Detecting Diabetic Retinopathy Using Machine Learning Algorithms: A Review

Abstract:

Diabetic retinopathy, a condition resulting from prolonged high blood sugar levels that damage the retina, can cause vision impairment and, if untreated, lead to blindness. With advances in medical imaging and the availability of fundus image collections such as Madrid Messidor and DRIVE, computer-aided diagnosis (CAD) systems have become instrumental in identifying and categorizing cases. Machine learning, a branch of artificial intelligence, has demonstrated remarkable success in medical image processing, showing great potential for the early detection of diabetic retinopathy—a condition often challenging to diagnose in its early stages due to a lack of symptoms. This review examines prior studies leveraging machine learning algorithms, such as convolutional neural networks (CNNs), support vector machines (SVMs), and k-nearest neighbors (KNN), for diabetic retinopathy detection using fundus image datasets. It also explores existing challenges, including dataset variability, computational demands, and the generalizability of models across diverse populations. Highlighting methodologies, datasets, and performance metrics like accuracy, sensitivity, and specificity, this article aims to provide a cohesive understanding of the current landscape, delineate strengths and limitations, and suggest directions for future research.

1. Introduction:

Diabetic retinopathy is a condition characterized by retinal damage caused by prolonged high blood sugar levels. If left undiagnosed and untreated, it can lead to vision loss and eventually blindness. It is the leading cause of vision impairment among diabetic individuals and one of the main causes of new cases of blindness worldwide. Current estimates suggest that by 2040, approximately 600 million people will have diabetes, with one-third at risk of developing diabetic retinopathy (DR) (Li et al., 2023). Only when a patient has diabetes for 10 years or longer and goes undiagnosed and untreated without having a proper eye examination can diabetic retinopathy develop. If diabetic retinopathy is identified early enough through routine medical examinations and diabetes management, it can always be avoided(Gadekallu et al., 2023). It is possible to become blind as the illness progresses. The primary treatment for this condition relies on early identification, which is vital in preventing many individuals from losing their sight and delaying the progression of the underlying disease(Oulhadj et al., 2022).

Medical imaging advances led to the creation of fundus image collections like Madrid, Messidor, and DRIVE. These datasets contain a variety of medical cases that can be used to readily detect and classify infected cases using computer-aided diagnosis (CAD). The DRIVE dataset's Figure (1) illustrates the variations between the normal and DR-infected retinas(Hasan et al., 2021).

(a) (b)

Figure (1) :Normal and DR Infected Retina (a) Normal (b) DR Infected

An artificial intelligence technique called machine learning (ML) uses data to create prediction models that automatically analyze data without the need for programming. Robotics, pattern recognition, natural language processing, data mining, share market prediction, and computer-aided diagnosis (CAD) have all seen impressive success with machine learning techniques. The detection task is challenging in the early stages of DR since there are no symptoms. Traditionally, doctors have classified cases of DR by interpreting aspects of the retinal picture. Recently, medical imaging has found great success with ML. In medical image processing, certain entity types, such as lesions and organs, can be too complex to accurately depict using a straightforward mathematical solution(Hasan et al., 2021).

The primary objective of this research is to conduct a comprehensive review of prior studies that have utilized machine learning algorithms for the detection of diabetic retinopathy, focusing specifically on the analysis of fundus image datasets. This review meticulously compiles and examines the various methodologies, algorithms, and datasets employed in the field, highlighting the performance of each approach. A critical aspect of this investigation involves presenting and scrutinizing the results of each study, particularly focusing on the accuracy of the algorithms as quantified by various performance metrics. Through this analysis, the research aims to provide a cohesive understanding of the current landscape in diabetic retinopathy detection, delineating the strengths, limitations, and potential areas for future advancements in this domain.

This review paper is systematically organized into seven sections: Section 2 presents diabetic retinopathy, Section 3 discusses machine learning algorithms, Section 4 examines retinal datasets, Section 5 outlines performance evaluation metrics, Section 6 reviews related work, and Section 7 offers the conclusion.

