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A SURVEY ON MACHINE AND DEEP LEARNING FOR DETECTION OF DIABETIC RETINOPATHY

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Abstract

Diabetic Retinopathy (DR) is one of the mainly causes of visual loss worldwide. In fact, DR is leading source of impaired vision in people between 25 and 74 years old. DR exists in wide ranged and its detection is a challenging problem. The gradual deterioration of retina leads to DR with several types of lesions, including hemorrhages, exudates, micro aneurysms, etc. Early detection and diagnosis can prevent and save the vision of diabetic patients or at least the progression of DR can be slowed down. The manual diagnosis and analysis of fundus images to substantiate morphological changes in micro aneurysms, exudates, blood vessels, hemorrhages, and macula are usually time-consuming and monotonous task. It can be made easy and fast with the help of computer-aided system based on advanced machine learning techniques that can greatly help doctors and medical practitioners. Thus, the main focus of this paper is to provide a summary of the numerous methods designed for discovering hemorrhages, microaneurysms and exudates are discussed for eventual recognition of non-proliferative diabetic retinopathy. This survey will help the budding researchers, scientists, and practitioners in the field.

Keywords:

Diabetic Retinopathy, Deep Learning, Machine Learning, Computer-Aided Diagnosis

1. INTRODUCTION

The eye is the most important sensory organs of the human visual process. Its role is inputting information into the visual system that one views in the world around. Thus, protecting the eye from a serious condition associated to vision loss or blindness is an important task. The early-stage recognition of diseases causing vision loss is hoped to early intervention curing them totally in time and prevent from entire blindness [1].

Diabetic Retinopathy (DR) is a typical complication of diabetes. DR is caused by high blood sugar levels that damage retina's blood vessels. In DR, blood vessels can leak and swell, thereby closing, stopping blood from passing through. Even, sometime abnormal novel blood vessels sprout on the retina. All these changes lead to vision loss or preventable blindness. The prevalence of DR is expected to grow exponentially. The World Diabetes Foundation (WDF) approximates that there will be more than 438 million people with diabetes worldwide and the number of DR patients will probably rise to 191 million by 2030 [6].

Inspired by recent progress in advanced machine learning, researchers and scientist have started studying development of automated diabetic retinopathy detection using computer vision and machine learning. In fact, retinal features are extremely interesting to investigate and detect diabetic retinopathy. Different retinal features can be extracted from surface of the eye and utilized in the identification of DR, as illustrated in Fig.1. The conventional features include retinal blood vessels, micro aneurysms, hemorrhages, exudates, optic disc (OD) and optic cup (OC). Depending on the medical section and type of input there are different steps of machine learning and deep learning algorithms that are being used to process the retinal images. Fig.2 shows the different phases. Note that those phases do not apply to all databases and medical sections. However, in general Deep or machine learning methods can be applied in one or more of these phases segmentation, features extractions, feature selections as well as classification.

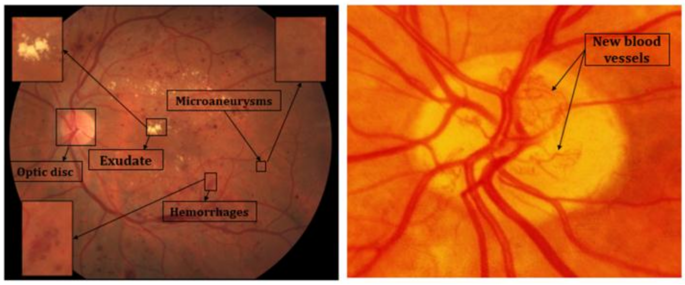

Fig.1. Diabetic retinal features [5] - Left: MA, EX and HM. Right: new blood vessel routes (PDR)

