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Survey on Convolutional Neural Network Based Efficient Automated Detection of Micro Aneurysm in Diabetic Retinopathy

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ABSTRACT

Diabetic Retinopathy (DR) is that the most typical explanation for visual disorder of the attention depends upon polygenic disorder. For this reason, early detection of diabetic retinopathy is of crucial importance. The primary sign of diabetic retinopathy within the membrane is that the presence of the micro aneurysms (MAs) that cause due to injury within the membrane as a long abnormality impact results in diabetic mellitus. Despite many makes an attempt, automated detection of micro aneurysm from digital body structure pictures still remains to be associate open downside. Early identification of the micro aneurysms (MAs) helps us to cut back and forestall diabetic retinopathy at the first stage. Diabetic Retinopathy (DR) could be a complication of polygenic disorder and a number one explanation for visual disorder within the world. It happens once polygenic disorder damages the little blood vessels within the membrane. If the blood vessels within the membrane get harm they develop a balloon like swelling referred to as micro aneurysms. The detection of micro aneurysms (MAs) in color body structure pictures remains associate open issue within the medical image process because of the low availableness of reliability. The most two sorts of diabetic retinopathy are Non-Proliferate Diabetic Retinopathy (NPDR) and Proliferate Diabetic Retinopathy (PDR). Picture analysis by trained people, which may be an awfully pricey and time intense task because of the massive diabetic population.

Keywords : Diabetic Retinopathy, Fundus Images, Micro Aneurysms, Proliferative, Non-Proliferative.

I. INTRODUCTION

Diabetic retinopathy (DR) could be a complication of polygenic disease and the leading reason for vision loss [1] to forestall vision loss, early detection and treatment of DR is important. The most typical disease associated with polygenic disease and therefore the main reason for vision loss in associate degree adult is that the DR. The modification within the veins of the tissue layer is caused because of health problem if DR isn't detected and known within the early part [2], [3]. DR won't show and indicate any signal until the top of pathologic process. Analysis of diabetic patients for the happening and therefore the

flow of signs of DR will ease off the warning of vision loss by quite fiftieth. At the first part of DR, there will be hardly any distinction within the tissue layer which will be determined, but delay, DR will get severe and cause visual defects. DR is characterised through its properties like; MAs, haemorrhages, and red lesions like exhausting exudates, soft exudates, and veins. The existence of MAs denotes the first indication of DR in diabetic patients. as a result of a micro aneurysm (MA) is associate degree early symptom of DR, MA detection will alter early detection of DR. Non-contrast retinal pictures are utilized in screening and periodical check-ups MAs seem as little dark dots in a very retinal image, as shown in Fig. 1

Early identification through regular screening is suggested to diabetic patients, which might facilitate them forestall visual defect and visual loss. MAs are small regions of the balloon like swelling among the tissue layer which might be thanks to native. However, an oversized quantity of diabetic patients must be screened annually, that poses an important work for ophthalmologists. Therefore, developing associate degree automatic DR screening system is important, which might not solely cut back the workloads of ophthalmologists, however conjointly improve the accuracy of detection. Thus, police work MAs in non-contrast retinal pictures is difficult. Many analysis teams are developing machine-driven MA detection ways victimization retinal pictures.

In this paper, we tend to compare a number of the ways for automatic detection of diabetic retinopathy on the premise of parameters like: sensitivity, specificity and accuracy.

The target of this paper is to review the relevant literature within the field of diabetic retinopathy detection and to produce researchers with an in depth resource of the on the market methodologies used for diabetic retinopathy detection.

Figure 1. Micro aneurysm Defected Eye

II. LITERATURE SURVEY

A. PRE-PROCESSING

Pre-processing is needed to confirm that the dataset is consistent and displays only relevant features. The large luminosity, poor contrast and noise invariably occur in retinal fundus images that have an effect on seriously the diagnostic process of DR and also the automatic lesions detection, particularly for MA. The calculations have been chosen dependent on relating writing suggestions for medical image processing.

The pre-processing strategies described below aim to boost the accuracy of micro aneurysm detection however every of them focuses on a different aspect of detection. The contrast enhancement technique by Walter and Klein [4] leads to a gray scale image with a smooth background, and emphasizes MA-like objects. The vessel removal and extrapolation method [6] aims to scale back the number of false positives caused by the similar look of vessel segments and micro aneurysms.

