Identification of Diabetic Retinopathy (DR) using Image Processing

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Abstract. Diabetes appears in two varieties: Type-1 and Type-2. The former is chronic and can last for years together, whereas the latter can be cured if identified and treated at a premature stage. The symptoms of diabetes affecting the eyes appear very subtle and hence, identifying irregularities in retinal images is a demanding process for medical practitioners. Thus, there was a need to find a method to detect these abnormalities by observing the retinal images non-invasively. After going through research projects and recent developments in identifying DR, we found various techniques/strategies employed, their advantages and drawbacks followed by the objective of overall findings, and the importance of a good DR detection system. Our proposed method calls to attention the importance of early screening, using geometrical relations, multiple thresholding methods and usage of convolutional neural networks as means of overcoming the factors that stand as obstacles in timely detection.

1. Introduction

More than 470 million people worldwide are currently diagnosed with diabetes and an increase of up to 700 million by 2045 is estimated, according to IDF (International Diabetes Federation). During the period spanning 2000-2016, a 5% increase in deaths related to diabetes was observed, with 1.6 million deaths each year [1][2]. Countries such as China, India, and the United States have the highest number of diabetes cases, mainly because its symptoms are indistinct, one can grow thirstier or become hungrier than usual, or we might not figure out why we’re more tired than usual. They can be considered a major public health problem [3], especially in developing countries. The meteoric rise in urbanization and industrialization, along with our lifestyle choices provides an ideal scenario for the prevalence of diabetes and its associated complications [4]. Foremost among them is Diabetic Retinopathy (DR), which is the diabetes complication affecting the retinal blood vessels, which is the primary cause of avoidable blindness. Interventions for an earlier diagnosis of DR can reduce the burden of medical professionals in providing an accurate prognosis.

It is observed that due to the steady and gradual growth of diabetes worldwide, there are variations in the ratio of medical professionals who specialize in ophthalmology to that of the patients, hindering the discovery and care of diabetic retinopathy. Hence, there was a need to address issues of screening time, higher costs, lower sensitivity and specificity of devices, etc. This led to the proposal of introducing Automated Detection Systems based on stand-alone algorithms. Prominent research areas include Screening and Diagnosis of DR, with many research scholars focusing to contribute towards...
its improvement [5]. Image processing methodologies have made the study of images captured, that is their characteristics, behavior, and their processing, facile and attest advantageously. Further, the growth of the new image processing procedures, classifications algorithms, and neural networks have contributed to the fast performance of computer-aided detection systems and are considered for the implementation of retinal analysis.

The said system models would aim to identify the need for referral for further treatment and future eye care. With the pace at which technology is advancing, it’s not far from where we can use these methods on our smartphones. The initiation of automated techniques for the screening processes and the resulting outputs achieved are traits of success and a potential failure. There already exist several algorithms for the identification of DR using the different processes of image processing and their associated techniques, but the efficacy and complexity of those techniques are further improvable. Here, we aim to provide an overview on building a similar application, by which the irregularities which occur due to DR in the eye retina can be detected.

2. Literature Survey
In the research paper [6], the author makes use of feature extraction, to identify the details unique to the image and extract them. Blob features are detected through Speeded-Up Robust Features (SURF). It is a type of detector algorithm which highlights specific points on images that are converted into a coordinate system. Matching is done through MSER (maximally stable extremal region). Extremal corresponds to the picture elements having varying intensity compared to the pixels in the outer boundary. The extracted image and the classified image are observed, compared to the input image counterparts.

In the research article [7], optical disk detection along with the blood vessel removal method is explained in detail. They serve as a point reference to identify other features. Detection is carried out here in 3 steps. The first step is Candidate area identification, followed by Sobel edge detection, and finally Estimation. Edge detection is employed through the kirsch methodology to identify the vessels. This calculates the gradient by utilizing the image convolution along with eight template impulse response arrays. A reference point/threshold is prepared to compare if the element belongs to the edge or not, i.e., after enhancement.

The authors of the paper [8] have proposed a distinctive algorithm to help in the identification of DR. They have utilized the green component, which is better than the other components, of the input image for pre-processing. This is further enhanced by applying the modified matched filter operation to accurately segment the blood vessels, where local entropy thresholding is utilized to obtain the threshold value. The prospective lesions are identified through morphological operations, which are utilized for training purposes.

