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A Review of Deep Learning Techniques on Fundus Images for Detecting Diabetic Retinopathy on Public Datasets

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Abstract

The primary source of vision loss in patients is mainly due to Diabetic retinopathy (DR), caused due to diabetes mellitus. It has become a significant reason for visual impairment among people within 25-74 years of age. If timely medical attention is provided to DR patients, over 90% of people can be saved from vision loss. It's crucial for the early diagnosis of the disease and provide the necessary treatment. The symptoms are more prevalent in type 2 diabetics than associated with type 1 diabetics. Unlike computer-aided diagnosis systems, the traditional procedures of DR detection using fundus photography are both time and cost-consuming. Among the numerous methods for screening and detecting DR, Convolutional Neural Networks are considered extensively in Deep Learning (DL) methods. This review article illustrates the different datasets, pre-processing steps, and DL techniques used in the fundus images for efficient DR detection at an early stage. The main motive of this review article is to provide the research community with an insight into the various pre-processing steps, Public datasets, DL models in DR detection, and some future research directions in this field.

Keywords: Convolution Neural Networks (CNNs), Deep Learning (DL), Diabetic Macular Edema (DME), Diabetic Retinopathy (DR), Fundus Images

1. Introduction

A leading cause of Diabetic retinopathy (DR) is that, patients suffering from high glucose levels, are likely to suffer from the damaged retinal blood vessels [1- 2]. It damages

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blood vessels in the retina, causing fluid leakage and blurry vision. Damage to the retina in diabetic patients leads to blindness. Methods like Fundus Photography and Optical Coherence Tomography (OCT) are implemented for diagnosing DR by ophthalmologists. The DR detection is characterized by three lesions, namely Micro Aneurysms (MAs), Haemorrhages (HM), and exudates (Hard and soft exudates).

The recent developments in Deep Learning techniques have predicted DR more accurately and precisely. Most of the research papers analyzed here use both public datasets [2 - 17], and very few have implemented using real-time clinical datasets. Session 2 depicts the different clinical grading levels of DR. The article outlines the DR stages and data preparation, followed by the DL methods and pre-processing techniques in section 3. Session 3 provides a detailed review of the available public datasets, an overview of the different DL architectures, and the recent works carried out in the recent years in DR detection using DL models. Session 4 summarizes the discussion on the related results from the recent works discussed in the literature review, and session 5 concludes by giving an insight into the future work the research community can take forward in this field.

2. Grading Protocols of DR

The gold standard does the clinical grading protocols of DR, which is the Early Treatment Diabetic Retinopathy Study (ETDRS) grading scheme [2]. Table 1 depicts the various stages of DR progression based on ETDRS.

Table 1. Classification of diabetic retinopathy based on Early Treatment Diabetic Retinopathy Study

Category	Abnormalities	Review time management for patients
Non-Proliferative Diabetic Retinopathy (NPDR)		
No DR	No abnormalities	A patient can be reviewed in 12 months
Very mild NPDR	Only Micro- Aneurysms (MAs)	A patient can be reviewed in 12 months
Mild NPDR	Any or all of the lesions like MAs, haemorrhages, exudates, and cotton wool spots	Patients were reviewed in the range of six to twelve months
Moderate NPDR	Severe Retinal haemorrhage is seen in one to three quadrants. In not more than one quadrant, venous beading is present along with Cotton wool spots	Patients reviewed in approximately six months. Proliferative diabetic retinopathy (PDR): 26%, High - Risk PDR: 8%

Severe PDR	Severe haemorrhages in all four quadrants & venous beading in more than two quadrants	Patients reviewed in four months. PDR: 50%, High-risk PDR: 15%
Very severe	The symptoms can be more than two lesions	The patient reviewed in two to three months. High-risk PDR: 45%
Proliferative Diabetic Retinopathy (PDR)		
Mild – Moderate	New vessels on the optic Disc (NVD) or New Vessels Elsewhere (NVE) are inadequate to meet high-risk criteria	Consider the diagnosis based on the prominent lesions, steadiness, and complete factors. Patients are reviewed for up to two months.
High-Risk	Any NVD present with haemorrhage and NVE greater than one or two disc areas with vitreous haemorrhage	A review of the patient is done immediately if a characteristic appearance is there with an excellent retinal image.

Figure 1 below depicts the stages of DR, where the progress of DR can be analyzed.

