A Scoping review of diabetic retinopathy detection techniques using deep learning: taxonomy, methods, and recent developments

Y. Sravani Devi, S. Phani Kumar
Research scholar, HOD-CSE, GITAM university Hyderabad, CSE

Abstract

Diabetic retinopathy can only be identified through medical eye examination and it is asymptotic. So, early screening of diabetic retinopathy (DR) is important to reduce the vision loss in a significant proportion. Disease identification and progression also plays vital role to prevent the future sight loss of diabetic patients. Nevertheless, early screening is not ensured due to the lack of ophthalmologist where important waiting times are registered specially in industrialized countries. Moreover, patient mobility is a limiting factor in particularly of aging patients. This paper addresses an overview of the methods based upon DL and CNNs in detection of retinal abnormalities related to the most severe ocular diseases in retinal images, challenges in the ongoing research. The research is justified by considering reductions in medical and health care costs and huge potential for new products in medical field.

Keywords:- Retinal images, Diabetic Retinopathy, CNN, Deep Learning,

I. INTRODUCTION

Diabetic retinopathy (DR) is one of the main causes of blindness in world and one of the leading causes of blindness in the countries and the western world working people [1, 2]. The condition occurs due to the effects of diabetes on the small blood vessels in the eye retina. Early screening is not ensured due to the lack of ophthalmologist where important waiting times are registered specially in industrialized countries. Moreover, patient mobility is a limiting factor in particularly of aging patients. Thus, there is a need of effort to create and develop different techniques to automate the screening of retinal diseases. Many CAD systems have been expanded and are widely used for diagnosing ocular diseases. In addition to that variety of imaging modalities been developed to capture the anatomic structure of the eye. The principal imaging technologies for the retina, are scanning laser ophthalmoscopy and optical coherence tomography and fundus imaging technique which is the commonly used to capture retinal images by fundus camera. Some CAD systems based on retinal analysis were developed for extracting the anatomic structures in retinal images, such as detecting lesions related to DR. Recently majority of the semantic segmentation problems are addressed by deep learning methods because of the trends and advancements in deep learning. Segmentation can be applied on retina anatomical structures called Optic Disk or Cup, Retinal Blood Vessel, Fovea/ Macular.

Optic Disk: It is the place where the bundle of nervous fibers forms the optic nerve.

Retinal Blood Vessel: They spread outward from OD, forms a fine network of vessels that supplies the retina with nutrients and oxygen.Fovea / Macular: Fovea, the center area of macula.

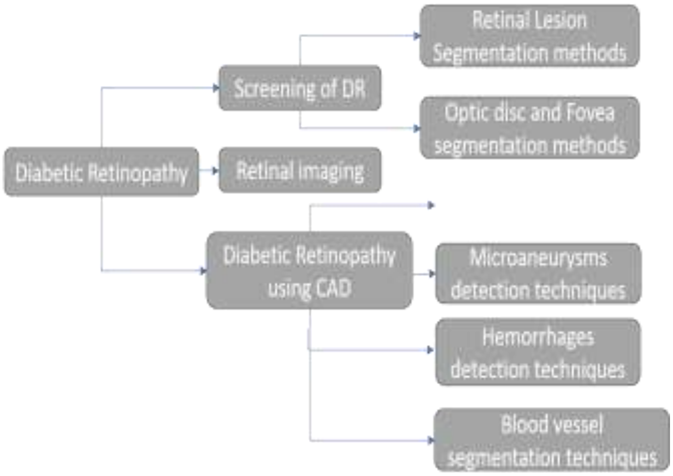

Figure:1System for diagnosis of DR using retinal images

The fundus image is direct optical capture of the eye. Figure:2 & 3 includes anatomic structures like fovea regions, Optic Disc, blood vessels, lesions such as red lesions, microaneurysms, hemorrhages, bright lesions such as hard and soft exudates, cotton wool spots or drusen and vascular abnormalities.

