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DETECTING COMPLICATION OF DIABETIC RETINOPATHY USING CNN CLASSIFICATION

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ABSTRACT

Diabetic retinopathy is getting to be a more predominant malady in diabetic patients these days. The shocking reality almost the malady is it takes off no indications at the starting organize and the persistent can realize the infection as it were when his vision begins to drop. In case the illness isn't found at the most punctual it leads to a arrange where the likelihood of curing the malady is less. But in case we discover the malady at that stage, the persistent can be in a circumstance of losing the vision totally. Thus, this paper points at finding the illness at the most punctual conceivable arrange by extricating two highlights from the retinal picture specifically Microaneurysms which is found to be the beginning side effect appearing include and Hemorrhage which appears indications of the other stages. Based on these two highlights we classify the organize of the illness as ordinary, starting, mellow and serious utilizing convolutional neural arrange, a profound learning strategy which decreases the burden of manual highlight extraction and gives higher exactness. We too find the position of these highlights within the disease affected retinal pictures to assist the specialists offer superior restorative treatment.

Catchphrases*: Microneurysm; analyze at the most punctual organize*

Keywords*: Diabetic Retinopathy, microneurysms, hemorrhage, Convolutional Neural Network, Retinal Veins.*

1. INTRODUCTION

Image Processing is broadly utilized to analyze the eye maladies in a simple and proficient way. It too bolsters Ophthalmologists to screen their patients and to do clinical consider as well. Major eye related infections that cause visual impairment around the world are Diabetic Retinopathy, Glaucoma, and age-related macular degeneration. It is found that in America, nearly 950,000 individuals got to be dazzle in 2002 and 2.5 million individuals have visionary issues due to these maladies.

As of now, the advance of diabetes is one of the foremost imperative challenges in therapeutic care. The sum of patients that endure from diabetes is expanding. Concurring to the Worldwide Diabetes League report, on a worldwide scale 382 million individuals have diabetes, and around 4.3 million of them are in Iran. In later years, diabetic retinopathy (DR) could be a common cause of visual impairment in diabetic patients. An early diagnosis of diabetes can increment the chance of avoidance of visual deficiency, additionally in most cases; the vision will steadily diminish. In any case, in case the patients careless approximately this condition, it'll increment the chance of harm to their vision. Hence, the early discovery of diabetes is pivotal to diminish the chance of vision issues and visual impairment. Specialists and ophthalmologists utilize a extraordinary gadget called “fundus camera” to decide the eye issues.

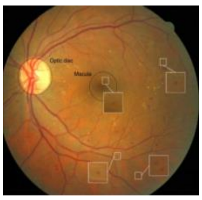

Fig 1 Retinal image with fundus points

The anatomy of blood vessels in the retina of the eye provides information on the changes that occur as a result of certain retinal illnesses. The vascular blood vessels, fovea, and optic disc (OD) are some of the eye features that are utilised to diagnose diabetic retinopathy (DR) and other eye illnesses. To diagnose DR, a variety of screening tools are available [4][5]. To obtain retinal vessel images, digital fundus cameras are utilised; as a result, excessive brightness, the environment, and the method of acquiring the fundus image decrease the image quality to some extent. As a result, image augmentation is necessary.

The ophthalmoscope is a device used by ophthalmologists to examine the eyes. Ophthalmologists image the retina in order to learn more about retinal disease. Image interpretation progress is sometimes aided by automated equipment. Computer Aided Diagnosis (CAD) refers to the systems that are produced by combining computers and medical science to analyse data. These CAD systems, which are developed to identify retinopathy, should be able to detect the first signs of retinopathy. As a result, the diagnosis is made using the criteria established by ophthalmologists. These devices use digital retina scans as input and, using an algorithm, assist ophthalmologists with image analysis. Image pre-processing, area of interest (ROI) definition, feature extraction and selection, and classification are the four basic phases of a conventional CAD system.

The improper retinal picture differentiate, as well as the rough foundation light, must be the significant components that make the division difficult. The uneven lighting is related to the securing technique, and the unacceptably high level of complexity is due to the procurement procedure as well as the process by which the various vessels stand out from the foundation. As a result, we yearn for the arrival of programmed vein identification equipment that can precisely slice the veins of the retina in a short period of time. With fragment retinal images, a variety of attempts have been done, and many strategies have been learned.

