

Dynamic Shape Features Based Retinal Lesions Classification Using Random Forest Classifier

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Abstract -- We describe a dynamic shape feature method to identify the lesion present in the retina. Diabetic retinopathy [DR] happens when these small blood vessels leak blood and different liquids. [4] This makes the retinal tissue swell, bringing about overcast or obscured vision. A PC supported screening and reviewing framework depends on the programmed discovery of injuries is required for Screening of diabetic retinopathy. DR show dim lesions, for example, Micro aneurysms (MA) and haemorrhages (HE) and bright lesions, such as, exudates and cotton-fleece spots. [6] The existing systems utilized normal strategies, for example, adaptive fuzzy thresholding [10] However, after finding the detected vessels, these lesions are lost and not recovered in resulting handling and gives less characterization precision.. Automatic detection of both micro aneurysms, haemorrhages and exudates in colour fundus image is described and validated based on new set of shape features called dynamic shape features (Elongation, eccentricity, circularity, solidity, rectangularity) that do not require precise segmentation of the regions to be classified. These features represent the evolution of the shape during image flooding and allow discriminating between lesions and vessel segments. Finally machine learning technique random forest classifier is used to classify the diabetic retinopathy type based on dynamic shape features.

Indexed Terms: Lesions, fundus, elongation, eccentricity circularity, solidity, rectangularity, Microaneurysms, Haemorrhages, exudates, random forest classifier

I. INTRODUCTION

Diabetic retinopathy is a condition that occurs in individuals who have diabetes. It makes dynamic damage the retina, the light-delicate covering at the back of the eye. Diabetes interferes with the body's ability to use and store sugar (glucose). [8] The ailment is depicted by an intemperate measure of sugar in the blood, which can cause hurt all through the body, including the eyes.

Diabetic retinopathy (DR) is an inconvenience of diabetes that can prompt impedance of vision and even visual defiance in the working-age populace.

One out of three diabetic individual presents indications of diabetic retinopathy and one out of ten experiences its most extreme and vision-underlining frames. DR can be overseen utilizing accessible medicines, which are compelling whenever analysed early. Since DR is asymptomatic until late in the illness procedure, ordinary eye fundus examination is important to screen any adjustment in the retina.

With the expanding predominance of diabetes and the maturing populace, it is normal that, in 2025, 333 millions diabetic patients worldwide will require retinal examination every year. Considering the set number of ophthalmologist, there is an earnest requirement for mechanization in the screening procedure so as to cover the huge diabetic populace while decreasing the clinical weight on retina authorities.

Our exploration centres around the improvement of a programmed telemedicine framework for PC helped screening and evaluating of DR. [8] Since PC investigation can't supplant the clinician, the framework goes for recognizing fundus pictures with suspected injuries and at arranging them by seriousness. At that point, the explained pictures are sent to a human master for audit, beginning with the speculated most extreme cases. Such a programmed framework can lessen the authority's weight and examination time, with the extra favourable circumstance of objectivity. Also; it can help to quickly distinguish the most extreme cases and to concentrate clinical assets on the cases that need increasingly dire and specific consideration.

A few techniques have been created for the programmed recognition of red sores in shading fundus pictures. A large portion they spotlight exclusively on the discovery of MAs. In view of their genuinely uniform round shape and restricted size

range, MAs can be identified utilizing morphological tasks, for example, width shutting and top cap change utilizing a direct organizing component at different introductions. The objective here is to recognize MAs from prolonged structures. Haemorrhages also classified. The random forest classifier is used for classification.

The organization of the paper is as follows. Section 2 explains overview of the existing related works. Section 3 explains about the proposed work which is detection of retinal lesions. Section 4 examines the outcome. Finally, this paper is finished up with the conclusion and thought regarding the future work.

II. PROBLEM IDENTIFICATION

Red lesions and dark lesions are segmented using the adaptive fuzzy thresholding method. The aim of pre-processing is an enhancement of the picture information that smothers undesirable twist or improves some picture highlights imperative for further preparing. From the information RGB image, green layer is extricated in light of the fact that it introduces the higher complexity among vessels and fundus background among different layers.

Line tracking method used to follow a line on the picture with a specific angular orientation and diameter. By using the picture histogram, the pixel zone limits will be resolved to be followed by the threshold value corresponding to the frequency of the intensity image. [1] After getting the tracking area, it will be done early in the initialization process for tacking pixel neighbours with direction and a predetermined diameter.

By calculating the value of the weight of each pixel neighbours, it will be selected the pixels that have the greatest weight and the value exceeds a predetermined threshold weight. If it is not eligible, it will be re-initialization process early pixels. If there is one that meets the pixel, the pixel is marked as a line pixel by providing trust value of "1", while the other pixels set "0". Furthermore, this process is repeated until all of the pixel are is completed tracking.