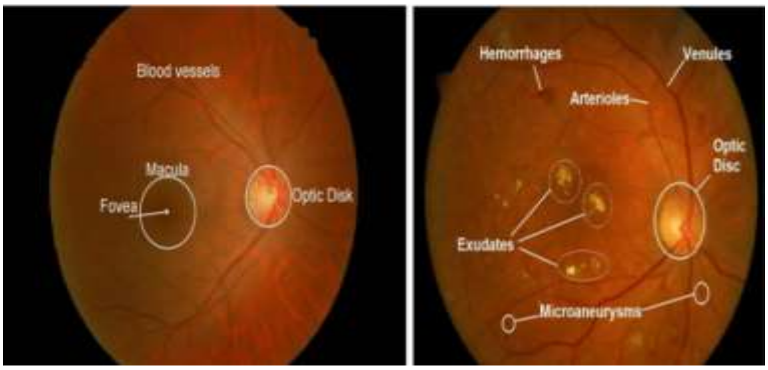

Figure:2 features in retinal images

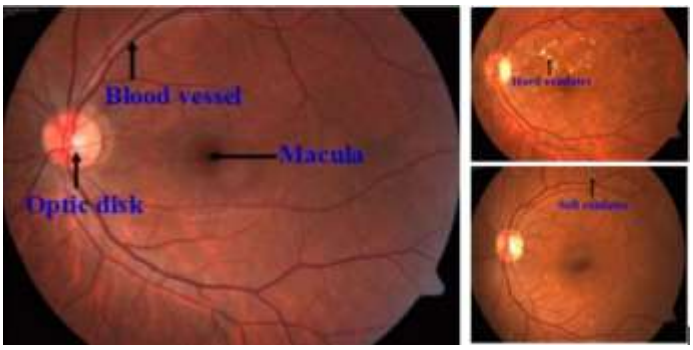

Figure-3 OD and Fovea regions in retinal images

II. Motivation & Contributions

The automated methods based on image analysis for ocular diseases diagnosis from both fundus and OCT images have been explored extensively.The DR diagnosis identified by the detection of abnormal structures in fundus in particular Exudates, Microaneurysms, Hemorrhages, Cotton Wool Spots, bright and dark lesions. Thus, it is important to segment accurately these components for better localization, detection and identification.

By considering present research in diabetic retinopathy techniques, we noticed the necessity of systematic survey in this area. A detailed review has been carried out to study various detection method for DR detection. Extraction outcomes, research implications, and future research directions in the area of eye diseases are presented.

III. Systematic Literature Review

In contrast with the conventional expert literature review, a “Systematic Literature Review (SLR)(or simply a systematic review) is a literature review focused on a research question that tries to identify, classify, select and synthesize all high-quality research evidence relevant to that research question”. An SLR is a step by step process that evaluates and interprets existing proof of research that is suitable to a specific research question. Hence, it follows a predetermined search group. An SLR provides a structure for locating new research tasks in the domain. Figure 4 shows the process of systematic reviews. SLR finds gaps in present research and suggests different areas for another investigation.

This survey paper included emerging approach for future direction of this area.

• There is no SLR on Retinal Image Processing (RIP) till date making research difficult in identifying gaps and present-day research trends.

For this, we conduct an SLR on RIP and recognize different DL methods and hybrid methods for detecting Diabetic Retinopathy.

• We acknowledged the research questions shown in Table 1 according to the guidelines of SLR [24].

• We included recently presented methods for DR detection and identification and accuracy.

• All publicly available datasets on which eye diseases are evaluated are listed.

The following electronic databases are used for searching studies for this SLR on detection of DR using deep learning as guided in [24]:

1. IEEE Xplore Digital Library (ieeexplore.ieee.org)
2. ACM Digital Library (dl.acm.org)
3. ScienceDirect (www.sciencedirect.com)
4. SpringerLink (www.spingerlink.com)

5. Taylor & Francis Online (www.tandfonline.com)
6. Investigative Ophthalmology & Visual Science (https://iovs.arvojournals.org/)
7. British Journal of Ophthalmology (https://bjo.bmj.com/)
8. Health technology assessment (https://www.journalslibrary.nihr.ac.uk/hta/#/)
9. World Scientific (www.worldscientific.com)
10. Diabetes care(https://care.diabetesjournals.org/)

11.Expert Review of Ophthalmology

(https://www.tandfonline.com/toc/ierl20/current).