2. LITERATURE SURVEY

For decades [1], predicting the presence of Microaneurysms in fundus pictures and detecting diabetic retinopathy in its early stages has been a serious challenge. Diabetic Retinopathy (DR) is caused by a high blood glucose level for an extended period of time, which causes microvascular problems and irreversible vision loss. The production of microaneurysms and macular edoema in the retina is the first symptom of diabetic retinopathy, and early detection can lower the risk of nonproliferated diabetic retinopathy. Deep learning is gradually becoming an efficient technology for providing an innovative answer to medical image analysis challenges, thanks to its rapid advancement. The suggested system analyses the presence of microaneurysms in fundus images utilising convolutional neural network methods with deep learning as a fundamental component, which will perform medical picture recognition and segmentation with high-performance and low-latency inference. The fundus image is classified as normal or diseased using the semantic segmentation technique. To identify the feature of microaneurysm, semantic segmentation splits the picture pixels based on their common connotation. This allows ophthalmologists to grade fundus images as early NPDR, moderate NPDR, or severe NPDR using an automated technique. A Prognosis of Microaneurysm and Early Diagnosis System for Non-Proliferative Diabetic Retinopathy has been proposed, which is capable of effectively training a deep convolution neural network for non-proliferative diabetic retinopathy.

A deep [2] learning system for the categorization of diabetic retinopathy (DR) grades from fundus pictures is presented in this research. There are three steps to the suggested framework. The fundus image is first pre-processed with intensity levelling and enhancement. Second, a ResNet Convolution Neural Network (CNN) model is used to generate a compact feature vector for grading from the pre-processed image. Finally, to detect DR and define its severity (mild, moderate, severe, or Proliferative Diabetic Retinopathy (PDR)), a classification step is performed. The difficult ISBI'2018 Indian Diabetic Retinopathy Image Dataset is used to train the suggested architecture (IDRiD). The data is balanced to guarantee that each DR grade is represented with the same number of photos during the training phase, removing the training bias.

This research proposes [3] a method for detecting diabetic retinopathy that extracts the precise area and quantity of microaneurysms from colour fundus pictures. Diabetic retinopathy can be detected and treated with regular eye exams. Diabetic retinopathy (DR) is an eye disease caused by retinal damage as a result of long-term diabetes mellitus. Microaneurysms (MA) are small red spots on the retina caused by the ballooning of a weak blood artery. Recognizing MA in the primary stage is critical, as it is the first step in preventing DR. Several methods for detecting and diagnosing DR have been proposed. Two characteristics of MA have been determined in this paper: the number and area of MA.

Glaucoma, a kind of Diabetic Retinopathy [4], is a disease that causes vision loss by distorting the optical nerve system. Due to its ability to characterise the retinal vasculature, fractal dimension is one of the feature extractions that can be used in retinopathy fields. In this study, we propose fractal dimension-based research that distinguishes not only healthy participants from diabetic retinopathy patients, but also the severity of diabetic retinopathy patients. Using the MESSIDOR dataset and Random Forest as a Classifier, we discovered that fractal dimensions can discriminate between healthy participants and diabetic retinopathy patients, but that it cannot classify the severity of diabetic retinopathy patients (grade level).

Diabetic retinopathy (DR) [5] and diabetic macular edema (DME) are the leading causes of permanent blindness in the working-age population. Automatic grading of DR and DME helps ophthalmologists design tailored treatments to patients, thus is of vital importance in the clinical practice. However, prior works either grade DR or DME, and ignore the correlation between DR and its complication, i.e., DME. Moreover, the location information, e.g., macula and soft hard exhaust annotations, are widely used as a prior for grading. Such annotations are costly to obtain, hence it is desirable to develop automatic grading methods with only image-level supervision. In this article, we present a novel cross-disease attention network (CANet) to jointly grade DR and DME by exploring the internal relationship between the diseases with only image-level supervision. Our key contributions include the disease-specific attention module to selectively learn useful features for individual diseases, and the disease-dependent attention module to further capture the internal relationship between the two diseases. We integrate these two attention modules in a deep network to produce disease-specific and disease-dependent features, and to maximize the overall performance jointly for grading DR and DME. We evaluate our network on two public benchmark datasets, i.e., ISBI 2018 IDRiD challenge dataset and Messidor dataset. Our method achieves the best result on the ISBI 2018 IDRiD challenge dataset and outperforms other methods on the Messidor dataset. Our code is publicly available at https://github.com/xmengli999/CANet.