2. Diabetic Retinopathy:

The hallmark of diabetic retinopathy (DR) is aberrant retinal vasculature, which can develop into irreversible visual loss from bleeding or scarring. Gradual visual impairment and, in the worst-case scenario, blindness could result from this. It is not possible to cure the sickness; thus, treatment concentrates on maintaining the patient's present level of eyesight. In most cases, a patient's sight may be saved if DR is diagnosed and treated as soon as possible. To diagnose DR, an ophthalmologist should inspect images of the retina manually, which is an expensive and time-consuming process(Alwakid et al., 2023).

Diabetic Retinopathy, a leading cause of blindness globally, results from retinal blood vessel damage due to elevated blood sugar levels, necessitating early detection and treatment to prevent severe complications (Akram et al., 2025).

Diabetic retinopathy is divided into two main categories based on symptoms and severity: non-proliferative diabetic retinopathy (NPDR) and proliferative diabetic retinopathy (PDR). Furthermore, the International Classification of Diabetic Retinopathy (ICDR) scale is utilized to further classify these phases based on specific symptoms. Based on how severe the condition is, the International Classification System for Diseases (ICDR) places DR into five classifications. Table 1 defines the ICDR scale. Figure(2) displays examples of fundus pictures from every ICDR class(Macsik et al., n.d.-a).

Table(1): An explanation of the DR phases, ICDR scale

Level of Disease Severity	Results Noted During Dilated Ophthalmoscopy
No DR	No abnormalities
Mild NPDR	Microaneurysms only
Moderate NPDR	Microaneurysms and additional symptoms, but not as severe as NPDR
Severe NPDR	Moderate NPDR with any of the following: •Intraretinal hemorrhages (≥ 20 in each quadrant) •Definite venous beading (in 2 quadrants) •Intraretinal microvascular abnormalities (in 1 quadrant) •Moreover, proliferative retinopathy is not present.
Proliferative DR	Severe NPDR and 1 or more of the following: •Neovascularization. •Vitreous/preretinal hemorrhage.

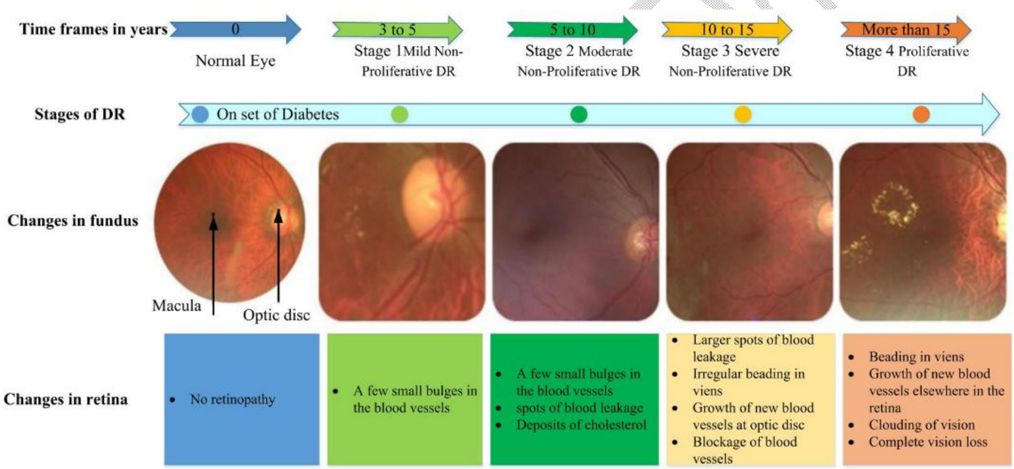

Figure (2): Examples of fundus images of different stages of DR

3.Machine Learning Algorithms

Machine learning is the study of statistical models and algorithms that identify pertinent spatiotemporal patterns and information using the variables in a dataset. Computer systems can conduct quick predictions from newly input data thanks to machine learning, which gives them completely new capabilities(Ayoub, 2020). Machine learning algorithms do not require programming; instead, they use sample data, or "training data," to create prediction models. By the model learning approach(Hasan et al., 2021).

