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Prediction and classification of diabetic retinopathy using machine learning techniques

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ABSTRACT

Diabetic retinopathy (DR) is a progressive and sight-threatening complication of diabetes mellitus, characterized by damage to the blood vessels in the retina. Early detection of DR is vital for timely intervention and effective management to prevent irreversible vision loss. This paper provides a comprehensive review of recent advancements in integrating machine learning (ML) and deep learning (DL) techniques for diagnosing DR, aiming to assist ophthalmologists in their manual diagnostic process. The paper presents a comprehensive definition of DR, elucidating the underlying pathological processes, clinical signs, and the various stages of DR classification, ranging from mild non-proliferative to severe proliferative DR. Integrating ML and DL in DR diagnosis has developed the field by offering automated and efficient methods and techniques to analyze retinal images. With high sensitivity and specificity, these techniques demonstrate their efficacy in accurately identifying DR-related lesions, such as microaneurysms, exudates, and hemorrhages. Furthermore, the paper examines diverse datasets employed in training and evaluating ML and DL models for DR diagnosis. These datasets range from publicly available repositories to specialized datasets curated by medical institutions. The role of large-scale and diverse datasets in enhancing model robustness and generalizability is emphasized.

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1. INTRODUCTION

Diabetes mellitus is a systemic metabolic disorder recognized as the leading cause of acquired blindness among adults aged 25 to 74 in Western countries, accounting for 12% of all cases of blindness [1]. Diabetes is characterized by the impaired processing of food as energy in the body, which lacks either the ability to respond to insulin or to produce it [2]. Insulin is a pancreatic hormone that acts as a key to promoting blood sugar entry into cells for energy use. However, in individuals with type 2 diabetes, cells do not respond adequately to insulin, leading to a condition known as insulin resistance. To compensate, the pancreas increases insulin production to elicit a cell response. Over time, it becomes overwhelmed, resulting in elevated blood sugar levels [3]. Persistently high level of blood sugar poses significant harm to the body, contributing to serious health complications such as heart disease, kidney disease, and vision loss. High blood sugar can damage the small blood vessels throughout the body, especially when it coexists with other systemic disorders (such as high blood pressure, obesity, and hyperglycemia) [4].

The retina is one of the membranes affected by this disease [5]. This thin membrane lining the back of the eye comprises visual cells traversed by many small blood vessels. It receives light impressions from the outside and transmits them to the brain via the optic nerve [6]. The macula is located at the center of the retina. It is the part of the retina that provides the most significant visual acuity, and it allows for greater precision of vision, perception of colors, fixation of objects, reading, and recognition of faces or even threading a needle [7].

2. DIABETIC RETINOPATHY

DR is a severe complication of diabetes, which encompasses all retina diseases caused by the deterioration of the retinal blood vessels of the eye. Each year, two out of every 100,000 individuals in the general population become blind due to DR [1]. Some symptoms of the disease appear after several years of diabetes onset and can lead to blindness [8]. Among these symptoms are: deformation of shapes observed, difficulty seeing in the dark, appearance of black spots in the field of vision, and appearance of shadows or uncertain bodies in the field of vision [9].

2.1. The process of DR

DR is characterized by the progressive deterioration of retinal blood vessels due to the high level of sugar in the blood [10], which weakens the walls of the capillaries (the capillaries are small blood vessels located at the end of the arteries that irrigate parts of the body and organs). The rupture of these capillaries causes a lack of oxygenation in extended areas of the retina. In response, the retina produces new, even more fragile blood vessels (neovascularization), which spread to the macula, causing a decrease in visual acuity [9]. The neovascularization invades the retina's surface and can cause bleeding, leading to traction of the retina and the risk of detachment, which can result in permanent vision loss [11].

2.2. The signs of DR

Identifying and classifying DR at an early stage is vital for preventing vision loss. A range of features as shown in Figure 1 can be utilized to detect and classify DR [12], enabling timely diagnosis and treatment. Some features of the disease and its classes are described below.

a) Microaneurysms (MAs):

These small, round bulges form in the retina's tiny blood vessels (capillaries). They occur due to the weakening of blood vessel walls caused by high blood sugar levels. Microaneurysms are typically observed as small red dots. They are 1 to 3 pixels in diameter or 10 μm to 100 μm [13].

b) Hemorrhages (HEs):

These are tiny spots of blood leakage from damaged blood vessels in the retina. They may appear as small dots or blotches with irregular margin sizes of upwards of 125 μm. Hemorrhages are categorized into two types: flame and blot, with superficial and deep areas, respectively [14].

c) Exudates (EXs):

