A Comprehensive Review of Computer Aided Diagnosis Models for Diabetic Retinopathy Detection and Classification

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Abstract

Diabetic retinopathy (DR) occurs due to the injury of retinal micro vasculature which are produced by diabetes mellitus. It may leads to loss of sight as an outcome of unchecked and extreme cases of DR. Manual examination of fundus images to check the morphological variations in microaneurysms (MAs), exudates, blood vessels, hemorrhages, and macula is a difficult and lengthy process. Computer aided diagnosis (CAD) models finds useful to develop DR diagnosis models to identify and classify the grades of DR. Several CAD models for DR diagnosis have been available in the literature. This paper performs a review of different CAD model for DR detection and classification. The presented survey mainly reviews MA detection models, haemorrhage detection models and DR classification models. Besides, a detailed survey of deep learning (DL) based DR diagnosis models have been performed. At last, internet of things (IoT) enabled DR detection and classification models have been reviewed. A detailed comparison of the reviewed techniques is also made to clearly understand the characteristics of reviewed models.

Keywords: Diabetic retinopathy, Classification, MA detection, Computer aided diagnosis

1. Introduction

Globally, diabetes is assumed to be the common disease which occurs for all peoples. Diabetes is a major reason for vision loss especially for elderly people. Many works have showed that maximum number of diabetic patients might be recovered from this disease by conducting the earlier diagnosis. An individual who is affected with diabetes leads to DR [1]. The blood is carried to the retina by tiny blood vessels that is susceptible for unrestrained blood sugar level. While there is an increase in glucose level, then the vessels shrink due to the inadequate oxygen supply to the overall human body. The blockage in vessels results in serious eye infection. Consequently, metabolic rate is reduced slowly and results in structural anomalous of vessels that leads to DR. A study showed that the number of DR patients will increase to a greater extent in the future days, as shown in Fig. 1.

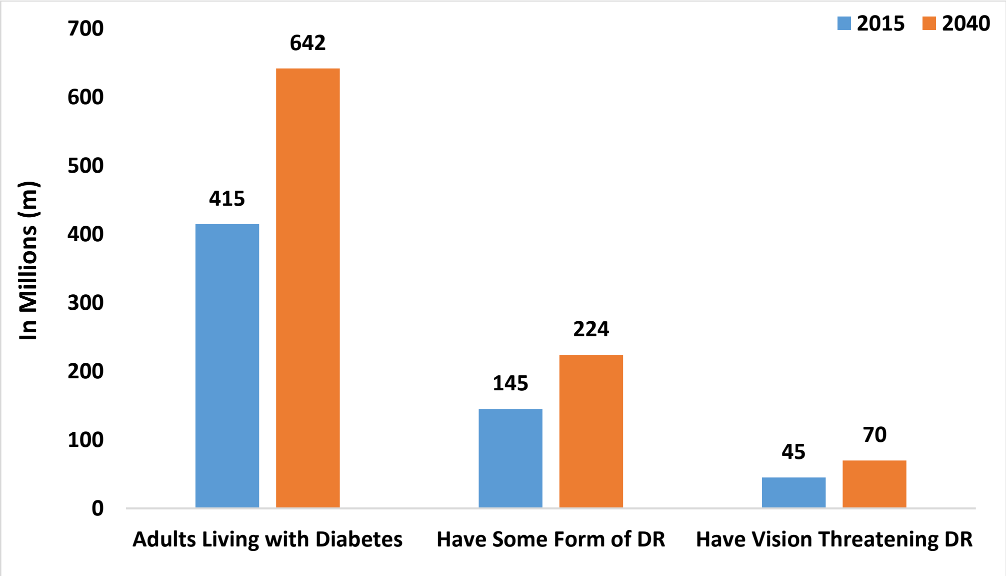

Fig. 1. Statistics of people affected by DR

MA is the major symptoms of DR. It refers that, size of blood vessels gets modified either by swelling or shrinking. The signs of DR are MAs, exudates (EXs), haemorrhages (HMs), inter-retinal micro vascular abnormalities (IRMA) and abnormal development of blood vessels. In general, DR is classified into 2 diverse phases like proliferative DR (PDR) as well as non-proliferative DR (NPDR). Initially, NPDR exists when the blood vessels are damaged and fluids starts leaking.

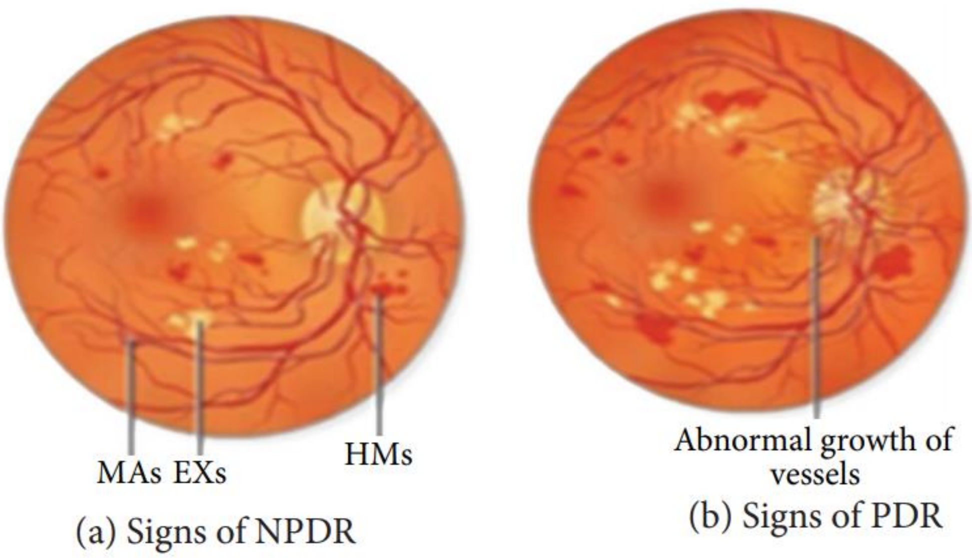

Fig. 2. Different stages of DR

Finally, retina is completely wet and swollen. Then, PDR happens while a new abnormal blood vessels is formed at any point of retina. It is assumed to be highly complicated which leads to eye blindness. DR is a developing disease and the primary detection is highly important to save the eyesight of a person which can be achieved by proper scanning and check-up. An automatic DR screening mechanism reduces the causes of becoming blind and also minimizes the overhead of ophthalmologists. For DR screening, CAD model has been deployed for classifying retina with DR from healthy retina. Fig. 2 implies the symptoms for diverse stages of DR. DR is a progressive disease which is developed at various stages for several humans due to the 2 significant vision pressuring complexities such as Diabetic Macular Edema (DME) and PDR. This is the major reason for lagging the advanced medical services for analyzing DR in an effective manner in last decades. Recently, the research community has provided massive approaches as depicted in Fig. 3 for primary DR prediction as explained in the following:

