Diabetic Retinopathy

[1]G SURYA,[2]Dr.V.V.Satyanarayana Tallapragada,
[1]M.Tech Scholar, Communication Systems,[2]Associate Professor,
[1,2]Department of ECE,
[1,2]Sree Vidyanikethan Engineering College, Tirupati, India.

Abstract: Visual deficiency is a major disorder which is caused due to Diabetic retinopathy(DR). This is primarily considered as the main source among the young generation in the recent days. Statistically, it is observed that in a year such deficiency is resulting in loss of vision in 3 out of 4 people who are in the age of 25 to 74. According to the medical sciences, DR advances due to chronic hyperglycemia. DR results in the damage of the microvascular network that exists within the eye, ultimately leading to loss of vision. Microaneurysms (MA) are identified in the patients having DR. This paper proposed a novel framework that grades the level of the ailment in such patients suffering from DR. Initially, morphological techniques are applied for extraction of the MA. Further, these are classified using Deep Convolutional Neural Network (DCNN) are classified and verified with the ground truths. Results show promising results in contrast to the existing techniques. Still, the doctors require further analytic systems that can grade the severity of the ailment. Hence, in this paper it is proposed to apply GLCM over the classified images. The region of occupancy by MA and the area that is occupied by the blood vessels is calculated and graded for further usage. Results show better understanding and grading of the ailment.

IndexTerms **- Diabetic Retinotpathy, Microaneurysms, Deep Convolutional Neural Network (DCNN), Gray Level Cooccurence matrix (GLCM),ailment.**

I. INTRODUCTION

In the recent past most of the commonly occurring ailment is Diabetic retinopathy (DR) that primarily damages the retinal blood vessels ultimately leading to blindness. Symptoms such as spots which are dark red in color need to be identified which are called as Microaneurysms (MA)[1]. These are observed using a funduscope. Early detection and treatment may give a way for blindness to vision. With the advent of technology and computer vision development of automated detection mechanism of MA is developed. But, the techniques that are developed are not on par with that of the human classification. Detection of various sizes of retinal structures under various illumination conditions does not exist. fluoresce in angiograms was the earliest published work [2] in this research domain. Figure 1 shows the normal retinal image. The normal retinal image consists of normal veinal structure which is clearly visible whereas the figure 2 shows the abnormal image.

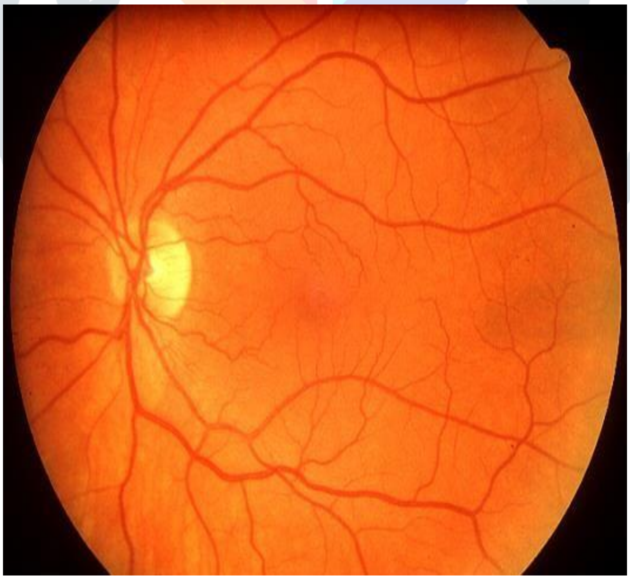

Figure: 1 Normal Retinal Image

Figure: 2 Abnormal Retinal Image

For those who are effected with Severe Diabetic Retinopathy (DR), they have to follow the doctors advise thoroughly. To analyze DR, Fluorescein angiography and Optical soundness tomography (OCT) techniques have to be follow. In OCT, ultrasound testing which utilizes light instead of sound to deliver pictures. Then you have to go for Screening. It is a method for identifying the condition ahead of schedule before you see any progressions to your vision. The screening results will give either there is retinopathy or no retinopathy. After detecting DR, preventive steps like monitoring of sugar level, managing of Diabetes, Blood pressure and cholesterol test have to be taken. If any treatment required for further emergency, Laser treatment is the best option and then eye injections have to be used. For severe in stage Eye surgery is needed. Treatment can helpful for adjustments in eyes and helps people to stop vision loss.