3. EXISTING SYSTEM

The Bayesian detection technique is utilised in the current system to classify changes in the retinal fundus image in order to identify diabetic retinopathy. Brightness variations, fundus picture artefacts, outliers, and segmentation mistakes can all be detected using this method. In order to detect differences in the fundus image, the optical disc, blood vessels, and fovea are segmented. Microancurysm, Exudates, and Cotton wool patches are just a few of the lesions that the algorithm may discover. In the fundus image, the algorithm failed to detect vascular alterations. People in industrialised countries are disproportionately affected by DR due to a lack of treatment and funding. Diabetes patients are 25 percent more likely to get DR. Blood vessels, secretions, haemorrhages, Microaneurysms, and textures are all features of the retinal eye that are utilised to detect DR[1]. When glucose levels approach their maximum limit, capillaries are destroyed, causing blood to flow into the retina. Exudates, microaneurysms, red spots, and crossover sites are detected and diagnosed using a number of classifiers and distinguishing factors with a set of conditions in Disease Classification/Abnormality Detection. Object Ratio Test, Compact Ratio Test, Length Test, Pixel Count Test, and Region Hole Test are some of the criteria used to detect picture background-based disease such as exudates, microaneurysms, and red spots. The image is then sent to the Vein-Processing step for crossover point detection utilising the Modified Crosspoint Number Method once these background illnesses have been detected and removed.

4. PROPOSED SYSTEM

A new technique for detecting blood vessels has been developed in our proposed system. The method begins with an excessively segmented image created by an edge detection algorithm. The blood vessels are then accurately detected using a new feature-based algorithm. For selective segmentation, this method considers retinal blood vessel features such as intensities, width ranges, and orientations. To estimate primary exudates, the extracted blood vessel tree and optic disc are subtracted from the over segmented image. The most recent exudates estimation is obtained through morphological reconstruction based on exudate appearance. In terms of sensitivity and specificity, this approach yielded promising results. Based on a new multi-layer architecture of active deep learning, an automatic recognition of the DR stage is proposed. The key to detecting DR is to search for little symptoms of haemorrhages and micro-aneurysms, which alert a clinician to the disease's prevalence and severity. Our proposed CNN classification on a novel image approach connected with a certain pathology and disease takes about twenty seconds to study the image and gets an accuracy score of 86 percent in disease classification. Two possible analyses were proposed for diabetes patients' fundus pictures. Micro aneurysms and exudates were detected automatically on two small image databases, and lesions were manually noted.

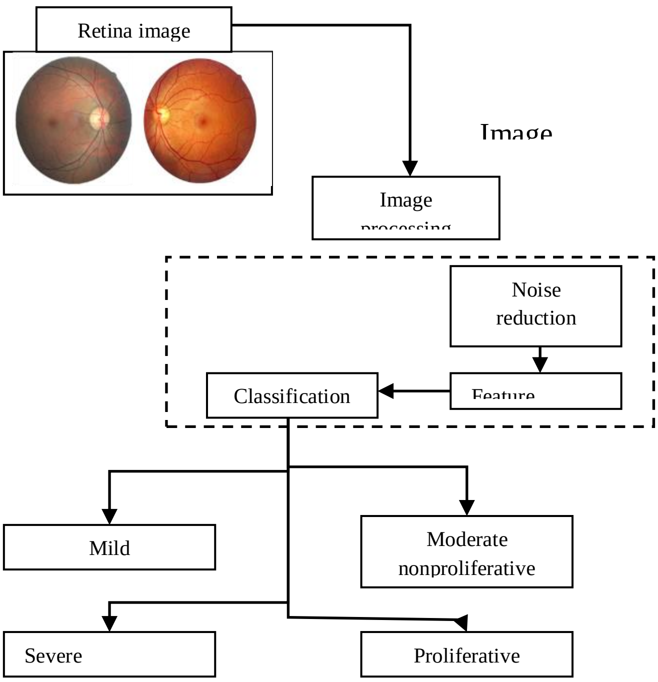

Fig 4 Proposed System Architecture

The computer-assisted diagnostic approach for grading and detecting diabetic retinopathy and macular edoema (ME) hazards has been improved, thanks to a huge database that includes both pathological and normal photos, as well as differential manual grading. Although the proposed method did not reach great accuracy, it did result in a reduction in consumption time when huge volumes of data were used.