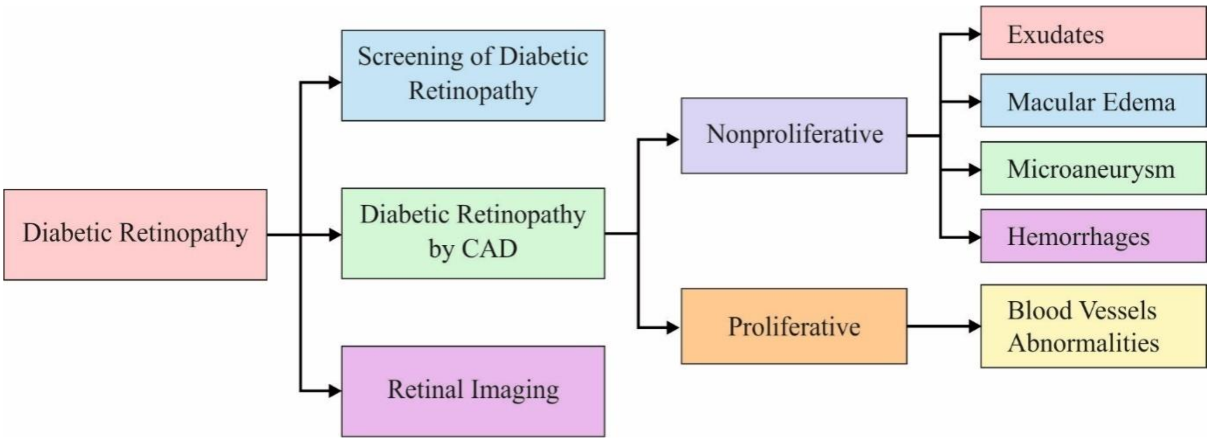

Fig. 3. Different DTR detection models

In past decades, manual ranking of DR screening was highly complex for ophthalmologists. But, as the population growth becomes exponential, many diseases like diabetes, BP and so on were increased. These diseases can be detected automatically using latest models which should be effective and low-cost by providing better results. Recently, the model Automated Retinal Image Analysis Systems (ARIAs), like GradingM, Retmarker, and EyeArt, mainly concentrates on classifying unhealthy and healthy portions of retina. Regardless, ARIAs method is not highly applicable for classifying various levels of DR, where identification of subtle modifications among the levels are complicated for medical image analysis. Also, the accuracy of medical image computation, mobility and portability of clinical tools are equally important.

Presently, the digital fundus images can be captured by the cooperative patient who sits in front of fundus camera without any distraction. The patient should look the camera and apply infrared fundus imaging to concentrate on the region of interest (ROI). The RGB image sensor is highly essential for offering the flash to take am images from visible light spectrum. Hence, the digital fundus imagers are often used in the hospital which is bigger and expensive. It reduces the ability while screening massive volume of images. The main aim of this work is to enhance the classification accuracy with the help of Artificial Intelligence (AI), and develop a novel approach for DR screening.

Automated detection and DR analysis is one of the complicated models that significantly limit the overhead of doctor's interms of efficient and financial constraints. A DR smart screening model depends upon color fundus images that are classified into 2 classes. Initially, it attains DR screening under the detection and lesion segmentation of MAs, HEs, EXs and NV. The main feature of primary DR diagnosis is to examine MAs retinal images. Diverse lesions predicted can be treated as the indicators for identifying and rank the seriousness of DR. According to the segmented lesions, retinal images are categorized into healthy and abnormal conditions. Secondly, an end-to-end DR screening has been carried out by a classifier that is trained with the help of massive labeled data. First, diverse morphological models and classical Machine Learning (ML) approaches are applied for screening DR. Currently, DL models, especially Convolutional Neural Networks (CNNs), plays a major role in DR screening.

Numerous models are presented to accomplish effective smart screening and classifications of DR. [2] have consolidated DR prediction system from 1998 to 2008. Recently, developers have changed to DL centric models. DL is considered to be highly effective which performs quite-well when compared with classical models with respect to classification accuracy. The primary objectives of traditional approaches are separated into 3 classes. (1) Traditional ML: A feature, which depends upon advanced knowledge, was obtained for training a classification method. Followed by, classifier filters candidate sets and selects the candidate region is healthy or abnormal. (2) Integration of traditional ML and DL. It applies DL for feature extraction and use ML for classification task. (3) End-to-end DL approach: training massive labeled data, pre-trained network screens fundus images in direct manner. The technical roadmaps of such models are depicted in Fig. 4.