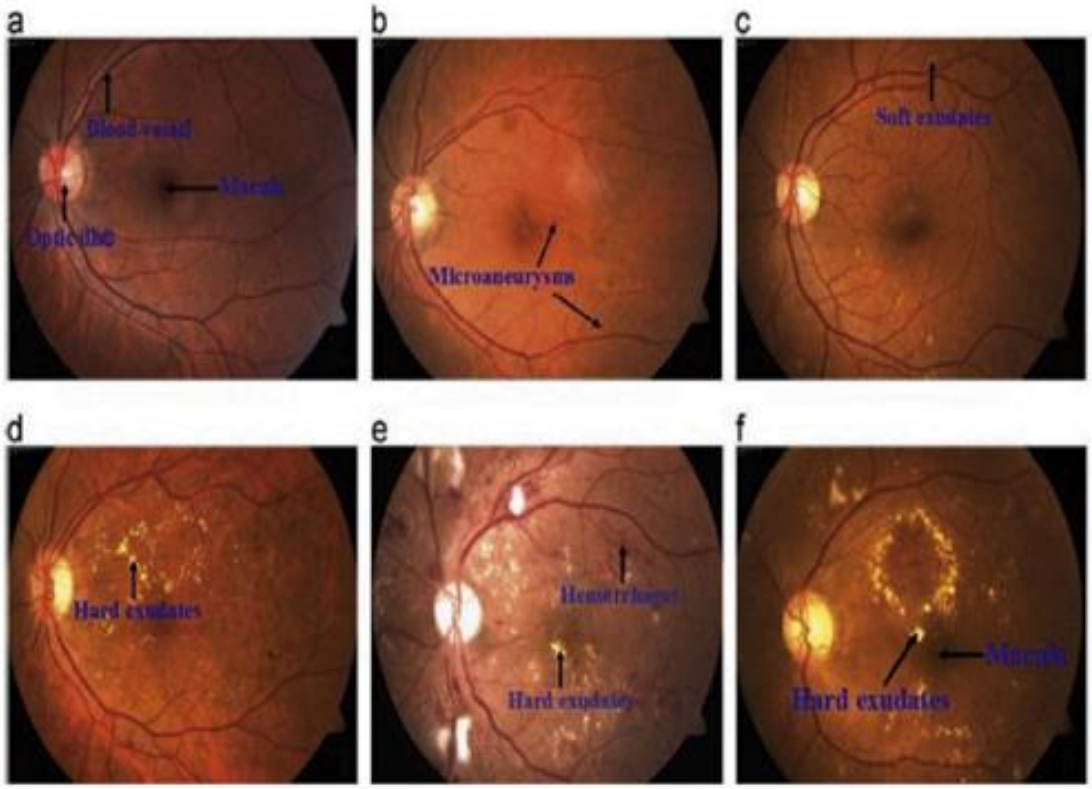

Figure 1. Stages of DR: (a) Normal (b) Mild (c) Moderate (d) Severe (e) Proliferative (f) Macular Edema [15]

The fundus images captured from the public datasets will have noise-induced due to the different environmental conditions and several other factors. These images have to undergo some pre-processing techniques to improve the performance measures of the DL model. Most of the reviewed articles in the literature survey use different pre-processing methods like Contrast Enhancement, Denoizing and Normalization techniques, Color Space Transformations, Cropping and Resizing, Augmentation techniques etc. [4- 20].

3. Deep Learning Methods

Manual examination of DR taken from the fundus images needs a high degree of knowledge, and the grading of ophthalmologists is required for an accurate prediction. Considering the conditions of densely populated areas where the diabetic patients and DR ratio is increasing, it will not be possible to meet the requirement of all as fewer ophthalmologists will be available. The computer-aided automatic diagnosis methods reduce the burden of ophthalmologists in the diagnosis.

After the massive success of Artificial Intelligence (AI) in medicine, DL techniques have been effectively implemented in DR detection and classification. This review article clearly explains the current methods [1-13] for detecting and classifying the DR stages. Most papers specify the analysis of publicly available and real-time clinical datasets, pre-processing techniques, and the different Deep Learning (DL) Models used in DR detection. The review papers analyzed in this article implemented DL techniques which exhibit a better performance measure in terms of accuracy, sensitivity, F- Score, ROC curve etc. These techniques have proved to be more accurate than conventional Machine Learning (ML). Figure 2 represents the overview of the DL techniques and the procedures followed in the review papers [1 - 9] regarding the detection of DR.