Optic disc are extracted using the morphological processing .After removal of optic disc adaptive fuzzy thresholding method is applied for lesion detection.

This division strategy consolidates two ground breaking thresholding systems: versatile neighbourhood thresholding and spatial nearby data based thresholding. This fundamentally comprises of three phases. 1)Fuzzy modelling, 2)fuzzy model accumulation, 3) binarization.

The fuzzy model was worked through premise steps: image fuzzification, fuzzy sets structures, and fuzzy relations. In binarization process the influenced region of retinal structure is distinguished dependent on fuzzy edge esteem. The paired image is computerized picture that has just two conceivable qualities for every pixel.

The lesions are only segmented not classified. Lesions are contains two terms. They are Dark lesions and bright lesions.

III. PROBLEM SOLUTION

A. Introduction about proposed system:
Diabetic retinopathy (DR) is a multifaceted nature of diabetes that can incite weakening of vision and even visual impairment. It is the most well – known behind visual lack in the working age populace. One out of three diabetic individuals available signs of DR and one out of ten experiences it most outrageous and vision bargaining structures. In this paper, we propose a system of the area of the MAs, HEs and EXs that does not require prior vessel division.

B. Block Diagram:

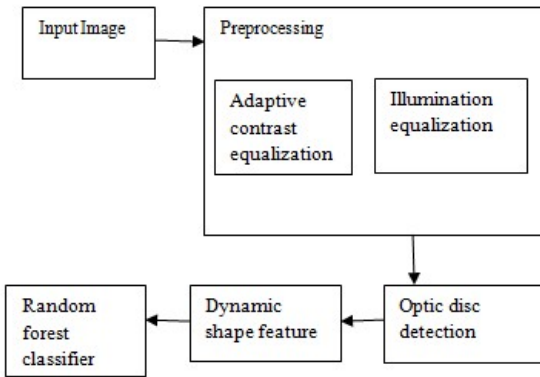


Fig. 1: Block diagram of lesion detection

C. Image pre processing:

Pre processing is a typical name for activities with pictures at the most minimal dimension of deliberation- both input and output are intensity images. The aim of pre processing is an enhancement of the picture information that smothers undesirable twists or improves some picture highlights imperative for further preparing. [14] Pre processing steps are very subject to the difficulties made by the idea of the target retinal structure a concise depiction of every anatomical structure is exhibited, trailed by the relating required pre processing steps. In the first place, the crude retinal picture was changed over into greyscale images

D. Illumination equalization:

The light in a retinal picture is non-uniform because of the variety of the retina reaction or the non-consistency of the imaging framework .The optical disc is described as the most splendid anatomical structure in a retinal picture. However, because of uneven enlightenment- vignetting specifically-the OD may seem darker than other retinal areas, particularly when retinal pictures are regularly caught with the fovea showing up amidst the picture and the OD to the other side.[12] OD limitation techniques, especially those dependent on power variety or just on force esteems, won't be direct.

To overcome the non-uniform illumination, each pixel is adjusted (equalized) using the following equation

$$I_{eq}(r, c) = I(r, c) + m \frac{I_w(r, c)}{I_w(r, c)} \quad (1)$$

Where m is the desired average intensity (128 in an 8-bit gray scale image) and $I_w(r, c)$ is the mean intensity value of the pixels within a window W of size N×N. The window varies between 30 and 50.

Running window of just a single size (40×40) was utilized to ascertain the mean force esteem. Despite the fact that the subsequent pictures look fundamentally the same as those utilizing the variable running window, the ROI of the retinal pictures is contracted by five pixels to dispose of the pixels close to the fringe where the odds of mistaken qualities are higher.

E. Denoising:

A small mean filter of diameter is applied to each color channel of the resulting image in order to attenuate the noise resulting from the acquisition and compression steps without smoothing the lesions.

F. Adaptive Contrast Equalization:

The complexity float is approximated utilizing the nearby standard deviation figured for every pixel in an area of measurement d1, for each shading channel. Zones with low standard deviation show either low complexity or smooth foundation. To upgrade low differentiation zones, we hone the subtleties in these specific regions.

Nearby picture subtleties are along these lines added to the denoised picture, weighted by the opposite of the difference float. The subtleties are acquired utilizing a high pass filter. The past denoising step forestalls unwanted commotion honing.

G. optic disc removal

The OD is a significant wellspring of false encouraging points in red injury location in this manner its evacuation is a fundamental advance.

