Survey on Techniques for Diabetic Retinopathy Detection & Classification

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Abstract: ***Diabetes is a very common disease among people who suffer from glucose abnormalities. Diabetic Retinopathy (DR) is a severe microvascular complication that is found only in diabetic patients that affects the retina of the patient and causes permanent partial or complete blindness to the affected person if not detected and cured at an early stage. However, many diabetic patients fail to detect this disease & lead themselves to visual impairments and this happens due to delay in detection as the patient needs to approach the ophthalmologist who screens the retina of the patient. This manual screening & traditional approach is time-consuming and delays the DR detection process which causes the disease to advance to further stages in the time window and also this manual processing isn't always accurate. This article surveys & reviews the latest research as well as survey papers discussing about the accurate diagnosis as well as Classification of DR into different categories from mild to severe based on the various techniques utilized for image pre-processing, disease detection & classification from fundus image datasets. In the end the article also proposes the novel model based on ResNet50 (CNN model) for more accurate diagnosis & classification of the DR disease.***

Keywords: Machine Learning, Diabetic Retinopathy, Fundus images, Convolutional Neural Network

1. Introduction

Diabetes is a disease where glands don't secrete enough insulin or the body is unable to process it properly. About 442 million people worldwide have diabetes as estimated by WHO this is a major issue as 77 million of these patients are in India making it the diabetes capital of the world [29]. As diabetes progresses, it slowly affects the circulatory system including the retina and causes long-term accumulated damage to the blood vessels, diminishing the sight of the patient leading to Diabetic Retinopathy [30]. When there is abnormal shooting up of blood sugar level, the excess blood sugar generated finds no other option but to get accumulated in blood vessels of the human eye. [31] After 10 to 15 years of diabetes, about 10% of people become blind and approximately 2% develop severe visual impairment. DR is the sixth largest cause of partial blindness among the working-age group. There are many stages of Diabetic retinopathy ranging from mild, Non-proliferative Diabetic Retinopathy (NPDR), Proliferative Diabetic Retinopathy (PDR), moderate and severe [29]. In NPDR, the retina gets swollen, due accumulation of glucose leading to blood vessel leakages in the eyes. The swelling could be so worse that the vessels could get completely blocked resulting, in partial vision loss of the patient. Whereas PDR occurs at a much advanced stage when new blood vessels start growing in the retina. The new blood vessels are extremely thin and fragile being more prone to form scar tissues which lead to detachment of the retina resulting in loss of central or peripheral vision causing complete vision loss.

The symptoms of NPDR & PDR include blurred vision, wool spots, hemorrhages, double vision, and microvascular abnormalities. The blood from the hemorrhage leads to partial or complete vision loss. Patients may also incur floaters, dark areas, and difficulty in perceiving colors.

The popular diagnosis of DR includes the doctor injecting a dye in the patient's arm vein, and pictures are taken as the dye flows through the blood vessels in the eyes detecting cases of blockages, leakages, and hemorrhage. In the other method, tests are conducted to take cross-sectional images of the retina which helps to identify issues pertinent to fluid leakages or damages in the retinal tissue. These traditional methods are expensive, time-consuming, laborious & aren't always accurate.

Hence it is evident that early detection of the disease plays a major role in saving patients from vision loss. The more time the disease gets lingered being ignorant or untreated, the consequences could be irreversible [30].

Machine learning (ML) algorithms have been a prevalent choice in the prediction of various diseases [1][31][32]. CNN has successfully contributed towards analysis & decision making in the fields of computer vision, drug design, medical image processing, etc. The implementation of such advanced machine learning approaches has significantly contributed towards pathological screening and disease predictions thereby reducing the burden of human interpretations. Having such glorifying results of CNN and ML in various other fields of healthcare, application of the same in the detection of diabetic retinopathy was a natural and inevitable point of interest with an objective to reduce the occurrence of diabetic retinopathy.

2. Literature Review

We studied and reviewed various research & survey papers in which different methods and techniques are used.

a) Machine Learning Techniques

The research published in MDPI 2020[1] proposed the use of Deep Neural Network (DNN) to detect & classify DR. Dataset was taken from University of California ML Repository and Messidor consisting of 64,000 Retinal Fundus Images for training the DNN for detecting (if present in the patient) and classifying the DR into 2 separate categories .i.e. Proliferative (PDR) & Non-Proliferative DR (NPDR). The DNN used PCA & firefly algorithm and was trained using the Adam-Optimizer. The author claimed that the model outperformed other popular hybrid ML algorithms with 96% accuracy.

