

A Systematic Review of Diabetic Retinopathy (DR) Comparing Algorithms, Datasets and Performance Metrics

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Abstract

Uncontrolled diabetes can result in a condition called diabetic retinopathy (DR), which can impair eyesight. The retinal blood vessels are significantly impacted, and the inner, light-sensitive covering of the fundus is diminished. For quick processing using AI approaches, timely identification and periodic examination of this disease are crucial. This study evaluates numerous papers based on the detection and grading of diabetic retinopathy in order to identify the most recent methods for checking and diagnosing DR. This paper showed various techniques, datasets and its efficiency in order to diagnose DR. In this paper, study limitations are also mentioned in order to show the comparison of each method. Considering the constant advancement and strategies used in industry, a few difficulties really need to be the focus. For the very high resolution images the processing of each of the datasets is still a very cumbersome task. The paper analyses the state-of-the-art image processing methodologies and algorithms used in various literatures. This review is beneficial to the researchers working on diabetic retinopathy (DR) based diagnosis.

Keywords— Diabetic retinopathy, diagnosis of DR, uncontrolled diabetes, image processing, medical imaging.

Introduction

The way your body converts nutrients into fuel is affected by diabetes, a chronic (long-lasting) health disease. Your body converts the majority of the food you consume into sugar, which is then released into your circulation. Your pancreas is notified by an increase in blood sugar to produce insulin. Blood sugar is let into your body's cells by insulin so that it may be used as energy. [1]

Diabetes comes in three basic forms: type 1, type 2, and gestational diabetes. It is believed that an autoimmune response is what causes type 1 diabetes. When you have type 2 diabetes, the liver struggles to properly use insulin and maintain appropriate blood sugar levels. In pregnant women who have never had diabetes, gestational diabetes can develop. [2]

A diabetes condition that impacts your vision is retinopathy caused by diabetes. The blood vessels of the retina, a photosensitive region in the interior of the eye, are damaged as a result of this condition. Initially, DR may not manifest any symptoms or may only result in minor vision issues. But it could result in loss of eyesight. [3]

Any person with type 1 or type 2 diabetes has the potential to acquire the illness. The likelihood of developing this ocular problem increases with the duration of being diabetic and the

degree of glucose management. Early DR symptoms may not present itself. You could experience it when the situation worsens. As time passes the diabetic patient may experience fuzzy vision, fluctuating vision, you can see stretches of darkness or emptiness areas. [4]

It is anticipated that 19.1 crore people would have DR by 2030. DR causes irreversible visual loss that manifests throughout adolescence and the advancing years. [5]

By catching the visual impairment in its initial phases, it might be greatly lowered. [6]

Reducing the risk variables, particularly hypertension and hyperglycemia, can stop the advancement of DR [7]. Through computerised diagnosis, it may be discovered both manually and automatically. It takes time to manually examine the retinal pictures. Since there are 1 doctor for every 10, 000 patients, it is challenging for an ophthalmologist to manually diagnose every patient with illness.

Since 1982, the CAD has been an essential tool for analysing medical images. The morphological abnormalities that manifested in the retina as a result of long-term diabetes can be used to diagnose and grade DR. [8]

The morphological abnormalities that manifested in the retina as a result of long-term diabetes can be used to diagnose and grade DR. DR can be detected via morphological changes in fundus images, such as MicroAneurysms (MAs), Hard EXudates (HEX), Soft Exudates (SE) or cotton wool patches, haemorrhages (HEM). [9]. Table I and Fig 1, shows the degree of the condition.