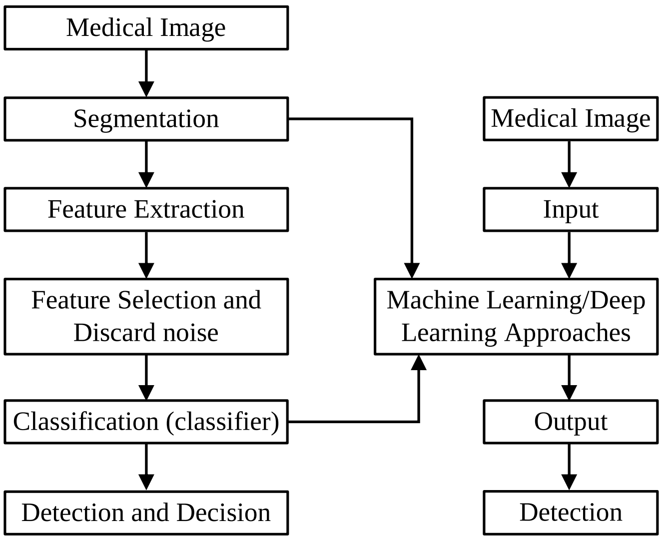

Fig.2. Block diagram of machine or deep learning system for DR detection [7]

In recent years, remarkable evolution of technology, especially in computer components (both hardware and software), has led to the development of new kind of computer-aided medical diagnosis (CAD) systems [2], including DR detection. For DR, existing method in the literatures are based on DR detection or segmentation techniques that investigate one or several retinal features. Before DR detection or segmentation methods an image enhancements (preprocessing step) is recommended in order to attain more correct and accurate classification of retinal features [3]. Besides, two categories of DR include proliferative diabetic retinopathy (PDR) and non-proliferative diabetic retinopathy (NPDR) [4].

In this paper, we provide a survey on effect of machine and deep learning in the DR detection by reporting most employed methods in DR identification. In general, we focus on recent research based on those two disciplines that give the readers more information and the challenges faced in developing a more effective DR process. In this article, we have chosen publications that were published between 2017 and 2020.

The reminder of the paper is as follows. The section 2 presents the publicly available DR detection datasets. Performance measures are outlined in section 3. The traditional machine learning and deep learning-based DR detection methods are discussed in section 4 and section 5, respectively. Finally, some conclusions are drawn in section 6.

2. PUBLICLY AVAILABLE DIABETIC RETINAL DATABASES

This section illustrates publicly available retinal image databases. Eight databases are publicly available, which are DRIVE, STARE, DIARETDB, e-ophtha, HEI-MED, Retinopathy Online Challenge (ROC), Messidor and CHASE_DB1, which are also summarized in Table.1.

2.1 DRIVE DATASET

The DRIVE stands for (Digital Retinal Images for Vessel Extraction) that contains 40 color fundus pictures with their ground truth images. The DRIVE dataset was recorded from a diabetic retinopathy screening program in The Netherlands. Every image in DRIVE dataset is digitized using a Cannon CR5 nonmydriatic 3CCD camera with a 45-degree field of view (FOV). All images are captured using 24-bits per pixel at the image size of 768×584.Each image has been JPEG compressed. These images were manually labeled, to create ground truth vessel segmentation. The FOV of each image is circular with a diameter of around 540 pixels and a mask image is presented that delineates the FOV. The selected population included diabetic patients with ages in the range of 25-90 years old. There are 40 images that are separated into training and a test data subset, each category contains 20 images.

2.2 STARE DATASET

STARE, which refers to Structured Analysis of Retina database, consists of twenty retinal fundus slides and their ground truth images. These images are digitized slides recorded by a Top Con TRV-50 fundus camera with 35 degree FOV. All images were digitized to create a 605×700 pixel of every image with 24-bits per pixel. All the images were analyzed by expert who carefully and manually marked the input images to generate ground truth vessel segmentation.

2.3 ARIA ONLINE DATASET

The Automated Retinal Image Analysis (ARIA) dataset was collected by cooperation of St. Paul’s Eye Unit, Royal Liverpool University Hospital Trust with the Department of Ophthalmology, Clinical Sciences, University of Liverpool, UK (http://www.eyecharity.com/ariaonline/). The ARIA dataset consists of three sets; first one contains92 images with age-related macular degeneration, second group is composed of 59 images of diabetes, and third group consists of 61 images that are considered as control group. The draw of blood vessels, the OD and fovea location is labeled by two experts. The images are captured at a resolution of 768×576 pixels in RGB color with 8-bits per color plane with a Zeiss FF450+ fundus camera at a 50° FOV were stored as uncompressed TIFF files.