The article [2] proposed a model for diagnosis of DR using DCNN to classify it into NPDR & PDR by using algorithms such as fractional max-pooling & support vector machine (SVM) to train & run the model. The raw images were taken from the Kaggle dataset with 34000 images on which image pre-processing techniques like re-scaling colour divergence removal & periphery removal are done to classify them with 91% accuracy.

The authors in [3] proposed auto-DR detection to classify the images into 5 grades. The model is based on Binocular Siameselike CNN & is trained & worked on the Inception V3 algorithm. EyePacs dataset consisting of 35000 images is fed onto the model after pre-processing techniques like scaling, normalization & high-pass processing on the retinal fundus images to classify them into different groups depending on the presence & DR severity.

[4] Automates DR diagnosis using Deep CNN to provide appropriate suggestions to the diabetic patients after grading the severities of their retinal images. This model works on ReLU, Inception v3 &Resnet algorithms. The dataset is taken from the E-Optha dataset consisting of 130 images & 88000 more from Kaggle. The output is classified as No Dr, NPDR, Mild PDR & Severe PDR. In [5] authors detected blood vessels and identified & classified the stages of DR into normal, moderate DR, and NPDR using DNN. STARE dataset consisting of 65 images is used. Efficiency can be increased with an increasing number of images in the dataset.

In one of the articles published in 2019 in springer[6], the researchers studied the use of DL methods to analyze fundus images of referral DR & use grading methods to classify macular edema using deep CNN. It used the inception v3 algorithm to train and the dataset consisting of 41000 retinal fundus images were taken from Digi-Fundus Ltd. Accuracy was 91% and the output was classified as referable & non-referable DR.

In [7] the model was built to automatically classify patients having DR & not having DR. Data set consisted of 30 high resolution fundus images in which 15 were healthy 15 were suffering from DR was used. In the learning process of the DCNN, they made use of Adam Optimizer.

The researchers worked on 5 deep CNN models (resnet50, Inception V3, Xception, Dense121, and Dense169) to get the best result by concatenating models into one for good result & improve the classification of different DR stages. They used the Kaggle dataset with 35,126 fundus images for training, testing & validation purposes with 64%, 20%, and 16% [9].

In [10] CNN was used for classifying the stages of DR. They used images from the Kaggle data set which contains 500 retinal images. HE filtering algorithm is used in pre-processing & for training stochastic gradient descent with momentum optimization algorithm is used. The proposed model which concatenated VGG 16 Alex Net & Inception net V3 provided a result of 81.1 % accuracy.

In [11] the authors proposed automated knowledge models to identify the key antecedent of DR. The model was trained with 3 times back propagation neural network, DNN & CNN. Hybrid model using image processing & DL to improve the result for predicting DR. The dataset used is from MESSIDOR having 400images. The HE & CLAHE for image enhancement were used. The classification of diagnoses was done using DL & CNN [12].

A study on the use of micro-aneurysms, exudate & hemorrhage features to detect DR was carried in [13].

Another used CNN model for DR screening using fundus retinal photography as input. They made use of features like microaneurysms & hemorrhages to detect DR[15]. For training have used 30000 fundus images from Kaggle. A small problem with this model was that it classified most of the class1 & class 2 images as class 0.

The purpose of t research [17] paper was the detection of DR using DL. The model was built on the inception-V3 model which is widely used image recognition having accuracy greater than 78.1% for the ImageNet dataset. The main programming language preferred for the algorithm was a python. Libraries used for this model were OpenCV for image pre-processing, image loading & image manipulations such as resize & rotation, NumPy for mathematical functions. Theano was used to handle multi-dimensional arrays efficiently [17].

Ab automated DR detection by analyzing the retinal abnormalities like hard exudates, hemorrhages, Micro aneurysm, & soft exudates was done in [20]. The dataset used is DIARETDB1, which includes 89 color fundus images.

