Eye Fundus Image Analysis for Detection and Diagnosis of Diabetic Retinopathy & Maculopathy using Deep CNN

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Abstract - Diabetes, characterized by insufficient insulin production, gradually affects the retina, leading to diabetic retinopathy and maculopathy. These conditions result in deteriorating vision, highlighting the importance of analyzing retinal images obtained through fundal cameras. The objectives of this study are to detect blood vessels, identify hemorrhages, and classify diabetic retinopathy into normal, moderate, and non-proliferative diabetic retinopathy (NPDR). Classification is based on the detection and quantification of blood vessels and hemorrhages within retinal images. Blood vessel segmentation relies on contrasting vessel and background intensities, while hemorrhage detection employs density analysis and bounding box techniques. Classification of disease stages utilizes Random Forests, considering parameters like area and perimeter of vessels and hemorrhages. Accuracy assessment demonstrates 90% accuracy in classifying normal cases and 87.5% accuracy in identifying moderate and severe NPDR cases. This approach holds promise for effective diagnosis and monitoring of diabetic eye diseases using deep learning techniques.

Keywords- retina, blood vessel, hemorrhages, classification, diabetic retinopathy, diabetic maculopathy.

I. INTRODUCTION

Diabetes is a disease which occurs when the pancreas does not secrete enough insulin or the body is unable to process it properly. As diabetes progresses, the disease slowly affects the circulatory system including the retina and occurs as a result of long term accumulated damage to the blood vessels, declining the vision of the patient leading to diabetic retinopathy. After 15 years of diabetes about 10% of people become blind and approximately 2% develop severe visual impairment. According to an estimate by WHO, more than 220 million people worldwide have diabetes [1]. It is the sixth largest cause of blindness among the people of working age in India, making it the world's diabetic capital.

Retinal images acquired through fundal camera with back- mounted digital camera [2] provide useful information about the consequence, nature, and status of the effect of diabetes on the eye. These images assist ophthalmologist to evaluate patients in order to plan different forms of management and monitor the progress more efficiently [3]. The retinal microvasculature is unique in that it is the only part of human circulation that can be directly visualised non-invasively in vivo, and can be easily photographed for digital image analysis [2].

Detecting diabetic retinopathy and diabetic maculopathy using deep convolutional neural networks (CNNs) represents a significant advancement in medical imaging and diagnosis. Diabetic retinopathy and maculopathy are two common complications of diabetes that can lead to vision impairment or even blindness if left untreated. Leveraging deep CNNs, a powerful subset of artificial intelligence, enables accurate and efficient detection of these conditions from retinal images.

The introduction of deep CNNs in this context signifies a paradigm shift in medical diagnostics, offering clinicians a reliable tool for early detection and intervention. These neural networks can automatically analyze retinal images with remarkable precision, detecting subtle abnormalities indicative of diabetic retinopathy and maculopathy. By effectively capturing complex patterns and features within the images, CNNs facilitate a thorough examination of retinal health, aiding in timely medical interventions to prevent vision loss.

This paper aims to explore the application of deep CNNs in detecting diabetic retinopathy and maculopathy, highlighting their potential to revolutionize diabetic eye care. Through an in-depth analysis of CNN architectures, training methodologies, and validation techniques, we elucidate the effectiveness and reliability of these models in clinical practice. Moreover, we discuss the challenges and future directions in deploying deep CNNs for widespread adoption in diabetic retinal screening programs, emphasizing the importance of interdisciplinary collaboration between clinicians, technologists, and policymakers.

Diabetic Retinopathy:

Diabetic retinopathy is a common complication of diabetes and a leading cause of blindness in adults. It occurs when high blood sugar levels damage the blood vessels in the retina, the light-sensitive tissue at the back of the eye. In the early stages, called non-proliferative diabetic retinopathy, small blood vessels in the retina weaken and leak fluid or blood, causing swelling and leading to vision problems. As the condition progresses, new abnormal blood vessels may grow on the surface of the retina, a stage known as proliferative diabetic

retinopathy, which can lead to severe vision loss or even blindness if left untreated.

Diabetic Maculopathy:

Diabetic maculopathy specifically affects the macula, the central part of the retina responsible for sharp, detailed vision needed for activities like reading and driving. It is a complication of diabetic retinopathy and occurs when fluid leaks into the macula, causing swelling (macular edema) or when abnormal blood vessels grow near the macula. Diabetic maculopathy can result in blurred or distorted vision, difficulty reading, and central vision loss. It can occur at any stage of diabetic retinopathy and is a leading cause of vision impairment in people with diabetes.