Table I: Grading of DR.

| Grade | Clinical Features |
|-------|--|
| 0 | No symptoms observed means no DR |
| 1 | MAs present means mild or early symptoms |
| 2 | MAs, HEM and HEX present means moderate symptoms |
| 3 | Microvascular anomalies inside the retina, venous beading and HEM larger value indicates severe symptoms |

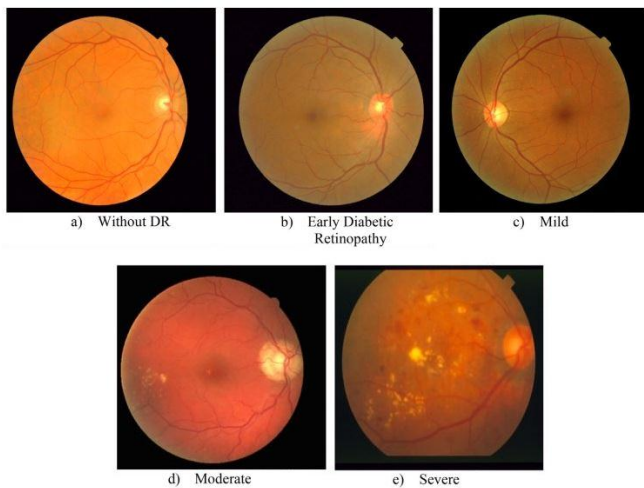


Figure 1: Stages of DR [10]

This study's goal was to give a concise summary of the various imaging algorithms, data sets, and literature used to find defects and diagnose retinopathy caused by diabetes.

Literature review

Wang et al. provide 1589 fundus photographs that were evaluated by three retinal specialists and four general physicians. The findings show that retinal specialists grade both the existence of DR-related characteristics and the severity of DR with more consistency than general ophthalmologists.

A novel technique for the automated identification of microaneurysms and haemorrhages in colour fundus pictures is presented by Seoud et al. and is detailed and verified. The key contribution is a novel collection of shape characteristics known as Dynamic Shape characteristics that do not need the areas to be classed to be segmented precisely. These characteristics allow for the differentiation between lesions and vessel segments and show the change of the form during picture flooding.

Experiments conducted on 89 retinal pictures of diabetic patients by Esmaeili et al. show that we can detect red lesions

with 94% sensitivity and 87% specificity.

A lesion localization model was created by Dorizzi et al. utilising a deep network patch-based strategy. The model's performance needed to be enhanced while its complexity was decreased. In order to do this, we developed an effective method for choosing the training patches, ensuring that the difficult cases would receive extra attention during training. Without the requirement for specialised training, a DR choice may be made for the initial picture using the region's labelling. Using 200 fundus pictures from the MESSIDOR database, Dhara et al. demonstrate that classification accuracy is expressed in terms of the area (Az) under the receiver operating characteristic curve.

According to Sakshi et al., the image-based DLS outperformed all models based on risk factors. Despite difficult picture capturing circumstances, this DLS showed a performance for the detection of referable DR that was clinically acceptable.

In order to assess the phases of diabetic retinopathy severity, Hajeb et. al, use fundus fluorescein angiography and colour fundus pictures concurrently, extract 6 features using the curvelet transform, and input them to the SVM.

Rahim et. al, study uses effective image processing and deep learning approaches to automatically diagnose diabetic retinopathy in retinal pictures.

Gao et al., implemented designs on a cloud-based platform and offered prototype DR diagnostic services to many hospitals. In the laboratory assessment, the platform obtained a consistency rate of 91.8% with ophthalmologists.

Qummar et. al, finds from experiments demonstrate that, in contrast to the latest methods on the same Kaggle dataset, the suggested framework detects all phases of DR.

The suggested method by Shanti et al. was verified using the Messidor database. Diagnostic precision of 96.6%, 96.2%, 95.6%, and 96.6% have been attained for healthy images, images of stages 1, 2, and 3 of DR.

Islam et al. created a unique deep convolutional neural network that conducts in its infancy detection by accurately labelling retina fundus pictures that are divided into five groups and recognising all MAs, the earliest indicators of DR.

Table II. presents the detailed comparison between above literatures and tries to identify the best of them based on algorithm and dataset used.