Abnormalities are made clearly visible because of high contrast & the CLAHE procedure for improving image brightness was used. It then categorizes the images into 4 classes i.e. normal, earlier, moderate, or severe stages using the Deep Belief Network (DBN) algorithm. Algorithm called Modified Gear & Steering-based Rider Optimization Algorithm is used for optimal feature selection [20]. Auto-DR Detection in fundus photographs was proposed using a deep transfer learning approach using the Inception-v3 network in [21]. This model attained 93.49% accuracy. In another approach, the entropy image is computed by using the green component of the fundus photograph. The dataset used is the Kaggle dataset to detect & classify DR into no referral (no apparent DR and mild NPDR) and referral (moderate NPDR, severe NPDR, and PDR). The UM technique is utilized to amplify the high-frequency parts of the gray level (luminance) & the green component of the retinal image before computing the entropy images. CNN-based DL system [23].

b) Data Mining Techniques

The authors Revathy R, NithyaB in [8] proposed a hybrid ML model which is a combination of SVM, KNN & RF. They used the Kaggle dataset which contains 100 images. The performance of their proposed model has an average accuracy of 82%. Another technique used the image processing, data mining, texture & wavelet features are extracted for DR detection. They took the dataset from DIARETDB1.

DWT Transform & GLCM algorithm are used for feature extraction & KNN is used for image classification [14]. The main goal of this research in [16] was to automatically classify the grade of NPDR at any retinal image. For this the initial image processing stage isolated the blood vessels, microaneurysms & hard exudates in order to extract features that can be used by an SVM) for figuring out the retinopathy grade of each retinal image.

The use of blood vessels, exudates &microaneurysms features to detect DR was studied in [18]. ANN was used for classification. DIARECTDB1dataset & local databases were used. Images were Pre-processed was carried before achieving a sensitivity of 95% & accuracy of 96% [18].

Back-propagation-based ANN is chosen as a pattern classification tool [19]. The dataset used is Messidor which predicts whether an image contains signs of DR or not, further which the dataset is divided into 2 groups. The training algorithm used is Lavenberg–Marquardt algorithm [19].

c) Review of Survey Articles

The study proposes a computer-aided screening system (DREAM) that detects & grades fundus images for the severity of DR using ML. The methods employed are Gaussian Mixture Model (GMM), k-nearest neighbor (kNN), SVM, among which GMM & KNN are found to be the best for bright & red lesion Classification. Here a 2 step hierarchical classification approach is proposed where the non-lesions or false positives are rejected in the first step and in the second step, the bright lesions are classified as hard exudates & cotton wool spots, and the red lesions are classified as hemorrhages and micro-aneurysms [24]. The survey [25] paper discusses numerous pre-processing & segmentation techniques that can be used to detect DR. This survey paper compares 12 research papers & articles. Comparison of various papers considering Datasets, classification algorithm, Processing parameters, Image processing techniques & accuracy [25].

Table 1: Comparison of research papers on Data Mining based Classification techniques

Ref No	Publisher & Year	Methodology	Model/ Algorithm	Data set	Image Processing technique	Accuracy (%)	Sensitivity (%)	Specificity (%)	Advantage	disadvantage	Output classification
[8]	2019 IJERT	KNN, SVM, RF	The hybrid model of all 3	Kaggle Dataset (1000 images)	RGB to HSV Adaptive Histogram equalization Thresholding	82	---	---	Higher accuracy Can work on the small dataset	Images must be of high quality. Accurate pre-processing needed	DR, NDR
[14]	ICCCI 2017	KNN	DWT transform GLCM	DIARE -TDB1	Resizing Sharping Laplace Edge Detection	97.7	100	93.1 0	Very good sensitivity	--	Normal DR Mild DR Severe DR
[16]	IEEE In 2017	SVM	Not mentioned	Messidor database	Image conversion (RGB to CMY) representation, Image binarization Dilation & erosion	85.5	49.4	88.4	Specificity is 100% for grade 1	Very bad sensitivity for grade 1 and 2 DR detection	Normal DR Mild DR Moderate Severe