In summary, diabetic retinopathy and maculopathy are serious complications of diabetes that can lead to vision loss or blindness if not detected and treated early. Regular eye exams and timely intervention are essential for managing these conditions and preserving vision in individuals with diabetes.

In summary, the integration of deep CNNs for the detection of diabetic retinopathy and maculopathy represents a transformative approach in diabetic eye care. By harnessing the power of artificial intelligence, we can enhance the efficiency, accuracy, and accessibility of retinal screening, ultimately improving patient outcomes and reducing the burden of diabetic eye diseases on healthcare systems worldwide.

The key innovation of CNNs lies in their use of convolutional layers, which apply filters or kernels to input data to extract relevant features such as edges, textures, and shapes. Through the process of training on large datasets, CNNs automatically learn to detect and recognize meaningful patterns in the input images.

RELATED WORK

Earlier, Otsu, (1979) [4] presented a non-parametric and unsupervised method of automatic threshold selection for picture segmentation. This utilises only the zeroth- and the first-order cumulative moments of the gray-level histogram. Chaudhuri et al., (1989) [5] addressed the problem of detecting blood vessels which have usually poor local contrast and emphasises that existing edge detection algorithm yield unsatisfactory results. They proposed an operator for feature extraction based on optical and spatial properties of the object to be recognized. Patton et al., (2006) [2] outlined the segmentation of retinal landmarks upon which retinal digital image analysis is based. Hatanaka et al., (2007) [6] described an improved method for detecting hemorrhages in fundus images. The overall detection scheme consisted of six stages - image digitisation, image normalization, extraction of optic nerve head, detection of hemorrhages candidates, elimination of false positives (FP) in blood vessels, and elimination of FPs by feature analysis. However, the method for elimination of the blood vessels for the successful detection of hemorrhage candidates was not dealt here. Yun et al., (2008) [3] proposed automatic classification of different stages of diabetic retinopathy - mild non-proliferative retinopathy, moderate non-proliferative retinopathy, severe non-proliferative retinopathy and proliferative retinopathy using neural network from six features extracted from the retinal images.

A new method of blood vessel extraction which is an improvement over the previously developed matched filter, a new method of hemorrhages detection and classify the retinal cases using an advanced non- parametric method with higher classification accuracy. The objectives of this work are: (i) detection of blood vessels, (ii) detection of hemorrhages, and (iii) classification of the detections into normal, moderate non-proliferative diabetic retinopathy (NPDR) and severe NPDR.

The paper is organised as follows: section II discusses the proposed algorithms for blood vessel, hemorrhage detection and a brief discussion on the Random Forest classification. Results of the algorithmic implementation on the data are presented in section III, followed by discussion and conclusions in section IV

In recent years, computer vision has leveraged deep learning for object detection in various medical imaging tasks. Budak et al. pioneered the extraction of microaneurysms using Gaussian filtering and other techniques, feeding these regions into a convolutional neural network (CNN) for classification. Omar et al. utilized Local Binary Pattern (LBP) to extract texture features of hard exudates, inputting them into an artificial neural network (ANN) for detection. Tan et al. developed a ten-layer fully CNN model to detect microaneurysms, hemorrhages, and hard exudates at the pixel level in fundus images. Sudha et al. employed a VGG-19 deep neural network trained on a feature set derived from the KAGGLE fundus image dataset, with segmentation methods proposed to detect various retina defects. Meanwhile, Kwasigroch et al. introduced a method for automatic diabetic retinopathy detection, integrating special class coding during CNN training and using quadratic weighted kappa kernel to assess model performance. They adopted a symmetric convolutional structure to enhance feature extraction, addressing issues like sample imbalance and overfitting. DenseNet architecture was utilized to ensure efficient training, maximizing information flow between layers through dense connections and concatenating features in dense blocks followed by transition layers, culminating in a classification layer. This approach represents a comprehensive utilization of deep learning techniques for accurate and efficient detection and diagnosis of diabetic retinopathy and related pathologies in fundus images.