5. MODULES

- Read Image
- Gray Scale Conversion
- Noise removal

- Image Sharpening
- Image Segmentation
- Feature Extraction
- Classification

5.1 MODULE DESCRIPTION

5.1.1 Read Image

Light enters the eye through the pupil and is focused on the retina. The lens assists in focusing images from different distance. The amount of light entering the eye is controlled by the iris, by closing when light is bright and opens when light is dim. To the outside of the eye is a transparent white sheet called conjunctiva. Ciliary muscles in ciliary body control the focusing of lens automatically. Choroids form the vascular layer of the eye supplying nutrition to the eye structures. Image formed on the retina is transmitted to brain by optic nerve. Optic disk is brighter than any part of the retina image and is normally circular is shape. It is also the entry and exist point for nerves entering and leaving the retina to and from the brain. Near to the centre of the retina is an oval shape object called macula. The fovea is near the centre of the macula and it contains packed cone cells. Due to high amount of light sensitive cells, the fovea is responsible for the most accurate vision.

By considering the binary region of interest (ROI) mask we get required input image. Having spatial resolution of the diameter is equal to 540 pixels, since this was the smallest ROI diameter we came across in the publicly available fundus image sets. It is possible to apply ROI on images of different size

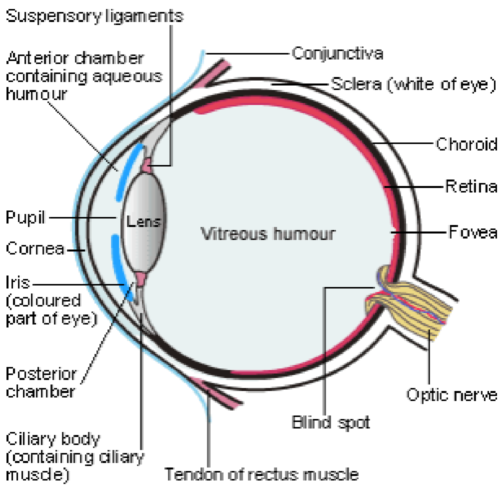

Fig 5.1 Eye structure with retina

5.1.2 Grayscale Conversion

Retinal images are routinely acquired and assessed to provide diagnostic for many important diseases like diabetic retinopathy. People with proliferative retinopathy can reduce their risk of blindness by 95 percent with timely treatment and appropriate follow-up care. The color constancy is used in this context to define the ability of the visual system to estimate an object color transmitting an unpredictable spectrum to the eyes.

In this paper, a Gray World method was proposed by assuming the average of the surface reflectance of a typical scene is some pre-specified value. The main idea based on illumination estimated using the statistical region data. The effectiveness of the Gray Word method and normal gray technique was calculated by using Mean Square Error (MSE) and Peak Signal to Noise Ratio (PSNR).

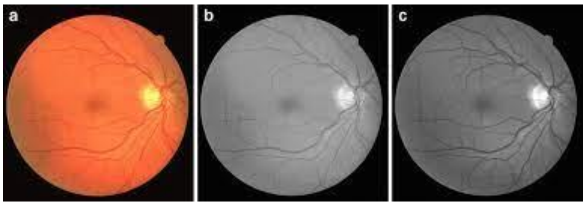

Fig 5.2 Gray scale conversion of retina image

The Gray World achieved the highest PSNR and lowest MSE proved that the image quality was improved. The proposed method can be used to help the ophthalmologist to detect a lesion in the retinal image automatically. Through the contrast variation in retinal images, the disease can be recognized very well.

5.1.3 Noise Removal

Preprocessing of any image gives smoothening before actual detection step. Because many fundus images are available in a lossy compressed format .This compression resulting in the distortion of small structures such as MAs. Since the method particularly relies on the local intensity distribution of MA, it is important to reduce the effect of noise. By applying convolution with a Gaussian mask with a variance of 1.0. Our experiments showed that this amount of smoothing suppressed noise sufficiently while preserving true MAs

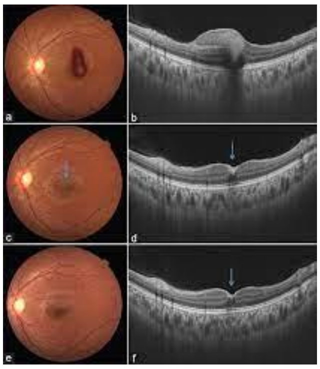

Fig 5.3 the unwanted noise is removed in the retinal image

Preprocessing usually consists of noise filtering and the other attempts in order to segment interesting patterns of the background. In the image pre-processing step, image distortions are eliminated and important features traits are improved. This way, a better corrected and more suitable image is produced. It is expected that, after applying preprocessing methods on images, the capability of understanding and analyzing information in images are greatly improved.

