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Advancing Eye Care: A Detailed Review of Diabetic Retinopathy Classification Methods and the Integration of AI Approaches

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ABSTRACT: Diabetic Retinopathy's (DR) is an eye-related infection, which is produced by an extra amount of sugar in retinal blood vessels that hinders vision. Early detection as well as prompt diagnosis reduces the severity of DR. To diagnose DR, researchers have worked on automating the classification of the illness using Machine Learning (ML) in addition to Deep Learning (DL) techniques. The main focus of this review is the research articles from 2021 to 2025 on the Support Vector Machine, K-Nearest Neighbour, as well as classification datasets. ML techniques by means of, Naive Bayes, Random Forest, Gradient Boosting classifier, Multi-class feature Extraction deep Forest are compared for DR analysis. Likewise, DL techniques such as, Convolutional Neural Network-Diabetic-Retinopathy-Estimation, CNN- Radial Basis Function, SVM- Deep Neural Network, Hybrid CNN- Singular Value Decomposition, CNN-DenseNet 121, Inception-ResNet-v2, DenseNet 121, VGG-16 and ViT –CNN. This assists the researchers in selecting the most appropriate pre-trained classification model for the relevant DR Dataset. Goal of this article is to provide researchers with access to the latest advancements in DR classification research.

Keywords: Diabetic Retinopathy (DR), Machine Learning (ML), Deep Learning (DL), Diabetic Retinopathy Dataset

1. Introduction

The World Health Organization (WHO) states that age-related vascular degeneration, glaucoma, and DR are major causes of visual impairment [1]. Conversely, microangiopathy develops as a long-term consequence of diabetes mellitus by DR. DR is the greatest widespread retinal vascular condition. After 15 years, three out of four patients are affected by DR. In 2017, approximately 451 million people worldwide had diabetes, and by 2045, that number is projected to rise to nearly 693 million. Diabetes is becoming a global public health concern due to the aging population. [2]. Figure 1 shows the normal eye and an eye affected by DR.

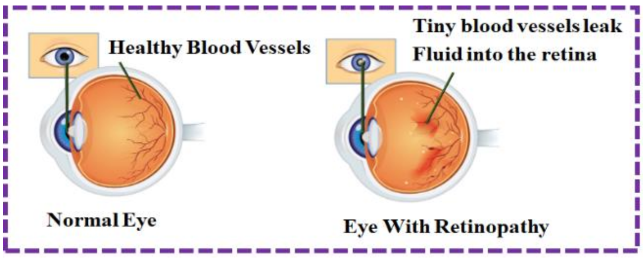

Figure 1: *Normal eye and Eye with DR*

DR is the fifth most common cause of moderate to severe vision impairment and the fifth most common cause of avoidable blindness globally in 2020 among individuals aged 50 and over [3]. Future risks of myocardial infarction, congestive heart failure, and cerebrovascular accidents are substantially correlated with DR [4-5]. DR is the main cause of visual loss and primarily affects patients with diabetes. Due to retinal blood vessel degeneration, DR is more common in patients with diabetes. To diagnose DR and help diabetic patients prevent early vision loss it is essential to locate and isolate the retina's blood vessels [6]. Whereas, the classification of DR is listed in table 1.

Table 1: *Classification of diabetic retinopathy [7]*

Scale of brutality for DR	Results of ophthalmoscopy observations
No retinopathy	• Nope anomalies
Mild non-proliferative diabetic retinopathy	• Microaneurysms individual
Moderate non-proliferative DR	• More severe than microaneurysms, but less severe than severe non-proliferative DR
Severe non-proliferative diabetic retinopathy	• When proliferative DR is not present, one of the following: (i) every four quadrants has more than 20 intraretinal haemorrhages. (ii) Two or more quadrants of distinct venous beading significant microvascular anomalies within the retina
Proliferative DR	• Neovascularization of the retina (NVE) or neovascularization at the disc (NVD) is an example of extra retinal neovascularization. • preretinal haemorrhage
Mild diabetic macular oedema	• Several hard exudates in the subsequent pole that are located far from the macula's centre
Moderate diabetic macular oedema	• Hard exudates or retinal thickening that approaches the macula's centre but does not involve it
Severe diabetic macular oedema	• Hard exudates or thickening of the retina affecting the macula's centre