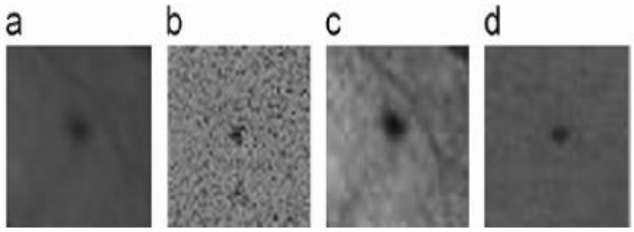

Figure 2. The result of different pre-processing methods to enhance the detection of micro aneurysms. (a) Original image, (b) Walter-Kelvin contrast enhancement, (c) CLAHE, (d) Vessel removal and extrapolation

As it can be seen in Fig.2, the extraction of MAs from the background varies depending on their environment and also the applied pre-processing technique.

Walter–Klein (WK) contrast enhancement

This pre-processing algorithm has been proposed by T. Walter et al [4]. This technique aims to boost the contrast of fundus images by applying a gray level transformation. Walter et al. characterize the local contrast operator in the accompanying way:

$$u = \begin{cases} \frac{1}{2} \cdot \frac{(u_{max}-u_{min})}{(\mu_f - t_{min})^r} \cdot (t - t_{min})^r + u_{min}, & t \le \mu_f, \\ -\frac{1}{2} \cdot \frac{(u_{max}-u_{min})}{(\mu_f - t_{max})^r} \cdot (t - t_{max})^r + u_{max}, & t \ge \mu_f, \end{cases}$$

Where $\{t_{min,\ldots,} t_{max}\}$, $\{u_{min,\ldots,} u_{max}\}$ are the intensity values of the gray scale and also the enhanced image, respectively, μ_f is the mean value of the gray scale image and r € R. If r=1, this operation is a linear contrast stretching, while r → ∞ yields a local thresholding at the gray level μ_f.

Contrast limited (CL) adaptive histogram equalization

K.Zuiderveld proposed a Contrast limited adaptive histogram equalization (also known as CLAHE) [5] is a common pre-processing technique in medical imaging, because it is very effective in making the usually interesting parts more visible. CLAHE depends on nearby histogram evening out of disjoint districts removed from the image. To eliminate the boundaries between the regions, a bilinear interpolation is additionally applied.

Vessel removal (VR) and extrapolation

Based on the idea proposed by *S. Ravishankear* [7], we've investigated the impact of processing images with the complete vessel system being removed. To fill within the holes caused by the removal, we tend to extrapolate the missing parts. Most of the false positives recognized throughout micro aneurysms detection are the results of the similar look of specific parts of the vessel system.

B. CANDIDATE EXTRACTION

Fundus image is an RGB color image, normally RGB images consist of three channels (red, green and blue). This can be accomplished by separation the retina image to three channels and using only one of them (Green channel), the blue channel is characterized by low contrast and doesn't contain abundant information. The vessels are visible within the red channel. The original (RGB) image is reworked into appropriate color space for additional processes. As shown within the fig 3 and 4, Color fundus image is first converted into a green channel image so as to facilitate the blood vessels segmentation. From visual observation, Optic Disk generally exhibits the greatest contrast from the background in the green band.

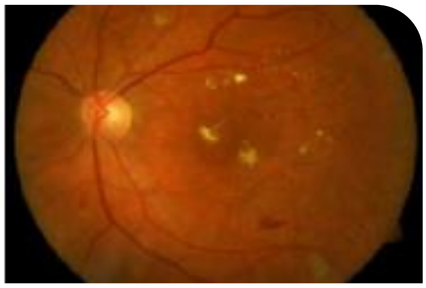

Figure 3. Retina fundus Image

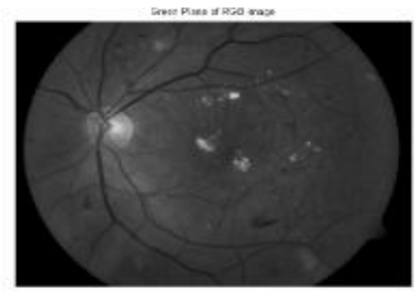

Figure 4. Green Plane of RGB Image

Lazar et al. [8] proposed an approach that the green channel of the image is inverted and smoothed with a Gaussian filter. A set of scan lines with equidistantly sampled directions between -90 ◦ and + 90 ◦ is mounted. For every direction, the intensity values along the scan lines are recorded in an exceedingly one dimensional array, and also the scan lines are shifted vertically and horizontally to process every pixel of the image. On every intensity profile, the heights of the peaks and their local maximum positions are used for an adaptive thresholding. The resulting foreground indices of the thresholding procedure are changed back to two dimensional directions, and stored in a map that records the number of foreground pixels of different directions corresponding to every pixel of the image. The maximal value for each position equals the number of different directions used for the scanning process. This guide is smoothed with an averaging kernel and a hysteresis thresholding methodology is connected. At last, the resulting components are filtered dependent on their size.