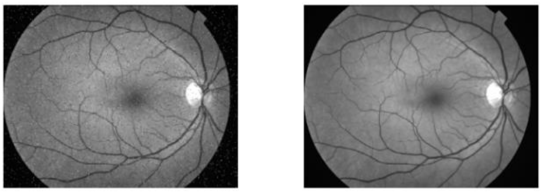

Fig 5.4 Median Filtering system

5.1.4 Image Segmentation

Simple thresholding is a simple method and highly intuitive method of segmenting image based on the pixel intensity value. It is based on the assumption that the intensity value of the image can be group into two non-overlapping groups namely object and background based on the perceived histogram of the image.

The K-means is another simple algorithm of segmenting or classifying images into k different clusters based on feature, attribute or intensity value. It is computationally efficient and does not require the specification of many parameters as compared to other method of segmentation. Unlike local thresholding, which can only group into two main classes while K-mean Algorithm can group into k different classes and that is part of the reason why we chosen as segmentation method for this work. The classification is done by minimizing the sum of the squares of distances between data and the corresponding clustering centroid. Type of distance calculation compatible with K-means Algorithm includes Manhalanobis and Euclidean distance etc. The basic K-means Algorithm is as given in Figure 3.5:

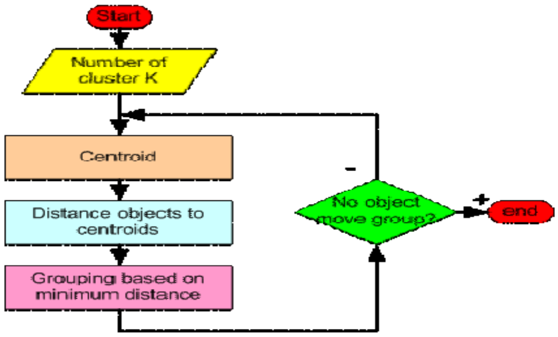

Fig 5.5 Segmented images with K means system

Algorithm for K-means Segmentation

Step 1: Input data and number of clusters

Step 2: Calculate cluster (group) centroids based on initial guess value

Step 3: Calculate distance of each pixel from Class centroid

Step 4: Group pixels into k clusters based on minimal distance from centroids

Step 5: Calculate new centroid for each cluster

Step 6: Classify into groups based on new centroid and distance

Step 7: Test if any of centroid changes its position.

Step 8: If there are changes repeat step 3- 8, else step 9

Step 9: end

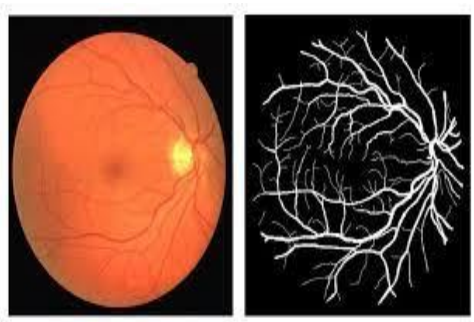

Fig 5.6 K means segmentation produces the variability

5.1.5 Feature Extraction

By applying Gaussian mask on image resulting in intensity distribution. MAs are local intensity maximum structures on the preprocessed retinal image. Which means that every MA region contains at least one regional maximum. A local maximum region (LMR), of a gray scale (intensity) image is a connected component of pixels with a given constant intensity value. Every neighboring pixel of the region has strictly lower intensity.

Fig 5.7 Extracted Feature points

Therefore, it is sufficient to consider only the LMRs of the preprocessed image as possible MA candidate regions. We applied a simple breadth-first search algorithm, similar to the one described in for the calculation of gray scale morphological reconstruction. In this algorithm pixels of the image are processed sequentially, and compared to their 8- neighbors. If all other neighbors of pixel have lower intensity, then the pixel itself is a LMR. If there is a neighboring pixel with higher intensity, then the current pixel may not be a maximum. A pixel is considered to be a possible maximum if all neighboring pixels have lower or the same intensity, in which case pixels with the same intensity are stored in a queue, and tested in the same way

Peak detection is performed to obtain cross-section profiles. These cross-section profiles decide whether a peak is present at the center of the profiles, i.e., at the location of the candidate point for a specific direction. We calculate several properties of the peak, and the final feature set consists of a set of statistical measures that show how these values vary as the orientation of the cross-section is changing. In this way, the variation of important characteristics, such as symmetry and shape of the structure, and its difference from the background can be numerically expressed.