[18]	BMEiCON 2016	ANN	Not Mentioned	DIARECTDB1 and local databases (214 images)	Smoothing Noise removal Conversion to greyscale.	96	95	--	ANN can easily train a large dataset	The number of images used is very less	Normal DR Mild DR Moderate Severe DR PDR
[19]	Springer, 2019	ANN	Back propagation neural network Lavenberg–Marquardt algorithm	Messidor image set	Not Mentioned	97.1	97	97	The proposed method has the highest accuracy among all methods & can be used effectively for DR detection.	If images are not obtained with accurate features, the effectiveness of a method may decrease	DR NO-DR
[22]	Springer 2019	NB SVM classifier	---	Lariboisi`ere and Messidor	Adaptive histogram equalization	0.8	1.0	0.67	Higher accuracy, sensitivity	Performance decreases if the MA part is removed.	DR NDR
[24]	IEEE2014	GMM, KNN SVM	---	MESSIDOR	Histogram equalization Contrast enhancement Scaling pixel intensities	---	100	53.16	Low computational complexity	Might give false positive, hence manual assessment may be needed	Severity of NPDR

DR can be classified as NPDR & PDR, also some possibility of mild NPR, moderate NPR, & severe NPR. Image acquisition techniques they studied were fundus imaging, color fundus photography & hyperspectral imaging. For pre-processing, they did grayscale conversion & used histogram equalization & large Median filter. The fast & efficient classification methods are the neural network, SVM & KNN. Performance parameters such as accuracy, sensitivity, positive predictive value & specificity in the above methods are determined effectively [26].

The authors in [27] surveyed different techniques that can be used to detect DR. They have compared 7 research papers on the basis of diagnosis, Database, classification algorithm, processing parameters, image processing algorithm, & accuracy. Most of the papers have used Messidor& DIARETDB1 datasets. Different Classification algorithms discussed are KNN, ANN, SVM, GMM, SVM, Ad boost, DT, NB. Pre-processing algorithms like canny edge detection, histogram equalization, Gaussian filtering, adaptive mask generation, image segmentation, edge detection, AM/FM. Exudates are the main symptoms of DR, an early detection of exudates prevents the patients from blindness [28]. For pre-processing, 2 steps were followed: normalization of the color of the dataset & then local contrast enhancement. Image as converted from RGB color space to HSI color space, by applying median filter & CLAHE. Exudates classification has been done through SVM classifier, Naïve Bayes classifier & Neural Network classifier and it has been found that Naïve Bayes & SVM are comparatively better than Neural Network classifier [28].

Table 2: Comparison of research papers on Deep Learning based Classification techniques

Ref No	Publisher & Year	Method-ology	Model/ Algorithm	Data set	Image processing technique	Accuracy (%)	Sensitivity (%)	Specificity (%)	Advantages	Disadvantage	Output classification
[1]	(MDPI) 2020	DNN	PCA Firefly algorithm Adam Optimizer	UCI- ML repository Messidor 64k-imgs	Augmentation, rotation & edge detection	96	90	94	Better performance of DNN-PCA-Firefly	Application of PCA on DNN & ML decrease efficiency	No DR NP-DR P-DR
[2]	Hindawi 2019	DCNN	Fractional max pooling SVM with TLBO	Kaggle 34k images	Rescaling, removal of Color divergence Periphery removal	91	89	99	Feasible, less time consumption for model training	Lesion Images were not enough to train the model which affect the performance	NP-DR (level 1,2) P-DR (level 1,2)
[3]	IEEE March	Siamese like the	Inception v3	EyePACS 35k images	Scaling, Normalization	94	82	70	Potential to diagnose DR	Difficult to train & test	1-No-DR 2-Mild

