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Bright Lesion Detection in Retinal Fundus Images for Diabetic Retinopathy Detection Using Machine Learning Approach

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ABSTRACT

The objective of the project is the detection and classification of bright exudates lesions in fundus images of eyes depending on the number of bright lesions present. Diabetic Retinopathy (DR) is a condition caused by diabetes which leads to microvascular difficulties and microaneurysm development. These are the primary underlying indicators of DR in the early stages. The proposed model helps make a prediction whether Diabetic Retinopathy can be classified on the basis of the amount of exudates present in the retinal fundus images. The model will also help in predicting whether there are less number or high number of exudates present. For the detection of exudates, several steps have been followed including resizing of images, extracting the blue channels, feature extraction using Local Binary patters (LBP), and classification using SVM. IDRID dataset has been used for performing the same task.

Keywords
Diabetic Retinopathy, Exudates, LBP, SVM, IDRID

Introduction

Diabetic Retinopathy or DR is a severe eye condition which is caused by diabetes and affects the eyesight. It is causes the damage to the light-sensitive tissue present in the retina which is located at the back of the eye.Early symptoms of DR consist of dark areas of blurriness, and the floaters of vision and it causes difficulty in perceiving and identifying the colors. At the later stages DR may become severe and blindness may occur. The early stage is the non-proliferative diabetic retinopathy (NPDR) which mainly consists of symptoms like microaneurysms and exudates.

The different grades in which DR is mainly classified into are – Mild, Moderate and Severewhich depends on the number of lesions present in the eye. As the only way to detect NPDR is by examination of fundus images directly or indirectly using an ophthalmoscope by a trained ophthalmologist currently this problem can be overcome by using machine learning algorithms in order to assist in correctly detecting and classifying DR in the early stages.The main idea behind this proposed method is to create a machine learning model that will be able to identify the diabetic retinopathic (Exudates affected) images.

In this paper, the main focus is on the early detection of DR by finding exudates in fundus images. The exudates are a form of yellowish fluid which deposits as hard white spots in the macula. The main steps of the model consist of pre-processing of the input coloured images and division into patches, extraction of the affected features and finally classifying the images. The images of the healthy eye and the retinopathic eye have been shown in the Figure 1.1 and Figure 1.2 respectively.

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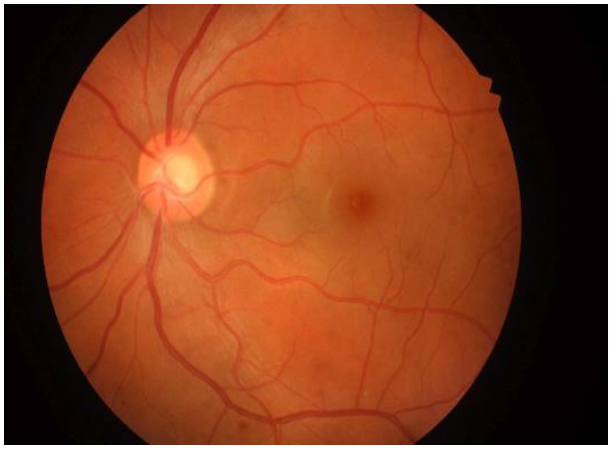