II. LITERATURE SURVEY

Depends on the nature of microaneurysms(MA),detection process will be done on different types of areas like its surrounding tissues, interest regions or blobs, adapted regions etc. For that reason multiple classifiers have to be trained to detect the exact information of MA and scale adapted features are to be extracted from that blob regions. Illumination and noise are the key challenges here. The performance of this can be evaluated on ROC database and can be showed best when compared with different databases [1]. To improve Microaneurysms(MA) detection, they mainly depends on preprocessing methods and candidate extractors such that they proposed ensemble based framework which it is ranked first in online competition in terms of performance. They classified the Diabetic Retinopathy (DR) and non Diabetic Retinopathy using messidor database over 1200 images based on the MA detection. A proper screen system is required for better performance [2]. With the help of Dynamic shape features, evolution of shape and discrimination among lesions and vessel segments will be done. Based on that, Microaneurysms (MA's) and hemorrhages will be detected in color fundus images. This finally gives out the multiple kinds of resolution from multiple types of sytems.Dynamic shape features will be helpful in other applications like clear boundary detection .For grading they are concentrating on bright lesions and neovessel detection [3]. For automatic MA detection in fundus images, gradient vector analysis is used. In gradient vector analysis, gradient field of an image can be analyzed which helpful in vessel removal. By using second order directional derivatives, MA's are detected. Differentiate in finding the actual Microaneurysms(MA) and unidentified Microaneurysms(MA) will be very difficult problem.So that many related features are to be gathered for different types of classification.It will perform well on different databases [4]. For automatic detection MA in digital fundus photographs, on the same set of data five different teams of researchers provide five different methods and then all results are compared.50 trained and 50 test images were used. Separate software will be used for train data to compare data results and test set will be examined by human expert. Final results shown that detecting MA's are challenging for both the automatic methods as well as the human expert [5]. To improve the utilization of computing resources inside the network, ImageNet Large-Scale Visual Recognition Challenge 2014 (ILSVRC14) is proposed in Deep convolution neural network (DCNN).For best quality these architecture decision made by hebbain principle. Quality gain is the main advantage in this method even we increase more layers. For classification and detection, same quality of result can be achieved [6]. Based on Dictionary Learning (DL) with Sparse Representation Classifier (SRC), blood vessel extraction can be done. Multi-scale Gaussian Correlation Filtering (MSCF) helpful in locating the MA candidates for MA detection. Dictionary Learning (DL) via SRC is used for classification. . Vessel center-line candidates are also classified with SRC. They tested on ROC dataset. In future they will use multiple datasets [7]. For the recognition of pattern, different scales of correlation and active type of threshloding is used in which MA detection and classification has to be done. Based on 2 levels it can be done. Candidate detection using coarse level and classification using fine level. The values of sigma plays a key role in getting the best coefficient of correlation by comparing the kernel with the different sizes of microaneurysms.They are using ROC and DIARETDB1 database [8]. Many researchers are worked on Diabetic Retinopathy (DR) problem. Many Repetitive screening techniques are identified for DR .But they are cost effective as well as costly. Again several studies are made on image analysis to get a solution for that problem. For that they made with a conclusion of getting maximum population to be involved to assess the efficiency of such programs. Such that low specificity and high sensitivity and low work load will be helpful [9]. Here MA detection can be done with the help of different profiles in which they are helpful for increasing pixels for preprocessing by operating that profiles on middle local highest pixels.The identification of the highest value will give the size, height and shape. False positives are reduced by cross section. It will be performed on both public ROC database and Private database. It gives best performance on public databases and outperforming on private database. Noise corruption, processing time is the key parameters are the reason for differences in performances [10]. To reduce the burden on the readers, detection of normal exams in a tele-ophthalmology network. So that a TeleOphta project involves in this which helpful in Screening of DR. e-ophtha EX is a database which includes contoured exudates. A segmentation step is involved in this to process images containing reflections, which are frequently found on young patients. This method not only performs on e-opththa database but also on various publicly available databases [11]. Computer aided scanning is required for eye examination. So, retinal elements are necessary as a result optic disc localization will be used here. Optical disc area has rich information, so its entropy value is more significant in this area. Sliding window technique is used for entropy on different patches. More features that are significant in the OD area. So we can also combine different algorithms to generate robust algorithm [12]. In the computer aided analysis of fundus images, automatic and correct division of vessels in the retina will get tougher. So matched filtering is introduced. so it utilizes minimum error thresholding technique to extract binary blood vessel tree. This method is evaluated using publicly available retinal databases and also shows results are comparable [13]. For normal and pathological retinal images discriminating, multiscale amplitude-modulation-frequency- modulation (AM-FM) method is used. Trained analyst uses 120 types of regions such as MA,exudates and neovascularization on the retina. The cumulative distribution functions of the instantaneous amplitude, frequency magnitude, and frequency angle from multiple scales are used as texture feature vectors. This can show the difference between normal retinal structures and pathological lesions based on AM-FM features [14]. If any reference images are given by the lab experts as related or unrelated so particular device to classify those images is needed to detect that. So the classifier is to be trained according that. Segmentation involves in this process. To find the relatable patterns in images, different types of image frame works are available. Trained on Messidor database, which gives high performance when compared to e-optha database. When comparing with the Different high intensity method, a single high intensity method is suitable for time of processing[15]. The accuracy of diagnostic screening of Diabetic retinopathy (DR) has be compared among experts and Computer aided programs. There is no certain confirmation of machines identification types of with the help of a normal standard set by Diabetic retinopathy(DR). For detection of recognized diabetic retinopathy (RDR) there are many detection process are there[16]. Very high Blood pressure and cardiovascular diseases are the major types of factors which can control the process of Diabetic Retinopathy(DR). Several studies are done on this to identify the area associated with disease. Almost in many areas like Asia, Africa, US, UK, china and India these studies have made. As a result major trends in progression and regression of DR. This clearly shows that in higher countries people are in less problem to get diabetes [17]. Depends on different kinds of its features like size, shape, color, texture, and Ophthalmologists identified Diabetic Retinopathy (DR) .So Ophthalmologists used new technologies of machines for eye checkups. So that they can be updated time to time in giving and exploring different machines and techniques for identification of Diabetic which will be very useful for future[18]. With the help of morphological operations exudates extraction will be done and results can be compared with the simple Fuzzy CMean clustering. By this performance can be measured and can be compared with hand drawn ground truth images by ophthalmologists. Some incorrect exudates also detected. They are in the form of noise. These may not affect the sensitivity. But performance can be better if low contrast exudates will be eliminated [19]. For automatic diagnosis of eye, lab experts used highly useful methods like the morphological processing, machine vector methods in which they used a separate device for sending of light and can clearly watch the condition of Diabetic retinopathy. So from that they can conclude the type of problem they had[20].

