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A Review Paper on Computerized Retinal Image Analysis

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Abstract

Diabetes occurs when the blood sugar level of the human body rises beyond normal and starts damaging the blood vessels on the back of the eye. This damage caused by diabetes to the blood vessels of the eyes is known as DR (Diabetic Retinopathy). DR generally affects both eyes. In this study, different research papers have been studied and analyzed in terms of problem statements, datasets, performance metrics, techniques, and findings. This survey paper provides a comprehensive review of the existing research in automated retinal image analysis to the readers. Automated computer-aided methods used to diagnose retinal diseases have been reviewed in this study.

Keywords: CLAHE, Diabetic Retinopathy, DRIVE, STARE, MESSIDOR, Vesselness

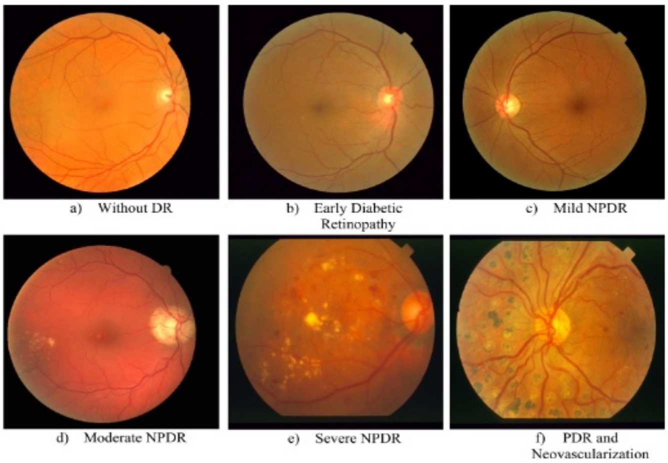
1. Introduction

DR is a major impediment to diabetes. Inhibition of retinopathy or decelerating of the development can be recognized by keeping exceptional control of blood sugar levels. Retinopathy is fundamentally reduced blood vessels in the retina which is the thin inner light-sensitive layer positioned in the back of the eyes. This causes blood vessels to leak or swell and can even get closed and restrict the flow of the blood. Occasionally abnormal new blood vessels come up on the retina. In the early stages of the disease, the impact is not that severe and a person may even not notice the changes his or her vision has undergone. The adverse impact of diabetes on the retina keeps on increasing with time. Over time, Diabetic Retinopathy may get worsen and result in permanent vision loss. Therefore, the detection of diabetic retinopathy at the early stages is of utmost importance and can be done by analyzing the segmented retinal nerve fibers. Diabetic Retinopathy can be broadly divided into four stages shown in Figure 1 and mentioned as under.

- **Mild Non-proliferative Retinopathy:** This is the first stage in which microaneurysms starts occurring. This looks like ballon-type swelling in the small blood vessels of the retina.
- **Moderate Non-proliferative Retinopathy:** At this stage, the blood vessels that nurture the retina are obstructed.
- **Severe Non-proliferative Retinopathy:** At this stage, the obstruction outspreads to many more blood vessels, resulting in depriving blood supply to numerous areas of the blood vessels.
- **Proliferative Retinopathy:** This is the final stage in which signals directed by the retina for sustenance activate the growth of new blood vessels. These new blood vessels are abnormal and

delicate. They propagate along the retina and along the surface of the clear, transparent gel that fills the inside of the eye. These blood vessels do not cause any vision loss by themselves. The problem occurs when the thin and fragile walls of these blood vessels leak blood which may result in blindness.

Figure 1: Stages of DR [1]



There are several benchmark datasets comprising retinal images which are publicly available. Some of the datasets providing fundus retinal images for research purposes are mentioned in Table 1.