EXSISTING METHOD

One existing method for eye fundus image analysis for the detection and diagnosis of diabetic retinopathy and maculopathy involves employing deep Convolutional Neural Networks (CNNs). In this approach, large datasets of labeled fundus images are collected and preprocessed to enhance quality and standardize features. A deep CNN architecture, often pretrained on large-scale image datasets, is then fine-tuned on the fundus image dataset to learn discriminative features indicative of diabetic retinopathy and maculopathy. During training, the model optimizes parameters to accurately classify images into different disease categories. Following training, the model is validated on a separate dataset to assess its performance metrics such as accuracy, sensitivity, and specificity. Once validated, the trained model can be deployed to analyze new fundus images, aiding ophthalmologists in diagnosing and managing diabetic eye diseases, thus integrating into clinical workflows for real-world application.

1) The anti-parallel pairs can be approximated by piecewise

K ' (x, y) = Ki (x, y) - mi

linear segments due to small curvatures present in the blood vessels.

2) Vessels have lower reflectance compared to other retinal surfaces, so they appear darker relative to the background. It was observed that these vessels almost never have ideal step edges. Although the intensity profile varies by a small amount from vessel to vessel, it may be approximated by an inverted Gaussian curve as given by (1)

Now, template matching can be employed to detect the blood vessel

For applying the entire algorithm of the matched filter, the G-plane of the image is considered (since it yields better results). After enhancing the contrast of the image, median filter is used to remove the noise. The designed matched filter is applied on the image to detect the blood vessels. Finally, a binarised image is obtained by thresholding.

f(x, y) = A -k exp› -

discontinuous lines in the detections. To improve on this,perception based binarisationwas carried out.

The straight line passing through the center of the of the blood vessel in a direction along its length, σ = spread of the intensity profile, A = gray level intensity of the local background, and k = measure of reflectance of the blood vessel relative to its neighbourhood.

3) Although the width of a vessel decreases as it travels radially outward from the optic disk, such a change in vessel caliber is a gradual one. The widths of the vessels are found to lie within a range of 2-10 pixels (36-180 μm).

The matched filter has the same inverted Gaussian response as the gray level profile of the blood vessel. The design of the matched filter is as follows: assuming that all blood vessels are of equal width, the Gaussian curve is truncated at u= ± 3s , u is a point in the rotated coordinate system, the length of piece- wise linear segment L=17, an angular resolution of 7.5º to span 225 degree directions were checked; for 75°, 90° and 105°, pixels in vertical direction and for 120°, 135° and 150°, pixels in 135 degree and 315 degree directions were checked. If gray value multiplied by a factor (say 1.2) was greater than the threshold, then that pixel was counted as blood vessel. Finally, the blood vessels are extracted pixel by pixel.

II. RESULTS

A. Blood Vessel Extraction

In a RGB retinal image, contrast is greater when the green channel alone is utilised in fundal image feature extraction. Adaptive histogram equalisation was used to enhance the contrast of the features of interest against the background. A 3 x 3 median filter was used to remove the random noise as displayed in Fig. 1. Blood vessels were detected (as shown in white pixels against black background in Fig. 2) after applying the designed matched filter. The matched filtered image was converted to binary equivalent with a global threshold value of 0.1490 determined empirically (Fig. 3), where presence of discontinuous lines were observed. Perception based binarisation was carried out by generating a matrix, to store the matched filter number, and then the pixel gray level in that particular direction, multiplied by a factor, was checked for a threshold level.

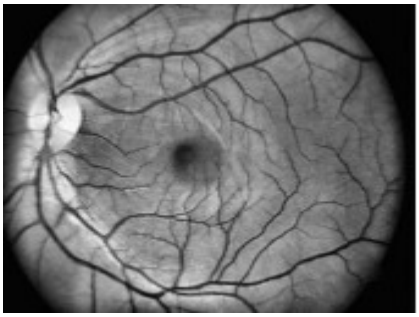


Figure 1. Retinal image after removing the noise.

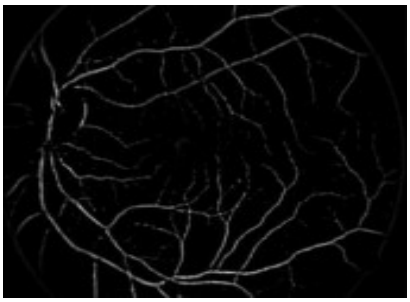


Figure 2. Image obtained after passing through the matched filter.

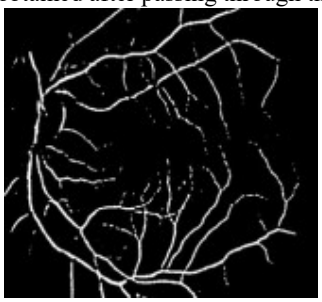


Figure 3. Figure 3: Binary image after thresholding.

