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MICROANEURYSMS DETECTION ON RETINAL IMAGES USING DEEP CONVOLUTION NEURAL NETWORKS

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Abstract:

In India, the number of diabetic patients is increasing rapidly. With an increasing number of diabetic patients, several diseases like vision loss, skin diseases, kidney failures, heart attacks, and nerves are affected. Now in this project, we are focused on visual loss. Visual loss can be identified by early detection and treatment of illness. Diabetic retinopathy is the source of vision loss, and Micro aneurysms (MAs) are an early side effect of this illness. The fundus assessment is very useful at the starting stage of diabetic retinopathy. However, identifying MAs on retinal pictures is challenging for doctors since MAs regularly show up as little dim spots. Hence, many investigations on robotized MA recognition have been conducted. This study proposes a MA identifier that consolidates three existing methods: the double-ring filter, the shape index on the Hessian framework, and the Gabor filter. Be that as it may, because deep convolutional neural networks (DCNN) have shown predominant execution in picture acknowledgment studies, this study conducts automated MA recognition utilizing DCNN. We organized the proposed method with a two-step DCNN and three-layer insight with 48 elements for false positives (FPs) decrease features. In the two-step DCNN, the principal DCNN is for starting MA discovery, second DCNN is for FPs decrease. By applying the proposed strategy to the DIARETDB1 information base, the proposed technique shows perfect execution. The AI model can be continually refined and improved over time, helping to ensure its accuracy and effectiveness in detecting and diagnosing diabetic retinopathy. The AI model can be trained using deep learning algorithms to identify the MA's.

Keywords: Diabetic retinopathy,Micro aneurysms (MAs),Deep convolutional neural networks (DCNN),Image recognition,Fundus images

1. Introduction

In recent times, Sweden and other parts of the world have been faced with an increase in age and society related diseases like diabetes. According to recent survey [1], 4% of the country population has been diagnosed of diabetes disease alone and it have been recognize and accepted as one of the main cause of blindness in the country if not properly treated and managed. Early detection and diagnosis have been identified as one of the way to achieve a reduction in the percentage of visual impairment caused by diabetes with more emphasis on routine medical check which the use of special facilities for detection and monitoring of the said disease [1]. The effect of this on the medical personnel need not be over emphasized, it has lead to increase work load on the personnel and the facilities, increase in diabetes screening activities just to mention a few. A lot of approaches have been suggested and identified as means of reducing the stress caused by this constant check up and screening related activities among which is the use medical digital image signal processing for diagnosis of diabetes related disease like diabetic retinopathy using images of the retina.

Diabetes is a disorder of metabolism. The energy required by the body is obtained from glucose which is produced as a result of food digestion. Digested food enters the body stream with the aid of a hormone called insulin which is produced by the pancreas, an organ that lies near the stomach. During eating, the pancreas automatically produces the correct amount of insulin needed for allowing glucose absorption from the blood into the cells. In individuals with diabetes, the pancreas either produces too little or no insulin or the cells do not react properly to the insulin that is produced. The build up of glucose in the blood, overflows into the urine and then passes out of the body. Therefore, the body loses its main source of fuel even though the blood contains large amounts of glucose. Basically there are three types of diabetes, Type 1 Diabetes, is caused as a result of auto immune problem. The immune system of the body destroys the insulin producing beta cells in the pancreas leading to no or less production of the required insulin by the pancreas. Type 2 Diabetes is a result of malfunctioning of the beta cell itself. This malfunction includes non production of insulin or a situation known as insulin resistance. In insulin resistance, the muscles, fat and other cells do not respond to the insulin produced. Type 3 is known as gestational diabetes and only occurs during pregnancy. During this stage, the body resist the effect of insulin produced.

The effect of diabetes on the eye is called Diabetic Retinopathy (DR). It is known to damage the small blood vessel of the retina and this might lead to loss of vision. The disease is classified into three stages viz: Background Diabetic Retinopathy (BDR), Proliferate Diabetic Retinopathy (PDR) and Severe Diabetic Retinopathy (SDR). In BDR phase, the arteries in the retina become weakened and leak, forming small, dot-like haemorrhages. These leaking vessels often lead to swelling or edema in the retina and decreased vision. In the PDR phase, circulation problems cause areas of the retina to become oxygen-deprived or ischemic. New fragile, vessels develop as the circulatory system attempts to maintain adequate oxygen levels within the retina. This phenomenon is called neovascularisation. Blood may leak into the retina and vitreous, causing spots or floaters, along with decreased vision. In the SDR phase of the disease, there is continued abnormal vessel growth and scar tissue, which may cause serious problems such as retinal detachment and glaucoma and gradual loss of vision.