2.4 IMAGE-RET DATASET

The Image-Ret dataset consists of two sub-databases, i.e., DIARETDB0 and DIARETDB1 [8]. TheDIARETDB0 data contains 130 retinal images; 20 of which are normal while 110 are of a variety of symptoms of diabetic retinopathy. The DIARETDB1 data consists of 89 images, which are distributed into 5 images that are from healthy retina, whereas 84 images contain at least various signs of mild proliferative diabetic retinopathy. The images are diagnosed and marked by four experts for the existence of microaneurysms, hemorrhages, and hard and soft exudates. The images are acquired with a 50◦ FOV using a fundus camera with unknown settings at a size of 1500 × 1152 pixels in PNG format.

2.5 MESSIDOR DATASET

The Messidor database [9] refers to method to evaluate segmentation and indexing techniques in the field of retinal ophthalmology. It was collected through the Messidor project. Messidor dataset have various uses including automatic evaluate of lesion segmentation, diabetic retinopathy grading methods and risk of macular edema. Besides, it is the biggest database that comprises 1200 retinal images and is publicly available with courtesy of the Messidor program partners. The images were acquired at three different ophthalmology departments using a non-mydriatic 3CCD camera (Topcon TRC NW6) at 45◦ FOV with a resolution of 1440 × 960, 2240 × 1488 or 2304 × 1536 pixels and are stored in TIFF format. Out of 1200 Images 800 are captured with pupil dilation.

2.6 REVIEW DATASET

The review dataset stands for Retinal Vessel Image set for Estimation of Widths [10]. It was collected by the Department of Computing and Informatics at the University of Lincoln, Lincoln, UK. The REVIEW dataset is composed of 16 mydriatic images with 193 annotated vessel segments that have 5066 profile points, which were manually labeled by three experts. Furthermore, 16 images are divided into four subsets, the high-resolution image set (HRIS, 8 images), the vascular disease image set (VDIS, 4 images), the central light reflex image set (CLRIS, 2 images) and the kick point image set (KPIS, 2 images).

Table.1. Existing databases for diabetic retinopathy

Reference	Database	Number of images	Device of acquisition	Resolution	Uses
[13]	DRIVE	40 images 20 for training 20 for test	3-CCD camera with 45-FOV	768 × 584 pixel	Exudates, hemorrhages, microaneurysms, and abnormal blood vessels detection
[14]	STARE	20 images	Top con TRV 50 fundus camera at 35-degree FOV	605 x 700 pixel	Exudates, hemorrhages, microaneurysms, and abnormal blood vessels detection
ARIA Online, Retinal Image Archive	ARIA	59 images with diabetes. 92 images with age-related macular degeneration 61 images of control group	Zeiss FF450+ fundus camera at a 50◦ FOV	768 × 576 pixels	abnormal blood vessels detection
eyecharity.com	Image-ret DIARETB0 DIARETB1	DIARETB0: 130 images (20 images are normal and 110 with DR) DIARETB1: 89 images: 5 images are normal and 84 images with DR)	camera at a 50◦ FOV	1500 × 1152 pixels	microaneurysms, hemorrhages, and hard and soft exudates.
[8]	Messidor	1200 retinal images	non-mydriatic 3CCD camera (Topcon TRC NW6) at 45◦ FOV	1440 × 960, 2240 × 1488 or 2304 × 1536 pixels	Exudates, hemorrhages, microaneurysms, and abnormal blood vessels detection
[9]	REVIEW	16 mydriatic images	-	-	blood vessels segmentation
[10]	CHASE_DB1	28 fundus images	a hand-held Nidek NM-200-D fundus camera at 30_ FOV	1280 x 960 pixels	blood vessels segmentation
[11]	e-ophtha	148 fundus images And 233 healthy images	-	-	microaneurysms or small hemorrhages

2.7 CHASE_DB1 DATASET

The CHASE_DB1 dataset consists of 28 fundus images acquired from multiethnic school children. These images are captured by a hand-held Nidek NM-200-D fundus camera at 30◦FOV, and the size of each image is of 1280×960 pixels. The CHASE_DB1 is annotated by two independent observers [11].