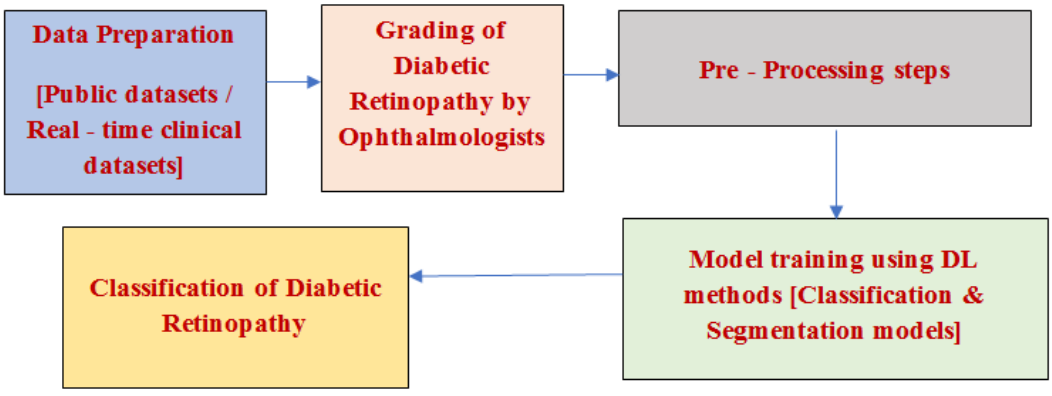

Figure 2. Overview of existing Deep Learning Techniques [1- 9]

Figure 3 represents the different pre-processing techniques used in the review papers [4 -20] to decrease the noise in the fundus images. Effectively using these techniques increases the performance measures for the classification models in DL methods.

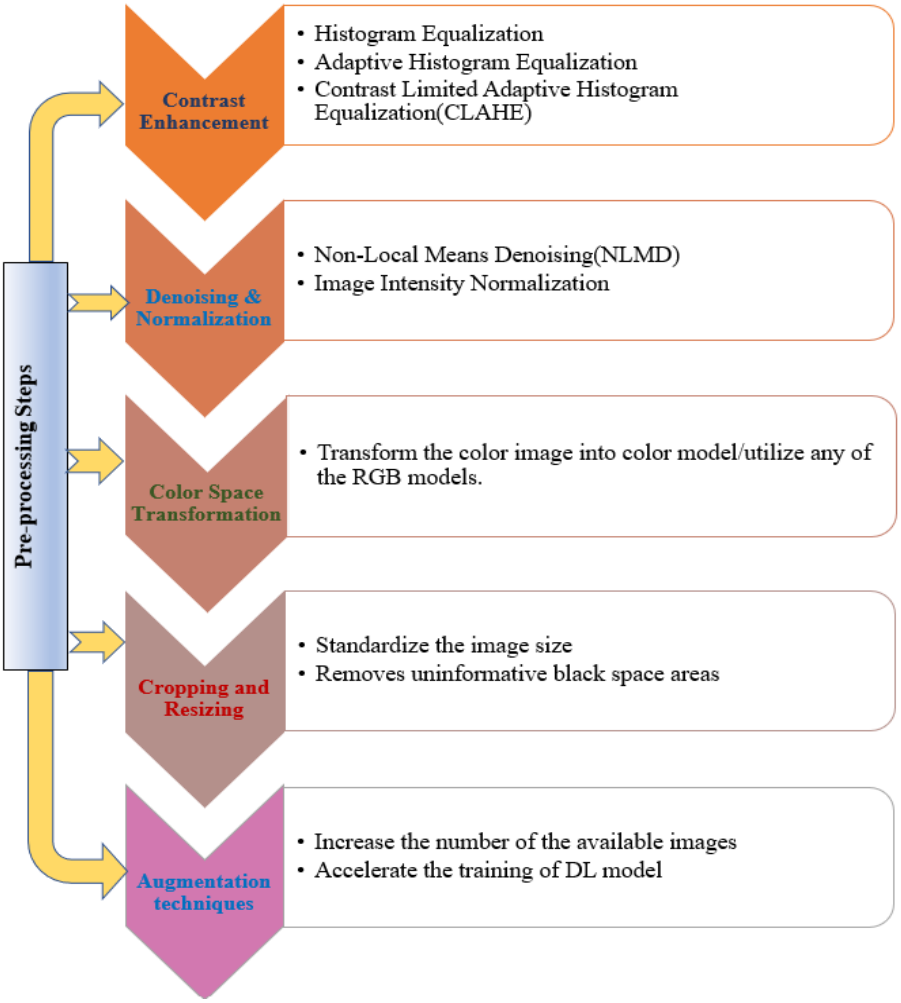

Figure 3. Pre-processing steps in DR detection [4-20]

4. Related Works

Figure 4 below clearly shows the different CNN architectures from the review done [12 -25] in the literature survey where improved performance metrics in Deep learning techniques have been proven.