This research work is one of the method of applying digital image processing to the field of medical diagnosis in order to lessen the time and stress undergone by the ophthalmologist and other members of the team in the screening, diagnosis and treatment of diabetic retinopathy. This work determine the presence of BDR and PDR or otherwise in a patient by applying techniques of digital image processing on fundus images taken by the use of medical image camera by a medical personnel in the hospital.

2. Related Works

There have been an increase in the use of digital image processing techniques for the screening of DR after it was recommended as one of the method for screening DR at the conference on DR held in Liverpool UK in 2005 [1] . With this increase more work have been done to improve some of the existing screening method while new methods have also been introduced in order to really increase the sensitivity and the specificity of this method. Sensitivity refers to the percentage of abnormal fundus image classified as abnormal by the method while specificity can be defined as percentage of normal fundus image classify as normal. The higher these two factors the better the method. Most of the available work done can generally be categorized into screening of BDR and PDR while diagnosis of SDR have been left for the ophthalmologist. However only few work have really been done in the detection of microaneurysm and exudates, most work done are in vascular abnormalities detection using colour fundus images. In this section, some of these past works are review and the results obtained are also discussed. Vallabha et al in their work titled automated detection and classification of vascular abnormalities in diabetic retinopathy [8] applied the use of scale and orientation of selective Gabor filter to detect and classify the retina images into mild or severe case. Scale and angle analysis were used because of its ability to distinguish images by virtues of its variation across scales and orientation. The input image is first filtered through Gabor filter banks. The banks consist of several filters tuned to specific scales and orientation and the operation is performed in Fourier domain. The output of which is then analyzed. Detection of NPDR (PDR) is done by analyzing the width of the blood vessels. The presence of one local maxima in the plot of energy vs. orientation.

In the work done by Chanwimaluang and Fan [9] as an improvement to the tracking-based method done by Zhou et al , [The detection and quantification of retinopathy using digital angiograms [10]] proposed a four step algorithm Matched filtering, local entropy thresholding, length filtering and vascular intersection detection for detection and extraction of blood vessel in retina images. The blood vessel was first enhanced by the use of Matched filtering, based on the assumption that blood vessels usually have lower reflectance compared with the background. Entropy based thresholding was then used to distinguished between background and vessels in the generated Matched Filter Response [MFR] image of step one. Length filtering was then employed to eliminate misclassified pixels before the application of a 3 X 3 and 11 X 11 neighborhood windows to probe for branching points and intersection or crossovers. The Algorithm work very well with normal fundus images without lesions but perform poorly with images with lesions.

3. PROPOSED SYSTEM

The proposed method was structured by MAs detection using DCNN, reduction of false positives (FPs) using DCNN, and FPs reduction using 48 kinds of features**.** Several research groups have been developing automated MA detection methods using retinal images provided a comparison of several methods using the Retinopathy Online Challenge (ROC) database . We also propose a method that combines three MA detectors: double-ring filter, Gabor filter, and shape index based on Hessian matrix . These previous methods had to set many

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parameters. However, because the deep convolutional neural network (DCNN) is a breakthrough technique in object classification and pattern recognition, this study presents an MA detection method based on DCN

MAs were detected using DCNN. In was applied as the DCNN. It scans the entire image and performs MA prediction for every pixel based on the image patch, the size of which in our study was 21 x 21 pixels. To train this DCNN, we used 246 MAs. These included 83 and 163 MAs from the training images of the DIARETDB1 and ROC databases [6], respectively. We augmented from 246 to 2460 MA patches by using horizontal inversion, vertical inversion, parallel moving, smoothing, and luminance adjusting. Therefore, we used a total of 2460 normal patches, which included no MAs, to train this DCNN

3.1.1 Working

Convolutional neural network (CNN) is a type of feed-forward artificial neural network where the individual neurons are tiled in such a way that they respond to overlapping re-gions in the visual field". They are biologically-inspired invariant of Multilayer Per-ceptrons (MLP) which are designed for the purpose of minimal preprocessing. These mod-els are widely used in image and video recognition. When CNNs are used for image recog-nition, they look at small portions of the input image called receptive fields with the help of multiple layers of small neuron collections which the model contains. The results we get from this collection are tiled in order for them to overlap such that a better represen-tation of the original image is obtained; every such layer repeats this process.