III. PROBLEM DEFINITION

Diabetic retinopathy is an ailment which need to be taken care if so can be detected at an early stage. The stages need to be identified by a doctor. Till now, there is no such classification mechanism that can classify the stages in diabetic retinopathy. Hence, there is a need for the development such techniques which classify the various stages of diabetic retinopathy.

IV. PROPOSED SOLUTION AND METHODOLOGY

Upto now, in existing method we are just detected a microaneurysms in a retinal image. So we are grading those microaneurysms in a retinal image in our proposed method.

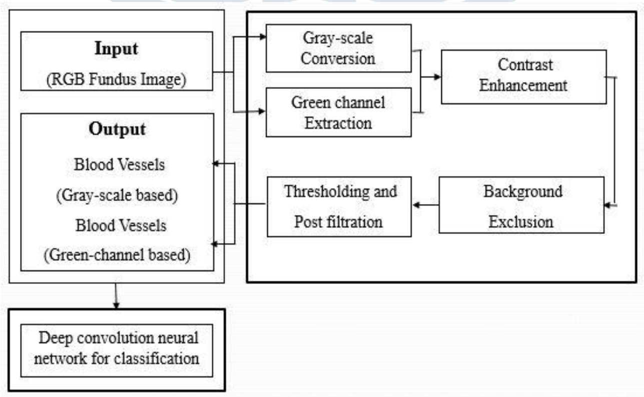

Figure: 1 Flowchart for Proposed methodology

Here we are taking an input image from the database of DIARETDB1 in which it is having 89 images of fundus. This input image as shown in Figure 2 is of RGB type.