As seen in Figure (3), machine learning algorithms can be broadly classified into four categories: semi-supervised learning, reinforcement learning, unsupervised learning, and supervised learning(Sarker, 2021).

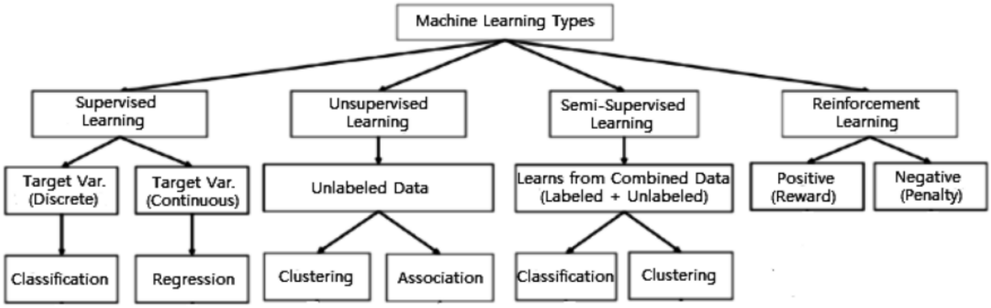

Figure (3): Various types of machine learning techniques

The bellow sectionsprovides a brief overview of different learning strategies:

3.1 Supervised Learning:

The learning process yields the goal function, which is an expression of a model that describes the data. During the learning process, the objective function is utilized to anticipate a variable's value. An enormous volume of labeled training data must be sent to the algorithm. After evaluating the output, the algorithm iteratively modifies the weights' values to produce the desired outcomes and constructs the classification model (classifier). To assign each input data set to its appropriate class (label), the classifier then generates predictions for a fresh set of unseen data. Classification and regression are the two primary supervised learning tasks(Hasan et al., 2021). Plateort Vector Machine (SVM), Naïve Bayes, Neural Network, Nearest Neighbors, Support Vector Machine (Discriminant Analysis), and Logistic Regression are typical techniques under the classification area. Ensemble methods, decision trees, random forests, linear regression, support vector regression (SVR), and other techniques fall within the regression group(Saranya et al., 2020).Supervised learning techniques, particularly those implemented through convolutional neural networks (CNNs), have advanced the automatic detection and classification of diabetic retinopathy, offering scalable and precise diagnostic solutions (Kumar et al., 2025)

3.2Unsupervised Learning:

Is a data-driven method that analyses unlabeled datasets without the need for human intervention. This is frequently used for exploratory reasons, groupings in findings, generative feature extraction, and the identification of significant patterns and structures. Clustering, density estimation, feature learning, dimensionality reduction, finding association rules, anomaly detection, and other unsupervised learning tasks are among the most popular ones(Sarker, 2021). Clustering algorithms that can be employed include K-Means, K-medoids, and C-Means. Methods for reducing dimensionality include Principle Component Analysis (PCA) and Singular Value Decomposition (SVD)(Saranya et al., 2020).Unsupervised learning approaches, such as clustering techniques and dimensionality reduction methods, are pivotal in identifying patterns and latent features in biomedical datasets. These methods enhance the ability to discover novel insights and assist in the diagnosis of complex conditions like diabetic retinopathy (Tsao et al., 2018)

3.3 Semi Supervised Learning:

Because it works with both labeled and unlabeled data, semi-supervised learning is characterized as a hybridization of the supervised and unsupervised approaches described above(Sarker, 2021).