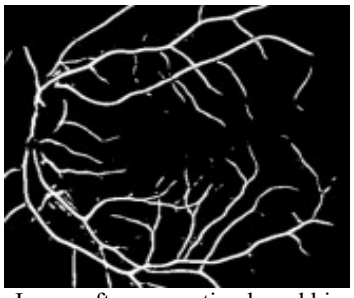


Figure 4. Image after perception based binarisation.

B. Hemorrhage Detection

Two smoothened images of different window sizes were obtained using smoothening filter and differenced to extract blood vessels and detect hemorrhage candidates. The image was thresholded using a global thresholding value as shown in the Fig. 5. The false positive blood vessels were eliminated using bounding box technique. The ratio of major axis length and the minor axis length of each segment were calculated and those with higher values (>1.57) were eliminated. The hemorrhages were detected and their density was calculated by finding the number of white pixels in the image (Fig. 6).

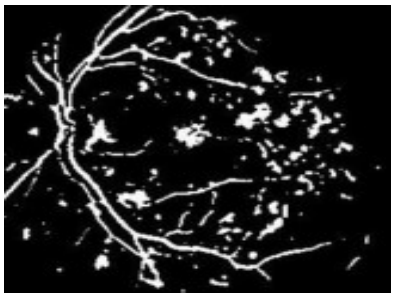


Figure 5.Thresholded Image obtained .

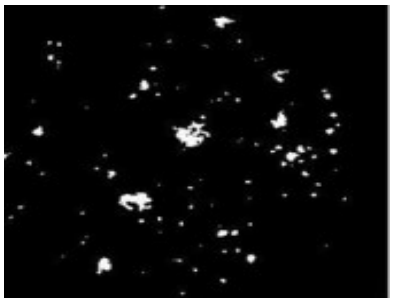


Figure 6. Hemorrhages in the retinal image.

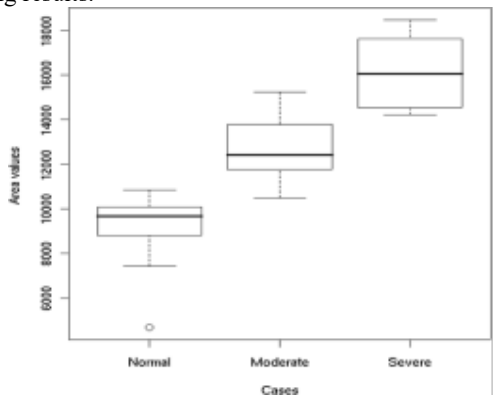
C. Classification of different stagges of Diabetic Retinopthay

Six features – area and perimeter in each of the R, G, B components of the blood vessels and hemorrhages were extracted. Area is the number of white pixels (blood vessel and hemorrhage candidates) present within the vessels and perimeter was determined by the number of pixels present on the periphery of the vessels. These extracted features were used as inputs to the RF classifier for categorizing the three stages of retinal images. The range of the area and perimeter values of blood vessels and hemorrhages for each stage of the diabetic retinopathy with the different RGB layers are shown in Table II and III.

The box plots of the area and perimeter ranges of the extracted features for different kinds of images are shown in Fig. 7 and 8. The box plot function in R statistical software provided comparisons between each stage of diabetic retinopathy. For the purpose of training and testing the classifiers, the 65 retinal images were divided into two sets – a training set of 39 arbitrary samples and a test set of 26 samples. A graphical representation of training and testing data set, and the number of testing data that is correctly classified is shown in Fig. 9. Table IV gives detail of the training and test data used for classification.

III. CONCLUSION

The analysis revealed that TP=14, FP=0, TN=9, FN=2, sensitivity=0.875, specificity=1, positive predicted value (PPV)=1, and negative predicted value (NPV)=0.8181. The unknown test cases were classified correctly by 88.46%. This shows that the proposed method of classification based on area and perimeter of blood vessels and hemorrhages produce motivating results.