In the research paper [13], the authors propose an innovative process to improve the prognosis. Identification of Retinal vessels and Microaneurysms is crucial as the severity and treatment plan for treating DR is based on it. Here, they find that the matched filter (MF) method is more efficient than the Sobel operator or Morphological operator as the sensitivity is easily optimized using genetic algorithms. For the process of detection of microaneurysms, a top-hat transformation of the image is considered. The system is trained with the help of ground truths of retinal images prepared by clinical experts and real-time detection to identify the points of irregularities between the resultant image and the ground truths.

In this research article [14], the authors propose a unique approach towards the segregation and extraction of lesions based on specific features. To segregate intensities of overlapping features, geometric characteristics and correlations are used. A unique constraint towards identifying Optic disks (OD) based on the intersection of retinal blood vessels to approximate its position, and further localized using color properties is observed here. This triangulation is achieved using Hough Transform, generating an intersection map.

In the paper [15], the authors, having conducted a comparative analysis of different techniques, have proposed a system with a yield of almost 98% accuracy, which is a better result when compared...
to an existing system with 96.62%, towards detection and prevention of diabetes in the initial screening phase. The mechanism includes starting with pre-processing techniques resizing, sharpening, Laplace edge detection, histogram thresholding followed by feature extraction whose combination is based on Discrete Wavelet Transform (DWT) and Gray Level Co-occurrence matrix (GLCM) for wavelet and texture features respectively, followed by the KNN classifier technique.

In the paper [17], the authors propose a system based on the working of Gabor filter and local entropy thresholding in identifying DR. It incorporates specific techniques complete tasks like extracting green channel components, equalizing contrast components, filtering, determining Entropy Thresholds, and Binary Conversion. To analyze and detect blood vessels, the kernel of the Sinusoidal Modulated Gabor filter is used. A Grey level co-occurrence matrix (GLCM) is utilized to store information regarding the level transformation within the image. This proposed system holds good as it produces maximum true positivity and reduces false vessel detection compared to other systems.

3. Research Gap
There were quite a few unique perspectives which came up during the Literature Survey, when it came to the methodology involving the screening process for Diabetic Retinopathy. We have identified three main concepts which we have taken into account for our proposed model, and which can be improved upon further.

- Protection of detailed features in retinal dataset in initial screening (Pre-processing)
- Reduction in the aggregate of false detection (False positives and False negatives)
- Holding the accuracy of screening models above 95%

If more and better systems are developed keeping these guidelines in mind, the efficiency of such a system would be way ahead of other similar system models.

4. Methodology
Any device providing a visual perception indicates a captured image which is a 2D function with coordinates x and y in the spatial domain represented by F (x, y). This acts as the primary source for digital image processing. In this regard, the images of interest here are Retinal Fundus images for identification of DR. These images are acquired from datasets that have pre-stored images. Digital image processing is a field that paves the path for manipulating the acquired digital images whose coordinates and amplitude are finite. The general procedure for the detection of desired lesions involves the following phases.

4.1. Image Acquisition
The obtained image is in digital form hence requires scaling followed by color conversion i.e., either RGB to grey or vice versa. Acquiring images is an easy task, but it must be kept in mind to choose retinal images with specifications desirable to the model being implemented to ensure it works efficiently. These can be obtained from the public open-source or privately owned data repositories. A few well-known ones have been mentioned below in Table I.

| Database Name   | No. of Images | Image size       | Camera               | Image Format |
|-----------------|---------------|------------------|----------------------|--------------|
| IDRiD           | 516           | 4288*2848        | Kowa VX-10α          | jpg          |
|                 |               | 1440*960         | 3CCD/                |
| MESSIDOR        | 1956          | 2240*1488        | Topcon TRC-NW6       | tiff         |
|                 |               | 2304*1536        |                      |
| Kaggle          | 88702         | 433*289          | Any Camera           | tiff         |
| E-Optha         | 463           | 3888*2592        | (EyePACS Platform)   |              |
| DIARETDB        | 219           | 1500*1152        | Zeiss FF450+         | png          |

Table 1. Retinal Image Data Repository
4.2. Image Pre-Processing

Pre-processing comprises extracting or enhancing the specific features of the image based on the requirement [18], reducing the effects that degrade the image, removal of noise in the image [19], keeping the resolution to an acceptable level, etc.