3.4 Reinforcement Learning:

An environment-driven approach, or reinforcement learning, is a kind of machine learning technique that allows software agents and computers to automatically assess the optimal behavior in a given context or environment to increase its efficiency. The ultimate objective of this kind of learning, which is based on rewards and penalties, is to use the knowledge gathered from environmental activists to take actions that will maximize rewards and reduce risks. Although it is not ideal to use it to solve simple or straightforward problems, it is a potent tool for training AI models that can help increase automation or optimize the operational efficiency of complex systems like robotics, autonomous driving tasks, manufacturing, and supply chain logistics(Sarker, 2021).

4.Retina Datasets:

Numerous databases containing retinal images are readily available for public use, offering a valuable resource for researchers in the field. These datasets play a pivotal role in the advancement of deep learning (DL) methodologies, particularly in the area of diabetic retinopathy classification. Among the most prominent and widely utilized datasets in this domain are EyePACS, DDR, DIARETDB, STARE, Messidor, RFMiD, APTOS, HEIMED, e-ophtha, ROC, and DRIVE. Each dataset presents a unique set of images and annotations, contributing to a diverse pool of data that aids in the development, testing, and enhancement of DL models(Ismail & Hassan, 2023). Table(2) presents a summary of all publicly available datasets concerning diabetic retinopathy (DR)(Agarwal & Bhat, 2023).

Table (2): presents a summary of all publicly available datasets

Dataset Name	**Availability**	**Number of Images**	**Resolutions**	**Camera**
HEI-MED	Public	115 abnormal, 54 healthy	2196x1958	45 fold-view with Zeiss visual-Pro fundus
MESSIDOR	Public	1200	1440x960, 2240x1488, 2304x1536	3CCD
MESSIDOR 2	Public	1784	Different resolutions	Non-mydriatic Topcon
FIRE	Public	134	-----	Nidek AFC-210
STARE	Public	400	605x700	TOP-CON-TRV 50 with 35 fold-view
E-OPHTHA-EX	Public	47 exudated & 35 no lesion	2048x1360	OPHDIAT
E-OPHTHA-MA	Public	233 No lesion & 148 small hemorrhage and microaneurysms	-----	-----
ROC (Retinopathy Online Challenge)	Public	1200	768x576, 1058x1061, 1389x1383	Canon
DR1 & DR2	Public	DR1: 234, DR2:	---	---

Dataset Name	Availability	Number of Images	Resolutions	Camera
		520		
DIARETDB0 & DIARETDB1 (Image-Ret)	Public	DIARETDB0: 130, DIARETDB1: 89	1500x1152	50-fold view
KAGGLE	Public	88,702 (Training: 35,126, Testing: 53,576)	Different resolutions	---
MADRID	Public	Segmentation: 81, Disease Grading: 516, Localization: 516	---	---
DRIVE	Public	Training: 20, Testing: 20	786 x 584	3CCD
ARIA	Public	142	---	Zeiss FF450
DriDB	Public	50	---	University of Zagreb
DR1 & DR2	Public	DR1: 234, DR2: 520	---	---

5.Metrics for performance evaluation

Numerous preprocessing methods exist to refine eye fundus photographs before their utilization in machine learning models for feature extraction and categorization. Different benchmarks are available to assess the robustness of these models. In medical imaging, the evaluation typically hinges on two key aspects: accurate identification of lesions in the imagery and the assessed accuracy and reliability of these identifications. Four primary terms are conventionally employed in the assessment matrix(Agarwal & Bhat, 2023):

•True Positive (TP) = represents the count of positive lesions correctly identified.

•False Positive (FP) = indicates the instances of negative lesions mistakenly marked as positive.

•True Negative (TN) = represents the count of negative lesions correctly identified.

•False Negative (FN)= represents the count of positive lesions inaccurately marked as negative.

