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Research paper

Early Diagnosis of Retinopathy of Prematurity using Image Processing

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Abstract

Retinopathy of prematurity may lead to blindness in neonates. Retinopathy of prematurity (ROP) is responsible for over 30000 blind children worldwide. Retinopathy of prematurity (ROP) mainly observes premature infants with low birth weight and a major cause for childhood blindness due to failure in early-stage detection. The proposed study enhances the feasibility of prediction of the Retinopathy of Prematurity from the retinal fundus image. It includes the retinal fundus image enhancement, retinal vessel segmentation and calculation of retinal vessel tortuosity. Finally, we use Support Vector Machine for classification of ROP. Experiment shows promising results, 92.38 % accuracy, a sensitivity of 93.83%, and a specificity of 91.68%.

Keywords: *Retinopathy of Prematurity, ROP, retinal vessels*

1. Introduction

In prediction of disease, diagnosis plays a very important role. Worldwide, retinopathy of prematurity is responsible for childhood blindness and mostly occurs in preterm neonates or neonates with low birth weight [1]. Retinopathy of prematurity is majorly observe in premature infants due to abnormal growth of blood vessels of retina that may lead to scarring, retinal detachment and blindness if untreated[2]. Retinopathy of Prematurity is identified through examination of dilated retina and can be cure by laser photocoagulation if detected at early stage. Moreover, the number of preterm babies at risk of ROP is increasing because of increase in survival rates for preterm infants, while the availability of adequately-trained ophthalmologists for ROP screening and treatment is decreasing[3]. So, it is very much required to develop a non-invasive method for diagnosis of Retinopathy of prematurity.

2. Literature Review

Retinopathy of Prematurity is major concern in infants having low birth weights, affected infants needs immediate intervention. Recent research has focused on applying various machine learning models such as logistic regression, Support Vector Machines (SVM) and Convolutional Neural Networks (CNN) for accurate classification of plus versus non-Plus disease in ROP.
Zhang et al. [4] shows the effective use of CNNs in achieving high accuracy in classifying retinopathy of prematurity, while Gupta et al. [5] shows the comparison between SVM, neural networks, and logistic regression. Results conclude that neural networks outperform over other methods. Jiang et al. [6] proposed a hybrid model by combining SVM and deep learning features for improved classification accuracy. Feature extraction methods have also been explored, with Lee et al. [7] introducing a novel approach based on vascular morphology and fractal analysis, Wang et al. [8] using local binary patterns and wavelet transforms for classifying retinopathy of prematurity. Vessel-based features are combined with texture analysis by Chen et al. [9] to improve results. As segmentation of vessels plays an important role in extraction of features, Liu et al. [10] designed a structure-adaptive segmentation algorithm. Patel et al. [11] proposed a graph-based segmentation approach, and Liang et al. [12] presents a multi-scale segmentation technique which helps in feature extraction.
Ensemble learning techniques for improved classification accuracy was shown by Jiang et al. [13], while Kim et al. [14] proposed a deep learning framework incorporating attention mechanisms for feature extraction and refinement. Wu et al. [15] showcase the use of transfer learning to adapt pre-trained models for ROP classification, shows the promising results. Other studies have focused on optimizing techniques for feature extraction. For instance, Huang et al. [16] introduced a method for combining texture and shape features to enhance

discrimination between Plus and non-Plus disease, while Li et al. [17] shows the use of wavelet-based features for improved classification performance. Moreover, segmentation techniques are improved, Zhou et al. [18] proposed a region-growing algorithm which is incorporating spatial information for accurate vessel segmentation which helps in calculating the tortuosity of retinal blood vessels.
A deep learning-based approach for automatic segmentation of optic disk was designed by Wang et al. [19]. Further work by Tan et al. [20] explored the use of fuzzy C-means clustering for improved feature extraction, while Guo et al. [21] showcase a method based on principal component analysis (PCA) for dimensionality reduction in Plus Disease classification. Zhang and Wang [22] show the use of gradient-based features combined with SVM for accurate classification of ROP, while Yang et al. [23] proposed a framework based on genetic algorithms for optimizing feature selection. Segmentation methods have also been refined, Wang et al. [24] presenting a hybrid segmentation approach for integrating level sets and deep learning, and Liu et al. [25] introducing a method based on active contour models for precise vessel delineation. These advancements in classifying retinopathy of prematurity highlight the potential for automated diagnosis systems to improve ROP management and results in early prediction of retinopathy of prematurity.

3. Methodology

I. Color Channel Selection

The retinal image comprising three components: Red, Green, and Blue. Among these, the Green channel (FG) exhibits the highest contrast compared to the other two channels, making it the preferred choice for blood vessel extraction. Meanwhile, Red channel is suitable to mark the region of interest because it offers a more unvarying brightness distribution than the remaining channels [26].