2.8 E-OPHTHA DATASET

The e-ophthadataset was collected by E. Decencière [12]. It is made of two sub databases called e-ophtha-MA (Microaneurysms) and e-ophtha-EX (Exudates). It comprises148 fundus images with 1306 microaneurysms or small hemorrhages, and 233 healthy images which are manually annotated by ophthalmology experts.

3. PERFORMANCE MEASURES

This section describes the common utilized performance measures in the classification of retinal features, which represent candidate regions for disease. The candidate feature trait is either classified as retinal feature or a non-retinal. Four principal measures are generated by the process of classification for retinal features, which include True Positive (TP) and True Negative (TN); while the other two are named misclassifications denoted as False Positive (FP) and False Negative (FN), as shown in Table.2.

Table.2. Retinal feature classification measures

Measures	Retinal feature	Non-retinal feature
Retinal feature detected by algorithm	True Positive (TP)	False Positive (FP)
Non-retinal feature detected by algorithm	False Negative (FN)	True Negative (TN)

There are several metrics of retinal feature classification have been used to calculate performances and thereby validating algorithms for retinal feature identification. These performance metrics are:

- *Accuracy* (*Acc*): It is considered as the ratio between the numbers of number of pixels that accurately recognized as retinal features and the entire pixels in the candidate area.
- *Sensitivity* (*SN*): It is the capability of algorithm to identify retinal features (in term of number of pixels) among candidate area.
- *Specificity* (*SP*): It measures the efficiency to detect non-retinal features (pixels) among candidate regions.

- *Positive Predicted Value* (*PPV*): It refers to the probability that recognized retinal feature pixel is true positive.
- The False Detection Rate (FDR): It stands for the probability that recognized retinal feature is false positive.

Table.3. Parameters of performance

Performance Measure	Formula
Acc	$(TN + TP) / (FP + TP + FN + TN)$
SN	$TP / (FN + TP)$
SP	$TN / (FP + TN)$
PPV	$TP / (FP + TP)$
FDR	$FP / (FP + TP)$

Furthermore, the Receiver Operating Characteristic (ROC) curve is plot of Sensitivity (SN) and the false positive fraction (1-SP). Area under ROC curve (AUC) is a good measure that used to evaluated of a given algorithms.

4. TRADITIONAL MACHINE LEARNING BASED METHODS

Machine learning (ML) is a part artificial intelligence (AI) that can learn from data and take decisions. It is a set of techniques that permit computers to act without the human interaction. Machine learning methods have been used in various areas, including speech recognition, computer vision, robot control, accelerating empirical sciences, and bio-surveillance and product recommendations and computer-aided diagnosis (CAD) systems [15] - [17]. Machine learning methods have been applied on DR medical care sections in the literature, which is the main focus of this section.

Bandara and Giragama [18] presented an image enhancement method to create segments of blood vessels through fundus photographs. Three methods, i.e. enhancement technique, Tyler Coye algorithmic and the improved the Hough line transformation-based vessel segmentation, were combined to construct the image enhancement technique. The framework was tested on two publicly datasets (i.e. STARE and DRIVE) and achieved 94.89% and 94.11 of accuracy for each dataset, respectively.

Hossain and Reza [19] presented a retinal image segmentation method, where the Markov random field (MRF) has been applied. The authors used MRF to create segments of blood vessels through fundus photographs. However, Bayesian rule and Markov-Gibbs equivalence have been used to generate the joint distribution and energy of clique sets respectively. The proposed process has been evaluated on HRF and DRIVE datasets. The reported results are 77.31 % and97.67% of sensitivity and 78.63%and97.11% of specificity.