Table II: Comparison of various techniques used in diagnosing DR.

| Ref. ID | Dataset Used | MAs | HEM | Algorithm Used | Description | Performance Metrics |
|---------|---|-----|-----|--|--|---|
| [11] | Dataset prepared on LAB (not available to everyone) | ✓ | ✓ | Logistic Regression technique is used | Proposed method effectively detects MAs and HEMs with grading of these. | 91.2% of accuracy obtained |
| [12] | Multiple dataset such as Diaretdb1 and Messidor | ✓ | ✓ | Candidate Extraction with spatial image processing | Proposed method detects MAs and HEMs both | ROC = 0.8 |
| [13] | Private Dataset (not available to everyone) | ✓ | ✓ | Equalisation Algorithm | Proposed method detects MAs and HEMs both | Sen = 0.9 |
| [14] | Messidor | ✓ | ✓ | Convolution Neural Network | Less complex model which also enhances the performance of the classifier | ROC = 0.9 |
| [15] | Messidor | ✓ | ✓ | Support Vector Machine, Geomorphologic Features | - | AUC metrics Mild: 0.9, Mod.: 0.8 and Sev. 0.9 |
| [16] | DIARETDB0 | ✗ | ✗ | OTSU algorithm | Author used blood vessel detection technique for detecting DR | Sen = 0.73 |
| [17] | Private Dataset (not available to everyone) | ✓ | ✗ | Canny Edge Detection Technique, Support Vector Machine | Detection of DR using MAs | Sen = 1.0 |
| [18] | Local Dataset | ✓ | ✓ | Grey scale conversion, image edge detection, k-nearest neighbour algorithm | Detection of DR using both MAs and HEMs | Accuracy = 56% |
| [19] | Dataset prepared on LAB (not available to everyone) | ✓ | ✓ | CNN with 48 layers deep | Detection of DR using both MAs and HEMs with all 4 different gradings | Accuracy = 88% |
| [20] | Kaggle | ✗ | ✗ | CNN with 48 layers deep, Resnet50 and DENSE algorithm | Uses 5 levels of DR | - |
| [21] | Messidor | ✓ | ✓ | CNN | Detection of DR using both MAs and HEMs with all 4 different gradings | Avg. Accuracy = 96% |
| [22] | Kaggle | ✓ | ✗ | Image pre-processing with edge detection and data augmentation | Detection of DR using only MAs with all 4 different gradings | AUC = 0.8 |

Conclusion

A thorough analysis of numerous academic works was conducted, and the results were compiled into a number of highest-quality datasets, algorithm, and performance metrics. The primary goal of the article is to inform readers of the research that has been done thus far about the computerised identification and categorization of DR. First, numerous disease types—including MAs, HEM, and exudates of DR have been studied, along with various methods for their identification. To precisely understand the benefits and drawbacks of the approach, analyses of all clinical features and parameters have been conducted and then discusses the downside in the literature. It is anticipated that this evaluation would be beneficial for scientists studying images related to the medical field where large features from the images need to be extracted.

In the modern era, healthcare imaging is a significant field where doctors can view the body's insights via different visualisations that can be examined and confirmed through

computer-assisted diagnosis, which makes it easier for the doctor to make an accurate diagnosis quickly.

References

- [1] Singh, A., Dutta, M.K., 2017. A robust zero-watermarking scheme for teleophthalmological applications. *J. King Saud Univ.-Comput. Inform. Sci.*
- [2] Williams, R., Airey, M., Baxter, H., Forrester, J.K., Kennedy-Martin, T., Girach, A., 2004. Epidemiology of diabetic retinopathy and macular oedema: A systematic review. *Eye* 18 (10), 963–983.
- [3] Leontidis, G., Al-Diri, B., Hunter, A., 2017. A new unified framework for the early detection of the progression to diabetic retinopathy from fundus images. *Comput. Biol. Med.* 90, 98–115.
- [4] Molina-Casado, J.M., Carmona, E.J., García-Feijóo, J., 2017. Fast detection of the main anatomical structures in