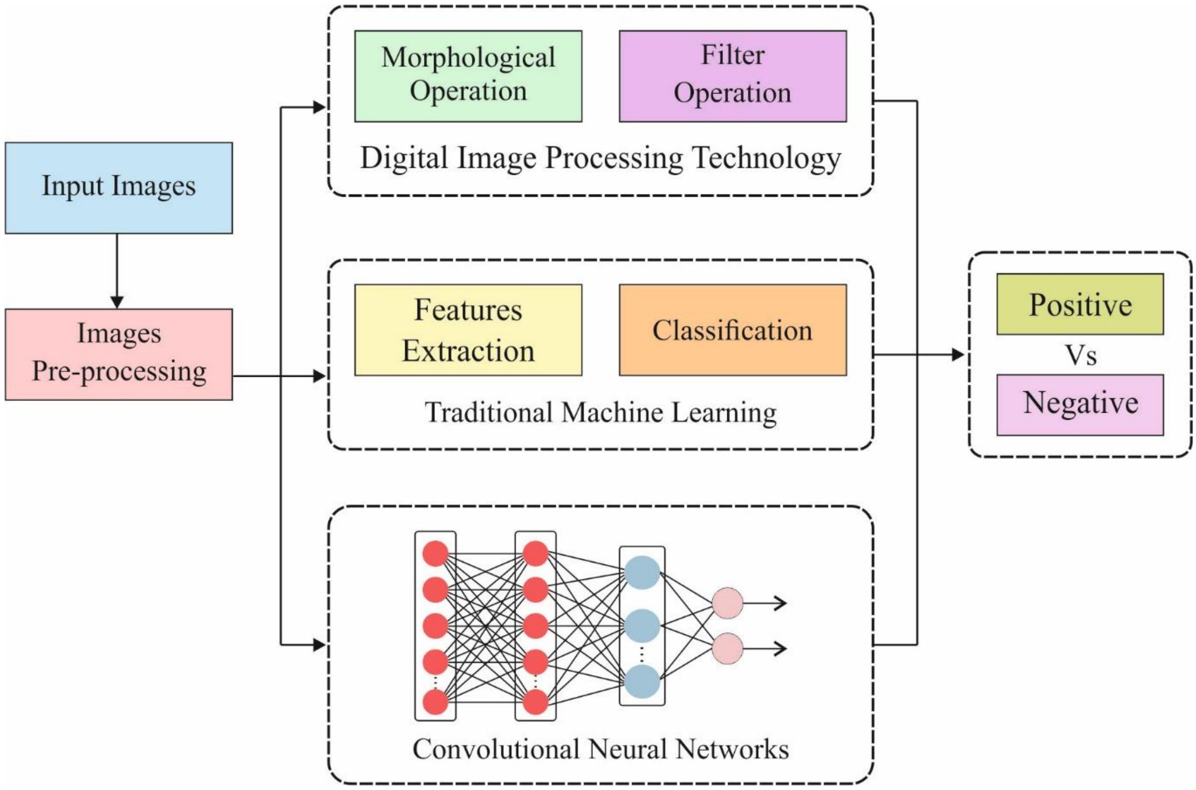

Fig. 4. General structure of DL based DR diagnosis model

Several CAD models for DR diagnosis have been available in the literature. This study undergoes a survey of diverse CAD model for DR detection and classification. Brief explanations of the available databases are provided. The presented survey mainly reviews MA detection models, haemorrhage detection models and DR classification models. Besides, a detailed survey of DL based DR diagnosis models have been performed. At last, IoT enabled DR detection and classification models have been reviewed. A detailed comparison of the reviewed techniques is also made to clearly understand the characteristics of reviewed models.

2. DR Databases

Specific public datasets are developed for automated feature extraction of DR are available. In particular, various datasets have been deployed with labels of lesion areas as defined in the following sub-section.

ImageRet

Kauppi et al. [3] is composed of DIARETDB0 and DIARETDB1. The image undergoes annotation for existence of MAs, HEs, and EXs. Annotated images are integrated for generating ground truth images. DIARETDB0 has 136 color fundus images, where 20 are normal whereas 110 have lesion of DR. DIARETDB1 is comprised of 85 color fundus images, among them 80 are at the initial stage of NPDR, and 5 are from normal conditions.

MESSIDOR

Decencière et al. [4] have 1200 color fundus images obtained from color video 3CCD camera on a Topcon TRC NW6 non-mydriatic retinographies at 45 degrees field of view (FOV) from 3 ophthalmologic teams. The images are present in various dimensions: 1440*960 pixels, 2240*1488 pixels, and 2304*1536 pixels. Every images are acquired from specific department were classified as subsets which depends upon the disease severity level.

Stare

Hoover et al. [5] has 397 color fundus images obtained from a TOPCON TRV-50 fundus camera at 35 degrees FOV with image dimension of 700*605 pixels. The major purpose of applying this dataset is to process the vessel segmentation. Also, 91 images are used for DR screening, where 22 images are PDR. High resolution fundus (HRF) dataset is composed of 15 normal and 15 diabetic images. The images are collected from CANON CF-60UVi camera at a high dimension of 3504*2336 pixels.

Indian diabetic retinopathy image dataset (IDRID)

Prasanna et al. [6] contains 413 color fundus images which are obtained from Kowa VX-10 alpha digital fundus camera at 50 degrees FOV. The images exit in the dimension of 4288×2848 pixels. From this dataset, 130 are normal, 275 are DR, where 45 are PDR.

Kaggle

Kaggle [7] is an open competition dataset offered by EyePACS obtained from fundus cameras at various FOVs. The Kaggle dataset has greater training images followed by DR grade labels as well as sample images with no grading. The quality of image are uneven and it can be enhanced by optimizing the classifying algorithm. Additionally, the pre-defined datasets, like E-Ophtha, ROC, ARIA Online, and DRiDB, were used for exploring better results.

3. Review of DR diagnosis and classification Models

This section reviews the MA, HMs and DR classification models under diverse aspects. Besides, a set of DL based DR diagnosis models are also surveyed. Table 1 provides a detailed comparative analysis of the reviewed techniques interms of aim, methodology involved, and performance results.

3.1. Existing MA detection models for DR

Puranik and Malode [8] presented a model for detecting the presence of DR among patients. This study has developed a model for the identification of retinal red lesions known as MA by the use of morphological operations. The presented model is able to discriminate among the normal and abnormal images. It can be incorporated to other lesion identification models to develop an entire DR diagnosis model.

Kamble and Kokare [9] developed an effective MA detection model using the variations in local intensities of the retina fundus image. The presented model has utilized a local rank transformation to separate the Mas exist in the retina images. Next, an effective blood vessel extraction technique is presented by the use of gradient of guided filter. At last, the candidate Mas are chosen by the exclusion of vessels and post processing approaches. A set of simulations takes place on 3 open access dataset namely E-Ophtha, Diaretdb1, and Messidor. The experimental outcome showed the faster and precise detection of Mas over the existing models.

Dashtbozorg et al. [10] applied a new and stable approach for automated MA analysis in fundus images. Initially, various preliminary MA candidates were obtained using gradient weighting and iterative thresholding frameworks. Secondly, intensity and shape descriptors depends upon local convergence index filters which are obtained for every candidates. It is estimated on images with diverse resolutions and modalities with the help of 6 publicly available data sets and Retinopathy Online Challenges (ROC) data set. The presented approach attains maximum sensitivity on the ROC data set performs state-of-the-art models in wider fashion.