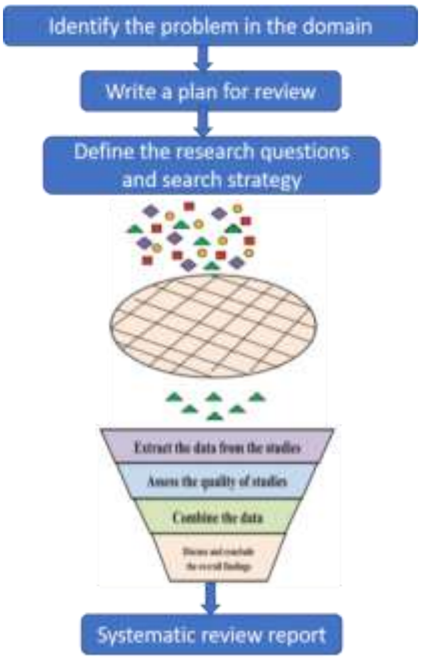

Figure: 4 steps of systematic review

Search criteria:

We improve the review scope of the SLR by various search strings used in this SLR are given in Table 1. This SLR included quantitative and qualitative research articles written in English

S. No	Research Questions	Motivation
1	what are the current trends for detection and identification of diabetic retinopathy	The main objective of this review is: i) To get the deep review on the state of art of DR detection methods. This study presented and
2	how to detect retinal lesions in fundus images	
3	how to predict area of optic disc and fovea in retinal images	

4	how to detect diabetic retinopathy using deep learning algorithms git hub code	compared the different deep learning methods. ii) To design future research through relative investigation of existing research iii) To get the clear understanding of research gap that needs to be addressed and to find the future directions in this area of research.
5	what are the open issues and challenges in the detection of diabetic retinopathy	
6	thesis reports on detection of diabetic retinopathy	
7	how semantic segmentation can be used in detection of diabetic retinopathy	
8	detection of diabetic retinopathy using semantic segmentation git hub code	

Table:1 searching criteria using research questions

IV. Deep Learning methods for DR detection and grading

DR is a microvascular complication of diabetes, providing morphological changes and abnormalities in the fundus. These changes concern mainly the microaneurysms (MAs), exudates (EXs, Hard and Soft Exudates), blood vessels[3] such as the abnormal growth of the blood vessels, hemorrhages (HMs), macula inter retinal micro vascular abnormalities (IRMA). The appearance of MAs and hard exudates are the earlier signs of DR.

It is particularly important that people who are having diabetes are advised to go for screening of DR every year by a local diabetic eye screening center; this is present case. However, diagnosis is challenging as the disease has less symptoms at its early stages and it is hard to detect based on symptoms.

Literature	**Data set**	**DL method**	**Features extracted**	**Performance**
Harry Pratt et all.	Kaggle DR	CNN	DR five classes 0- no DR 1- Mild 2- moderate 3- severe 4- Proliferative DR[15]	Accuracy- 75% Specificity- 95% Sensitivity- 30%
M D Abramoff et all.	MESSIDOR-2	GoogLeNet DNN	Exudates, Haemorrhages, Microaneurysms and Blood vessels	Accuracy- 96%
Hidenori Takahashi et all.	Private custom dataset	DCCN Gradient Boosting	Retinal Lesions	Accuracy- 89.4 for Hard Exudates, 88.7 for Red Lesions, 86.2 for micro, 76.1

				for Blood Vessel detection
Kele Xu et all.	Eye PACS	DR ineterpretable classification	DR classes(yes/no)	Sensitivity -90% Specificity-- 90%
Jordi de la Torre et all	Eye PACS	ResNet,Inception V3 & DenseNet	DR classes(yes/no)	Accuracy- 97.7% Sensitivity- 97.5 Specificity- 97.7
Wei Zhang et all	MESSIDOR	DL & CNN	Exudates, Haemorrhages, Microaneurysms and Blood vessels	Accuracy- 97% Sensitivity- 94 Specificity-- 98
D Judde Hemanth	MESSIDOR	Inception V4	Exudates, Haemorrhages, Microaneurysms and Blood vessels	5 classes Accuracy- 88.4% Accuracy- 96.9 with no DR images Accuracy- 57.9% for mild and worse NPDR images
Rory Sayres et all	Eye PACS	Forward NN and DNN	DR classes(yes/no)	Accuracy- training- 89.6 Accuracy- testing- 86.3
Sivaji Dutta et all	Kaggle DR	Inception, ResNet V2 module	DR five classes 0- no DR 1- Mild 2- moderate 3- severe 4- Proliferative DR	Accuracy (VGGNet)- training- 76.4 Accuracy- testing- 78.3
Kang Zhou et all	Eye PACS & Kaggle	Pre-Trained GoogLeNet and AlexNet	Exudates, Haemorrhages, Microaneurysms and Blood vessels and DR classes	Sensitivity- 95%
Jordi de la Torre et all	Eye PACS	CNN	DR classes(yes/no)	Sensitivity - 90% Specificity-90%
Bhargav J Bhatkalkar	DRIONS-DB, RIM-ONE v.3, and DRISHTI-GS.	DeepLab v3+ and U-Net models	Exudates, Haemorrhages, Microaneurysms and Blood vessels	Overall Accuracy: 99%
Jaemin Son et al.	DRIVE	CNN	Exudates, Haemorrhages, Microaneurysms and Blood vessels	Specificity-99%