	2020	CNN model			High-pass processing				more efficiently Improvement in screening rate of DR	dataset with paired fundus images	Moderate 4-Severe 5-P-DR
[4]	IEEE January 2019	DCNN	Inception v3 ResNet	E-ophtha 130 images Kaggle-88k images	Size, shape, and color normalization	89	---	---	The model focuses on various locations of DR images	Results are obtained on the relatively small dataset	No DR NPDR Mild PDR Severe PDR
[5]	Research Gate 2016	DNN	-----	STARE database (65 images)	Digitalization HSV & gamma correction	88	87	71	More Efficient. Efficiency increases with more dataset images	Less no. of features extracted from the images	Normal Moderate NPDR Severe NPDR
[6]	Springer 2019	DCNN	Inception v3	Digi-fundus Ltd. (41k images)	Image cropping Resizing Border & annotations removal	91	85	96	Less costly in screening & diagnosis & have high efficiency	Increasing dataset images increases computation cost.	Referable and nonreferable DR (R-DR, NRDR)
[7]	2018 IEEE	CNN	Adam optimizer	Benchmark dataset 30 images	Conversion into Weighted greyscale, Resizing Rescaling	91	1.0 or 100	---	High accuracy Works with a small dataset	The dataset must be of high resolution & accurate for training	NPDR and PDR
[9]	2019 IEEE Access	DCNN	Resnet50 Inceptionv3, Dense - 121 Dense169	Kaggle 35k images	Augmentation Rotation of images	80.8	---	86.7	Better performance Can detect all the DR stages	Time costly as have to design every model and ensemble it.	NPDR Mild Moderate Severe PDR
[10]	2019 IRJET	DCNN	AlexNet, Vgg16, InceptionNet V3	Kaggle dataset-500 images	Downsize & resize images Conversion to monochrome Histogram equalization Filtering	80.1	---	---	Combination of 3 models which are best	Difficult & time costly. Optimize with a huge no. of parameters in Stochastic gradient descent	NPDR Mild Moderate Severe PDR
[11]	2018 IJGDC	BNN, DNN, CNN (VGGNet)	VGGNet (CNN)	Kaggle 2000 images	Fuzzy C-means clustering Edge detection	78.3	---	---	The better result among the three models.	Requires high resolution fundus images.	Mild NPR Moderate NPR Severe PR
[12]	2018 Springer	CNN	---	MESSIDOR database(400 images)	HE technique CLAHE technique	97	94	98	High accuracy and specificity.	Input data should accurately be pre-processed	DR, NDR
[13]	Elsevier 2016	CNN	Stochastic gradient descent with Nestrov momentum	Kaggle (80K image)	Normalization Image resizing Image rotation (0-90 degrees)	75	30	95	Can easily detect Healthy eye	Very low Specificity. Skewed datasets	No DR Mild DR Moderate Severe PDR
[15]	SPIN 2017	CNN (LeNet-5)	Nesterov momentum	Kaggle (30k)	Cropping Resizing to squares, Normalization, Denoising	85	--	--	--	Dataset is highly imbalanced	No DR Mild DR Moderate Severe Proliferative
[17]	IEEE 2017	CNN	Inception-v3	Kaggle dataset	Normalization Mean	88	97	87	Big dataset Improves	--	DR NO DR

				(40K)	subtraction & PCA				accuracy. Better in training		
[20]	Springer April 2020	(DBN)	(MGS-ROA)	DIRECTD B1	RGB image conversion to the green channel, Image enhancement using CLAHE.	93.1	86.3	95.4	Better algorithm for computing accuracy.	DBNS don't account for the 2D structure of an input image, affect performance applicability in computer vision.	Normal DR Earlier DR, Moderate DR Severe DR
[21]	tvst. journals 2019	Deep transfer learning	Inception-v3	Messidor-2	Pixel scaling & downsizing (CLAHE) Contrast enhancement.	93.49	96.93	93.45	Excellent sensitivity, accuracy & specificity. High reliability.	Transfer learning leads to declining performance. Tested on the small dataset	No DR Mild DR NPDR Severe NPDR PDR
[23]	Hindawi 2020	CNN	Bichannel CNN model	Kaggle dataset	Resizing Luminance conversion from RGB	87.8	77.8	93.88	Provides better accuracy & sensitivity. Advances detection of referable DR	Input data should be properly pre-processed.	No DR, Mild DR Severe DR

Table 3: Review of survey papers

Year/ publisher	No of the papers discussed	Image processing technique	Methodology Discussed	Conclusion
IJRTE 2018	12	Image cropping, Segmentation Thresholding, Feature-based GL extraction, green channel extraction, noise removal, Smoothening & contrast enhancement & Intensity Measure	Artificial Neural Network, KNN, Support Vector Machine, Convolution Neural Network	Different concepts relating to DR that could be detected at an early stage were presented in a nutshell in this survey paper which made use of the pre-processing, segmentation & feature extraction schemes.
2017 IJERCSE	10	Greyscale conversion, Histogram equalization Large median filtering.	Neural Network, Support vector machine (SVM) &K-Nearestneighbour (KNN)	Method studied are fast, efficient, and effective in performance.
IEEE 2018	7	Canny edge detection, Gaussian filtering, image adaptive mask generation, image segmentation, edge detection, AM/FM	KNN, ANN, SVM, GMM, SVM, Adaboost, DT, NB	Different DR detection techniques were studied to help ophthalmologists to detect early symptoms of diabetic retinopathy with ease
IEEE,2017	18	conversion of an image from RGB colour space to HSI colour space and normalization of grey levels using CLAHE	Naive Bayes, SVM, The neural network, GMM	The detailed survey was performed on many methods which highlighted the improvement achieved by the algorithms. And it was noted that very little research was done using evolutionary algorithms to detect the hard exudates.