Wang et al. [11] have deployed a combined scheme for automatic MA prediction with maximum accuracy. Candidate objects were placed initially under the application of dark object filtering task. The correlation coefficient among the computed profile and a common MA profile is determined and applied as a scale factor to modify the structure of candidate profile. It enhances the variations among original MAs and alternate non-MA candidates. The collection of statistical features are obtained for a K-nearest neighbor (kNN) classifier.

Xu et al. [12] deployed a new approach with 2 diverse ways from the point of MAs turnover as well as abnormal risk factors for DR analysis. In particular, the first module applies conventional image analysis relied roadmap in order to accomplish MAs turnover. The alternate model examines 7 abnormal features, which is associated with MAs turnover, to differentiate the unaffected, novel, and solved MAs with respect to statistical analysis as well as pattern classifiers. The Grampian diabetes database exhibits that the projected image analysis model is capable of reaching maximum sensitivity and specificity whereas the classification approach also accomplishes higher sensitivity and specificity, correspondingly.

Chudzik et al. [13] provided an automated model for predicting MA in fundus images. A new patch-based fully CNN and batch normalization (BN) layers as well as Dice loss function has been presented. When compared to alternate models which need 5 processing stages, but it acquires only 3 models. Moreover, to the well experienced developers, it is referred to be the first paper which implies the efficiency of transfer knowledge among the datasets in MA detection domain. It is operated using 3 publicly available datasets such as E-Ophtha, DIARETDB1, and ROC. It is capable of accomplishing optimal outcomes than state-of-the-art models by applying FROC.

Budak et al. [14] have projected a mechanism for detecting the MAs in colored fundus images. There are 3 phases in the presented approach. At the first stage, pre-processing steps are applied for making effective input images for MA screening. Then, green channel degradation, Gaussian filtering (GF), median filtering, back ground computation, and subtraction tasks were utilized for input colored fundus images. Once the pre-processing is completed, candidate MAs extraction is carried out for detecting potential regions. Consequently, DCNN with reinforcement sample learning principle has been employed for training the presented mechanism.

Thammastitkul et al. [15] deployed a model for enhancing the computerized MAs analysis with the help of feature optimisation. Candidate MAs are predicted with the help of arithmetic morphological approaches. Actually, it is provided with 20 features. The best feature set is explored using ML model, such as Naïve Bayes (NB) and Support Vector Machine (SVM) classification models. The experimental validation have exhibited that the proposed best feature set is capable to enhance the MA detection.

Derwin et al. [16] have established novel computer-aided MA prediction method according to the texture features. The histogram of texture descriptor shows the texture of pixels that significantly improves the accuracy of MA detection. The features obtained with the help of Local Binary Pattern (LBP) has been applied at the time of discriminating lesions using SVM classifier. A validation depends upon free-response receiver operating characteristic value as well as Area under Curve (AUC) has been accomplished for ROC, MESSIDOR and DIARETDB1 dataset. The potency of image processing with diverse intensities as well as minimum computation time ensures the efficiency of this model.

3.2. Existing HM detection models for DR

When compared to MA prediction, HE examination obtains minimum concentration. Template matching as well as normalized cross-correlation has been applied for extracting HE candidates. Xiao et al. [17] employed rule-based as well as classical ML approaches for detecting HEs. Furthermore, the HE regions can be detected and enhance the detection accuracy of HEs which is closer to retinal blood vessels. Tang et al. [18] developed a new splat feature classifier. Here, splat is a segment of non-overlapping portion that conceals entire fundus image. It is composed of pixels which distribute same color as well as spatial location. Next, collection of features has been obtained from every splat on the basis of texture data, the response of diverse filter banks, and communication of neighboring splat. Barath et al. [19] have obtained the co-occurrence matrix features from splat features at gray level, and employed SV for detecting HEs. Grinsven et al. [20] analyzed HE prediction with the application of 9-layer CNN. Recently, DL oriented models are employed in HE detection. The major complication of this method is that, classification of dot HEs from MAs, hence HEs and MAs are named as red lesion analysis. Morphological task, wavelet operations, and artificial based features were integrated with statistical classifiers for the purpose of predicting red lesions. Seoud et al. [21] analyzed collection of morphological features named as dynamic morphological features for discriminating the vessel segments and lesions. Adal et al. [22] presented an automated detection of longitudinal changes caused by tiny red lesions on normalized fundus images, and applied SVM for identifying red lesions on the basis of the intensity as well as shape relied features.

3.3. DL based DR Classification Models

Morales et al., [23] have examined the discrimination abilities in the texture of fundus images to classify the healthy and anomalous photographies. It can be accomplished by applying LBP as a texture descriptor where fundus images are found and related with alternate descriptors like LBP filtering (LBPF) and Local Phase Quantization (LPQ). The main aim of this approach is to discriminate DR interms of age-related macular degeneration (AMD) and healthy fundus images by analyzing the texture of retinal background instead of analyzing the lesion segmentation. In this approach, 5 experiments have been developed and verified using the newly presented model which provides effective final outcome. For every experiment, numerous classifiers were sampled. This newly developed model is capable of providing better sensitivity and specificity and satisfy the AMD detection.

Rubini and Kunthavai [24] deployed 2 models for detecting MAs and HMAs. Initially, semi automatic model uses semi automated hessian centric candidate selection mechanism (SHCS) and thresholding for the prediction of actual MAs and HMAs. The newly developed scheme applies Automated HCS (AHCS), feature extraction and SVM classification under the application of 20 images that has been trained manually. These 2 methods are executed and sampled on the actual images acquired from retinal scanning. The results shows that, the prediction score of automatic model than the semi automated method is said to be lower with a probability $p<0.005$.

Bhatkar and Kharat [25] have concentrated on Multi Layer Perception NN (MLPNN) for detecting DR in color fundus images. In this work, MLPNN classifier is mainly applied for the classification of healthy and pathological images. A feature vector has been developed with the application of 64-point Discrete Cosine Transform (DCT) and diverse statistical attributes like Entropy, mean, SD, average, Euler number, contrast, correlation, energy and similarity. Gulshan and Peng [26] employed a DL model for automated DR prediction and DME in fundus images. In particular, the type of NN is optimized for image classification so called as Deep Convolutional NN (DCNN) which undergoes training under the application of retrospective development data.