Progressive intraretinal microvascular changes are a characteristic feature of Non-Proliferative DR (NPDR). The development of new formed blood vessels on the retina or optic disc is a symbol of PDR. Microaneurysms, dot-blot intraretinal hemorrhages, as well as exudates are the main indicators of NPDR [8]. Conversely, dilated capillary remnants known as intraretinal microvascular anomalies develop as a result of severe capillary network closure between arterioles and venules. They are caused by blockage of a retinal arteriole, which causes retinal ischemia. Additionally, the segmental dilatation of retinal veins it serve as efforts of vein endothelial cell growth is known as venous beading [9]. Moreover, new vessels on the optic disc from the optic disc are a characteristic of PDR, and fibrous tissue growth is a feature of advanced PDR [10].

This study provides a comprehensive review of DR detection using ML and DL classifiers from eye images. By evaluating these approaches and estimating their benefits and limitations, the performance and precision of the system is increased. The most significant goal of this review is to identify the DR by employing ML techniques and DL techniques. The classification of these approaches is intensively discussed below.

- To analyse the DR by using ML techniques.
- To analyse the DR by using DL techniques.
- To predict DR survival rate of the patients.

- To enhance the precision and performance of these techniques.

2. Review of Comprehensive Analysis of diabetic retinopathy by Using ML Methods

2.1 Support Vector Machine and Binary Trees for DR

The author of [11-12] describes a classification of diabetic retinopathy using SVM and Binary Trees (BT). It classifies the diabetic and non-diabetic retinal images. The classification accuracy and performance of the DR is good compared to the other method. The drawback of SVM is, it is not suitable for the applications involving large datasets and it takes long time to train the input data.

2.2 SVM-RBF for DR

This work [13] presented an enhanced SVM-RBF combined with a DT and KNN for the classification of DR. It precisely forecast the existence of microaneurysms and exudates that is utilized for grading. Simple to use and comprehension, flexibility in response to new data, and a limited number of hyper parameters. Cons include sensitivity to irrelevant features and data scaling, high memory and processing costs, and poor scalability.

2.3 K-Nearest Neighbors for DR

To classify non-DR and DR [14-15] KNN and SVM is used. KNN classify the DR with higher accuracy when compared to the SVM. Because SVM methods finds either microaneuryms only or exudates only. The study is conducted in two parts: one for microaneurysms and one for exudates. While micro aneurysms are graded by counting them, exudates are graded according to their distance from the macula. It is used on the MESSIDOR dataset; the system clearly outperforms the other state-of-the-art techniques in terms of accuracy while requiring a lot less computing time.

2.4 Naive Bayes for DR

In this field [16] to automatically segment and classify retinal images, sophisticated ML-based techniques have been developed. Techniques for segmentation and classification analyze retinal images to pinpoint diseased regions and determine the disease's stage. Through this procedure, ophthalmologists concentrate on the diseased areas and administer the right therapies to conflict the disease. From the original input image, ML approaches attempt to extract and use retinal properties such lesion segmentation, vascular enhancement, and optic disk detection. The images are then classified using methods like KNN, SVM and NB are compared. NB classifies the DR with higher accuracy.

2.5 XG-Boosting for DR

In order to identify common predictors of DR, a boruta method is on publicly available cross-sectional data from a Chinese cohort of 6374 respondents. Based on the revealed predictors, trained and optimized model XG boosting to predict patients with DR. XG-Boosting classifies the DR with higher accuracy and performance.