Table 1: List of Available Benchmark Datasets

Dataset	Number of Images	Field of View	Resolution (pixels)	Motivation
MESSIDOR	1,200 fundus images	45	1440 × 960, 2240 × 1488	Detecting lesions
MESSIDOR-2	1,748 fundus images	45	1440 × 960, 2240 × 1488	Detecting lesions
DIARET DB0	120 fundus images	50	1500 × 1152	Detecting lesions
DIARET DB1	189 fundus images	45	720 × 576	Detecting lesions
DRIONS-DB	110 fundus images	-	600 × 400	Detecting OD
DRIVE	• 20 color fundus, • 20 training images	45	768 × 584	Detecting lesions
STARE	400 fundus images	35	605 × 700	Detecting HM and exudates
E-OPHTHA	• 47 fundus images with exudates, • 35 fundus images without lesions, • 148 images with MAs and HEM, • 233 fundus images	45	1440 × 960 to 2544 × 1696	Detection of exudates and Mas

	without lesions			
CHASE-DB1	28 fundus images	30	1280 × 960	Retinal vessel segmentation
HEI-MED	169 fundus images	45	2196 × 1958	Detection of exudates
HRF	66 fundus images	45	3504 × 2336	Automatic segmentation algorithm
ONHSD	99 fundus images	45	640 × 480	Detecting optic nerve
IDRID	516 color fundus images	50	4288 × 2848	Screening of DR
FIRE	134 fundus images	35	2912 × 2912	Detection of the dark and bright lesion
RODREP	1,120 fundus images	45	2000 × 1312	Screening of DR

The conducted research work is evaluated in terms of performance evaluation metrics. The performance assessment of the retinal image processing algorithms is a very significant phase in computer-aided detection. Metrics are used for the comparison of the modified images using proposed methods with standard truth images. The most common estimation metrics are TPR (True Positive Rate), FPR (False Positive Rate), sensitivity, specificity, accuracy, and precision. Sensitivity (also called recall) is defined as the competence of the algorithm to identify the vessel pixels and specificity is the capability of the algorithm to detect non-vessel pixels. Accuracy measures the ratio of correctly classified pixels (both vessel and non-vessel) to the total number of pixels in the image FoV (Field of View). F1-score is the weighted average of precision and recall. It takes both false positives and false negatives into account. PPV (Positive Predictive Value) and NPV (Negative Predictive Value) describe the performance of the diagnostic test. PPV is the probability that the subject with the disease will test positive. All these measures are attained through the pixel-to-pixel comparison between the segmented image and reference ground truth. Table 2 illustrates a few of the prominently used performance parameters.

Table 2: Performance Metrics

Measure	**Description**
Sensitivity (Recall)	TP / (TP + FN)
Specificity	TN / (TN + FP)
Accuracy	(TP + TN) / (TP + FN + FP + TN)
Precision	TP / (TP + FP)
AUC	(Sensitivity + Specificity) / 2
F1-score	2 * (Sensitivity * Precision) / (Sensitivity + Precision)
PPV	TP / (TP + FP)

2. Literature Review

In 2018, Américo Oliveira et al. [2] emphasized the importance of vessel segmentation in diagnosing and monitoring the condition of retinal vascular as a dependable biomarker of multiple cardiovascular diseases. The authors proposed an innovative method for combining the multiscale analysis offered by SWT (Stationary Wavelet Transform) and FCNN (Fully Convolutional Neural Network). This enables management with fluctuating direction and width of vessel structures. The authors proposed method made use of rotations operations for handling data augmentation and prediction. The authors made use of benchmark databases of STARE, DRIVE, and CHASE_DB1 to calculate ACC (Accuracy) and AUC (Area under Curve) via minimizing the values of FP (False Positive) and FN (False Negative) parameters signifying the efficacy of deep learning. Based on the obtained results, the authors claimed that the proposed method can be used for real-world applications dealing with screening and diagnostics. The proposed method makes use of non-complex convolutional nature which makes its execution fast. The time taken for fully segmenting the retinal image is 2 seconds. The authors claimed that the research work would enable to obtain of multiple biomarkers from retinal images and can be applied for different medical accomplishments. The same method can be used beyond retinal images on other human organs. The obtained extra features can be used for exploring future aspects related to diabetic retinopathy.