Jen Hong Tan	DRIVE	7-layer CNN	Exudates, Haemorrhages, Microaneurysms and Blood vessels	Sensitivity-90%
Zhongyu Li	IDRiD	FCN based DLA method	diabetic retinopathy (DR) and diabetic macular edema (DME)	Sensitivity:70%, Specificity- 95%
Yoon Ho Choi	IDRiD	U-net based algorithm	diabetic retinopathy (DR) and diabetic macular edema (DME)	sensitivity:74%, Specificity- 99%
B. Harangi	ISBI 2018	AlexNet, and GoogLeNe	Exudates, Haemorrhages, Microaneurysms and Blood vessels	Accuracy:91.04%

Table-2: Deep-Learning methods for DR detection

Harry Pratt et al. [18] suggested a method with architecture of CNN and data augmentation. This can identify the main characteristics of DR like microaneurysms, exudates and hemorrhages. The CNN network trained on Kaggle dataset got 95%, 30% and 75% for specificity, sensitivity, and accuracy, respectively. In [19] the DL method aims localization of the particular and visual understandable features of DR. This method is accomplished by joining the regression activation map (RAM) of an input image.

In [20] a fully randomly determined GoogLeNet deep learning NN is proposed. In [21] a DCNN technique is proposes survey for the automatic classification of DR disease from retinal image. The results specified the following classification accuracies called 89.4% for Hard exudates, 88.7% for Red lesions, 86.2% for microaneurysms and 79.1% for Blood vessel detection. In [22] a latest model for the explanation of DL classification models is proposed. This method is based on the distribution of scores.

In [23] an automated DR recognition and grading system (DeepDR) detects the existence and severity of DR disease from retinal images via transfer and group learning. The proposed identification method performed with a a specificity of 97.7%, sensitivity of 97.5%, and an accuracy of 97.7%. The evaluating model achieved a specificity of 98.9%, sensitivity of 98.1% and an accuracy of 96.5%. In [24] a hybrid method for detecting DR includes both image processing and DL model.

In [25] The DL method was trained using the Inception v4 model architecture and a huge data of more than 1.6 million retinal images, then adjusted to a set of 2000 images that had labels agreed on by three ophthalmologists as a reference standard. Overall, the model exibited a 5-class accuracy of 88.4%, with an accuracy of 96.9% for images with no DR and 57.9% for images with mild or worse NPDR. In [26] the suggested method based upon CNN network using VGG network architecture have been trained with back propagation

NN, Deep Neural Network (DNN) and CNN. In [27] a Multi-Cell Multi-Task CNN (MCNN) is proposed. In [28] the proposed method is based on Transfer learning on pretrained GoogLeNet and AlexNet models from ImageNet.[29] a DR image classification model was described. This model is used for grading the level of the DR. The EyePACS dataset is used to get a training set which is composed of 35,126 images and the test set 53,576. A proposed DR interpretable classifier achieved more than 90% of sensitivity and specificity and allow it to detect more severe cases of DR disease.

DR is ongoing disease and needs its identification at an timely stage because it is fundamental to prevent the development of DR disease. Similarly, protecting a patient's vision needed regular screening which generates developing efficient and reliable frameworks of computer assisted diagnosis of DR as CAD system. The DR diagnosis identified by the detection of abnormal structures in fundus in particular Exudates, Microaneurysms, Hemorrhages, Cotton Wool Spots, bright and dark lesions Thus, it is important to segment accurately these components for better localization, detection and identification. Supervised and Unsupervised learning techniques are the major methods used the detection of the main clinical components of DR Disease providing automated screening based on retinal images.