Figure: 2 Input image

Actually RGB image is indicated by 3 channels in which each channel having 8 bits. So the amount of information stored in that type of image will be high. Total amount of information may not be needed for further process. Therefore, we are converting RGB image to **Gray scale conversion** image which can be seen in following figure 3. Later from RGB input image, **green channel extraction** will be done separately like gray scale extraction. Why we are extracting only green channel means, in green channel, the reflection of blood Vessels will be seen clearly when compared to red and blue channels as a result green channel is extracted from an input image. Then the resulted

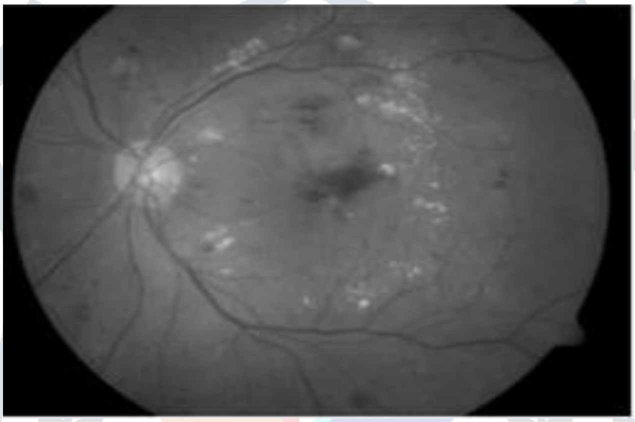

Figure: 3 Gray Scale image

Green type channel and gray scale picture can be combinedly go through the process of **contrast enhancement**. Due to some problems like camera's default options, images taken in dark conditions, resultant images can be in very dark condition. So here images are enhancing by a kind of technique called as adaptive histogram equalization in which it includes the enhancing of contrast. Here Contrast stretching is applied to both green channel and gray scale images. So that it gets the full dynamic image range. After the image is illuminated, we will get the variations in those images. so it will be eliminated by **background exclusion.** In Background exclusion, the background variations of an image are eliminated. This is performed by subtracting original intensity image from average filtered image Average filter. The main idea of averaging filter is to replace the pixels which are they are in the centre with the help of following equation.

$$\widehat{g}(x,y) = \frac{1}{N \times M} \sum_{i=1}^{N \times M} g_i \quad \text{----(1)}$$

For Clear background elimination we are using Morphological operations such as Dilation and Erosion[19].Morphological erosion removes very small objects so that only particular and needed objects remained. Later **thresholding and post filtration** will be done. Here in thresholding, a binary image is produced in which it is having a value of either 0 (background) or 1 (blood vessels). Based on the threshold T the objects are extracted from the background. There is also a chance of getting noise into the image. So to eliminate noise and to correct shade, filtration process done. So that we can detect microaneurysms easily.Later unwanted area elimination can be done and the required microaneurysms can be identified. For increase the enhancement Gaussian filter is helpful to eliminate the dull areas in an image. The morphological operations are applied for vessel removal. Finally MA detected image will be shown in following Figure 4.

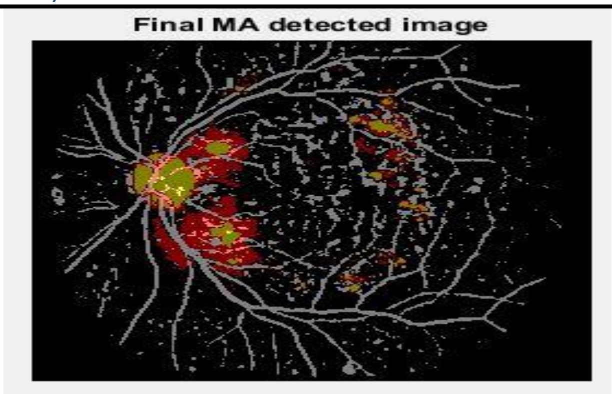

Figure: 4 Final MA detected image.