The calculations of accuracy, specificity, and sensitivity are based on these four terms. PSNR, which stands for Peak Signal to Noise Ratio and is expressed in logarithmic decibels, indicates that higher PSNR values suggest the processed images are of higher fidelity compared to the original images. Accuracy, specificity, and sensitivity are the metrics typically used to determine the performance efficacy of classification models in medical imaging(Agarwal & Bhat, 2023):

5.1Accuracy:

Represents the proportion of predictions a classifier correctly makes relative to the true label values during the testing phase. It can also be described as the quotient of the number of accurate evaluations over the total number of evaluations conducted. The formula for calculating accuracy is as follows(Gadekallu et al., 2023):

$$\text{Accuracy} = \frac{(\text{TN} + \text{TP})}{(\text{TN} + \text{TP} + \text{FN} + \text{FP})}$$

5.2Sensitivity:

Refers to the proportion of actual positives accurately identified by the classifier during the testing process, and its calculation is based on the corresponding equation(Gadekallu et al., 2023):

$$\text{Sensitivity} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

5.3 Specificity:

Is the proportion of actual negatives that a classifier correctly identifies during the testing phase, and it is determined using a specific formula(Gadekallu et al., 2023):

$$\text{Speci icity} = \frac{\mathbf{TN}}{\mathbf{TN} + \mathbf{FP}}$$

And there are some other performance metrics, as follows:

$$\text{Precision} = \frac{\mathbf{TP}}{\mathbf{TP} + \mathbf{FP}}$$

$$\text{Recall} = \frac{\mathbf{TP}}{\mathbf{TP} + \mathbf{FN}}$$

$$\text{F1} - \text{score} = \frac{\mathbf{2} * \text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}}$$

6. Literature Review

Zaaboub and Douik(Zaaboub&Douik, 2020) presented a method for detecting hard exudates in color fundus retinal images, stressing their importance in the early diagnosis of diabetic retinopathy. They used a combination of intensity

thresholding and the Random Forest algorithm to generate a binary mask for exudate detection.
Praveen Kumar et al.(Praveen Kumar et al., 2020) discussed the use of Support Vector Machine (SVM) and K-Nearest Neighbors (KNN) algorithms in detecting diabetic retinopathy. Their methodology was to apply preprocessing techniques like adaptive histogram equalization, contrast stretching, and median filtering on a database for grading the severity of diabetic retinopathy.
Reddy et al.(Reddy et al., 2020) used ensemble learning with Random Forest, Decision Tree, Adaboost, K-Nearest Neighbor, and Logistic Regression algorithms. Preprocessing was done using min-max normalization on a dataset of 1151 instances with 20 attributes from the UCI machine learning repository.
Maneerat et al.(Maneerat et al., 2020) explored hard exudates detection by unsupervised classification. The authors applied k-means clustering to the DIARETDB0 and DIARETDB1 datasets with preprocessing, such as optic disc removal and green channel selection. Feature extraction was also performed: by dilation, erosion, entropy analysis, and standard deviation analysis.
Zadeh et al.(Zadeh et al., 2020) introduced an approach for identifying retinal lesions by utilizing Hierarchical Self-Organizing Maps (HSOM). Preprocessing, extraction of the lesion features, and the actual classification were stages in the suggested framework, where MESSIDOR database was pivotal to their study.
Mishra et al.(Mishra et al., 2020) utilized DenseNet and VGG16 convolutional neural network (CNN) architectures for the detection of diabetic retinopathy using the Kaggle APTOS 2019 Blindness Detection dataset. Their preprocessing approach included image cropping, resizing, and rotation techniques.
Sharma et al.(Sharma et al., 2021) used machine learning methods like Weighted KNN, Cubic SVM, and Simple Tree for the detection of diabetic retinopathy. Preprocessing steps in their work were the conversion to grayscale and Canny edge detection for databases like DIARETDB0 and DIARETDB1.
Soni and Rai(Soni & Rai, 2021) developed a machine-learning-based approach for the early detection of diabetic retinopathy by using histogram equalization as a preprocessing step and k-means clustering for segmentation; their study tested the performance of classifiers such as the Support Vector Machine and Random Forest.
Amalia et al.(Amalia et al., 2021) proposed a method based on a combination of CNN and LSTM for lesion detection in retinal fundus images and provided descriptive lesion descriptions. Their preprocessing consisted of cropping, histogram equalization, and rotation of the images.