In 2018, Hugo Aguirre-Ramos et al. [3] stated that the major cause behind the blindness of adolescents is eye diseases. The early detection of the disease can help for effective treatment. The proper detection enables physicians to reach an appropriate conclusion. The authors proposed a method to reduce the noise present in the Green Channel of RGB images via a Low Pass Radius Filter. The structures of the blood vessels and their contours are enhanced using 30 element Gabor filter and Gaussian fractional derivative. The occurrence of false-positive pixels has been reduced dramatically using threshold and morphological decision rules. The proposed method is effective in detecting and removing an optic disc from the result obtained after the threshold. The DRIVE database was used for the assessment of the proposed method. The proposed method showed better results as compared to existing methods like Adaptive Threshold, Frangi filter, and Otsu method. After applying simulations, it can be concluded that the proposed method is more consistent and modest in the case of blood vessel segmentation. The method maintained a perfect balance between sensitivity, accuracy, and balanced accuracy metrics. The main outcome of the research work is the combination of the fractional Gaussian derivative with a GFB.

In 2020, Adrián Colomer et al. [4] stated that the development of novel algorithms is mandatory for the automatic classification of retinal tissue into healthy or unhealthy categories. The author's proposed method avoids the use of lesion segmentation before the classification. The use of locally obtained binary patterns and granulometric profiles are calculated to obtain information relevant to texture and morphological aspects. The multiple combinations of the obtained information offer classification algorithms to differentiate between dark and bright lesions of healthy tissues. The difference between the surface of healthy and pathological areas within an image is determined using the proposed feature vector. The authors tried multiple experiments to identify the existence of diabetic retinopathy signs on different benchmark databases with higher variability without image exclusion. The authors elaborated on the classification methods for identifying pathological patches containing microaneurysms, hemorrhages, and exudates. The collaboration of morphological and texture descriptors has enhanced the results as compared to using any one of them. The authenticity of the result is proved by using crossvalidation on different categories of classifiers. The classifiers can be used with different benchmark databases. The proposed method is simple and robust.

In 2019, Lizong Zhang et al. [5] stated that microaneurysms (MA) are the first to be detected in case of patients suffering from diabetic retinopathy. Therefore, the detection of these microaneurysms is very important as far as early detection of diabetic retinopathy is concerned. But there are several challenges encountered in accomplishing these detections. The authors proposed an innovative MA detection method built on the deep neural network utilizing a multilayer consideration mechanism for retinal fundus images. The primary step is to perform a series of equalization operations to increase the quality of fundus images. Thereafter, the fusion of multiple feature layers and target features is achieved by implementing a series of equalization operations. In the final step, the spatial relationships are conducted between MA's and blood vessels to achieve subordinate screening of the initial test results to achieve final MA detection results. The authors used the retinal images obtained from the open IDRiD dataset. One type of camera was utilized to obtain the fundus images. Multiple cameras can be used to introduce new features and produce images with different layouts. In the future, even more, images can be included to enhance the general capability of the projected method.

In 2019, Yun Jiang et al. [6] stressed the popularity gained by automatic retinal vessel segmentation in the recent past as an important tool for screening diabetic retinopathy. But, several such methods suffer from multiple problems like poor generalization and accuracy. This problem is primarily because of the presence of symmetrical and asymmetrical patterns among blood vessels and also because the contrast factor between the vessel and the background has been considerably low due to poor illumination. The authors projected an agenda making use of FCN (Fully Convolutional Neural Networks) for assimilating innovative methods for data preprocessing and augmentation. This would act as a complete framework for performing automatic and effective segmentation of retinal vessels. The authors made use of DRIVE, STARE, and CHASE_DB1 datasets achieving high F1-score, average accuracy, and RoC. The authors concluded that multiple experiments conducted proved that M3FCN is much more generalized for multiple datasets which indicates the potential carried for performing practical applications. The authors made use of GPU to make it fast. The results obtained show that symmetric and asymmetric patterns can be used by computer-aided diagnostic systems. In future work, the emphasis can be laid on combining novel methods and applying them to more benchmark databases.