Beginning from the pre-processed picture, we first utilize an entropy-based methodology to gauge the area if the OD's inside. Essentially, the OD is situated in a high force district where the vessels have maximal directional entropy. [9] A consequent

improvement step at that point evaluates the OD's range and refines its position. This comprises in convolving a multi-scale ring shaped coordinated filter to the picture in a sub-ROI focused on the first estimation of the OD's middle, of span equivalent to 33% of the ROI's sweep. The range and position of the coordinated filter that limits the convolution are chosen as the OD's final span and focus position.

H. candidate extraction:

Since blood vessels and dark lesions have the most elevated complexity in the green channel, the last is separated from the pre-processed picture. The red and blue channels are utilized later to extricate shading highlights.

In the green channel, MAs and HEs show up as structures with nearby negligible force. A brute force approach is separate all the territorial minima in pre-processed image. A provincial least is a gathering of associated pixels of consistent force, with the end goal that all the nearby pixels have carefully higher powers. Sadly, this strategy is highly sensitive to noise. Contingent upon the smoothness of the picture, the quantity of territorial minima would thus be able to be expansive.

To defeat this restriction, we adopt the dynamics transformation. Which rates local minima as indicated by their neighbourhood differentiate. Loud minima as a rule have lower differentiate than red injuries. In a topographic portrayal of Gp, the dynamic of a base is registered as the distinction in power between the given least and the most brilliant purposes of the ways achieving at least lower force. The primary favourable position of this definition is that the subsequent complexity estimation is free of the size and state of the local least.

Utilizing this change, we can choose the minima by thresholding the subsequent complexity picture. Now, we might want to dispose of from the arrangement of competitors whatever number neighbourhood minima comparing to commotion as would be prudent. [16]So as to appraise the noisy intensity, we process the nearby standard deviation in an area of the extent of the papilla and think about the most minimal standard deviation inside the ROI,

which would compare to a locale in the retinal foundation with insignificant flag power.

At long last, a chose least ought to have a force lower than the mean power in Gp to be viewed as a candidate region. This is bolstered by the way that we are searching for red sores, which are darker than the retinal foundation.

Contrast and illumination equalization gain importance at this point. Without these pre-processing steps, worldwide difference and force thresholding would be difficult to accomplish.

Also, all candidates whose separation to the OD's middle is littler than the OD's span are expelled from the arrangement of applicants and not considered any further.

I. Dynamic shape features

Among the candidates, several regions corresponds non-lesions, such as vessel segments and remaining noise in the retinal background. To discriminate between these false positives and true lesions, an original set of features, the DSFs, mainly based on shape information, is proposed. Six curves are obtained for each candidate ,one per shape attribute: Rarea(i), Elong(i),Ecc(i) ,Circ(i), Rect(i) and Sol(i) as a function of the flooding level i.

J. Random forest Classifier

Random forest classifier is ensemble algorithm. Ensembled algorithms are those which combine more than one algorithms of same or different kind of classifying objects. For example, running prediction over Naive Bayes SVM and decisions tree and then taking vote for final considerations of class for test object.

Random forest classifier creates a set of decision trees from randomly selected subset of training set. It then aggregates the votes from different decision trees to decide the final class of the test object.

IV. RESULT AND DISCUSSION

1. Image with retinal lesion:

Image processing is a strategy to play out a few activities on a picture, with the end goal to get an improved picture or to remove some helpful data

from it. It is a type of signal processing in which input is a picture and yield might be picture or attributes related with those picture.

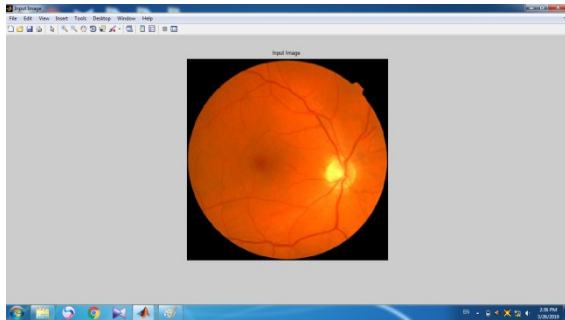


Fig. 2: Input Image

2. gray scale images:

Gray scale picture is a scope of monochromatic shade from dark to white.