3. Review of Comprehensive Analysis of DR by using DL Methods

3.1 CNN Created Segment Level of DRE Classifier for DR:

To determine DR earlier CNN-DRE [21] used to classifying every retinal image. The probabilities of DR are then estimated by feeding them into a CNN constructed segment level DRE classifier. Let $P \times P$ be the descending window, stride is s pixels, and M denotes preprocessed image with a pixel size of $H \times W$. The fixed image divisions are then $\{k_c, d\}$, created by decomposing$M$. The vertical index stands $c \in \left\{1,2,..\left[\frac{W-P}{S}\right]+1\right\}$, while the horizontal index is $d \in \left\{1,2,..\left[\frac{H-P}{S}\right]+1\right\}$. The spatial data of the segment is recorded via these indexes. The position for every $\{k_c, d\}$, segment is provided by,

$$h_c = \begin{Bmatrix} [1 + (c-1) * s \quad if\ (c-1) * s + p \leq H] \\ [H - (P-1)] \ \ Otherwise \end{Bmatrix} \quad (1)$$

And

$$w_d = \begin{Bmatrix} [1 + (d-1) * s \quad if\ (d-1) * s + p \leq W] \\ W - (P-1) \ \ Otherwise \end{Bmatrix} \quad (2)$$

Each segment in this case have a different amount of sectors. These could resized to fitting the CNN i/p dimension. Lot of labeled training data, having high computing requirements, and being prone to over fitting is the drawback of CNN-DRE.

3.2 A hybrid Convolutional Neural Network-Radial Basis Function (CNN-RBF) for DR:

By using hybrid CNN-RBF the DR and non-DR of the trained DR image is classified. And the potential of CNN for DR disease is to find the interpretability and classification accuracy. For eye disorders a mechanism is used to build a reliable computer-aided diagnosis. The drawback of this method is it needs large amount of labelled data to calculate and it takes long time to train the input data [22].

3.3 Support Vector Machine –Deep Neural Network (SVM-DNN) for DR:

A SVM-DNN is constructed from several artificial neurons that each resembles a biological neuron. It is used to classify the DR [23].

$$Y = \varphi(\textstyle\sum_{i=1}^{N} W_i * X_i + B) \quad (3)$$

Where, the output Y is obtained by taking the weighted i/p $W_i * X_i$ (the bias (B), as well as an activation function (φ). An artificial neuron has a processing unit with an X_i activation function and a summation to generate an output (Y) and N inputs to collect the input data. In order to convert the weighted sum of the inputs into an output, the activation function is used. The neural network's capabilities and performance are greatly influenced by the activation function that is selected. Although there are more activation functions available, the most widely used ones are rectified linear unit (ReLU), sigmoid, and $tanh$. It is computationally expensive and takes more time to access.

3.4 Hybrid Convolutional Neural Network Singular Value Decomposition (CNN-SVD) model for DR:

Without the use of hominoids, DL algorithms swiftly identify enhanced characteristics in retinal images [24]. To detect retinal lesions and classify spot images, a DL model is generated. 243 retinal images that confirmed by ophthalmologists examined during this process. The Kaggle input dataset is divided into image patches that show the normal retinal structure as well as microaneurysms, hemorrhages, and exudates. CNN-SVD is being used by the authors to identify lesions and categorize them into five grades. Frameworks based on collections have been shown to enhance the detection of microaneurysms. Over fitting problem and highly expensive is the drawback of CNN-SVD.

3.5 Inception-ResNet-v2 for DR:

To create the hybrid model for the recognition of DR, a tradition block of CNN layers is placed on first of Inception-ResNet-v2 [27]. It is used to classify the DR with higher accuracy and performance. It assessed the suggested model's performance using the APTOS 2019 blindness detection (Kaggle dataset) and the Messidor-1 diabetic retinopathy dataset. It takes more time to process when it have large datasets.

3.6 Hybrid network connecting VGG-16 as well as XGBoost Classifier, then DenseNet 121 network for DR:

The DenseNet 121 model's exceptional performance demonstrates how successful it is in this field. Both patients and healthcare professionals gain from the use of such automated techniques, which greatly increase the effectiveness and precision of DR diagnosis. It have extensive training datasets to attain the best possible accuracy and possible training computational overhead [28].