For Grading we will go for classification by using **Deep Convolution Neural Network (DCNN)**. In which it consists of multiple layers Such as Convolution layer, Pooling layer, ReLu layer, Fully Connected layer is shown in following Figure 5.

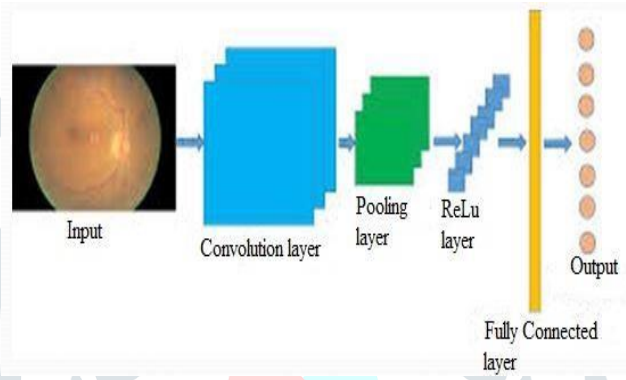

Figure: 5 Deep Convolution Neural Network (DCNN)

From Figure 5, multiple layers are there in DCNN. In **Convolution layer** extraction of multiple features from the input taken image. It takes two inputs such as image matrix and a filter or kernel.It will calculates the weighted average here. Then, the filter matrix is convoluted with the image by taking weighted average. In **pooling layer,** the size of images will be reduced if any high data or high size images are there. This is of two types. Maximum pooling and Average pooling. Pooling simply decreases the dimensionality and then it takes the maximum values from that. It is called as maximum pooling. If the same dimensionality is reduced by taking the average values it is called as average pooling. In **ReLU layer**, there is a decrease in the nonlinearity values will be done. How it will decrease means, it reduces the negative values to zero so that the complexity of the system is very low and computation time will be less. Here there are Max Pooling and Average Pooling. In **Fully connected layer,** the features are extracted from each layer and then they are transferred to next layers with the help of multiple neurons. Then it will calculate the weights at each and every stage. This weight updating process is continued and collected at each and every stage. Based on these features which get by weight updating classification will depend finally classification process done with help of this DCNN network at the output. Finally, after classification stage, grading of an image will be clearly shown with the help of dialog box based on the input fundus image. If any MA's are present, it will shows as "MA's are abnormal" and if no MA's are there it will grade as normal eye.

V. RESULTS

DIARETDB1 database is used in this work which consists of 89 fundus images. Among those images, single images will be given as input for the process took place. Let the input will be as shown in Figure 1 below.

Figure: 1 Input image

The input image is applied based on the methodology that is been defined in the previous section. The output of the morphological operation provides the data of MA. Finally, MA are detected along with the area of the blood vessels which is shown in figure 2. Based on the identified MA which are now graded based on the GLCM features that are extracted from the MA identified image. The distance between the ground truth image and MA identified image is now taken as the grade value. As the graded image contains MA, which is now classified as abnormal image which is shown in figure 3.

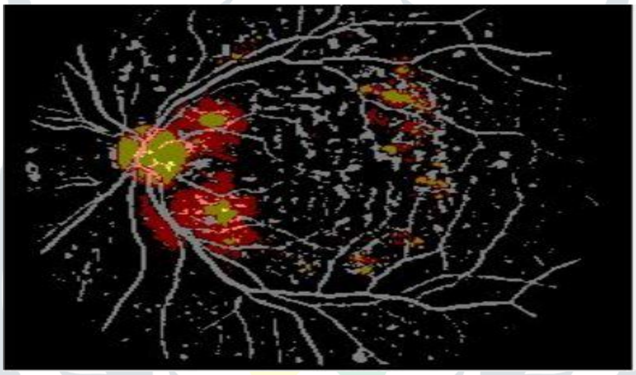

Figure: 2 Final Microaneurysms(MA) detected image

Figure: 3 Grading of MA detected image

. Let an image of without having MA's will be select as shown in Figure 4.