Emon et al.(Emon et al., 2021) conducted a comparison between different machine-learning methods in predicting diabetic retinopathy using the UCI repository Diabetes Retinopathy Debrecen dataset. The authors employed such methods for classification: Naive Bayes, Sequential Minimal Optimization, and Logistic Regression.
Yaqoob et al. (Yaqoob et al., 2021)proposed a hybrid approach that combines ResNet-50 for deep feature extraction with a Random Forest classifier. The performance of their model was tested on various datasets such as Messidor-2 and EyePACS, where it was also compared with other CNN architectures.
Asia et al.(Asia et al., 2022) used CNN models including ResNet-101, ResNet-50, and VGGNet-16 for the diagnosis of diabetic retinopathy based on fundus photographs. Their approach was built on heavy preprocessing and validation upon datasets from Xiangya No. 2 Hospital and others.
Macsik et al.(Macsik et al., n.d.-b) introduced Local Binary Convolutional Neural Networks (LBCNN) as an alternative to conventional CNNs in diabetic retinopathy classification using deterministic filters to achieve maximum performance in the case of small data.
Lahmar and Idri(Lahmar &Idri, 2022) conducted a comparative effectiveness of seven deep learning architectures, including DenseNet201, MobileNet_V2, and VGG19, for the diagnosis of referable diabetic retinopathy using cross-validation techniques with different preprocessing techniques such as resizing and normalization.
Hardas et al.(Hardas et al., 2022) used Support Vector Machine (SVM) for the classification of retinal fundus images for the detection of diabetic retinopathy. Preprocessing steps included resizing and grayscale conversion followed by median filtering and histogram equalization along with GLCM-based feature extraction.
Pragathi and Nagaraja Rao (Pragathi & Nagaraja Rao, 2022) developed an integrated machine-learning framework based on normalization, Principal Component Analysis (PCA), and moth-flame optimization. Their work used algorithms including Decision Tree, Naive Bayes, Random Forest, and SVM.
Mijeeb Rahman and colleagues(Mujeeb Rahman et al., 2022)compared the application of Support Vector Machine (SVM) and Deep Neural Network (DNN) models for the automated screening of diabetic retinopathy with a focus on feature extraction using grey-level co-occurrence matrices.
Sivapriya et al.(Sivapriya et al., 2022) used RNNs to classify diabetic retinopathy through different preprocessing techniques: histogram equalization, pseudo-colour processing, and features extraction based on GLCM.

Naz et al.(Naz et al., 2022) proposed a hybrid approach based on Fuzzy C-Means Clustering and Convolutional Neural Networks (FCCNN) to analyze retinal images. The steps involved were normalization and segmentation of images to enhance the classification rate.

Mhasawade et al.(Mhasawade et al., 2023) used SVM, KNN, and Decision Tree for diabetic retinopathy diagnosis, which a five-layer CNN assists for feature extraction from the Gaussian-filtered images.

Vijayan and S (Vijayan & S, 2023) proposed a regression-based diabetic retinopathy diagnosis model based on the EfficientNet-B0 architecture. The preprocessing steps included center-cropping, resizing, and application of Graham's method.

Das et al.(Das et al., 2023) compared deep learning networks, EfficientNetB4 and DenseNet169, for the detection of diabetic retinopathy using the Kaggle EyePACS dataset. Experiments were performed on these models with different preprocessing methods.

Minarno et al.(Minarno et al., n.d.) applied the EfficientNet-B7 model for diabetic retinopathy classification and tested different preprocessing techniques to enhance the performance of the CNN.

Adak et al.(Adak et al., 2023)combined several image transformers, notably the Vision Transformer (ViT) and Data-Efficient Image Transformers (DeiT), for the classification of diabetic retinopathy severity and emphasized preprocessing techniques to enhance data quality.