3.7 ViT-CNN for DR:

Early detection of DR diseases is essential to stop the progression of eye impairment. The main goal of this article is to use ViT-CNN to accurately identify and analyse ophthalmoscopy images of various eye diseases, such as cataracts, diabetic retinopathy, and glaucoma. ViT-CNN successfully identifies the eye damage in the early stage with belter performance. Cons include sensitivity to irrelevant features and data scaling, high memory and processing costs, and poor scalability [30].

Table 2: *Comparable analysis of DR detection using ML techniques.*

S.No.	Author/Year of publication	Method	Advantages	Disadvantages
1.	Venkatesh *et al* (2024) [17]	This study proposed a Random Forest (RF) to categorize the DR	This method requires less time to access the DR and non-DR	The sample sizes of the available features are not enough to train the model and it is not suitable to handle large datasets.
2.	Tăbăcaru *et al* (2023) [18]	In this work Gradient Boosting Classifier (GBC) is proposed to classify DR.	Highly flexible and adaptable when detecting DR	Computationally expensive, particularly when working with large datasets.
3.	Qin *et al* (2023) [19]	This study presents Multi-class feature Extraction deep Forest to classify diabetic retina.	It improves the classification accuracy with high performance.	Complex and requires large datasets.

Table 3: *Comparable analysis of DR detection using DL techniques.*

S.No.	Author/Year of publication	Method	Advantages	Disadvantages
1.	Syed *et al* (2023) [25]	This study proposed a Concatenated Convolutional Neural Network (CCNN) to categorize the multi-class DR	It is a precise method with high accuracy and performance.	It is more expensive.
2.	Atcı *et al* (2024) [26]	In this work DenseNet121 CNN model is proposed to classify DR.	Less parameter, a stronger feature reuse, and a less severe vanishing gradient issue than some other models.	Such possible validation accuracy instability and increased computational expense in comparison to simpler models
3.	Khan *et al* (2021) [29]	This study presents VGG-16 to classify DR	Model's training and convergence times are decreased.	Requires significant memory and computational costs

3.8 Accuracy comparison for ML and DL technique

Table 4: *Comparative analysis of accuracy in ML techniques*

Methods	Accuracy
Gradient Boosting Classifier [18]	92%
Decision Tree [15]	99.9%
K-NN classifier [14]	100%

Table 4 represents an accuracy comparison of DR analysis using ML techniques. From the table, it is verified that the K-NN classifier [14] model achieves higher accuracy of 100% when compared with gradient Boosting classifier [18] model and DT [15] model.

Table 5: *Comparative analysis of accuracy in DL techniques*

Methods	Accuracy
Inception-ResNet-v2 [27]	82.18%
DenseNet 121 [28]	97.30%
ViT-CNN [30]	98.1%

Table 5 represents an accuracy comparison of DR analysis using DL techniques. From the table, it is verified that the ViT-CNN classifier [30] model achieves higher accuracy of 100% when compared with DenseNet 121 [28] model and Inception-ResNet-v2 [27] model.

4. Conclusion

The early identification and categorization of DR using advanced techniques have become increasingly important in today's society. Researchers have developed numerous methods to enrich the classification accuracy of DR. This approach utilizes hybrid algorithms and large number of training datasets to obtain more accurate classification results. In this research, several ML and DL techniques are reviewed for the DR detection from eye images ensuring high accuracy and performance. Initially, ML models such as, SVM, DT, K-NN, NB, RF, Gradient Boosting classifier, multi-class feature extraction deep forest are compared for the analysis of DR. Likewise, DL techniques such as, CNN-DRE, CNN-RBF, SVM-DNN, Hybrid CNN-SVD model, CCNN, CNN-DenseNet 121, Inception-ResNet-v2, DenseNet 121, VGG-16 and ViT - CNN are compared for the diabetic retinopathy analysis. It is verified that, the CNN based DL model results better performance and higher precision rate compared to several ML techniques. Furthermore, future study is prolonged towards the use of advanced optimization algorithms for the multiclass classification.

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