Noise results in degradation of the image which can be caused by a variety of factors,

- Gaussian Noise (aka electronic noise due to amplifiers/detectors, also through natural sources due to thermal atomic vibrations)
- Salt and Pepper Noise (aka data drop noise as it reduces the value of the original image pixels)
- Periodic Noise (due to interference in electronic instruments, especially during image acquisition)

This noise is reduced by using appropriate filters to enhance the result obtained. We have utilized an (Adaptive) median filter in our model [20], as it is considered the best statistic filter. The median value is obtained using,

$$\hat{f}(x, y) = \text{median}\{g(s, t)\}_{(s, t) \in S_{xy}}$$

Once the noise is removed, Histogram Equalization (HE) is performed to get a better intensity image. A variant of HE called Contrast Limited Adaptive Histogram Equalization (CLAHE) is used in the later parts of the implementation. The value for HE is generally calculated using,

$$h(v) = \text{round}\left(\frac{cdf(v) - cdf_{\text{min}}}{M \times N - cdf_{\text{min}}} \times (L - 1)\right)$$

wherein,

cdf holds the value of cumulative distribution function
MxN gives the image's number of pixels
L gives the number of gray levels used

In simpler terms, the pixel values of the retinal image are adjusted and excess noise removed, to make the image look more detail-oriented which is helpful for further processing. The results of pre-processing can be beheld below in figure 1.

![Pre-processing of retinal image](image)

**Figure 1.** Pre-processing of retinal image

4.3. Background Subtraction

Here, we detect blood vessels and optical disks (OD) to eliminate them. The identification of vessels after pre-processing gives a better output when compared to its earlier counterpart. The positioning of vessels & optic disk is a crucial step to simplify the process of identification of the exudates and microaneurysms [21].

The identification of vessels is as follows,

- The output of pre-processing is further enhanced using CLAHE.
- Background exclusion of image against the original ground truth.
- The threshold value was obtained using Isodata algorithm [12].
The identification of optic disk went on as follows,

- The output of pre-processing is further enhanced using CLAHE.
- Overall intensity of image is normalised.
- The threshold value is obtained using Otsu’s method,

\[ \sigma_\omega^2 = \omega_0(t)\sigma_0^2(t) + \omega_1(t)\sigma_1^2(t) \]

wherein,
\[ \omega_0 \& \omega_1 \] are probabilities of the classes by a threshold \( t \)
\[ \sigma_0 \& \sigma_1 \] are the variance of the classes

- Thereafter, morphological operations such as Erosion, Dilation, Closing, and Filling are carried out.
- The center is calculated in accordance with the blood vessels and represented as optic disk.
The output obtained is as shown in figure 2.

![Figure 2. Subtracting the Background from the pre-processed image](image)

a) Detected blood vessels b) Detected Optic Disk

4.4. Lesion Detection

Microaneurysms (MAs) and Hard exudates (EXs) are symptoms usually observed in the mild and moderate stages of DR. The exudates are represented by the yellow flecks of lipid residues which are clear lesions. Microaneurysms appear as tiny red dots.

For identification of exudates, top-hat morphological operation is utilized.
- Threshold is obtained using Maximum Entropy method [16].
- The Circular edge is eliminated, along with optic disk and blood vessels.
- The required bright components are obtained.

For identification of microaneurysms, top-hat morphological operation is utilized.
- The complement of pre-processed image is enhanced using CLAHE.
- Overall intensity is normalised.
- DWT transformation is applied [16], boundaries are traced and the lesions are localized.

The general overview of DWT transformation is shown below in the figure 3. The identified MAs and EXs are highlighted on the original ground truth, as shown in figure 4.
4.5. Classification

Assigning a label to the output image, indicating whether the image is healthy or not, based on descriptors. Identification of the irregularities in retinal images manually is taxing for medical professionals, and hence the need for utilizing (CNN) convolutional neural networks [22] to simplify this process. We have utilized AlexNet [23] as the means for training and testing our model, and classifying the images based on the severity levels considered, and classified them using Support Vector Machine (SVM) Classifier. CNNs are deep learning algorithms which are used in the field of image processing to complete tasks like recognizing specific images, detection of specific image elements and segmentation of image. Generally, they are made up of three layers-Convolutional, Pooling and Fully connected layers.