Yellowish deposits accumulate in the retina due to fluid leakage from damaged blood vessels. These deposits can be observed as small, waxy spots and are commonly found around the macula. Exudates can have soft boundaries and foggy structures, known as soft EXs, or rigid boundaries and brilliant structures, known as hard Exs [15].

d) Cotton wool spots (CWSs):

These are white patches on the retina caused by blockages or infarctions in the nerve fiber layer. Cotton wool spots indicate areas of reduced blood flow and oxygen deprivation. Compared to MAs and EXs, they exhibit irregular, hazy formations with soft borders [16].

e) Intraretinal microvascular abnormalities (IRMAs):

Abnormalities in the retinal blood vessels develop due to retinal ischemia (restricted blood flow). IRMAs are seen as tangled and dilated blood vessels, suggesting a more advanced stage of DR [13].

f) Neovascularization (NV):

This refers to forming new, fragile blood vessels on the retina's surface. These abnormal blood vessels are prone to leakage and can cause severe complications, such as vitreous hemorrhage or retinal detachment [13].

By analyzing these features with clinical examination and imaging techniques, professionals can classify and stage DR into different classes, ranging from mild NPDR to severe PDR. This classification aids in determining the appropriate treatment approach, monitoring disease progression, and assessing the risk of vision loss. Regular screening and accurate classification of DR help ensure timely interventions and improved patient outcomes.

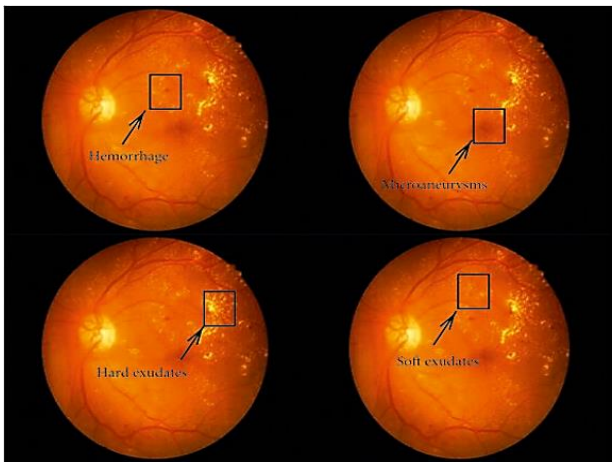

Figure 1. The DR features [17]

2.3. Classification of DR

The classification of DR is based on one hand on the severity of retinal ischemia, and on the other hand on maculopathy. The simplified classification used in clinical practice is that of the American Academy of Ophthalmology (AAO), in 2003, the society classified DR into four classes illustrated in the as shown in Figure 2 [18]:

a) Noncl-proliferative retinopathy (absence of neovascularization):

- Mild non-proliferative diabetic retinopathy (Mild NPDR) is characterized by the presence of microaneurysms, which are swellings in the small blood vessels of the retina, appearing in a round or punctate (dot-like) form [19].
- Moderate non-proliferative diabetic retinopathy (Moderate NPDR) is a mild NPDR accompanied by retinal hemorrhage produced by dilating small retinal vessels, appearing in punctate, flame-shaped, or red spot form. This stage is also characterized by the presence of exudates (diffusions of lipids in the retina) and a Cotton wool spot (whitish lesions indicating the occlusion of pre-capillary arterioles) [19].
- Severe non-proliferative diabetic retinopathy (Severe NPDR) is a moderate NPDR accompanied by extensive peripheral retinal ischemia produced by the lack of oxygenation through the blood vessels. At this stage, the risk for the development of neovascularization can be higher in intra-retinal microvascular abnormalities [20].

b) Proliferative retinopathy (PDR): this stage is characterized by the development of neovascularization. The eye attempts to generate new vessels to maintain normal oxygenation and nourishment of the retina, but unfortunately, these new vessels are very fragile and can bleed profusely into the surface of the retina, causing an intravitreal hemorrhage (inside the vitreous) and leading to retinal detachment. This ultimately results in decreased vision and permanent loss [21].