Yang et al. [27] have presented the automatic DR detecting model which depends upon 2 phases of DCNN. When compared to traditional DCNN based DR detection approaches, the presented scheme is composed with better merits namely, (1) the newly developed model points the type and location of lesions in the fundus images, and shows the seriousness of DR. Furthermore, as retina lesions as well as DR severity appears with diverse scales in fundus images, the combination of local and global networks are highly suitable for DR analysis. (2) Under the establishment of imbalanced weighting map, maximum focus would be provided to the lesion patches for DR scanning that enhances the function of newly deployed method. In this work, massive lesion patches were labelled and re-annotate the DR ranks of fundus images from Kaggle competition dataset.

Ardiyanto et al. [28] presented a DL centric cheaper embedding system which is helpful for the physician to analyze the DR from color fundus images. For this purpose, the effective DL method is termed as Deep-DR-Net which is applicable on minimum embedding board. The theme of Deep-DR-Net is to arrange the cascaded encoder-classifier system with the help of residual style which assures the small model size. The application of diverse convolutional layers significantly ensures the effective features for DR analysis. The presented system is remarkable in predicting the existence of DR and ranks the severity level of DR.

Khojasteh et al. [29] have projected a new model for CNN structure by incorporating a pre-processing layer and convolutional layer that enhances the efficiency of CNN classification model. Here, 2 image enhancement approaches such as 1- Contrast Enhancement (CE) 2- Contrast-limited adaptive histogram equalization (CLAHE) have been incorporated separately in the projected layer and compares the simulation outcome. In order to find the exudates, HM and MAs, the proposed model has accomplished the overall accuracy of 87.6%, and 83.9% for CE and CLAHE layers, correspondingly. But, the overall accuracy of the CNN with no pre-processing layer was around 81.4%. Finally, the novel CNN structure with the presented pre-processing layer enhanced the function of CNN.

Gao et al. [30] have introduced an automated DR diagnosing model and offered proper suggestions for DR patients. A new dataset has been developed for DR fundus images which provide better treatment for the DR patients. With the application of this dataset, DCNN were trained for grading the DR severities from fundus images. Also, it is capable of reaching maximum accuracy for a 4 degree classification. These methods are used on Cloud Computing (CC) environment and offers a mobile DR diagnostic facilities in the medical estimation and the model have attained maximum consistency by illustrating the efficiency of this method.

Kathiresan et al. [31] proposed a DL based automatic prediction and classification method for fundus DR images. The presented model is composed of diverse processes like pre-processing, segmentation and classification. The technique is initiated with pre-processing stage where unwanted noises in the edges are eliminated. Followed by, histogram oriented segmentation is carried out for extracting helpful sites of an image. Followed by, Synergic DL (SDL) approach has been utilized for DR fundus image classification. The projected SDL method was computed on Messidor DR dataset. The experimentation result shows that the proposed SDL method provides optimal classification when compared with previous technologies.

Gadekallu et al. [32] have established a NN method in conjunction with Principal Component Analysis (PCA) as well as firefly (FF) approach for classifying DR dataset. The dataset has been gathered from the commonly available UCI Machine Learning (ML) repository. The data which has been gathered from the public domain is composed of unwanted attributes and similar parameters would enhance the overhead of ML method. Thus, PCA approach is executed for feature extraction from DR image dataset. Furthermore, the classification results can be improved using FF model which reduces the dimensional size. The finally attained limited dataset is provided into the DNN model offers improvised classification of the DR dataset.

Hagos and Kant [33] applied a pre-trained Inception-V3 model to capture the merits of Inception modules while processing the DR analysis. The insufficiency problem can be handled by using the minor version of the Kaggle DR classification which is a challenging dataset for model training and sampled the method's accuracy on existing data subset.

3.4. IoT and Cloud Enabled DR Classification Model

Though several DR classification models based on DL and ML concepts, there exist only a few IoT and cloud enabled DR diagnosis models. These models finds are helpful in diagnosing the disease from remote areas with free of cost, high detection rate and minimal diagnosis time. This section reviews some of the IoT with cloud based DR diagnosis model available in the literature.

Das et al. [34] presented the extensible cloud related teleophthalmology model through the Internet of Medical Things (IoMT) for AMD diagnosis. In this proposed model, the victims carry a head mounted camcorder to transmit the retinal fundus photographs to its protected and confidential cloud memory disk for customizing the deduction of disease severity and predictive progression diagnoses. The projected AMD-ResNet CNN with 152 layers determines the photographs in order to analyse AMD disease severity. The programme was trained with age related eye disease study (AREDS) imagery from the National Institute of Health (NIH) around 130,000 fundus photographs caught in 12 years. A sequential Long–Short Term Memory (LSTM) DNN for precision medication and AMD predictive progression is planned. The individual diagnosis of victims helps for better targeted concern, less adverse effects, and a larger interaction to treatments by modifying medical care on each patient basis.

The public EyePACS Kaggle DR dataset [35] was posted into Microsoft Azure™ cloud platform. The 2 CNN was trained such as “Quality Assurance”, and “Classifier”. Then, DRCNN working were evaluated both on ‘un-curated’ and the ‘curated’ test dataset made by the “Quality Assessment” CNN technique. At last, the DRCNN sensitivity was improved by 2 post training methods. The DRCNN verified to be strong, since the efficiency was equal to ‘curated’ and ‘un-curated’ evaluated datasets. The performance of ‘cascading thresholds’ and ‘max margin’ methods leads to considerable improvement in the sensitivity of DRCNN, whereas it enhances the specificity of other grades.

Balaramesh et al. [36] process starts from own device which securely sends details with IoT level and regular language for the portable applications are used for better function. These levels often collect a massive data count and are saves in the secured database. It mingles the data receives from IoT devices and which is applies for survey to predict important data deals with the medical requirements. The results revealed by the implementation of the proposed technologies are almost the same with the present platform in associations with affectability accuracy, and individuality. The planned models perform higher and unique in the experiment arrangement.