Wu et al. [20] introduced a scheme for automatic detection of microaneurysms in retinal fundus images. The scheme consists of four steps: (i) preprocessing including image enhancement, contrast limited adaptive histogram equalization (CLAHE) and smoothing, (ii) candidate extraction that consists of Peak detection and region growing, (iii) feature extraction with two methods: Hessian matrix based features (HMBF) and shape and intensity features (SIF), and (iv) classification by K-Nearest Neighbor (KNN). The proposed scheme was evaluated on two publicly available datasets: Retinopathy Online Challenge (ROC) and e-ophtha databases. The achieved results were 37.6% and 57.3% of sensitivities for each database, respectively.

Xu et al. in [21] proposed novel features for retinal artery and vein classification that integrated first and second order texture features considered from the vessel profile and an image patch around the target pixel. For classification process a KNN classifier was used. The method was evaluated on DRIVE database with 92.30% of accuracy.

Fraz et al. [22] have proposed a scheme for localization and segmentation of exudates in retinal fundus image. The compilations of classifier of bagged decision tree was then applied. The algorithm has been extensively evaluated on four databases, which are DIARETDB1, e-Ophtha, HEI-MED and Messidor. The achieved results are 87.72 %, 95.77%, 89.25% and 98.36% for each dataset, correspondingly.

Fan et al. [23] have considered a paradigm, named hierarchical image and matting model, to extract blood vessels from fundus images. The model was evaluated on three datasets, including Drive, Stare and CHASE_DB1 with the reported results as 96%, 95.70% and 95.1%, respectively.

Bourouis et al. in [24] developed a framework for diabetic retinopathy classification, where the scaled Dirichlet mixture model (SDMM) based SVM classifier was used to generate kernels considering the structure of extracted features. Three kernels have been considered, including Fisher, Kullback-Leibler and Bhattacharyya. The Messidor and DRIVE datasets were used in evaluation process. The reached results in term of accuracy are as follows on DRIVE dataset, the (SDMM+ Fisher kernel) was 90.87% and (SDMM+ Bhattacharyya kernel) was 91.33%. While, on Messidor dataset, the (SDMM+ Fisher kernel) was 100% and (SDMM + Kullback-Leibler kernel) was 100%.

Chamoso et al. [25] have proposed an agent-based architecture for retinal image classification. Two kind of agents (vissel Type and Manager Type) whose role are to suggest a classification vessel to the users were used. The architecture is implemented using the Case Based Reasoning – Belief Desire Intentions (CBR-BDI) model [26]. The presented method accomplished 85.03% of accuracy.

Chowdhury et al. [27] developed a random forest classifier (RFC) technique to assist the ophthalmologists identifying perfectly the abnormalities in the retinal images. The experiment was conducted on DIARETDB1 dataset, which exhibited the classification accuracy of 93.58%.

Long et al. [28] introduced dynamic threshold with Support vector machine classifier (SVM) based model for automated detection of hard exudates (HE). The scheme was evaluated on DIARETDB1 database that achieved result of 97.7 % accuracy.

Yadav and Singh [1] designed an approach to classify the normal (healthy) and abnormal (disease infected) retinal images using machine learning classification architectures. Numerous methods were used, including PCA-based color to grayscale conversion method [29] and the quality image enhanced by CLAHE in the preprocessing step. Texture features of image such as gray-level co-occurrence matrix (GLCM) features, Tamura's features, wavelet features, Laws' texture energy (LTE) features, and Histogram of Oriented Gradients (HOG) features were employed. SVM classification was used in classification step. The HRF and STARE datasets were utilized in evaluation process; 77.3% of accuracy was reached on both datasets.

Cao et al. [30] have considered an automatic method for cataract detection and grading using retinal images. In the classification stage, the improved Haar wavelet features were used. The method was evaluated on publicly available datasets [31]: HEI-MED, Messidor and DIARETDB1. Different protocols of classification were tested that achieved result of 94.83% accuracy. Dos Santos et al. [32] designed a scheme based on artificial neural network (ANN) and CLAHE filter. A multilayer ANN was applied to optimize the values for CLAHE filter for blood vessel detection. This method was tested on the DRIVE database, which attained 95.05 % of accuracy. Derwin et al. [33] investigated a new method for feature extraction, named Generalized Rotational Invariant Local Binary Pattern LBP (GRILBP) with SVM based radial basis function (RBF) kernel for detection of microaneurysms in fundus images. Retinopathy Online Challenge (ROC) public database was used in evaluation process of the system with f-score equals to 0.421. A brief description of representative traditional machine learning based methods is presented in Table.4.