5.1.6 Classification

For classification, we used a CNN classifier. Which is simple and robust probabilistic algorithm that assumes the individual features to be independent. The training set obtained from cross-section profiles consists of both positive and negative MA examples. Usually, it is rather straightforward to obtain the feature vectors of positive instances of the training set, since in most public datasets the coordinates of MAs on the images are given. The non-MA set consists of false positives. The training of a CNN classifier means the estimation of the class priors and feature probability distributions. Following the common practice when dealing with continuous data, we assume that the feature values in each class are of Gaussian distribution. This also means that the parameters of the distribution can be estimated using the sample means and variances of the training data for the given feature. Experiments showed that there was only a minimal difference in the final performance, but CNN gave a slightly better result. Besides, its low computational time and its robustness are also advantageous.

The final step of the proposed method is the non-maximum suppression. All points of the region are considered as candidate pixels. Non-maximum suppression at this point refers to the operation of selecting the point with the highest score from every maximum region that will represent the corresponding candidate. Therefore, points with nonmaximal score in a candidate region are neglected, and the output is a set of coordinates and the corresponding score values. We note that the MA scores are not normalized values. Optionally, it is possible to have a binary output for the MA candidates with an appropriate Thresholding of the score values.

According to the density of vessels, some possible regions for localization of the optic disc are considered. After detection of the optic disc, the average brightness intensity of it is calculated and the regions with brightness intensity higher than 0.8 brightness intensity of discovered OD are considered as exudates area. Samples of detected optic disc and exudates