Figure 1.1. Healthy Eye

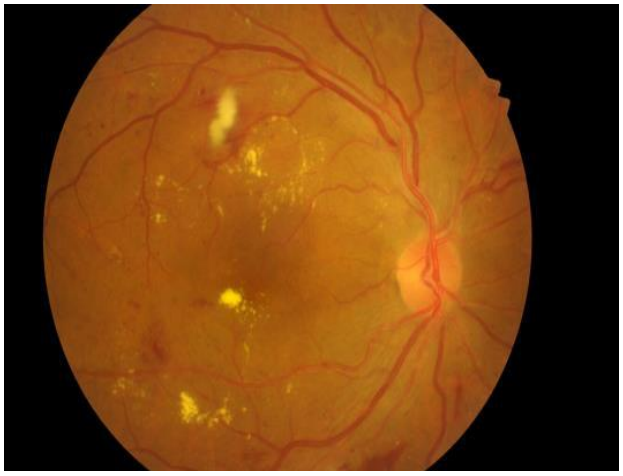

Figure 1.2. Retinopathic Eye

Literature Review

Hard exudates are one of the most commonly present symptoms in the fundus images of DR eye. S. S. Kar and S. P. Maity [1] proposed an idea and implementation for lesion detection system which uses the kernel fuzzy c-means [6] where blood vessels and optical disks can be removed at very beginning stages. The evaluation is performed by randomly selecting 50% images from each of the DIARETR1, ROCh, DRIVE [7] databases resulting in an average accuracy of 99.7%. Kumar et al [2] mentions the use of database DIARETDB1 and perform Adaptive histogram equalization (ADHE) for contrast enhancement which is followed by green channel enhancement and detection of hard exudates. PCA is used in reduction of dimensions. Here, it is used to convert a matrix of three dimensions of the (RGB) format to 2-dimensional matrix (grey). Further CLAHE [9] is used for contrast enhancement. The DR was detected using the SVM classifiers. Herliana et al [3] made use of Particle Swarm Optimization and dividing the diabetic retinopathy dataset into10 parts by the usage of 10 folds of cross validation methods. After training data and testing data is validated using neural network, the last step is the classification of data and

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presentation of the result.The result by using feature selection method shows that there has been an increase of 4.35% from previous result which was 71.76% by the application of the Neural Networks method.

Benzamin et al [4] make use of IDRiD [10] dataset and deep learning methods thus generation of an image in which hard exudates were detected by prediction of the class of every pixel. Bhargavi et al [11] had proposed a four stage system for CADe for lesion detection which consists of pre-processing of fundus images followed by removal of the optic discs and then extraction of the required features and finally classification into various classes. DIARETDB1 [8] and MESSIDOR [7] datasets are used and the CADe screening is done on these images. The obtained AUC value for this method is 0.966. Kajan et al [12] used technique of CNN (Neural Networks) and concentrated on the bright lesions which are present in the fundus images of the MESSIDOR dataset. The model focuses on increasing the accuracy of classification stages of the different DR present. Aleena et al [10] used the SVM technique to classify into dark and bright lesions. Top hat and Bottom hat approach are used to enhance the input fundus images especially for dark lesion detection.

Proposed Work

The method proposed here is inspired by the work done by Avula Benzamin and Chandan Chakraborty. The Dataset is consisted of the fundus images of eyes. We have generated 616 patches of images of dimension 75*75. There are 154 IDRID images present and each image have been divided into 4 patches. The System adopts three basic procedures for the identification of the bright lesion (i.e, Hard Exudates) which are preprocessing, Feature Extraction and the feature classification based on the SVM (Support Vector Machine). The SVM classifies the Hard exudates based on the intensities of the Exudates presence, i.e, Mild Exudates or Severe Exudates. The Procedures involved in the identifications of the bright lesion (Hard Exudates), has been divided into the following procedures as discussed below

Methodology

The Methodologies for the identification of the Exudates (Bright Lesions) have been discussed below in the following points.

1. Pre-Processing

Pre-processing of fundus images and theimages will be resized to 300*300 size of the images and the Channel Splitting is done so that colour channels are split into red, green and blue. The blue channel is selected and HSV (Hue Saturation Value) colour transformation on blue channel is performed. Patch Segmentation is performed for division into 4 patches i.e. 2 horizontal pieces and 2 vertical pieces. The division of the patches of the input fundus images have been shown in the Figure 4.1.

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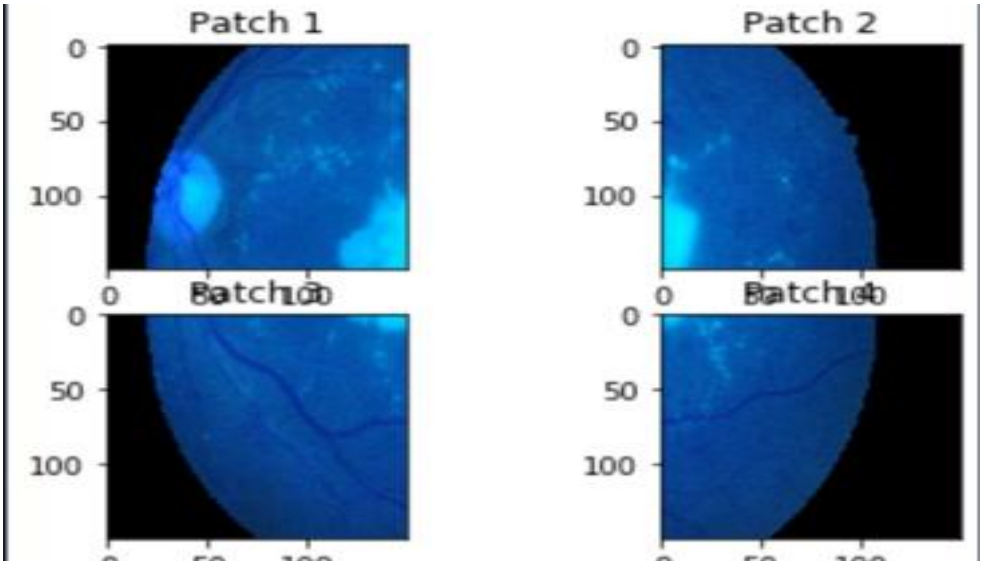