Table 1 Comparison of different DR detection models

References	Year	Aim	Method	Process	Results
Morales et al. [23]	2017	To develop a method for screening DR using texture of fundus images	LBPF	Texture feature extraction	DR: higher than 0.86 sensitivity and specificity
Rubini and Kunthavai [24]	2015	To introduce a set of two methods for detecting MAs and HMAs	SHCS, AHCS, feature extraction and SVM	Candidate selection, feature extraction and classification	probability p<0.005
Bhatkar and Kharat [25]	2015	To develop a DR diagnosis model using MLP	64-point DCT and MLPNN	feature extraction and classification	-
Gulshan et al. [26]	2016	To develop a DL model to diagnose DR in color fundus image	DCNN	feature extraction and classification	Sensitivity of 96.1% and Specificity of 93.9%.
Yang et al. [27]	2017	To develop a DL model to detect, locate and grade DR	2-stage DCNN, imbalanced weighting map	feature extraction and classification	AUC is 0.9590
Ardiyanto et al. [28]	2017	To develop a DL based DR model with embedded system	Deep-DR-Net, cascaded encoder	feature extraction and classification	Accuracy of 95.71, sensitivity of 76.92 and specificity of 100
Khojasteh et al. [29]	2018	To develop an automated DL based model for DR diagnosis	CNN, CE, CLAHE	image enhancement	Accuracy of 87.6%, and 83.9% under CE and CLAHE
Gao et al. [30]	2019	To built a dataset of DR fundus images and determine the severity level of DR	DCNN	Feature extraction and classification	accuracy of 88.72%
Gadekallu et al. [32]	2020	To develop an automated DL based model for DR diagnosis	PCA, FF algorithm	Feature extraction and classification	-

Hagos and Kant [33]	2019	To develop a DL based transfer learning model for DR diagnosis	Inception-V3 model	Feature extraction and classification	Accuracy of 90.90%
Das et al.[34]	2019	To develop an IoT and cloud based DR diagnosis model	ResNet, LSTM	Feature extraction and classification	sensitivity and specificity of 94.97 ± 0.5% and 98.32 ± 0.1%
Xie et al. [35]	2020	To implement a DR diagnosis model in New Zealand	DRCNN	DRCNN	Accuracy: 90.64
Imayan and Chinnusamy [38]	2017	To develop an automated DR model using color fundus images	CLAHE, Median filter, HT, SVM	Preprocessing, Feature extraction and classification	Accuracy: 95.00
Wan et al. [39]		To develop an automated DL based model for DR diagnosis	DCNN	Feature extraction and classification	Accuracy of 95.68%
Shanthi and Sabeenia [40]		To develop a modified Alexnet architecture to classify DR	Modified AlexNet, softmax	Feature extraction and classification	Accuracy of 96.25%

Jebaseeli et al. [37] research aims to recover the patient’s life from blindness. The procedure begins from the gadgets itself which sent data in protected manner with IoT domain and assure the linguistic familiarity in smart phone applications for collaboration.They integrate the collected details from IoT sensing gadget and apply analytics to expect important information to satisfy medicinal requirements. The simulation outcomes shown by the execution of the proposed technique are equivalent to complicated models in associations of sensitivity, specificity and accuracy. The planned model performs higher than other models.

Imayan and Chinnusamy [38] has presented DR automatic detection algorithm have suggested based upon thresholding, Median filter, Morphological Structural Elements, Circular Hough Transform (CHT), CLAHE and Wireless data transmission by Raspberry PI to drives. In addition, ML and SVM classifiers are utilized to sorts the fundus photographs to standard or occurrence of MA. The image is collected via portable Non-mydriatic Fundus Camcoder linked to Raspberry Pi which broadcast to drives. The proposed technique has been evaluated for the imagery obtains from Cloud Storage database through MATLAB cryptogram.

Wan et al. [39] developed an approach in finding automated way of classifying the provided set of fundus images. The newly proposed model uses CNNs for DR analysis with 3 complicated phases: classification, segmentation and detection. The integration of transfer learning and hyper-parameter tuning applies AlexNet, VggNet, GoogleNet, ResNet, and determine the efficiency of DR image classification. Also, it uses publicly available Kaggle platform for the purpose of training such methods. An optimal classification accuracy is 95.68% and final outcome have exhibited the best accuracy of CNNs and transfer learning on DR image classification. Shanthi and Sabeenian [40] mainly concentrated on DR classification of fundus images on the basis of disease severity using CNN and applicable Pooling, Softmax and Rectified Linear Activation Unit (ReLU) layers for achieving maximum classification accuracy. The function of the presented method is verified under the application of Messidor database. For healthy images, images of stage1, stage 2 and stage 3 of DR classification accuracies of 96.6% and 96.2%, 95.6% and 96.6% were accomplished.