5. DEEP LEARNING-BASED METHODS

Deep learning is a subcategory of machine learning that has shown a high potential in solving problems in different fields. Deep learning methods usually consist multilayered neural network algorithm that enables extracting universal features in very complex datasets [34].

Deep learning tools have demonstrated the efficiency and effectiveness for various tasks, including natural language understanding, particularly topic classification, sentiment analysis, question answering and language translation [35] [5]. In this section, we focus on deep learning methods that have been applied on various medical care sections in the literature.

Table.4. Representative traditional machine learning based methods

Reference	Dataset	Method/Approach	Performance	
[18]	STARE DRIVE	Enhancement technique, Tyler Coye algorithmic and the improved Hough line transformation	Accuracy 94.89% 94.11%	
[19]	HRF DRIVE	Markov Random Field	Sensitivity 77.31% 78.63%	Specificity 97.67% 97.11%
[22]	DIARETDB1 e-Ophtha HEI-MED MESSIDOR	A set of classifiers of bagged decision trees	Accuracy 87.72 %, 95.77%, 89.25% 98.36%	
[20]	ROC e-ophtha	(CLAHE) and Smoothing+ HMBF and SIF+ KNN	Sensitivity 37.6% 57.3%	
[21]	DRIVE	First and second order texture features +KNN.	Accuracy 92.30%	
[23]	DRIVE STARE CHASE_DB1	Hierarchical image and matting model	Accuracy 96% 95.7% 95.1%	
[24]	DRIVE MESSIDOR	(SDMM+ Fisher kernel) (SDMM+ Bhattacharyya kernel) (SDMM+ Fisher kernel) (SDMM+ Kullback-Leibler kernel)	Accuracy 90.87% 91.33%. 100% 100%.	
[25]	-	Agent-based architecture	85.03%	
[27]	DIARETDB1	Random forest classifier	Accuracy 93.58%	
[28]	DIARETDB1	Dynamic threshold + SVM	Accuracy 97.7%	
[1]	HRFand STARE	Set of machine learning methods	Accuracy 77.3%	
[30]	DIARETDB1 and MESSIDOR HEI-MED	Improved Haar Wavelet	Accuracy 94.83%	
[32]	DRIVE	ANN+CLAHE	Accuracy 95.05%	
[33]	ROC Database	GRILBP+ SVM based RBF kernel	F-score 0.421	

Brancati et al. [36] introduced a supervised vessel segmentation scheme based on a Convolutional Neural Network (CNN). The implemented CNN architecture consists of a specific layer to calculate the directional features. The scheme has been evaluated on DRIVE database with 94.7% of accuracy.

Dasgupta et al. [37] proposed an architecture with fully convolutional neural network F-CNN capable of structured prediction for retinal vessel segmentation task. The architecture was tested on DRIVE database that reached accuracy of 95.33%.

Li et al. [38] designed a Multi-Scale Convolutional Neural Network (Multi-Scale CNN) architecture using loss function LCE (Le Cross Entropy) for blood vessel segmentation. The scheme has been evaluated on DRIVE and STARE databases with 95.10 and 95.6% of accuracy, respectively.

Mo et al. [39] proposed a powerful method based on cascaded residual network to identify diabetic macular edema (DME). It consists of two stages: segmentation and classification. The cascaded framework was evaluated on HEI-MED and e-ophtha databases with 92.55% and 92.27% of sensitivity for both datasets, respectively.

Khojasteh et al. [40] have combined residual networks (ResNet-50) with SVM for detection of retinal exudates. Also, different convolutional neural networks methods have been investigated for an enhanced method with the higher accuracy of exudates identification. For experimental analysis, DIARETDB1and e-ophtha datasets have been used. The reported accuracies were 98% and 97.6%.