- digital retinal images based on intra-and interstructure relational knowledge. *Comput. Methods Programs Biomed.* 149 (October), 55–68.
- [5] Mookiah, M.R.K., Acharya, U.R., Chua, C.K., Lim, C.M., Ng, E.Y.K., Laude, A., 2013. Computer-aided diagnosis of diabetic retinopathy: A review. *Comput. Biol. Med.* 43 (12), 2136–2155.
- [6] Kaur, J., Mittal, D., 2018. A generalized method for the segmentation of exudates from pathological retinal fundus images. *Biocybern. Biomed. Eng.* 38 (1), 27–53.
- [7] Nagpal, D., Panda, S.N., Gupta, N., 2021. Recent advancement for diagnosing diabetic retinopathy. *J. Comput. Theor. Nanosci.* 17 (11), 5096–5104.
- [8] Soomro, T.A. et al., 2019. Deep learning models for retinal blood vessels segmentation: A review. *IEEE Access* 7, 71696–71717.
- [9] Ting, D.S.W. et al., 2019. Deep learning in estimating prevalence and systemic risk factors for diabetic retinopathy: A multi-ethnic study. *NPJ Digit. Med.*, 1–8.
- [10] Mansour, R.F., 2018. Deep-learning-based automatic computer-aided diagnosis system for diabetic retinopathy. *Biomed. Eng. Lett.* 8 (1), 41–57.
- [11] Wang, J., Bai, Y., Xia, B., 2019. Feasibility of diagnosing both severity and features of diabetic retinopathy in fundus photography. *IEEE Access* 7, 102589–102597.
- [12] Seoud, L., Hurtut, T., Chelbi, J., Cheriet, F., Langlois, J.M.P., 2016. Red lesion detection using dynamic shape features for diabetic retinopathy screening. *IEEE Trans. Med. Imag.* 35 (4).
- [13] M. Esmaeili, H. Rabbani, A. M. Dehnavi, and A. Dehghani, “A new curvelet transform based method for extraction of red lesions in digital color retinal images,” no. April 2014, 2010.
- [14] Dorizzi, G. Tozatto, R. Varej, E. Ottoni, and T. Salles, “Diabetic retinopathy detection using red lesion localization and convolutional neural networks ~o Andre a,” vol. 116, no. November 2019, 2020.
- [15] Dhara, A.K., Mukhopadhyay, S., Bency, M.J., Rangayyan, R.M., Bansal, R., Gupta, A., 2015. Development of a screening tool for staging of diabetic retinopathy in fundus images. *Med. Imag. 2015 Comput. Diagnosis* 9414, 94140H.
- [16] Sakshi Gunde, A.A., Gupta, S.D., 2020. Diabetic retinopathy detection using nonmydriatic fundus images. *Our Herit* 1, 141–145.
- [17] Hajeb Mohammad Alipour, S., Rabbani, H., Akhlaghi, M.R., 2012. Diabetic retinopathy grading by digital curvelet transform. *Comput. Math. Methods Med.*
- [18] S. S. Rahim, V. Palade, C. Jayne, A. Holzinger, and J. Shuttleworth, “Detection of Diabetic Retinopathy and Maculopathy in EYe Fundus images using Fundus image processing,” vol. 9250, pp. 275–284, 2015, 10.1007/978-3-319-23344-4.
- [19] Gao, Z., Li, J., Guo, J., Chen, Y., Yi, Z., Zhong, J., 2019. Diagnosis of diabetic retinopathy using deep neural networks. *IEEE Access* 7, 3360–3370.
- [20] Qummar, S. et al., 2019. A deep learning ensemble approach for diabetic retinopathy detection. *IEEE Access* 7, 150530–150539.
- [21] Shanthi, T., Sabeenian, R.S., 2019. Modified Alexnet architecture for classification of diabetic retinopathy images *R. Comput. Electr. Eng.* 76, 56–64.
- [22] S. M. S. Islam, M. M. Hasan, and S. Abdullah, “Deep Learning based Early Detection and Grading of Diabetic Retinopathy Using Retinal Fundus Images,” pp. 1–12, 2018.