Nissen et al.(Nissen et al., 2023)assessed the performance of RetinaLyze, a Support Vector Machine tool, for detecting diabetic retinopathy using fundus photos from the Danish National Screening Programme.

Table(3): Summary of the literature review

Author	**Year**	**Algorithm(s)**	**Dataset**	**Results: Accuracy (%)**	**Specificity (%)**	**Sensitivity (%)**
Zaaboub&Douik	2020	Random Forest	Color fundus retinal images	94.38	-	91.40
Praveen Kumar et al.	2020	SVM, KNN	Diabetic retinopathy severity grading database	98.06	100	83.67
Reddy et al.	2020	Ensemble: RF, DT, Adaboost, KNN, Logistic Regression	UCI machine learning repository	-	-	-

Author	Year	Algorithm(s)	Dataset	Results: Accuracy (%)	Specificity (%)	Sensitivity (%)
Maneerat et al.	2020	k-means clustering	DIARETDB0, DIARETDB1	-	97	-
Zadeh et al.	2020	Hierarchical Self-Organizing Maps (HSOM)	MESSIDOR database	97.87	-	98.51
Mishra et al.	2020	DenseNet, VGG16 CNN architectures	Kaggle's APTOS 2019 Blindness Detection(Ismail & Hassan, 2023)	96.11	-	-
Sharma et al.	2021	Weighted KNN, Cubic SVM, Simple Tree	DIARETDB0, DIARETDB1	85.8 - 88.6	-	-
Soni & Rai	2021	SVM, Random Forest	89 color images	96.62 (RF)	-	-
Amalia et al.	2021	CNN, LSTM	MESSIDOR	90	-	-
Emon et al.	2021	Naive Bayes, SMO, Logistic Regression	Diabetes Retinopathy Debrecen dataset (UCI)	75	-	-
Yaqoob et al.	2021	ResNet-50, Random Forest	Messidor-2, EyePACS	96 (Messidor-2), 75.09 (EyePACS)	-	-
Asia et al.	2022	ResNet-101, ResNet-50, VggNet-16	HRF, STARE, DIARETDB0, MESSIDOR, XHO, Xiangya No. 2 Hospital Ophthalmology	98.82 (test), 98.88 (train), Varied across datasets	-	-
Macsik et al.	n.d.	Local Binary Convolutional Neural Network (LBCNN)	EyePACS, APTOS	Comparable to traditional CNNs	-	-

Author	Year	Algorithm(s)	Dataset	Results: Accuracy (%)	Specificity (%)	Sensitivity (%)
Lahmar &Idri	2022	Inception_ResNet_V2, Inception_V3, ResNet50, VGG16, VGG19, MobileNet_V2, DenseNet201	APTOS, Kaggle DR, Messidor-2	93.09 (MobileNet_V2 on APTOS), 85.79 (DenseNet201 on Messidor-2), 84.74 (DenseNet201 on Kaggle DR)	-	-
Hardas et al.	2022	Support Vector Machine (SVM)	DIARETDB1	77.3	74.1	90.2
Pragathi & Nagaraja Rao	2022	SVM, PCA, moth-flame optimization	UCI Machine Learning Repository	97.5	-	95.8
Mujeeb Rahman et al.	2022	SVM, Deep Neural Network (DNN)	Not specified	- (mean AUC 97.11% for SVM, 99.15% for DNN)	-	-
Sivapriya et al.	2022	Recurrent Neural Network (RNN)	Messidor	97	99	95
Naz et al.	2022	Fuzzy C-means Convolutional Neural Network (FCCNN)	Not specified	98.6	-	-
Mhasawade et al.	2023	SVM, KNN, Decision Tree, CNN (feature extraction)	3662 Gaussian-filtered images	94.679 (SVM)	-	-
Vijayan & S	2023	Regression model, Efficientnet-B0	APTOS, DDR, IDRiD	85.5	-	-
Das et al.	2023	EfficientNetB4, DenseNet169	Kaggle's EyePACS	79.11 (EfficientNetB4), 76.80 (DenseNet201)	-	-
Minarno et al.	2023	EfficientNet-B7	APTOS 2019 Blindness Detection	89 (training), 84 (test)	-	-
Adak et al.	2023	ViT, BEiT, CaiT, DeiT (ensemble)	Kaggle APTOS 2019 Blindness	94.63 (wm), 91.26 (mv)	-	-