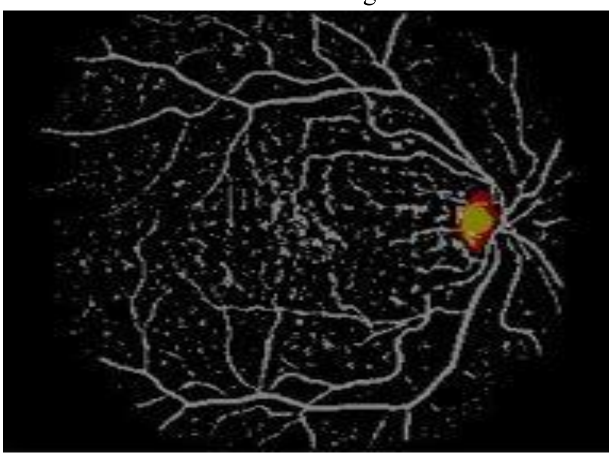

Figure: 4 No MA detected image

If any MA's cannot be detected in an image its grading image will be as "Normal eye" can be shown in figure 5.

Figure: 5 Grading of Non-MA detected image

Based on the detection of Microaneurysms(MA) we will get the values for different parameters like accuracy, sensitivity, specificity and False Positives(FP). Accuracy means comparison of our output values to the ground truth values. Sensitivity means it's the ratio of no. of true positives to the ratio of no. of true positives added with no. of false negatives. Specificity means it's the ratio of no false negatives to the ratio of no. of false negatives added with no. of true positives.

The comparison of sensitivity and specificity among our proposed, existing as shown in Figure 6.Here our proposed method gets a sensitivity of 90% and specificity of 92% which is very high when compared to Existing method having a sensitivity of 81% and specificity of 80%.

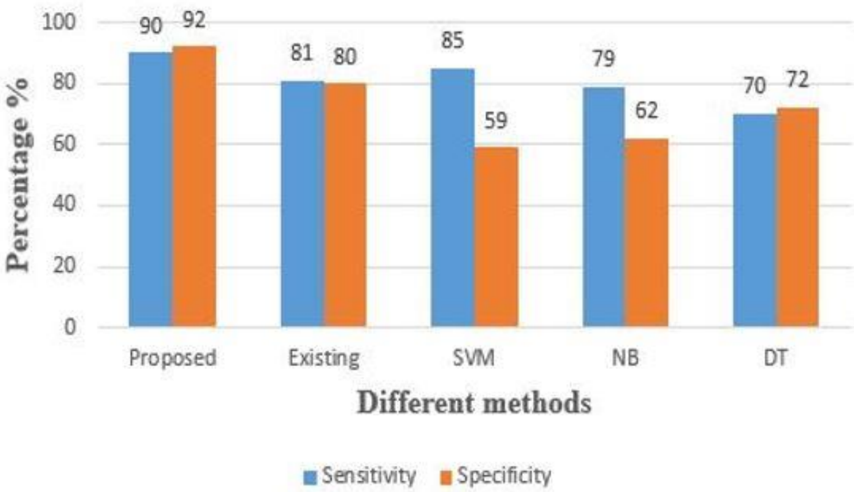

Figure: 6 Comparison of Sensitivity and Specificity among different methods.

The comparison of Accuracy among our proposed, existing methods as shown in Figure 7.Here our proposed method getting an accuracy of 97% which is very high when compared to Existing method having an accuracy of 86%.

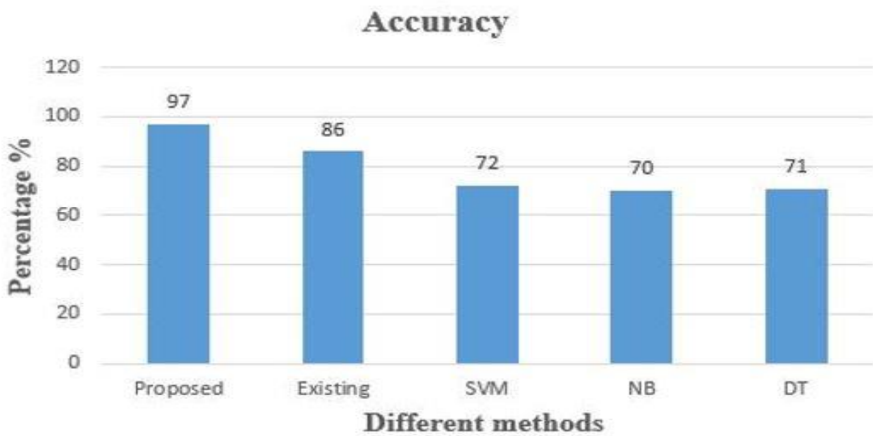

Figure: 7 Comparison of Accuracy among different methods.