AlexNet is a neural network with eight learned layers, i.e., five convolutional layers and three fully connected layers. This allows for maximizing the average training cases with higher accuracies even on challenging datasets. SVM is a well-known classifier which is utilized to find the specific hyperplane to segregate the data linearly into two components or more as desired, ensuring a wide margin between the components.

5. Results and Discussion

During implementation, the focus is to be directed towards the significance of image resolution as it is vital and concerns the performance of the model, especially for the extraction and classification of Microaneurysms and Exudates. This can also be observed in many well-performing approaches. Image resolution is very important as it is critical for the classification of disease severity. Compressing image size results in a decrease in the accuracy of segmentation.

The presence of lesions is usually used to corroborate the severity, and the minuscule ones tend to get excluded at low resolutions. This is further validated by confusion matrices which leads to the indication of misclassified instances. Comparatively, it is observed that the resolution of the input image has a minimal effect during the application of localization parameters. This can be explained by the fact that that OD and fovea have lesser chances of being excluded due to the presence of specific
geometrical constraints. The result obtained after classification is represented in the form confusion matrix as can be observed in figure 5.

![Confusion Matrix](image)

**Figure 5.** Obtained results after implementation
a) Considering up to first severity level b) Considering up to second severity level

We have attained an accuracy of 98.3% considering up to mild severity level, with sensitivity and specificity of 100% and 94.3% respectively. We have also tried to include the moderate severity level and acquired an accuracy of 77.8% in it. We are still working on it as it isn’t satisfactory, and also to include the other severity levels, which are as shown in Table II. The comparison of performance values obtained along with training/testing validation is observed in Table III and IV respectively.

| ICDRa Severity Level | Score | Observations |
|----------------------|-------|--------------|
| No DR                | 0     | No irregularities (Lv10 ETDRSb) |
| Mild non-PDR         | 1     | Microaneurysms only (Lv20 ETDRSb) |
| Moderate non-PDR     | 2     | Lesser than severe PDR (Lv35,43,47 ETDRSb) |
| Severe non-PDR       | 3     | Intra-retinal hemorrhages (Lv 53 ETDRSb) |
| PDRc                 | 4     | Neovascularization, pre-retinal hemorrhages (Lv61,65,71,75,81,85 ETDRSb) |

a ICDR-International Clinical Diabetic Retinopathy  
b ETDRS-Early Treatment of Diabetic Retinopathy Studies  
c PDR-Proliferative Diabetic Retinopathy

| Method                        | Sensitivity | Specificity | Accuracy |
|-------------------------------|-------------|-------------|----------|
| RS Mangrulkar [6]             | NA          | NA          | 88%      |
| Sangwan et al [7]             | NA          | NA          | 92.6%    |
| Mane et al [8]                | 96.4%       | 100%        | 96.6%    |
| Kande et al [11]              | 100%        | 91%         | 96.2%    |
| Ravishankar et al [14]        | 95.7%       | 94.2%       | NA       |
| Anant et al [15]              | 93.1%       | 100%        | 97.75    |
| Saumitra Kumar Kuri [17]      | NA          | NA          | 97.72    |
| Proposed Method               | 100%        | 94.3%       | 98.3%    |
Table 4. Performance Analysis of proposed model for testing/training constraints
[considering mild severity only]

| Images Dataset [620 images] | Performance Parameters |
|-----------------------------|------------------------|
| Training/Testing Validation | Sensitivity | Specificity | Accuracy |
| Training – 70%              | 96.7%       | 96.2%       | 96.6%    |
| Testing – 30%               | 100         | 94.3%       | 98.3%    |
| Training – 80%              |             |             |          |
| Testing – 20%               |             |             |          |

6. Conclusion

Based on the observation of various parameters in realizing and developing effective algorithms/techniques to detect Diabetic Retinopathy (DR), we can say that utilizing geometrical relations corresponding to specific features in combination with morphological operations provides an effective and robust analysis system for retinal images.

Although automated grading of DR is advantageous, it has its limitations. This can be either in the utilization of Neural networks or irregularities of retinal images. Although much research and experimental work are being carried out worldwide, it’ll take a long time till we acquire the most efficient method of identifying Diabetic Retinopathy. We should look forward to the newer advances with time, which will help us diagnose it better.

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