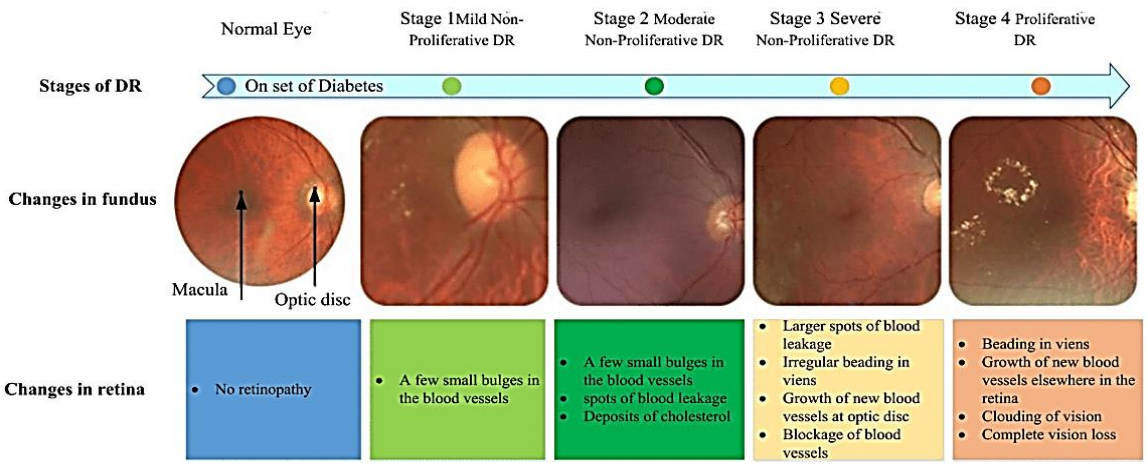

Figure 2. DR classification [22]

DR develops silently and can remain silent throughout its progression. Its signs appear late, starting with a gradual decline in vision and ending in blindness. That is why ophthalmologists recommend early diagnosis of the disease (after the onset of the first signs).

2.4. Diagnosis of DR

The diagnosis of DR aims to detect earlier the signs of retinal damage, such as microaneurysms, hemorrhages, exudates, or neovascularization, allowing for timely intervention and management of the condition. To establish the diagnosis of DR, the most common exams adopted by ophthalmologists are:

2.4.1. Fundus examination

After dilating the pupils using instilled mydriatic eye drops, the specialist uses a slit lamp (a type of microscope) to take photos of the retina as shown in Figure 3 to monitor changes affected by diabetes, such as the presence of abnormal blood vessels, edema, hemorrhages, or fatty deposits in the retina, appearance of neovascularization, vitreous hemorrhages, and retinal detachment [23].

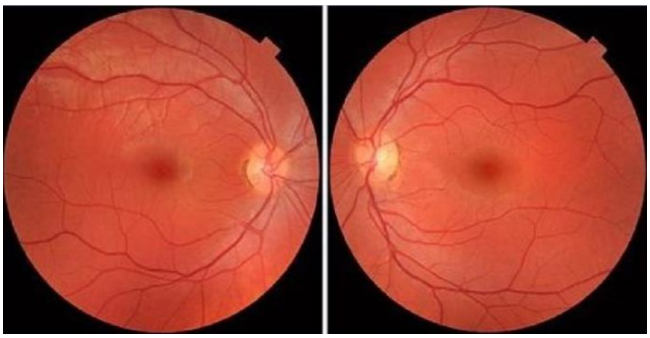

Figure 3. Fundus image of a normal retina [24]

2.4.2. Fluorescein angiography

It is a supplementary examination and is no longer routinely performed; the doctor carries it out when deemed necessary to accurately determine the severity of DR. This examination involves the intravenous injection of a dye (fluorescein) to observe any leaks or occlusions in the retinal blood vessels as well as the extent of retinal ischemia as shown in Figure 4 [23].

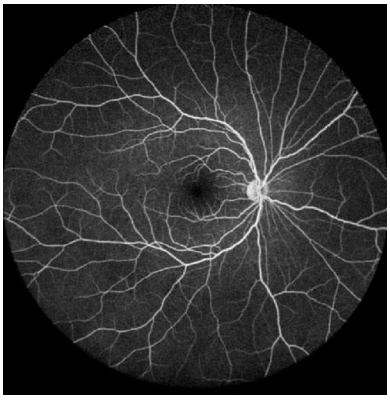

Figure 4. Fluorescein image of a normal retina [25]

2.4.3. Optical coherence tomography (OCT)

It is a type of laser scanner that allows for the precise measurement of the central retina's thickness to detect macular edema. Figure 5 shows a normal retina thickness scanned by the OCT technique [26], [27]. Other diagnostics are also available: retinal thickness analyzer (RTA) [28], scanning laser ophthalmoscopy (SLO), adaptive optics, OCT Angiography [29], Doppler OCT [30], and many others.