In 2020, Muhammad Usman Akram et al. [7] stated that the approach developed in the analysis of fundus images made use of 100 high-quality images obtained from AFIO (Armed Forces Institute of Ophthalmology), Rawalpindi, Pakistan. The images were of an equal number of males and females within the age group of 25 years to 80 years. The TOPCON TRC-NW8 was used to arrest the images. The poor-quality images were excluded. The datasets have been analyzed to classify the images under study into three categories of diabetic retinopathy, hypersensitive retinopathy, and papilledema. The authors made use of detailed explanations for retinal blood vascular patterns, veins, and arteries to compute AVR (Arteriovenous ratio), ONH (Optic Nerve Head), and various other anomalies comprising cotton wool spots and hard exudates.

Table 3 summarizes the studied research papers in terms of the problem identified, used benchmark datasets, adopted techniques, performance evaluation parameters, and the findings.

Table 3: Summarized State-of-the-Art

Reference Number	Problems	Datasets	Techniques	Parameters	Findings
[8]	Summarizing, classifying, and analyzing the recent developments	STARE, DRIVE, IDRiD, HRF	CNN, ANN, SVM	Accuracy	150 research articles provided a comprehensive overview of the latest developments
[9]	The low visual quality of the fundus image	Local hospital in Malaysia	Green channel conversion and Top-hat filters	MSE, PSNR, Entropy	The quality of the fundus image is Improved
[10]	Examining existing work	Kaggle, DRIVE, STARE, HRF, DIARETDB0, DIARETDB1, MESSIDOR	Machine Learning and Deep Learning techniques	Accuracy, Sensitivity, Specificity, Precision, Recall, AUC, F1-Score	Conducted relative analysis among databases, performance metrics, and ML and DL techniques
[4]	Automatic classification of retinal tissue into healthy and pathological stages	E-OPHTHA, DIARETDB1	SVM, RF, GPC (Gaussian processes for classification)	Accuracy, Sensitivity, Specificity, AUC Local Binary Patterns (LBP)	DIARETDB1 (Sensitivity = 0.7561_0.0301, Specificity = 0.7562_0.0290, AUC = 0.8344_0.0330)
[11]	Retinal images are prone to non-uniform illumination, poor contrast, transmission error, low brightness, and noise problems	DRIVE, MESSIDOR	HE, AHE, CLAHE, ESIHE	Entropy, MSE, PSNR, SSIM, CNR	novel medical fundus image enhancement tool for DR grading
[12]	To improve the contrast of retinal structures	Clinical retinal images	CLAHE, Gaussian filter, Grayscale adjustment,	Color Difference	Enhanced the visibility of hidden retinal structures
[13]	Conducted review of the	DIARTDB, HRF, STARE,	Optical disc	Accuracy, Specificity,	Emphasized feature extraction,

	methods of the low, middle, and high-level vision for automatic detection and classification of DR	KAGGLE, DRIVE, HASEDB1, DRIONS, MESSIDOR, ROC (Retinopathy Online Challenge)	characterization	Sensitivity, AUC,	development of the detection and classification algorithms
[14]	Improving contrast enhancement	DRIVE, STARE	CLAHE, LUM, Wavelet, Contorulet, LN, Sauce	TPR, FPR, Accuracy	SAUCE comes out to be the best enhancement technique
[15]	Qualitative and quantitative experiments are conducted on datasets	DRIVE, STARE, CHASE	Vesselness filter, Orientation histogram	Accuracy, Specificity, Sensitivity	Comprehensive experimentations show that the proposed method outperforms existing methods
[16]	Performing accurate segmentation of blood vessel	DRIVE	SVM	Sensitivity, Accuracy	Average sensitivity = 77% and Average accuracy = 93.2%

3. Conclusion

With the development in technology, the conduct to analyze fundus images has been critically enhanced. Almost all the techniques from image processing to machine learning have been meaningfully discovered. In this paper, a review of the state-of-the-art retinal image analysis algorithms and techniques is exemplified. The basic steps of retinal image analysis are discussed with a brief overview of the history of retinal imaging. Retinal image datasets have diverse image resolutions. The accessible images have altered morphological features such as lesions, tissue structures and noise. So the performance estimation of different algorithms differs with the datasets. There is no best technique or algorithm for retinal image analysis. There are several factors like accuracy, time, computational complexity and robustness, which play a key role in determining which methodology is the best.

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