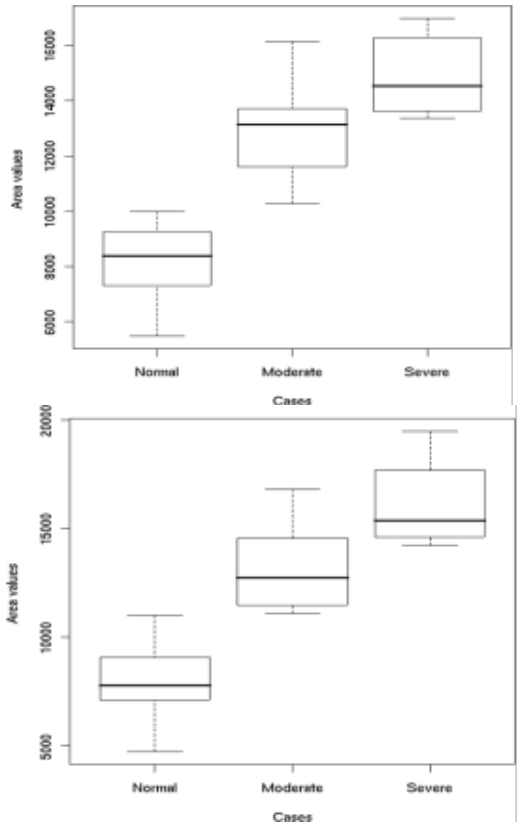


Figure 7. Area values of blood vessels and hemorrhages in RGB layers.

Sinthanayothin et al., (2003) reported sensitivity of 80.21% and specificity of 70.66% while differentiating diabetic retinopathy from normal images. Here, the retinal images we preprocessed using adaptive, local, and contrast enhancement. They adopted a neural network based classification.

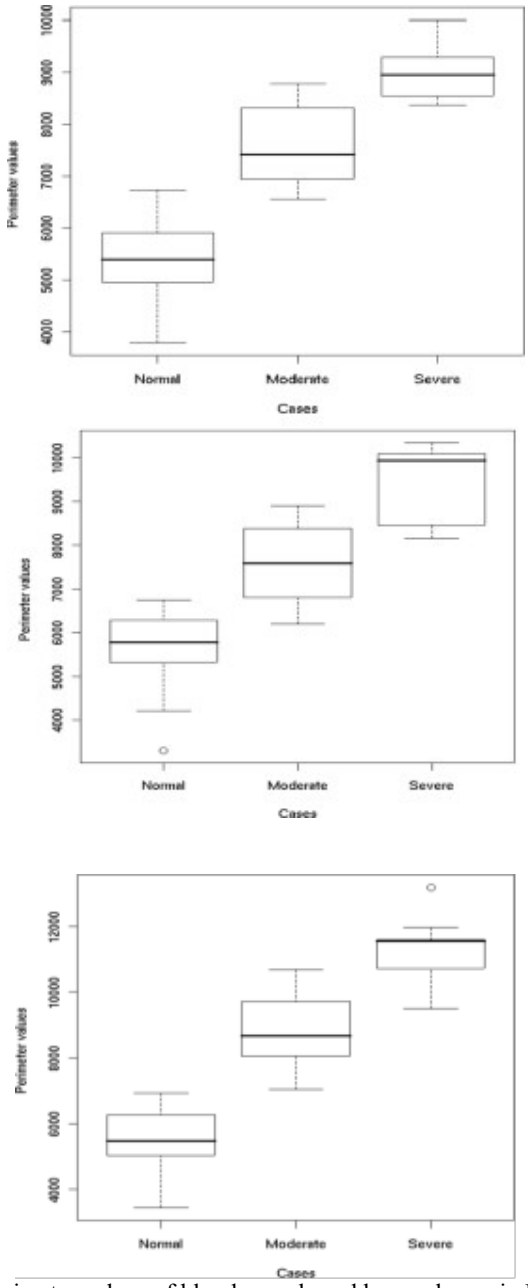


Figure 8. Perimeter values of blood vessels and hemorrhages in RGB layers.

Similar results have been reported by Larsen et al., (2003), where hemorrhages and microaneurysms were detected to diagnose diabetes. Their method had 71.4% specificity and 96.7% sensitivity in detecting diabetic retinopathy. The results obtained from our method of feature extraction and classification scheme revealed that normal cases were classified with 90% accuracy while moderate and severe NPDR cases were 87.5% accurate, which are better in terms of sensitivity, specificity and positive prediction accuracy considering three cases during classification (normal, moderate and severe) compared to the four cases (in Yun et al., 2008) [3] namely, normal, moderate NPDR, severe NPDR and proliferative NPDR. However, the scope and direction for further work are to include more instances of retinal images to construct a robust classifier for detecting different stages

of diabetic retinopathy (i.e. for training and testing) to achieve higher accuracy. The efficiency of the correct classification can also be improved by extracting more number of features from the images.

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