Based on *T. Spencer–A.J. Frame* [9, 10] this approach is one in all the foremost wide used candidate extractors, originally proposed in [9 10]. The algorithm uses shade correction as pre-processing. First, a background image i_{bg} is made by applying a median filter on the green channel of the original image i_{green}. Then, the shade corrected image i_{sc} is generated within the following way:

$$i_{sc} = i_{bg} - i_{green}$$

The actual candidate extraction is accompolished by subtracting the maximum of multiple morphological top-hat transformations, which are defined as follows:

$$T(f) = f \bullet s - f$$

Where $\bullet$ denotes morphological closing. For this step, 12 rotated structuring elements are used with a radial resolution 15. Then, the resulting image is subtracted from i_{sc} to remove the largest components from the image. As a contrast enhancement operator, a 2D Gaussian coordinated channel is connected on the obtained image. The resulting image is then binarized with a settled limit. Since the candidates don't seem to be correct representations of the actual lesions, a region growing step is also considered. Slightly modified versions of this method are proposed in [11-13], respectively.

Based on the idea presented by *S. Abdelazeem* [14], we've developed a technique that appearance for small circular spots in the image. Candidate extraction is gotten by recognizing circles on the images using circular Hough transformation. The radius of the circles is limited based on the observed size of MAs identified in a training set.

Zhang et al. [15] proposed that this technique is predicated on multi-scale correlation filtering and dynamic thresholding. For the first task, five Gaussian masks with totally different sigmas are used. The maximum coefficients from the five responses are then combined by taking the maximum of them at each location.

C. REGION GROWING

Region growing approach is the opposite of the split and merge approach and it's a bottom up approach. An initial set of small areas are iteratively converged by likeness limitations. Begin by selecting an arbitrary seed pixel and compare it with neighbouring pixels. Region is grown from the seed pixel by adding in neighbouring pixels that are similar, increasing the scale of the region. When the growth of one region stops we simply select another seed pixel which does not yet belong to any region and begin once more. This whole process is sustained till all pixels belong to some region.

Spencer and Frame et al [9, 10] have used morphological top-hat transformation for vasculature detection. Then region growing algorithmic rule was used to find a final candidate object set.

Then *Cree et al.* [23] proposed a technique for automatic detection of micro aneurysms. During this paper, the author has used region growing algorithm to search out the underlying candidate morphology and then to distinguish micro aneurysms from different objects, features classification algorithm was used. The images are taken from the hospital of the same patient at totally different visits. This system has achieved a sensitivity of 82% for detecting DR and specificity of 84%.

Streeter et al. [17] proposed a micro aneurysm detection method using region growing algorithm in color fundus images. After the preprocessing, the blood vessels are removed. At this point thresholding and region growing algorithm is applied by taking seed image of candidate. After region growing, the features are extracted. The dataset for this methodology was created by scanning non-mydriatic retinal images from slide film using a Nikon LS-2000 scanner. This system has accomplished 5.7 false positives per image with 56% of sensitivity.

D. NEURAL NETWORK CLASSIFICATION

Alireza osareh and Bita shadgar [22] proposed a multilayer neural network using fuzzy c-means clustering for segmentation which has the sensitivity of 96.0% and specificity of 94.6%. For the detection of exudates in fundus images.

By *Hunter et al.* [20] the neural network (NN) was trained to distinguish exudates from druse based on 16×16 pixel patches. The authors introduced a hierarchical feature selection technique, in view of analysis to distinguish the most relevant features. The final NN architecture had 11 input variables and accomplished 91% injury based (fix goals) execution utilizing 15 retinal images. The reported performance was based on whether each 16×16-pixel patch contains exudates, and no image-based and pixel-level validation was reported.

Usher et al. [19] also used neural network to detect the micro aneurysms. First of all, preprocessing is done. After preprocessing, micro aneurysms are extracted using recursive region growing and adaptive intensity thresholding with "moat operator" and edge enhancement operator. The images for the outcome assessment are taken from the doctor's facility. For this method, the sensitivity of detecting the micro aneurysms is 95.1% and specificity is 46.3%.

Clara i. sanchez [29] proposed a classification methodology specifically fisher's linear discriminant analysis methodology for the detection of hard exudates within the retinal images. This methodology achieves the accuracy of 100% and sensitivity 88%. This algorithm performance is based on the database containing 58 retinal images with variable color, brightness and quality.