This is the reason they are able if the input image is translated in any way. The outputs of neuron clus-ters are combined by local or global pooling layers which may be included in convolutional networks. Inspired by biological process, convolutional networks also contain various com-binations of fully connected layers and convolutional layers, with point-wise nonlinearity applied at the end of or after each layer. The convolution operation is used on small regions so as to avoid the situation when if all the layers are fully connected billions of pa-rameters will exist. Convolutional networks use shared weights in the convolutional layers i.e. for each pixel in the layer same filter (weights bank) is used which is advantageous because it reduces the required memory size and improves performance. CNNs use rela-tively less amount of pre-processing as compared to other image classification algorithms, meaning that the network learns the filters on its own which are traditionally manually-engineered in other algorithms. CNNs have a major advantage over others due to the lack of a dependence on prior-knowledge and the difficult to design hand-engineered features.

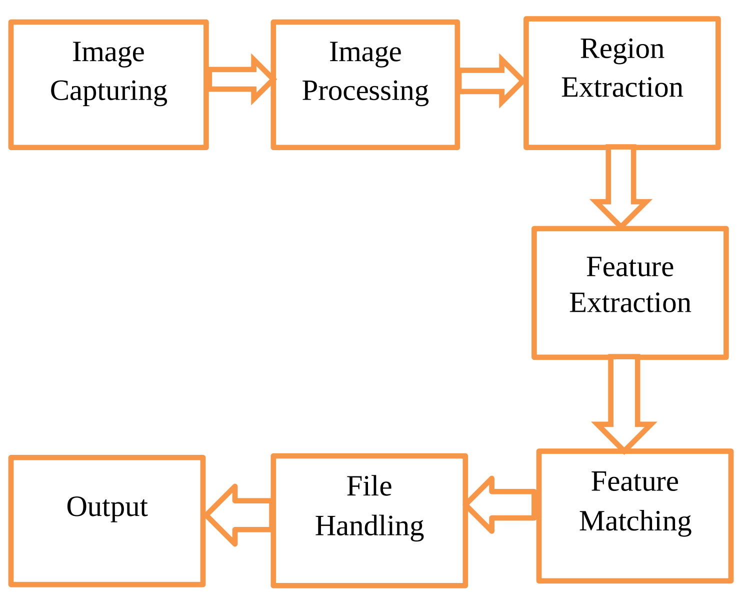

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Figure 1:- Data Flow of the Proposed Method

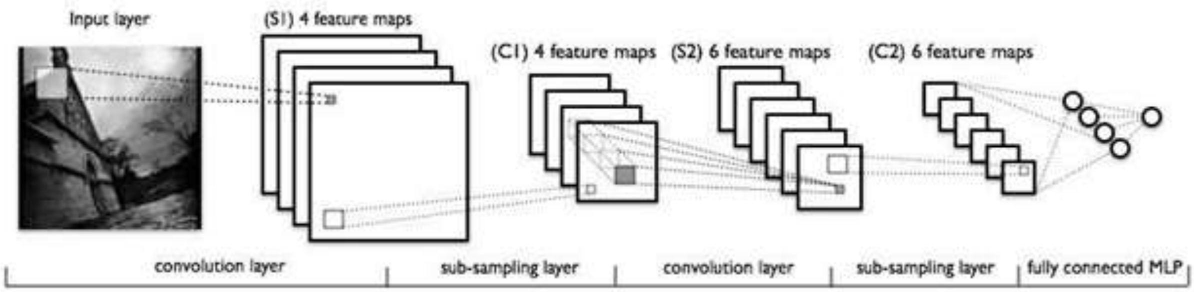

Figure 2: Deep Convolution Neural Network(DCNN)

4. Results and Discussion

This chapter starts with presentation of result obtained from diagnosis of twenty five fundus images which were used for detection and diagnosis. For each set of data, the Receiver Operator Characteristics (ROC) curve is also presented and this is shortly followed by the analysis of the result and some of the thresholds used in obtaining the ROC.