3. Proposed Methodology

A. Dataset

The dataset for this research-based project is to be taken from Kaggle. In the total of 35,000 retinal fundus images. These images are to be split into 2 parts to train and test the model (60% to train & 40% to test). These images contain noise and are unbalanced hence need to be pre-processed to resize the images to achieve the best possible results. They are to be cropped to a size of 224 x 224 pixels, to optimize and retain all the features of this fundus retinal images.

B. Pre-Processing

Different pre-processing techniques are to be used to make the input image data clearer & more effective, for the model to learn the features efficiently. For this, we are using the OpenCV library from Python. Gaussian blur will be used to filter the input images, to extract clearer feature of retinal images. Cropping will be performed on the uninformative region of the image.

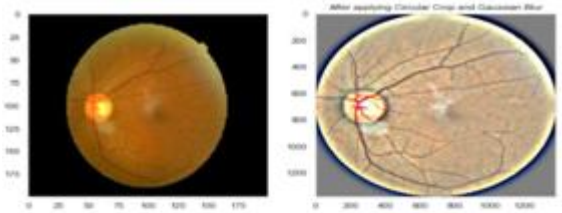

Figure 1: Blurring & cropping example

C. Data Augmentation

Image augmentation will be used to study every image in various aspects to understand it more effectively. The images will be rotated in various angles and cropping & padding is done using ImageDataGenerator.

D. Classification

The CNN model with transfer learning is proposed to be used for image classification four categories as shown in figure 2. From our survey, we studied that CNN is more effective in identifying Diabetic Retinopathy and classifying its Severity. The model we are based on ResNet50, one of the powerful available models with skip connection which can train much deeper network & optimizations for better & more accurate classification.

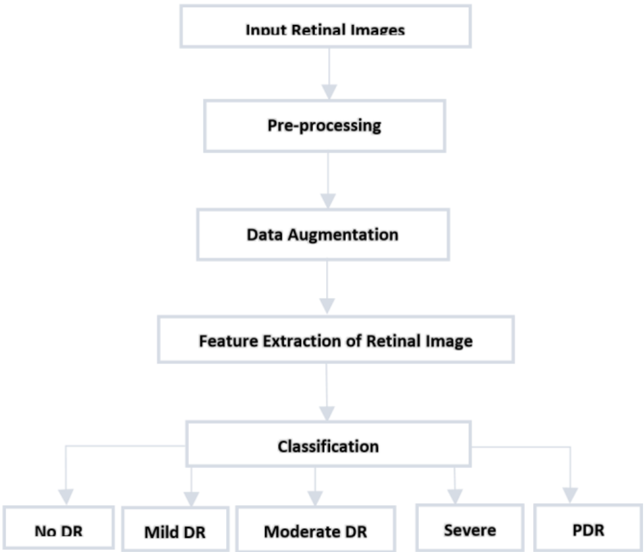

Figure 2: Proposed methodology

4. Conclusion

Diabetic Retinopathy is one of the common vision problems associated with diabetes patients. It's early diagnosis & then accurate classification is necessary for proper and accurate treatment.

This article surveyed 25 research & survey articles that discuses and survey the major techniques used for the diagnosis & classification of Diabetic Retinopathy. The survey reviewed various techniques in all the stages such as Pre-processing, Feature extraction as well as Classification. It also highlighted some major improvements achieved by these algorithms. The survey showed that, for clinical purposes, Machine Learning or a deep-learning method can be more favorable and effective in minimizing the progression of diabetic retinopathy among patients and allowing the ophthalmologist to accelerate further care of the retina. The rising number of diabetic patients with DR has given rise to a great need to build alternate DR identification systems to conventional methods. As such at the end of the article, we also proposed the model based on ResNet50 as shown in figure 1 and discussed above based on the review we carried on different techniques of disease detection & Classification.

This survey will assist the researchers in this field to know about the already available techniques and methods for detecting & Classifying DR and will help them to drive their research ahead.

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