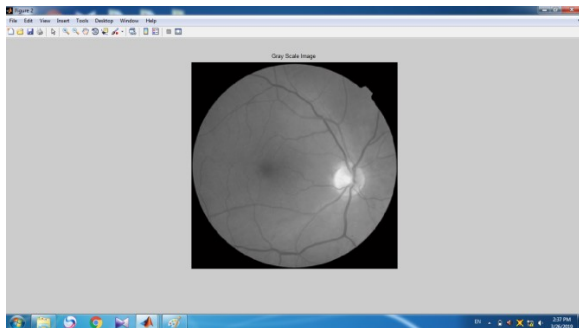


Fig. 3: gray scale Image

3. Filtered image:

The median filter is a non-linear digital filtering technique, often used to remove noise from an image or signal. Such noise reduction is atypical pre-processing step to improve the results of later processing.



Fig. 4: filtered image

4. Adaptive contrast equalization

Adaptive contrast equalization is a PC picture handling procedure used to improve differentiates in picture. It contrast from conventional histogram adjustment in the regard that the versatile technique processes a few histogram, each comparing to a particular area of the picture, and uses them to redistribute the delicacy estimations of the picture.

It is along these lines reasonable for improving the neighborhood differentiate and upgrading the meanings of edges in every region of a picture.

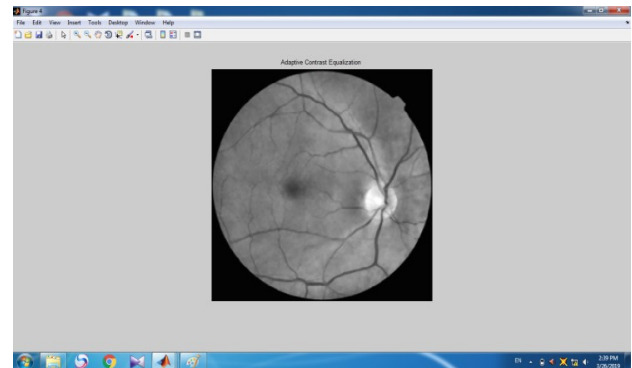


Fig. 5: adaptive contrast equalization image

5. illumination equalization image:

The objective of enlightenment adjustment is to evacuate uneven brightening of the picture brought about by sensor defaults (e.g., vignetting), non uniform light of the scene, or introduction of the articles surface.

Illumination revision depends on foundation subtraction. This kind of revision expects the scene is made out of a homogeneous foundation and moderately little articles more splendid or darker than the foundation. After this process the dynamic shape feature is used. Then the random forest classifier is used for classification.

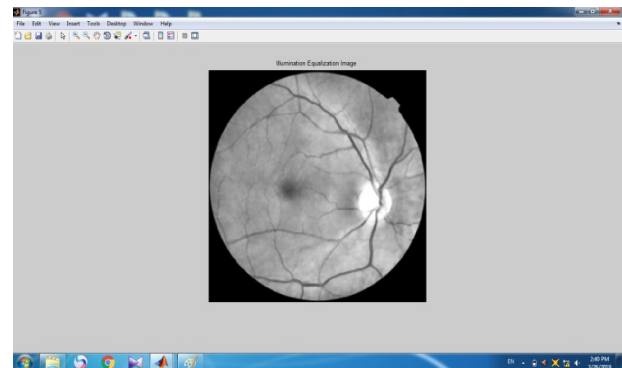


Fig. 6: illumination equalization image

6. lesion classification:

Micro aneurysms are a minor aneurysm, or swelling, in the side of an intense vessel. In individuals with diabetes, micro aneurysms are now and again found in the retina of the eye. These smaller than expected aneurysms a can burst and break blood. It shows up as reddish, littler and circular dots.

Hemorrhages are the name used to portray blood misfortune. It can allude to blood misfortune inside the body, called inward dying. It can allude to blood misfortune outside of the body, called outer dying. Haemorrhage is the name used to portray blood misfortune. They generally show up as bright red spots/patched with considerable changeability in shaped and appearances.

Exudates are a fluid discharged by a life form through pores or a wound, a procedure known as exuding or exudation. They contain protein, lipid and cellular debris. They generally show up as yellowish, bright patches of variable shapes and estimated with sharp outskirts.

Random forest classifier is a managed characterization calculation that builds woodland with a few choice trees. Most astounding precision results are accomplished with the higher number of trees. Random forest classifier is utilized for the two primary classifications of the framework.