Semantic segmentation is a high-level task in the image processing and mainly used for perfect picture understanding. Semantic segmentation [8] methods for the identification of Diabetic Retinopathy in two ways:

1. Retinal Lesion Segmentation
2. Optic disc and Fovea detection.

	Selection of studies
Retinal Lesion Segmentation	1. Automated segmentation of retinal lesions using deep convolutional neural network.[11] 2. Mask R-CNN for Diabetic Retinopathy Retinal Lesion Detection and Segmentation. 3. The automated segmentation of retinal lesions and optic disk in fundus images using a deep fully convolutional neural network for semantic segmentation. 4. Hard and Soft exudates segmentation using deep layer aggregation.[6] 5.U-NET for retinal lesion segmentation.

Optic disc and Fovea detection	1. Optic Disc and Fovea detection using global and local encoders. 2. Optic Disc and Fovea detection in fundus images. 3. Segmentation of optic disc, fovea and retinal vasculature using a single convolutional neural network. 4. Methods used for segmentation of Optic Disc and Fovea.

Table:3 Selection of studies

4.1 Retinal Lesion detection methods:

J. Orlando et al. [29] identified only lesions with red color in Diabetic Retinopathy images by incorporating Deep Learning methods with for feature understanding. Then, the retina images were classified by applying the Random Forest classifier. The fundus images of the MESSIDOR [30], E-ophtha [31] and DIARETDB1 [32] datasets were preprocessed by extracting the green channel and dialating the Field of view, and applying a Gaussian, r-polynomial transformation, thresholding operation and morphological closing functions.

P. Chudzik et al. [33] used custom CNN architecture to detect Microaneurysms from DR images. This study we used three datasets:, E-ophtha [35], ROC [34] and DIARETDB1 [32].in these first extracting the green plane and then resizing, generating mask using Otsu thresholding, and using a weighted sum and morphological functions. The system suggested by Refs. [36], recognizes the hard and soft exudates from DR retina images with the generating CNN with Circular Hough Transformation (CHT). Y. Yan et al. [37] recognized DR red lesions in the DIARETDB1 [32] dataset by combining the attributes of a handcrafted and revised pretrained LeNet architecture using a Random Forest method. In the images the portion of green channel was taken, and they were increased by CLAHE. H. Wang et al. [38] recognized hard exudates in the E-ophtha dataset [39] and the HEI-MED dataset [40] by combining the attributes of a handcrafted and custom CNN using a Random Forest method. These datasets were preprocessed by performing color normalizing, cropping, modifying a camera aperture and recognizing the candidates by using dynamic thresholding and morphological construction. J. Mo et al. [41] detected exudate lesions in the E-optha [39] and the HEI-MED [40] datasets by segmenting and classifying the exudates using deep learning.

Location of OD and Fovea detection:

1. It is a regression task to locate the OD and Fovea in the retinal image. First, extract the whole image features, roughly estimate the OD and foveal center extract the overall image attributes and recognize the centre of OD and fovea through a CNN encoder.

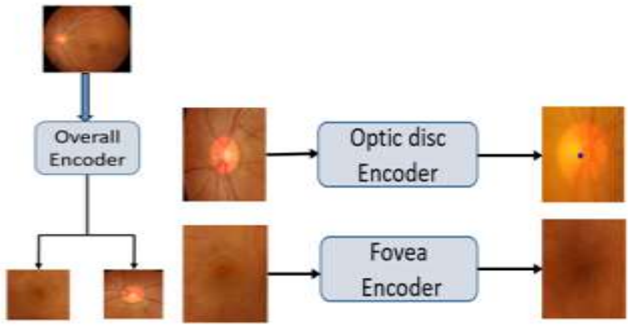

Figure-5: roughly estimating OD and Fovea(left) and predicting accurate OD and Fovea(right) centers

2. Calculating Jaccard index and Euclidean distance for OD segmentation and Fovea localization.

The Jaccard index called as intersection over union. It measures similarity between OD estimated mask OD_{est} and OD ground truth mask OD_{gt}. Euclidean distance is straight line distance between two points (x_{est},y_{est}) and (x_{gt},y_{gt}). The localization points are estimated from geometric center of OD/Fovea region.