6. OUTPUT SCREEN

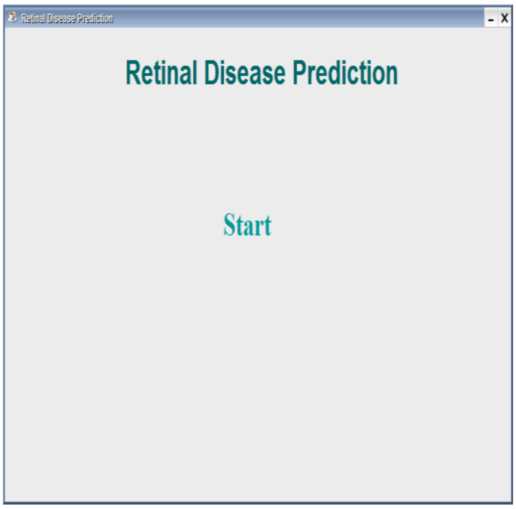

Fig 8.1 Home page of retinal disease detection

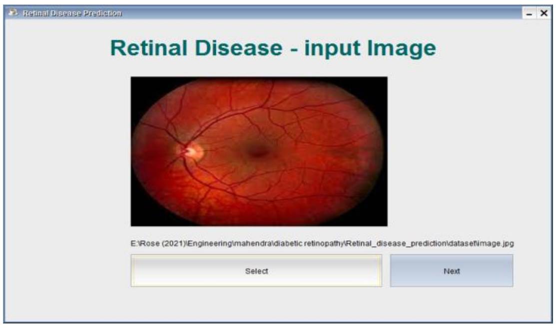

Fig 8.2 Image acquisition/Read image

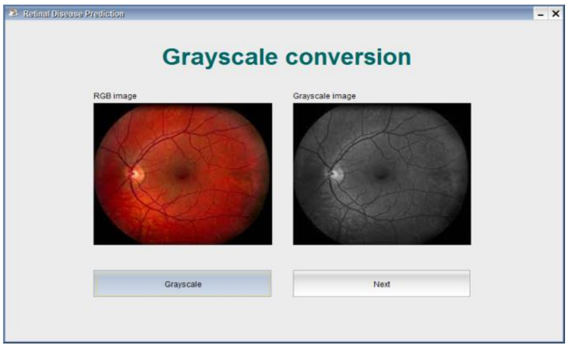

Fig 8.3 Gray Scale Conversion

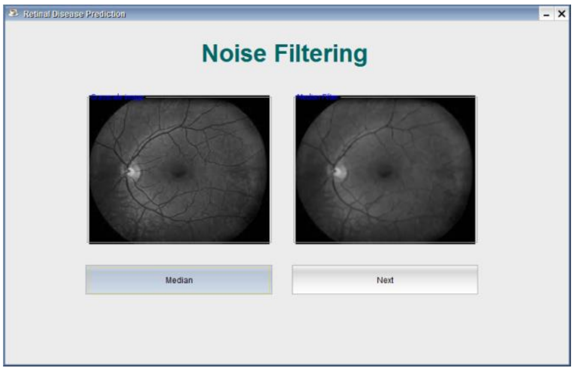

Fig 8.4 Noise Filtering

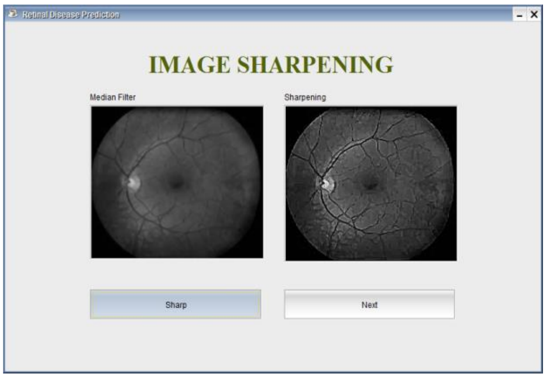

Fig 8.5 Image Sharpening

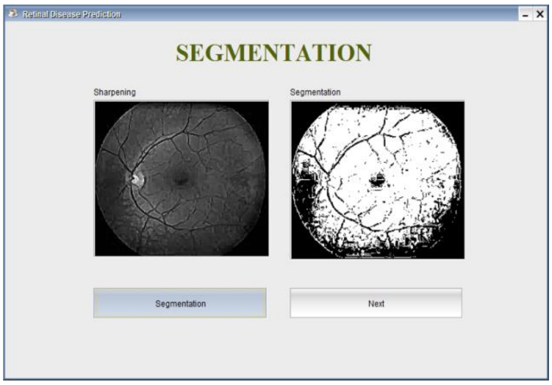

Fig 8.6 Image Segmentation

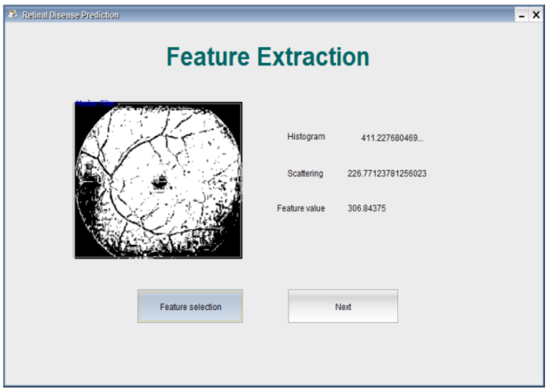

Fig 8.7 Feature Extraction

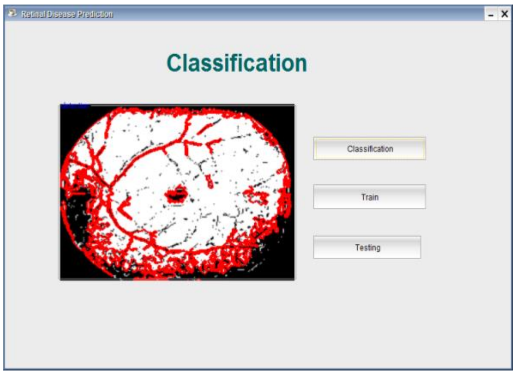

Fig 8.8 Classification (CNN)