Author	Year	Algorithm(s)	Dataset	Results: Accuracy (%)	Specificity (%)	Sensitivity (%)
			Detection			
Nissen et al.	2023	RetinaLyze, SVM	Danish National Screening Programme	-	89.9	

7. Discussion:

As shown in thetable(3). In the realm of algorithm performance, deep learning models, particularly convolutional neural networks (CNNs) and their variants, stand out for their high accuracy. For instance, Asia et al.(Asia et al., 2022) employed ResNet-101, ResNet-50, and VggNet-16, achieving remarkable training and testing accuracies, with the highest being 98.88% and 98.82% respectively. These models were tested across various datasets, including HRF, STARE, DIARETDB0, MESSIDOR, and XHO, consistently demonstrating their effectiveness in diabetic retinopathy detection. Similarly, Naz et al.'s(Naz et al., 2022) novel approach using a Fuzzy C-means Convolutional Neural Network (FCCNN) achieved an impressive accuracy rate of 98.6%, underscoring the potential of hybrid and advanced CNN architectures.

On the other hand, traditional machine learning models like Support Vector Machine (SVM), K-Nearest Neighbors (KNN), and Decision Trees also showcased commendable performance, especially when integrated with robust feature extraction techniques. For example, Mhasawade et al.(Mhasawade et al., 2023) reported a testing accuracy of 94.679% using an SVM, which outperformed other models in their study. These models, while perhaps not reaching the peak performance of deep learning systems, still play a significant role due to their efficiency and less computational expense.

The choice of dataset is another critical factor influencing model performance. Publicly available datasets like MESSIDOR, APTOS, and EyePACS are widely used, providing a common ground for benchmarking different algorithms. The size and quality of these datasets vary, which can significantly impact the results. For instance, the studies by Yaqoob et al.(Yaqoob et al., 2021) and Minarno et al.(Minarno et al., n.d.) , both utilizing the APTOS dataset and employing different architectures, provide valuable insights into how dataset characteristics can influence the effectiveness of specific models.

When considering the results in terms of accuracy, specificity, and sensitivity, it's clear that accuracy is the most reported metric, with several studies achieving remarkable results. However, specificity and sensitivity are crucial, especially in medical diagnostics, to ensure true positive cases are not missed and false positives are minimized. Studies that provide a comprehensive evaluation, including all three metrics, offer a more holistic view of the model's performance.

8. Conclusion:

In conclusion, this comprehensive review underscores the pivotal role of machine learning in advancing the detection and diagnosis of diabetic retinopathy. Deep learning models, particularly those harnessing the power of convolutional neural network (CNN) architectures, have consistently demonstrated superior accuracy in identifying this vision-threatening condition. Despite this, traditional machine learning models continue to be invaluable, especially when synergistically combined with robust feature extraction techniques. The dynamic progression in model architectures, paired with sophisticated preprocessing and feature extraction methods, paints a promising landscape for the future of diabetic retinopathy detection. As this field continues to evolve, it holds the potential to significantly enhance the accuracy, efficiency, and reliability of diagnostic systems, thereby making strides in the management and treatment of diabetic retinopathy. This review not only highlights the current achievements but also sets the stage for future innovations in the domain of medical image analysis using machine learning.

Disclaimer (Artificial intelligence)

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Author(s) hereby declare that NO generative AI technologies such as Large Language Models (ChatGPT, COPILOT, etc.) and text-to-image generators have been used during the writing or editing of this manuscript.

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