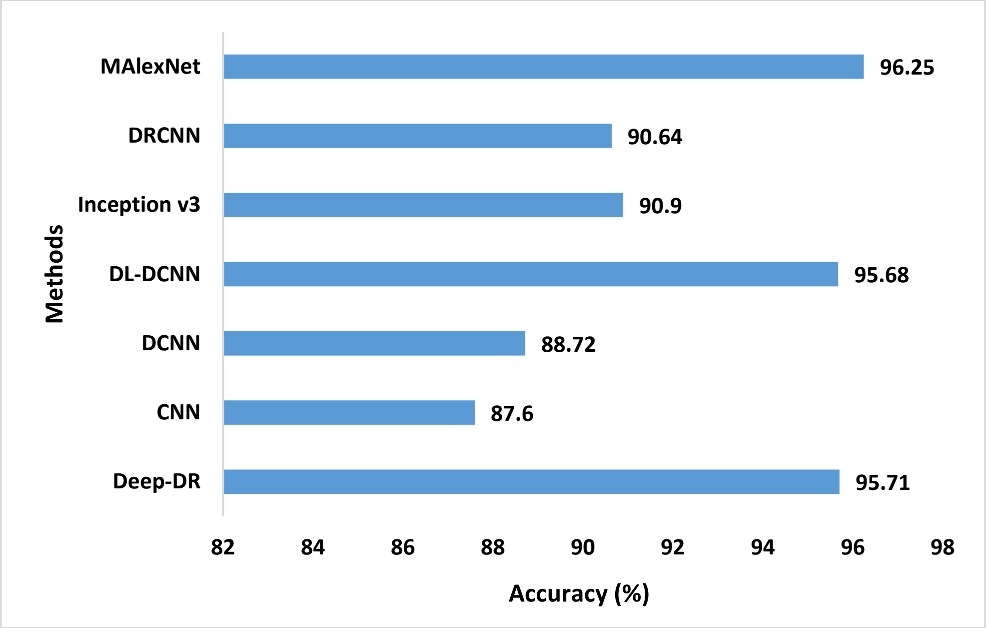

Fig. 5. Accuracy analysis of different DR diagnosis models

Fig. 5 examines the performance of the DR diagnosis models interms of accuracy on the applied color fundus images. The figure notified that the CNN model has exhibits worse DR classification process by attaining a minimum accuracy of 87.6% whereas the DCNN model has reached to a slightly higher accuracy of 88.72%. Along with that, the DRCNN and Inception v3 models have exhibited somewhat higher and closer accuracy values of 90.64% and 90.9%. In the same way, the DL-DCNN and Deep-DR models have also demonstrated near identical accuracy values of 95.68% and 95.71% respectively. At last, the M-AlexNet model has shown maximum detection performance by offering a higher accuracy of 96.25.

5. Conclusion

This paper has performed a detailed review of different CAD models available for the diagnoses of DR. Brief discussions of different benchmark DR databases are also provided. The survey encompasses the different MA detection, HM detection and DL based DR classification models. Furthermore, a survey of IoT and cloud enabled DR diagnosis models have been presented. At last, a comparison of different reviewed techniques is made to clearly understand the features of the reviewed methods. As an outcome of the review, it is identified that the IoT and cloud based DR diagnosis models are needs to be developed. In future, we intend to develop a new IoT and cloud enabled DR diagnosis model to detect and grade the severity levels of DR with maximum detection rate and minimum computation time.

References

[1] N. H. Cho, J. E. Shaw, S. Karuranga et al., “IDF Diabetes Atlas: global estimates of diabetes prevalence for 2017 and projections for 2045,” Diabetes Research and Clinical Practice, vol. 138, pp. 271–281, 2018.

[2] Winder RJ, Morrow PJ, Mcritchie IN, et al. Algorithms for digital image processing in diabetic retinopathy. Comput Med Imaging Graphics 2009; 33(8):608-22. doi: 10.1016/j.compmedimag.2009.06.003.

[3] Kauppi T, Kalesnykiene V, Kamarainen J, et al. DIARETDB0: evaluation database and methodology for diabetic retinopathy algorithms. 2006.

[4] Decencière E, Zhang XW, Cazuguel G, et al. Feedback on a publicly distributed image database: The messidor database. Image Anal Stereol 2014; 33(3):231- 4. doi: 10.5566/ias.1155.

[5] Hoover A, Kouznetsova V, Goldbaum M, et al. Locating blood vessels in retinal images by piecewise threshold probing of a matched filter response. IEEE Trans Med Imaging 2000; 19(3):203-10. doi: 10.1109/42.845178.

[6] Prasanna P, Samiksha P, Ravi K, et al. Indian Diabetic Retinopathy Image Dataset (IDRiD): a database for diabetic retinopathy screening research. Data 2018; 3(3):25-32. doi: 10.3390/data3030025.

[7] Kaggle Inc. Diabetic Retinopathy Detection. https:// www.kaggle.com/c/diabetic-retinopathy-detection/ data. Published 2015; accessed February 28, 2019.

[8] Puranik SS, Malode VB. Morphology based approach for microaneurysm detection from retinal image. 2016 Processing of the International Conference on Automatic Control and Dynamic Optimization Techniques. 2016 Sep 9-10; Pune, India. Los Alamitos: IEEE Computer Society Press; 2016. p.635-9. doi: 10.1109/ ICACDOT.2016.7877663.

[9] Kamble R, Kokare M. Detection of microaneurysm using local rank transform in color fundus images. ICIP 2017: Processing of the 24th IEEE International Conference on Image Processing. 2017 Sep 17-20; Beijing, China. Los Alamitos: IEEE Computer Society Press; 2017. p.4442-6. doi: 10.1109/ ICIP.2017.8297122.

[10] Dashtbozorg B, Zhang J, Huang F, et al. Retinal microaneurysms detection using local convergence index features. IEEE Trans Image Processing 2018; 27(7): 3300-15. doi: 10.1109/TIP.2018.2815345.

[11] Wang S, Tang HL, Turk LIA, et al. Localizing microaneurysms in fundus images through singular spectrum analysis. IEEE Trans Biomed Eng 2016; 64(5):990- 1002. doi: 10.1109/TBME.2016.2585344.

[12] Xu J, Zhang X, Chen H, et al. Automatic analysis of microaneurysms turn over to diagnose the progression of diabetic retinopathy. IEEE Access 2018; 6: 9632-42. doi: 10.1109/ACCESS.2018.2808160

[13] Chudzik P, Majumdar S, Calivá F, et al. Microaneurysm detection using fully convolutional neural networks. Comput Methods Programs Biomed 2018; 158:185– 92. doi: 10.1016/j.cmpb.2018.02.016.

[14] Budak U, Şengür A, Guo Y, et al. A novel microaneurysms detection approach based on convolutional neural networks with reinforcement sample learning algorithm. Health InfSciSyst 2017; 5(1):14. doi: 10.1007/s13755-017-0034-9.

[15] Thammastitkul, A., Uyyanonvara, B. and Barman, S.A., 2020. Improving microaneurysm detection from non-dilated diabetic retinopathy retinal images using feature optimisation. *International Journal of Computer Aided Engineering and Technology*, *12*(3), pp.355-369.

[16] Derwin, D.J., Selvi, S.T. and Singh, O.J., 2020. Discrimination of microaneurysm in color retinal images using texture descriptors. *Signal, Image and Video Processing*, *14*(2), pp.369-376.

[17] Xiao D, Yu S, Vignarajan J, et al. Retinal hemorrhage detection by rule-based and machine learning approach. 2017 39th Annual International Conference of the IEEE Engineering in Medicine and Biology Society. 2017 Jul 11-15; Seogwipo, South Korea. Los Alamitos: IEEE Computer Society Press; 2017. p.660-3. doi: 10.1109/EMBC.2017.8036911.