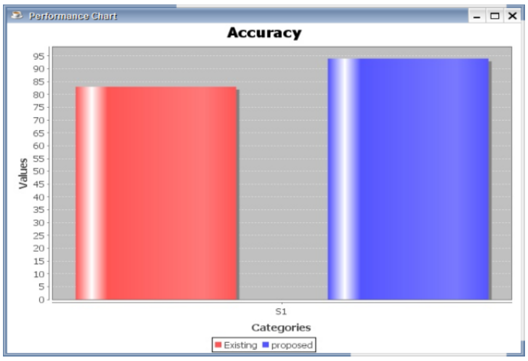

Fig 8.9 Accuracy of Existing and Proposed

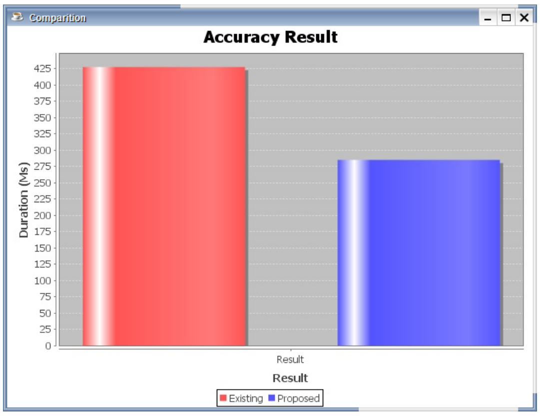

Fig 8.10 Extraction duration of classification

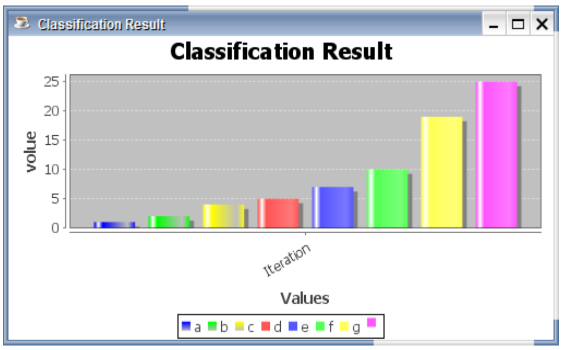

Fig 8.11 Classification Iteration Features

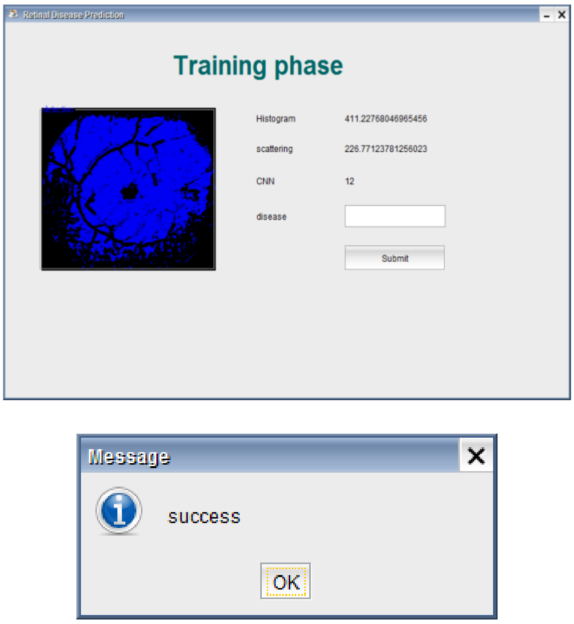

Fig 8.12 Training phase of disease

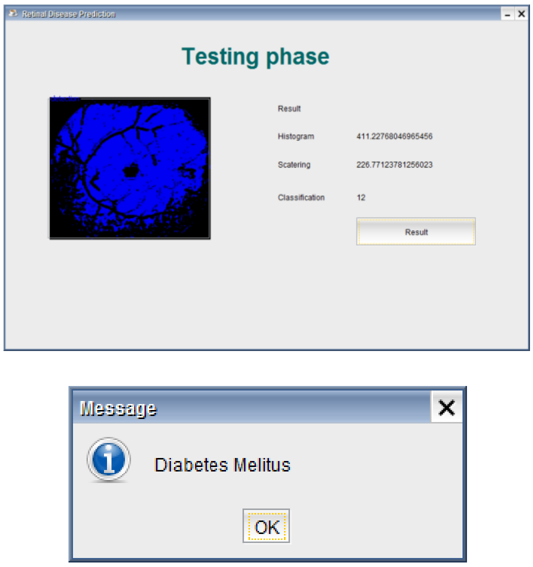

Fig 8.13 Testing phase of diabetic retinopathy

7. CONCLUSION

The method proposed in this paper give more speed for processing of each image. This increase in speed is due to the lower number of candidate pixel, the fast feature extraction and classification. The number of pixels to be processed is significantly reduced by considering the local maxima of the preprocessed image. We use the classifier setup obtained on the ROC training set, which proves the robustness of the proposed method. The fact that the performance difference between the currently proposed and previous method is its tolerance against noise corruption from different image sources. By adding optic disk detection step it is possible to distinguish the MA candidates. This cross section analysis based method can be used for other medical related image processing. It involves recognition of circular or slightly elongated structures of image. It is able to distinguish vessel bifurcations and crossings.

Further upgrades later on might incorporate the use of a superior calculation something like a Fuzzy neural system which can help in arranging the pictures well than the present utilized classifier individually. Aside from that, highlights like helpline or client manual ought to be given in the graphical UI, to be useful for the clients who probably won't be acquainted with innovative progressions and utilization of the application

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