Wenhua et al. [24] proposed a methodology to detect the micro aneurysms using SVM (Support Vector Machine) in retinal fundus images. During this method, first of all a generalize histogram algorithms are used to enhance the images. Then blood vessels and any object which is too massive to be a red lesion are removed. Then finally, extraction of micro aneurysm is performed and its result is given as the input to the SVM to classify the micro aneurysms. The pictures are taken from Clemson and STARE database. This method has achieved an accuracy of 90%. For the detection of red lesions like micro aneurysms, this approach may be a fascinating approach.

III. PERFORMANCE MEASURES

In order to evaluate the performance of pattern classification systems the binary classification performance has to be measured. For automated detection of Diabetic retinopathy, three measures are mostly used: sensitivity, specificity and accuracy. Confusion matrix is used for measuring the sensitivity and specificity, quantifying its performance to false positive and false negative (FN) instances such measures are generally excluded in such image processing algorithms [27]

The sensitivity, specificity and Accuracy are computed using Equation 1, 2 and 3 respectively. These metrics are as follows:

Sensitivity is the percentage of the actual exudates pixels that are detected (i.e.) the probability of a positive test given that the patient has disease and it is given by:

$$\text{Sensitivity} = \frac{TP}{TP + FN}$$

Specificity is the percentage of non-exudates pixels that are correctly classified as non-exudates pixels, (i.e.) the probability of a negative test given that the patient has no disease.

$$\text{Specificity} = \frac{TN}{FP + TN}$$

Accuracy is the ratio between the total numbers of correctly classified instances and the test size, given by:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

Sensitivity is basically how great a test is at discovering something on the off chance that it is there, means the proportion of actual positives which are correctly identified. Specificity is a measure against false positives, how precise a test is, means the proportion of negatives which are correctly identified. We have classified the papers based on evaluation approach. As we seen below the figure 5 shows the result of MA detection.

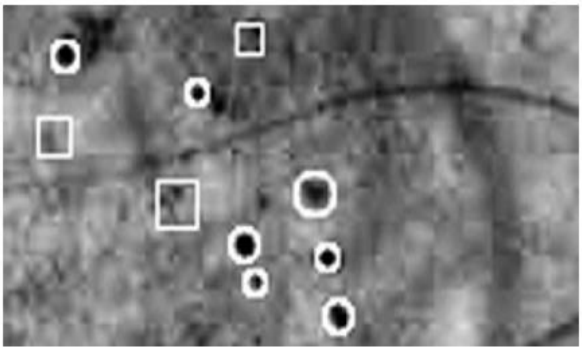

Figure 5. Result of MA detection, circles depict TPs and squares represent FPs

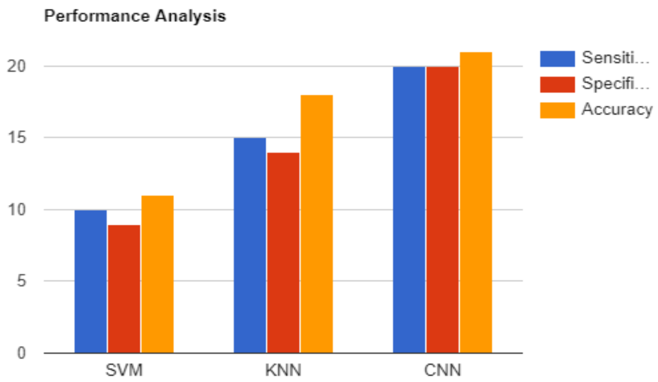

Figure 6. Performance analysis: sensitivity, specificity, accuracy based on 3 approaches: SVM, KNN and CNN.

IV. CONCLUSION

A Survey of automated detection of micro aneurysm is proposed. The automatic detection of the diabetic retinopathy presents various challenges. The DR affected area in the image is hard to distinguish from background variations because it typically low contrast. The accuracy of the detecting system depends on the following factors.

i. The segmentation technique used for segmenting the blood vessels and optic disc. The correct segmentation yields the new vessel pixels correctly.

ii. The features selected for further classification. The methods for feature sub selection ought to be effective so that irrelevant and redundant features with no useful information should be selected.

iii. The performance of the classifier classifying the new vessels and non-new vessels.

This paper work reviews all existing strategies to give a complete view of the field. Moreover, the process time of the adopted learning machine and its accuracy have to be thought of as they are crucial in machine learning and data mining applications. Based on this work, researchers will get a vantage of the matter and might develop better and more effective algorithms.

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