Figure 4.1 Division of the fundus image channels into four patches

Grey Scale Conversion is performed on the obtained patches using the formula for grey scale conversion –

1) The lightness method averages the colours which are more or least prominent: (maximum(RED, GREEN, BLUE) + minimum(RED, GREEN, BLUE)) / 2.
2) The average method simply averages the values: (RED + GREEN + BLUE) / 3.
3) K = 0.299 RED + 0.587 GREEN + 0.114 BLUE.

2. Feature Extraction

Feature Extraction is then performed in order to extract the exudates from the converted images.

a) LBP construction (Localised Binary Pattern) - The first step particularly involves the constructionof the LBP texture descriptor which converts the image to grayscale format. For every pixel which are in the grayscale image, we have selected a neighbourhood pixel which is of size which are surrounding the centre pixel. The value of an LBP is then calculated for the pixel which is in the center and stored in the output 2D array with the same width and height as the input image.
b) LBP calculation –It takes the 8-bit binary neighbourhood pixel of the centre pixel and converts it to a decimal representation.
c) LBP Output – The value of calculated LBP is then stored in an output array which has the same width and same height as the original input image.

Generation of Test Features includes Generation of test features from LBP (Local BinaryPattern). The image before and after applying LBP is shown in the figure 4.3 (a) and (b).

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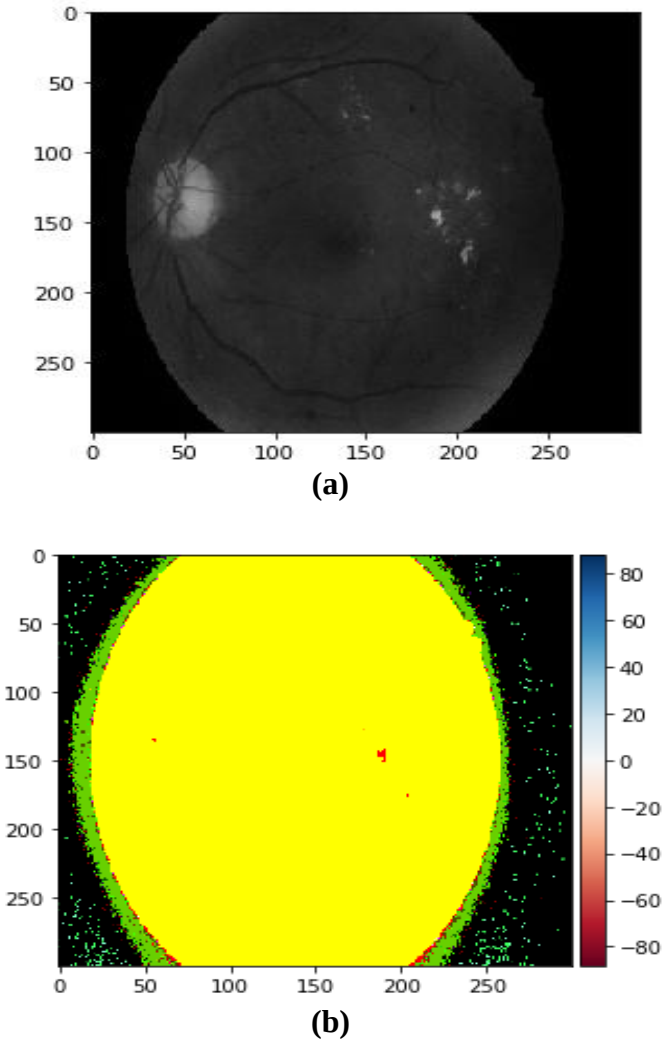

(a)

(b)

Figure4.3.(a) Image before applying LBP, (b) Feature extraction using LBP.