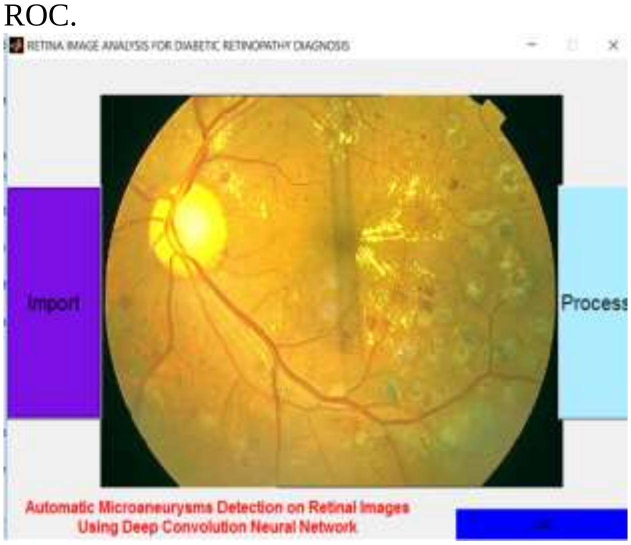

Figure 3:- Input Image

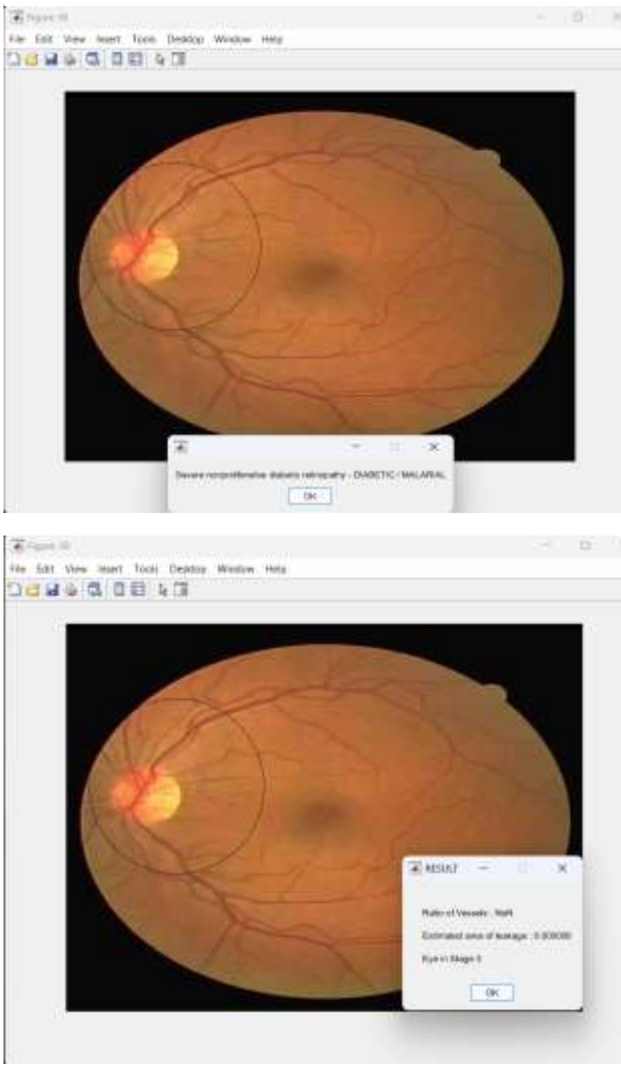

Figure 4:- Output Images

5. Conclusion

In test images from the DIARETDB1 database, we tested the proposed method. Fig. 4 shows free-response receiver operating characteristic (FROC) curves. Overall performance of the proposed method was superior to four other methods, as shown in Fig. 4. When the number of FPs was fewer than three, the proposed method was the best. However, when the number of FPs was more than three, our previous method was slightly better. In this study, the previous FPs reduction method was applied to the proposed method with no change. Therefore, we would have to improve that method. The performance results of the proposed method showed that the sensitivity was 84% of 8.0 FPs per image. This result was the same as that of the previous method . One of the problems of the previous method was the existence of too many rules. Several parameters such as the threshold values of double-ring filter, Gabor filter, and shape index, as well as parameters for combining MA detectors, were all experimentally determined from test results. In the proposed study, these parameters could be automatically learned. The method could be further improved by optimizing the network architecture and adding a post-processing method.

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