Table 2 gives a detailed analysis of the different datasets used, DL models, and performance measures (accuracy, sensitivity, specificity and F score) reviewed in recent papers. Table 3 below provides insight into different public datasets available for researchers in DR detection.

Figure 4. Different CNN architectures for DR detection [12-25]

Table 2. Summary of the Literature Review Papers

References	Methodology	DL Models	Datasets	Performance Measures			
				Acc. (%)	Sen. (%)	Spe. (%)	F Score
Shu -I -Pao et al. [18]	Data Augmentation, Pre-processing, Bichannel Convolutional Neural Network	DNN-PCA-GWO model	Kaggle Diabetic Retinopathy	87.33	77.81	93.88	0.93
Qiao et al. [10]	Deep Convolution Neural Network (DCNN)	Lesions Detection & Template Matching Algorithm	Indian Diabetic Retinopathy Image Dataset (IDRiD)	95.3 %	98.4%	97.1%	-
Li X. et al. [5]	Cross-Disease Attention Network (CANet)	RESNET - 50, RESNET - 34 Dense Net 161	Messidor, IDRiD	96.3	92	90.6	91.2

Kaushik et al. [11]	Stacked CNN Model	RESNET - 50 & VGG - 16	EyePACS	97.9	97.7	100	-
Qureshi et al. [13]	ADL – CNN Model	-	EyePACS	98	92.2	95.10	93
H. Leopold [14]	Pixel BNN Model	-	DRIVE, STARE and CHASE_DB1	91.73	75.25	93.02	56.88

Table 3. Summary of Different Fundus Images Available in Public Datasets

Author	Dataset	Number of datasets	Resolution
Nikos Tsiknakis et al. [1]	EyePACS	88702	Varying
	APTOS	5590	Varying
	Messidor	1200	1440 x 960 2240 x 1488 2304 x 1536
	DRiDB	50	768 x 584
	IDRiD	516	4288 x 2848
Wejdan L . Alyoubi et al. [3]	Kaggle	88702	Varying
	Diaret DBI	89	1500 x 1152
	E-ophtha	107799	Varying
	IDRiD	516	4288 x 2848
Lei Zhu et al. [5]	IDRiD	516	350 x 350
	Messidor	1200	350 x 350
K. Shankar et al. [6]	Messidor	1200	1440 x 960 2240 x 1488 2304 x 1536
Jonathan Krause et al. [7]	Clinical Validation Dataset (EyePACS-2) & Messidor-2	1958	779 x 779
Borys Tymchenko1 et al. [8]	EyePACS	35126	640 x 480
	IDRiD	413	640 x 480
	Messidor	1200	640 x 480
Lifeng Qiao et al. [10]	IEEE dataport	100	-
Zubair Khan et al. [8]	EyePACS Dataset	88,702	-

Harshit Kaushik et al. [12]	DIAREDBI Messidor DDR IDRiD STARE E-Ophtha	89 1200 13673 516 20 381	-
Mohammed Z. Atwany et al. [13]	EyePACS APTOS Messidor IDRiD DDR	88702 3660 1200 516 13673	433 x 289 to 5184 x 3456 Varying 1400 x 960 to 2304 x 1536 4288 x 2848 Varying
Imran Qureshi et al. [14]	EyePACS	54000	-
Henry A. Leopold et al. [16]	DRIVE STARE CHASE_DB1	20 400 28	565 x 584 700 x 605 1280 x 960

5. Discussion

The primary concern while using public datasets is the quality of the datasets and their diversity. Even though these images on public datasets are of high - quality, noises are present due to the variety of camera models and non-typical conditions, causing a decrease in the performance measures. Poor-quality images adversely affect the performance and the training procedure of DL models. This problem can be rectified by using good pre-processing techniques. The datasets available in public datasets should be graded by two or more ophthalmologists so that a standard grading can be followed and the models can be more accurate and reliable without misclassifications. The researchers can focus on working on real-time clinical datasets to solve these shortcomings in future work for a better, more precise and reliable DL architecture for DR classification.

6. Conclusion and Future Work

Deep Learning (DL) techniques can be more influential in diagnosing and detecting early stages of Diabetic retinopathy (DR) than traditional techniques. DL techniques obtain the optimal output with better performance as the number of databases increases. This paper reviews the various methodologies used to detect DR stages and identify DR lesions. The different datasets, methods and performance metrics were analyzed for multiple DL

methodologies and frameworks for different datasets. Even though DL techniques in the DR classification have achieved remarkable progress, improvement can be made in the performance measures. The use of more real-time clinical datasets and integration of hardware modules with DL techniques can be further implemented.

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