II. Preprocessing of Image

Uneven lighting conditions during image capture may reduce contrast, which is a common challenge in image processing. Infant retinal images generally have low gray-level contrast, which can result in issues such as noise, uneven brightness from the annular light source, and unbalanced reflections from the retinal surface. These conditions may affect the classification process, as lesions and vessels in some of the area are not visible clearly. Another issue is, there is a difference between preterm infant and adult retina as shown in figure 1.
Enhancement of image will improve the quality of visual appearance. It will reduce the noise from image, reduces blurring, and helps to increase contrast.

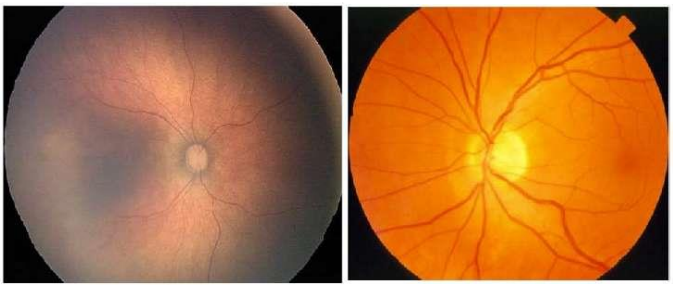

Fig. 1: (a) Retinal fundus image of infant (b) Retinal fundus image of adult

Enhancement using Guided Filter
The most common method for enhancement of image contrast if Adaptive Histogram Equalization (AHE). Adaptive Histogram Equalization maps the pixel's short range to pixel's wide range and also generates strong edges. AHE is a very effective method for contrast enhancement, but it is very sensitive to noise. Therefore K.L. Nisha Sreelekha et. Al. propose a method, enhancement using guided filter, which will preserve edges as well as smoothen the image. This method is used to reduce flat region noise. To make vessels more brighter as compared to background, the green channel (FG) of image is inverted (IG). [26].
Following are the steps to follow for enhancement using guided filter:
Guided Filtering: A guided filter with radius 3 x 3 is used to filter the input image IG. Small filter size is selected to smooth identical areas and it also preserve edges, thereby avoiding the amplification of random noise pixels. The resulting smoothened image is denoted as IGF.
Base Layer Extraction: A two-dimensional Gaussian filter with a standard deviation of 16 is used to obtain base layer ILP.
Detail Layer Extraction: To obtain detail layer, subtract base layer from guided filtered image.
This layer to be stored as it contains details of edges.
Amplification: to enhance the details, detail layer is multiplied with constant. Then the resultant layer is added with guided filtered image.

$$IGFE = k * (IGF - ILP) + IGF, \quad k > 1 \tag{1}$$

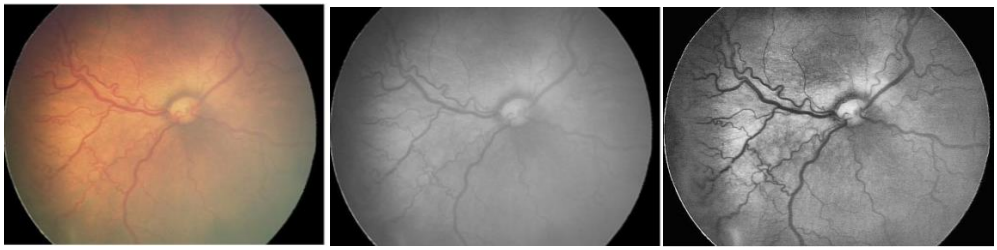

Fig. 2: (a) Input image (b) Enhancement using Adaptive Histogram Equalization (c) Enhancement using Guided Filter

In terms of contrast improvement, guided filter works better as compared to AHE as shown in figure 2. The comparison of performance of guided filter enhancement and AHE is done using various quality evaluators such as Entropy (Ent) and Standard Deviation (SD). Table 1 shows that, the guided filter-based enhancement is better than AHE in terms of quantitative parameters.

Table 1: Comparison of Enhancement Methods

Image No.	SD_AHE	SD_AHE_GFE	Ent_AHE	Ent_AHE_GFE
1	1.066114	1.579466	1.893423	2.357436
2	1.271867	1.758115	1.524808	2.274738
3	1.091649	1.66278	1.326686	1.963951
4	1.228643	1.816548	1.220855	2.029794
5	1.056489	1.533038	0.757092	1.574546
6	0.053171	0.942021	0.007671	0.679409
7	1.188325	1.701176	0.717769	1.775557
8	1.108419	1.576088	1.863148	2.352882
9	1.276176	1.789106	1.635998	2.372441
10	1.374288	1.97326	1.382543	2.305773
Avg	1.0715141	1.6331598	1.2329993	1.9686527

Vessels Tortuosity Analysis

Vessel tortuosity calculation is based on vessel centreline. Select the centre of ONH and its diameter with circumference with radius of 50 pixels.