3. Classification

Classification starts by loading the dataset from the directory.Then we Split test and train for classification which is done using SVM Classifier which is first imported. Finally classification into Low Number of Exudates and High Number of Exudates is done to indicate the level of exudates present. The classification is based on the density of exudates present in the images. The images are being classified as low exudates and high exudates.

ResultsAnd Discussions

The results having the average specificity value of 96% and the average sensitivity of around 89%, and having accuracy of 96.95%, we have achieved a feature extraction and classification technique for the bright lesions and this results were being calculated over 154 IDRID images and having their patches being divided into 4 parts and later the mean features being deduced and

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classified using the SVM (Support Vector Machine Classifier) over a linear kernel.The performance evaluation graph has been shown in Figure 5.1 and values are demonstrated in the table 1.

$$J(w,b,a) = \sum \alpha i + \tfrac{1}{2}\, w^T w - w^T - \sum \alpha i d i x i - b \sum \alpha i d i$$

$$Q(\alpha) = \sum_{i=1}^{N} \alpha_i \; - \; \frac{1}{2} \sum_{i=1}^{N} \sum_{j=1}^{N} \alpha_i \alpha_j d_i d_j \, \phi(x_i) \cdot \phi(x_j)$$

$$where \; 0 \le \alpha_i \le C \; \forall \; i$$

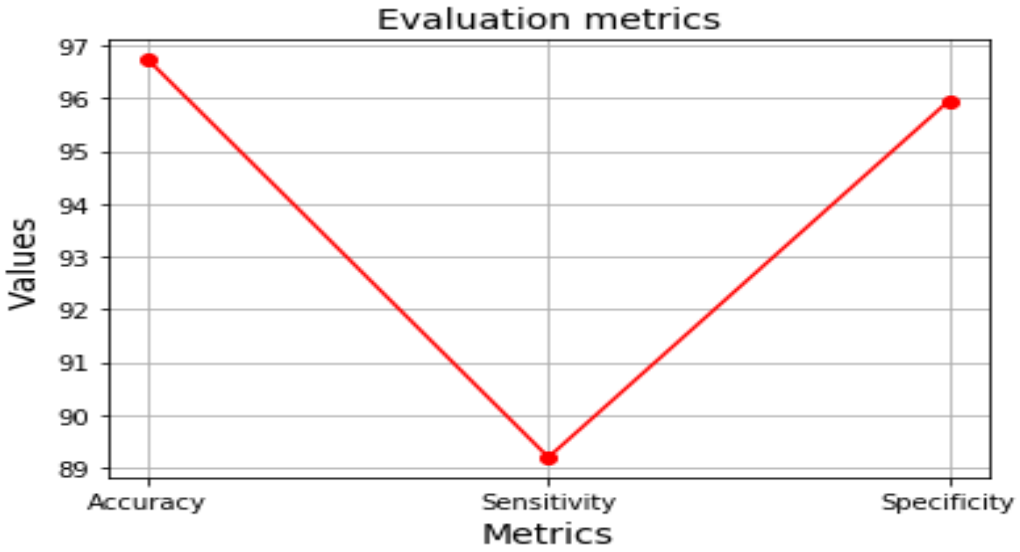

Figure5.1. Graph for the performance metrics evaluation

Table1. Performance evaluation

Metrics	**Values (%)**
Accuracy	96.95
Sensitivity	89
Specificity	96

Conclusion

The diabetic Retinopathy is one of the most difficult diseases to identify and detect. This work will be very much useful to detect the bright lesion (exudates) in the retinopathic eyes. This being the easiest method to detect and classify the exudates, is easy to implement and understand and can give the results by inputing fundus images.

The scope for this work is varied and can be useful to the people that can be incorporated at the later stages, and it can save time and resources to get the reports done and tested based on the

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input fundus images of the eyes. The methods in Machine learning and image processing based bright lesion detection can prove to be a boon to the health industry where the advancements and rigorous practices to solve the disease detection challenges, can be contributed with the bright lesion detection model.

Limitations and Future Studies

The current model has some limitations as it is a Machine learning approach of feature extraction and classification using a SVM classifier, it might not perform well and can give slower or inaccurate results for huge datasets. The future of the Lesion detections and its research prospects are high and can be a boon for the medical field research studies. There are several models having used the neural networks to segment out the lesions. But this, Machine learning model being one of the quickest ways to implement as well as segregate the Lesions based on the severity, and is very much efficient for the medium range datasets. The research involved in this particular field, have a lot of scope for the education as well as researches, that might be one of its kind to develop a state of art techniques, to detect the early stages of diabetic retinopathy in the future.

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