The comparison of False positives (FP) among our proposed, existing methods as shown in Figure 8.Here our proposed method gets a false positive of 0.029 which is very low when compared to Existing method having a false positive of 0.123.

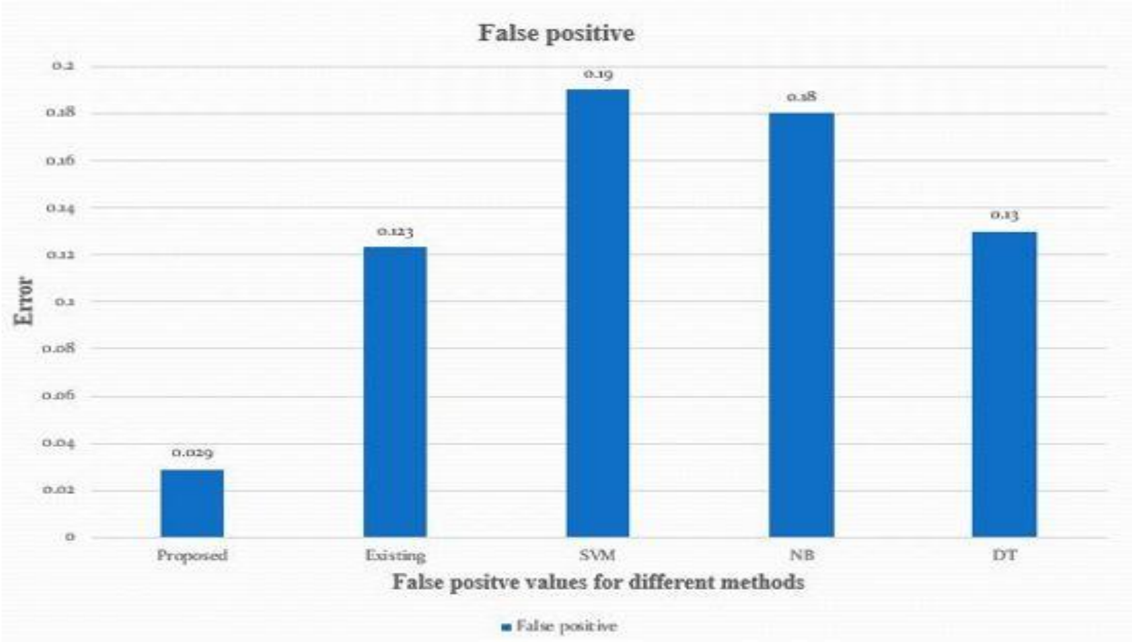

Figure: 8 Comparison of False positives among different methods.

VI. CONCLUSION

In Existing method, there is only Microaneurysms (MA) detection in a fundus image. Here in this paper we proposes an automatic method for Microaneurysms (MA's) identification and also grading in Colour fundus pictures. In this process it undergoes with two stages namely MA detection and classification. Many techniques are helpful for MA detection such as Gray scale image conversion and green channel extraction for clear identification of blood vessels in a retinal image, Contrast enhancement for removing nonlinearities in an image using Contrast limited adaptive histogram equalization (CLAHE) method, background exclusion for only extraction of vessels and thresholding for required areas of vessels in an image. Later for classification Deep Convolution Neural Network (DCNN) will be used which helpful for grading of an image. This paper is well performed on a DIARETDB1 database of getting an accuracy which is of 97%, sensitivity which is of 90%, specificity which is of 92% and the false positives (FP) of 0.029 which is best when compared to existing method of which it has an accuracy of 86%, sensitivity of 81%, specificity of 80% and false positive (FP) of 0.123.

References

[1] K.M. Adal, D. Sidibe, S. Ail, et al., "Automated detection of microaneurysms using scale-adapted blod Analysis and semi-supervised learning," Comput. Methods Proqrams Biomed., vol. 114, pp. 1–10, April 2014.