Pekala et al. [41] proposed an automatic segmentation of Retinal Optical coherence tomography (OCT).DenseNet, Fully convolutional Network (FCN) and Gaussian process (GP) have been applied. Publicly available U. of Miami OCT dataset was utilized for evaluation [42]. The achieved result was 98%accuracy.

Wang et al. [43] proposed a coarse-to-fine deep learning framework based on classical Convolutional Neural Network (CNN), i.e., U-net model [44], to efficiently and automatically segment the optic disc appear on color fundus images. In evaluation phase, six publicly available fundus image datasets with the collected color fundus images (CFI) acquired on different subjects in the Shaanxi Provincial People’s Hospital were used to validate the developed method. The datasets included were DIARETDB0, DIARETDB1, DRIONS-DB, DRIVE, MESSIDOR and ORGIA. The achieved result was 96.9% of accuracy with 9.39% of sensitivity.

Chai et al. [45] designed a deep learning scheme to segment peripapillary atrophy (PPA) areas automatically from retinal image. This framework was named multi-task fully convolutional network model (MFCN). The model was trained and evaluated based on a real dataset that was collected 73 glaucomatous images and 47 physiologic large cup retinal images from a Beijing Tongren hospital. The reported result was 89.28% of an average precision.

Table.5. Representative deep learning-based methods.

Reference	Dataset	Method/Approach	Performance	
[36]	DRVIE	CNN	Accuracy 94.7%	
[37]	DRIVE	F-CNN	Accuracy 95.33%	
[38]	DRIVE STARE	Multi-Scale CNN	Accuracy 95.10% 95.60%	
[39]	HEI-MED e-ophtha	Cascaded Residual Network	Sensitivity 92.55% 92.27%	
[40]	DIARETDB1 e-ophtha	ResNet-50+ SVM	Accuracy 98% 97.6%	
[41]	U. of Miami OCT dataset	DenseNet+FCN +GP	AUC 98%	
[43]	CFI DIARETDB0, DIARETDB1, DRIONS-DB, DRIVE, MESSIDOR ORGIA. Overall (2978 images)	CNN based U-net model	Accuracy 0.967 0.947 0.936 0.954 0.889 0.970 0.989 0.969	Sensitivity 0.935 0.895 0.873 0.909 0.778 0.940 0.979 0.939
[45]	73 glaucomatous images and 47 physiologic large cup retinal images from a Beijing Tongren hospital	MFCN deep learning model	An average precision: 89.28%	
[46]	In-house IDRID and e-ophtha	Deep learning algorithm	AUC 96.2% to 99.9% 94.7% to 98.0%	

Son et al. [46] developed a deep learning model to detect fundus in retinal fundus images. The evaluation of model was done on three databases, including in-house dataset, Indian Diabetic Retinopathy Image Dataset (IDRID) (https://idrid.grand-challenge.org) and e-ophtha dataset. The AUC for diabetic retinopathy-related findings tested were 96.2% to 99.9%for in-house dataset, while 94.7% to 98.0% for the other ones. A brief description of representative deep learning-based methods is presented in Table.5.

6. CONCLUSION

In this article, an overview of recent methods and frameworks based on machine and deep learning methods for retinal diabetic diagnosis have been presented. Earlier DR related disease recognition and timely treatment can possibly avoid the onset of the malady or help to stop the progression at an earlier stage. It is hoped that this paper will facilitate the task of DR identification and classification research more interesting for budding scientists, researchers and practitioner. This survey has outlined, in different sections, most publicly available databases, performance, DR classification methods used machine and deep learning, which have shown a growth in diabetic retinopathy identification. For brevity, we have summarized the existing methods, in Table.4 and Table.5, to provide a clearer insight on the applied techniques and research progress. According to findings of this survey, one can see that deep/machine learning are capable of aiding diseases diagnostic process related to diabetic retinopathy with high automatic identification performance. For researchers, we also provided, in Table.1, some of the most publicly known databases as it is a very important part of any experimentation. All in all, we can state that the future is quite promising for developing machine learning and deep learning-based schemes for DR detection and related medical fields. As a future work, we plan to explore different machine learning and deep learning architectures to design a hybrid scheme to identify and classify diabetic retinal features.

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