4.2 Optic Disc/ Fovea detection methods:

Yaxianshen et al. presents global feature encoder followed by two separate VGG Neural Network and Euclidean distance of 21.072 between ground truth and automatically located coordinates in OD detection & fovea detection. BHARGAV J. BHATKALKAR et al. developed CNN for the segmentation of OD in retinal images using Attention gates and conditional random fields. Jaeminson et al. designed CNN(Unet) for Optic Disc and Fovea detection on DRION dataset and Euclidean distance of OD is 26.4/ Fovea is 39.21. Ana Maria Mendonca et al. Existing localization methods only extracting either global or local features using different CNN architectures.

Datasets available:

Name	**No of Images**	**Resolution**	**Features of retinal images**
DRIVE	20 trian images, 20 test images	768 × 584	Haemorrhages, Microaneurysms, Blood vessels and Exudates [5]
Image-Ret(DIARETB0, DIARETB1)	B0: 20 are normal 110 with DR B1: 5 are normal, 84 are DR	1500 × 1152	Haemorrhages, Microaneurysms, Blood vessels and Exudates [7]
MESSIDOR[30]	1200 images	1440 × 960,2240 × 1488,2304 × 1536	Haemorrhages, Microaneurysms, Blood vessels and Exudates
Retinopathy Online Challenge	100 digital fundus images	768 × 576, 1058 ×	Microaneurysms

		1061,1359 × 1383	
E-ophtha MA[31]	148 images with lesions and 233 healthy images	2048 × 1360	Microaneurysms
STARE	400 fundus	605 × 700	Haemorrhages, Microaneurysms, Blood vessels and Exudates
HEI-MEI	115 images have exudates and 54 are healthy	2196 × 1958	Exudates detection
Kaggle DR detection[42]	35126 fundus images		DR five classes
IDRid	516 retinal images	4288 × 2848	diabetic retinopathy (DR) and diabetic macular edema (DME)

Table 4: Datasets available for detection of DR

V. Discussion and challenges in research

In medical imaging, automatic recognition of DR from retinal images has been a lively research for a long term. The research is explained by significant reductions in health care costs and huge potential for new products in medical field. The automated methods on image analysis for ocular diseases and other part deep learning-based AI in eye diseases diagnosis, it shows that there is an strong effert to create and design methods to automate the screening of ocular diseases. Many CAD systems for ocular diseases have been developed and are widely used. Nowadays the automated methods based on analysis of image for ocular diseases diagnosis from both fundus and OCT images have been explored extensively.

The skill and hardware [4] required in areas where the diabetes people are more and detection and identification is needed. As the diabetes patients are increasing, the equipment[4] is needed to prevent the vision loss due to DR even it is taking more clinician time will be consumed by the performance of the classification task.

The identification of DR can be done by ophthalmologists and an automatic system too. In the manual system, the analysis and generating reports of retinal images need ophthalmologist, which consumes more time, but in the automated method deep learning is used to perform major role in the area of ophthalmology and specially in the early screening of diabetic retinopathy over the traditional recognition methods.

Recently, some researchers are interested to the quality of fundus images which are captured by Smartphone with respect to the clinical employment and then an interest is focused on the design of CAD systems based DL using Smartphone for detection of retinal abnormalities. However, until now less research work is published. The ophthalmic diagnosis can be major direction for coming research. The design of CAD systems based upon Deep learning and using

Smartphone platform for detection of retinal abnormalities. The CAD system proposed in [28] uses the D. Eye lens to capture and process fundus images in real-time on Smartphone platforms for retinal abnormality detection. It is based on convolutional neural network and the transfer learning method.

VI. Conclusion

This systematic review report states automated methods based on image analysis for eye diseases and other part deep learning models in ocular diseases diagnosis. It is an strong effort to create and design methods to automate screening of ocular diseases. Many CAD systems for ocular diseases have been developed and are widely used. It was also noticed that the automated methods for ocular diseases diagnosis from both fundus and OCT images have been explored extensively. In future, we will develop automated smart phone based deep-learning model which can take fundus images through phone camera and detect the ocular diseases like DR, Glaucoma and ARMD. Due to the increasing cases of DR every day, it needs lot of equipment and ophthalmologists to identify the early screening of Diabetic Retinopathy, so there is a need of smart phone-based system to identify the early detection of DR.

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