[2] B. Antal and A. Hajdu, "An ensemble-based system for microaneurysm detection and diabetic retinopathy grading," IEEE Trans. Biomed. Eng., vol. 59, pp. 1720–1726, June 2012.

[3] L. Seoud, T. Hurtut, J. Chelbi, F. Cheriet, and J.M.P. Langlois, "Red lesion detection using dynamic shape features for diabetic retinopathy screening," IEEE Trans. Med. Imag. 32, 1116–1126 (2016).

[4] B. Dai, X. Wu, and W. Bu, "Retinal microaneurysms detection using gradient vector analysis and class imbalance classification," Plos One 11, 0161556 (2016).

[5] M. Niemeijer, B.V. Ginneken, M.J. Cree, et al., "Retinopathy Online Challenge: Automatic detection of microaneurysms in digital color fundus photographs," IEEE Trans. Med Imag. Vol. 29, pp. 185–195, Jan. 2010

[6] C. Szegedy, W. Liu, Y. Jia, et al., "Going deeper with convolutions," IEEE Computer Vision and Pattern Recognition, pp. 1–9, 2015.

[7] B. Zhang, F. Karray, Q. Li, L. Zhang, Sparse representation classifier for microaneurysm detection and retinal blood vessel extraction,Information Sciences, 200(1): 78-90, 2012.

[8] B. Zhang, X. Wu, J. You, Q. Li, & F. Karray, Detection of microaneurysms using multi- scale correlation coefficients, Pattern Recognition, 43(6): 2237-2248, 2010.

[9] M. D. Abr`amoff, J. M. Reinhardt, S. R. Russell, J. C. Folk, V. B. Mahajan, M. Niemeijer, and G. Quellec, "Automated early detection of diabetic retinopathy," Ophthalmology, vol. 117, no. 6, pp. 1147–1154, 2010.

[10] I. Lazar and A. Hajdu, "Retinal microaneurysm detection through local rotating cross-section profile analysis," IEEE transactions on medical imaging, vol. 32, no. 2, pp. 400–7, 2013.

[11] X. Zhang et al., "Exudate detection in color retinal images for mass screening of diabetic retinopathy." Medical image analysis, vol. 18, no. 7, pp. 1026–1043, 2014.

[12] A. M. Mendonc¸a, A. Sousa, L. Mendonc¸a, and A. Campilho, "Automatic localization of the optic disc by combining vascular and intensity information." Computerized medical imaging and graphics, vol. 37, no. 5-6, pp. 409–17, 2013.

[13] J. Odstrcilik et al., "Retinal vessel segmentation by improved matched filtering: evaluation on a new high-resolution fundus image database,"IET Image Processing, vol. 7, no. 4, pp. 373–383, 2013.

[14] C. Agurto et al., "Multiscale AM-FM methods for diabetic retinopathy lesion detection." IEEE transactions on medical imaging, vol. 29, no. 2,pp. 502–12, 2010.

[15] G. Quellec et al., “A multiple-instance learning framework for diabetic retinopathy screening.” Medical image analysis, vol. 16, no. 6, pp. 1228–40, 2012.
[16] M. D. Abr`amoff et al., “Automated analysis of retinal images for detection of referable diabetic retinopathy.” JAMA ophtalmology, vol.131, no. 3, pp. 351–357, 2013.
[17] R. Lee, T. Y. Wong, and C. Sabanayagam, “Epidemiology of diabetic retinopathy, diabetic macular edema and related vision loss,” Eye and Vision, vol. 2, no. 1, p. 1, 2015.
[18] E. Sehirli, M. K. Turan, and A. Dietzel, “Automatic detection of microaneurysms in rgb retinal fundus images,” studies, vol. 1, no. 8, 2015.
[19] A. Sopharak, et al., Fine Exudate Detection using Morphological Reconstruction Enhancement. 2010.
[20] U.R. Acharya, et al., Computer-based detection of diabetes retinopathy stages using digital fundus images. Proceedings of the Institution of Mechanical Engineers, Part H: Journal of Engineering in Medicine, 2009. 223(5): p. 545-553.

.