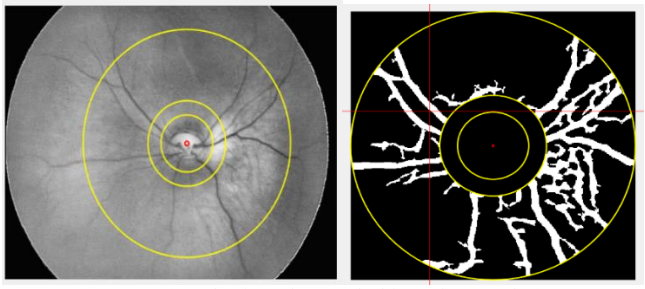

Fig. 3: (a) selection of ONH (b) binary image of (a)

The circumferences are centred on the ONH with radiuses of 1 time, 1.5 times and 4 times the radius of ONH. Select endpoints of the vessel of an interest in the binary vessel map (one vessel at a time) as shown in figure 4.

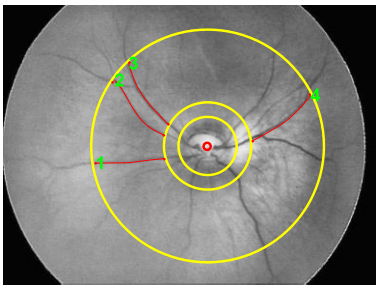

Fig. 4: Selection of endpoints of vessels

After selecting vessels, we are calculating parameters such as arch length, chord length, standard deviation etc. Values of this parameters are shown in Table 2. Table 2 contains following information:

- Vessel Num: Number of the vessel.
- Name: Name of the image (this becomes useful for integrating result from different images).
- Vessel Tortuosity Index (VTI): main measure of tortuosity. Calculation has to be done using following equation 2.

$$VTI = \frac{0.N.M.L_A 1SD_\theta}{L_C} \; M = \frac{1}{IP+2} \sum_{I=1}^{IP+2} \frac{L_{Ai}}{L_{Ci}} \tag{2}$$

Where, SDθ is standard deviation, number of critical points are represented with N. Average ratio of length of arch to its length of chord is represented as M. Finally, LA and LC are the length of arch and length of chord, respectively.

Table 2 and 3 contains the information such as Density Index, Distance Measure, number of Inflection points and Mean absolute curvature, Arch length, chord length and standard deviation, which need for calculation of tortuosity.

Table 2: Features Extracted from Image

Vessel No.	Image Name	Vessel Tortuosity Index (VTI)	Num Inflection Points (VII)	Density Index (DI)	Distance Measure (DM)	Mean Absolute Curvature (MAC)
1	Image1.jpg	0.027947497	2	0.008493	1.001174	0.000834
2	Image1.jpg	0.125785733	2	0.008087	1.022489	0.003403
3	Image1.jpg	0.097761156	2	0.007996	1.014511	0.001813
4	Image1.jpg	0.08744504	3	0.007888	1.011431	0.001943

Table 3: Features Extracted from Image

Vessel No.	Image Name	Standard Deviation	Num Inflection Points	Num Critical Points	Length of Arch	Length of Chord
1	Image1.jpg	0.027883	2	1	118.0203	117.8819
2	Image1.jpg	0.120022	2	1	129.5866	126.7364
3	Image1.jpg	0.096362	2	1	126.8727	125.058
4	Image1.jpg	0.086445	3	1	128.2472	126.7978

For each segment of skeletonized vessel tree, tortuosity is calculated. As number of vessel segments varies across images, the dimensions of these features also differ. To create a uniform feature vector representing each image, the average of tortuosity values is used to compress the segmental features effectively. For the entire vessel tree, single value is considered for leaf node and vessel density. This approach targets to classify images into two categories, affected with retinopathy of prematurity and non-affected with retinopathy of prematurity. Ground truth labelling is performed by a clinical expert. The classification is based on feature vectors extracted from these features using Support Vector Machine. The model achieved 92.38 % accuracy, a sensitivity of 93.83%, and a specificity of 91.68% by comparing the predicted output of the classifier with the ground truth labelled by the clinical expert. Salih et. al. proposed a method for classification of retinopathy of prematurity. Various classifiers, such as VGG-19, ResNet-50, EfficientNetB5 and CNN were used. The classification models achieved the accuracies 77.93, 83.79, 85.71, and 87.27% [27].

4. Conclusion

Identification of Retinopathy of Prematurity is one of the major challenges in current scenario. However, the proposed algorithm has shown a promising approach to classify the ROP condition. The results were compared with the clinical evidence by the expert clinician. The use of Adaptive Histogram Equalization followed by Guided filter method to enhanced the retinal image and results the 92% accuracy. Although the implementation of this algorithm on higher sample size a future prospect and integration of this program with any exiting retinal image system could be more effective way to give more societal benefit.

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