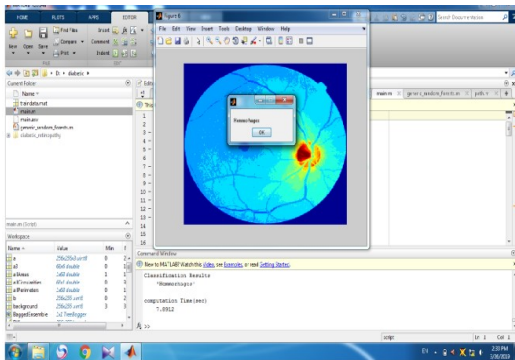


Fig. 7: lesion classification

V. CONCLUSION AND FUTURE WORK

In this project red lesions and bright lesions are identified naturally utilizing dynamic shape feature. These procedures, when consolidated in a successive and keen way, offer effective and efficient scheme to recognize the diverse lesions independent of their surface, shape and size. The outcomes show the solid performance of the proposed technique in identifying the MAs, HEs and EXs in fundus pictures of various goals and quality and from various securing frameworks. DSFs have turned out to be vigorous highlights, exceedingly fit of separating among injuries and vessel fragments.

To further enhance the strength and adequacy of the technique, we will improve the performance of the processing of bright lesions and time improvements in execution needs further consideration.

REFERENCES

- [1] Sudeshna Sil Kar and Santi P. Maity “Automatic detection of retinal lesions for screening of diabetic retinopathy” IEEE Transactions on BioMedical Engineering Vol.65, No.3, March 2018.
- [2] M. U. Akram, S. Khalid, A. Tariq, S. A. Khan, and F. Azam, “Detection and classification of retinal lesions for grading of diabetic retinopathy,” Computers in Biology and Medicine, vol. 45, pp. 161 – 171, 2014.
- [3] M. U. Akram, A. Tariq, S. A. Khan, and M. Y. Javed, “Automated detection of exudates and macula for grading of diabetic macular edema,” Computer Methods and Programs in Biomedicine, vol. 114, no. 2, pp. 141 – 152, 2014.
- [4] N. Cheung, P. Mitchell, and T. Y. Wong, “Diabetic retinopathy.” Lancet, vol. 376, no. 9735, pp. 124–36, 2010.
- [5] I. Figueiredo, S. Kumar, C. Oliveira, J. Ramos, and B. Engquist, “Automated lesion detectors in retinal fundus images,” Computers in Biology and Medicine, vol. 66, pp. 47 – 65, 2015.

- [6] A. Hoover, V. Kouznetsova, and M. H. Goldbaum, "Locating bloodvessels in retinal images by piece-wise threshold probing of a matched filter response.," *IEEE Transactions on Medical Imaging*, vol. 19, no. 3, pp. 203–210, 2000.
- [7] C. Baudoin, B. Lay, and J. Klein, "Automatic detection of microa-neurysms in diabetic fluorescein angiographies," *Revue d'épidemiologie et de sante publique*, vol. 32, pp. 254–261, 1984.
- [8] 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. 400–407, 2013.
- [9] M. Niemeijer, B. van Ginneken, J. Staal, M. S. A. Suttorp-Schulten, and M. D. Abramoff, "Automatic detection of red lesions in digital color fundus photographs." *IEEE transactions on medical imaging*, vol. 24, no. 5, pp. 584–92, 2005.
- [10] C. I. Sanchez, R. Hornero, M. I. Lpez, M. Aboy, J. Poza, and D. Absolo, "A novel automatic image processing algorithm for detection of hard exudates based on retinal image analysis," *Medical Engineering & Physics*, vol. 30, no. 3, pp. 350–357, 2008.
- [11] 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 Transactions on Medical Imaging*, vol. 35, pp. 1116–1126, April 2016
- [12] J. Odstreilik 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.
- [13] R. Winder, P. Morrow, I. Mc Ritchiea, and P. Hart, "Algorithms for digital image processing in diabetic retinopathy," *Computerized Medical Imaging and Graphics*, vol. 33, pp. 608–622, 2009.
- [14] B. Zhang, X. Wu, J. You, Q. Li, and F. Karray, "Detection of micro aneurysms using multi-scale correlation coefficients," *Pattern Recognition*, vol. 43, no. 6, pp. 2237 – 2248, 2010.
- [15] T. Walter, J.-C. Klein, P. Massin, and A. Erginay, "A contribution of image processing to the diagnosis of diabetic retinopathy – detection of exudates in color fundus images of the human retina.," *IEEE Transactions on Medical Imaging*, vol. 21, no. 10, pp. 1236–1243, 2002
- [16] G. Quellec et al., "A multiple-instance learning framework for diabetic retinopathy screening." *Medical image analysis*, vol. 16, no. 6, pp. 1228–40, 2012.
- [17] M. Niemeijer, B. van Ginneken, S. R. Russell, M. S. A. Suttorp-Schulten, and M. D. Abramoff, "Automated detection and differentiation of drusen, exudates, and cotton-wool spots in digital color fundus photographs for diabetic retinopathy diagnosis," *Investigative ophthalmology & visual science*, vol. 48, no. 5, pp. 2260–2267, 2007.