[18] Tang L, Niemeijer M, Reinhardt JM, et al. Splat feature classification with application to retinal hemorrhage detection in fundus images. IEEE Trans Med Imaging 2013; 32(2):364-75. doi: 10.1109/ TMI.2012.2227119.

[19] Inbarathi R, Karthikeyan R. Detection of retinal hemorrhage in fundus images by classifying the splat features using SVM. Int J Innovat Res Sci Eng Technol 2014;3(3):1979-86.

[20] Van Grinsven M, Van Ginneken B, Hoyng C, et al. Fast convolutional neural network training using selective data sampling: Application to hemorrhage detection in color fundus images. IEEE Trans Med Imaging 2016; 35(5):1273-84. doi: 10.1109/TMI.2016.2526689.

[21] Seoud L, Hurtut T, Chelbi J, et al. Red lesion detection using dynamic shape features for diabetic retinopathy screening. IEEE Trans Med Imaging 2016; 35(4): 1116-26. doi: 10.1109/TMI.2015.2509785.

[22] Adal KM, Van Etten PG, Martinez JP, et al. An automated system for the detection and classification of retinal changes due to red lesions in longitudinal fundus images. IEEE Trans Biomed Eng 2017; 65(6): 1382-90. doi: 10.1109/TBME.2017.2752701.

[23] Morales S, Engan K, Naranjo V, et al. Retinal disease screening through local binary patterns. IEEE J Biomed Health Inform 2017; 21(1):184-92. doi: 10.1109/JBHI.2015.2490798.

[24] Rubini SS, Kunthavai A. Diabetic retinopathy detection based on eigenvalues of the hessian matrix. Procedia ComputSci 2015; 47:311-8. doi: 10.1016/ j.procs.2015.04.001

[25] Bhatkar AP, Kharat GU. Detection of diabetic retinopathy in retinal images using MLP classifier. 2015 15th IEEE International Symposium on Nanoelectronic and Information Systems. 2015 Dec 21-23; Indore, India. Los Alamitos: IEEE Computer Society Press; 2015. p. 331-5. doi: 10.1109/iNIS.2015.30.

[26] Gulshan V, Peng L, Coram M, et al. Development and validation of a deep learning algorithm for detection of diabetic retinopathy in retinal fundus photographs. J Am Med Assoc 2016; 316(22):2402-10. doi: 10.1001/ jama.2016.17216.

[27] Yang Y , Li T , Li W , et al. Lesion detection and grading of diabetic retinopathy via two-stages deep convolutional neural networks. 2017 20th International Conference on Medical Image Computing and Computer-Assisted Intervention (MICCAI). 2017 Sep 10- 14; Quebec, Canada. Berlin: Springer; 2017. p.533- 40. doi: 10.1007/978-3-319-66179-7_61.

[28] Ardiyanto I, Nugroho HA, Rlb B. Deep learning-based diabetic retinopathy assessment on embedded system. 2017 39th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (CMBC). 2017, Jul 11-15; Seogwipo, South Korea. Los Alamitos: IEEE Computer Society Press; 2017. p.1760-3. doi: 10.1109/EMBC.2017.8037184.

[29] Khojasteh P, Aliahmad B, Sridhar PA, et al. Introducing a novel layer in convolutional neural network for automatic identification of diabetic retinopathy. 2018 40th International Conference of the IEEE Engineering in Medicine and Biology Society (CMBC). 2018 Jul 18-21; Honolulu, USA. Los Alamitos: IEEE Computer Society Press; 2018. p.5938-41. doi: 10.1109/ EMBC.2018.8513606

[30] Gao ZT, Jie Li J, GuoJX, et al. Diagnosis of diabetic retinopathy using deep neural networks. IEEE Access 2019; 7:3360-70. doi: 10.1109/ACCESS.2018.2888639.

[31] Kathiresan, S., Sait, A.R.W., Gupta, D., Lakshmanaprabu, S.K., Khanna, A. and Pandey, H.M., 2020. Automated detection and classification of fundus diabetic retinopathy images using synergic deep learning model. *Pattern Recognition Letters*.

[32] Gadekallu, T.R., Khare, N., Bhattacharya, S., Singh, S., Reddy Maddikunta, P.K., Ra, I.H. and Alazab, M., 2020. Early detection of diabetic retinopathy using PCA-firefly based deep learning model. *Electronics*, *9*(2), p.274.

[33] Hagos, M.T. and Kant, S., 2019. Transfer learning based detection of diabetic retinopathy from small dataset. *arXiv preprint arXiv:1905.07203*.

[34] Das, A., Rad, P., Choo, K.K.R., Nouhi, B., Lish, J. and Martel, J., 2019. Distributed machine learning cloud teleophthalmologyIoT for predicting AMD disease progression. Future Generation Computer Systems, 93, pp.486-498.

[35] Xie, L., Yang, S., Squirrell, D. and Vaghefi, E., 2020. Towards implementation of AI in New Zealand national diabetic screening program: Cloud-based, robust, and bespoke. Plos one, 15(4), p.e0225015.

[36] Balaramesh, C., Jerin, L. and Shanmugam, G., 2019. Sustainable Diabetic Retinopathy Diagnosis System Using Iot. International Research Journal of Multidisciplinary Technovation, 1(6), pp.71-80.

[37] Jebaseeli, T.J., Durai, C.A.D. and Peter, J.D., 2018. IOT based sustainable diabetic retinopathy diagnosis system. *Sustainable Computing: Informatics and Systems*.

[38] Imayan. C and Chinnusamy, Recognizing Diabetic Retinopathy Using IoT Enabled Nonmydriatic Fundus Camera Images with help of Morphological Functions and Transductive Support Vector Machines, International Journal of Scientific Engineering and Research (IJSER), pp. 27-31, 2017

[39] Wan, S., Liang, Y. and Zhang, Y., 2018. Deep convolutional neural networks for diabetic retinopathy detection by image classification. Computers & Electrical Engineering, 72, pp.274-282.

[40] Shanthi, T. and Sabeenian, R.S., 2019. Modified Alexnet architecture for classification of diabetic retinopathy images. *Computers & Electrical Engineering*, *76*, pp.56-64.