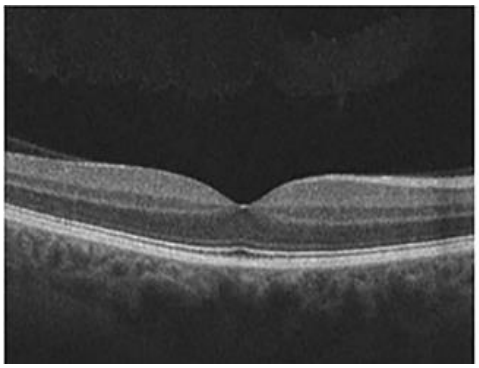

Figure 5. OCT image of a normal retina [27]

3. DIAGNOSIS OF DR USING ML AND DL

All the methods mentioned earlier are manual, tedious, time-consuming, and prone to errors. They require a working group, which may not always be feasible. Therefore, the proposal of a system based on artificial intelligence techniques that can detect and analyze early signs of DR using a large dataset is crucial for early detection of the disease, improving the lives of diabetic patients, and preserving their vision [31].

Numerous publications have been conducted on DR using different approaches and technologies in this context. There is variation in the sensitivity and specificity percentages depending on the proposed models, including image processing methods and the dataset used. The following section will present various works based on AI techniques (ML and DL), the treated signs of DR, the datasets used, and the obtained results.

3.1. Works in ML techniques

The Table 1 provides a comprehensive overview of various research achieved in the field of early DR detection using ML techniques. It lists the references to the original research works, the ML technique employed in each study, year of publication, features extracted from the retinal images, dataset used for training and testing the models and finally the performance values of each method, allowing for a quantitative comparison of their effectiveness.

Table 1. Literature review on ML-based models for early detection of DR

Ref.	ML method	Year	Extracted features	Dataset	Performance values
[32]	SVM	2020	EXs.	Kaggle DR detection	Specificity (SPE): 98%, Sensitivity (SEN): 94%
[33]	K-means, fuzzy C-means	2022	Blood vessels, EXs, MAs.	DIARETDB01	Not referenced
[34]	Probabilistic, geometric, KNN, tree-based methods	2017	EXs.	DIARETDB01, E-Ophtha, DRIVE, HRIS, VDIS, MESSIDOR, HRF, local datset.	Area under the curve (AUC): 0.98, Accuracy (ACC) > 98.58%
[35]	Novel decision tree (DT), SVM	2022	Not Ref.	Kaggle DR detection	SVM: ACC: 85.2%, novel DT: ACC: 92.8%
[36]	SVM, K-NN, Naïve Bayes (NB)	2020	Image texture	Messidor	SEN: 97.2%, SPE: 78.6%, ACC: 92.0%
[37]	SVM, KNN, DT, RF and ANN	2020	LBP and Wavelet T. based on EXs.	DIARETDB01	LBP: KNN: 94% ACC – 0.98 AUC – 0.95 F1, Wavelet: ANN: 100% ACC – 1.0 AUC – 1.0 F1
[38]	Fuzzy C-means, ELM, NB, multilayer perceptron (MLP)	2015	EXs.	DIARETDB0, DIARETDB01	ELM: SPE: 87%, ACC: 90%, SEN: 100%
[39]	KNN, DT	2015	EXs. Blood vessel.	Not referenced	Not Referenced
[40]	Ensemble: Alte- DT, KNN, AdaBoost, MLP, NB, RF, SVM, pattern classifier	2014	EXs. HEM. MAs.	Messidor	SEN: 90%, SPE: 91%, ACC: 90%, AUC: 0.989
[41]	SVM	2015	New vessels.	Messidor, local dataset	SEN: 91.83%, SPE: 96.00%
[42]	K-NN, SVM linear, SVM Polynomial, and DT	2021	EXs.	Local dataset	KNN: AUC: 1, ACC: 0.83, DT: AUC: 0.88, ACC: 0.67

3.2. Works in DL techniques

The Table 2 provides an overview of various works achieved in the field of early detection of DR using the techniques of DL. The table has the same structure as the previous one. Briefly, the work using ML and DL has shown promising results in aiding the diagnosis and detection of DR more quickly and accurately. The work conducted with ML focuses on extracting relevant features from retinal images and then using supervised learning algorithms to train a classification model. The results obtained with this approach have been encouraging, but determining which features are most important for classification is often challenging. The work carried out with DL involves using deep neural networks to learn relevant features from the images automatically. This approach has demonstrated even better results for detecting DR, as it can learn more complex and non-linear features that are often difficult to extract manually.

Table 2. Literature review on DL-based models for early detection of DR

Ref.	DL method	Year	Extracted features	Dataset	Performance values
[43]	Hybride: EyeNet, DenseNet	2022	DR stages	APTOS 2019, Messidor, EyePACS, IDRID.	ACC: 91.2%, SEN: 96%, SPE: 69%, dice similarity coefficient (DSC): 92.45%, Quadratic Kappa score (QKS): 0.883.
[44]	CNN	2020	DR stages	APTOS 2019.	ACC: 88%-89%, SEN: 87%-89%, SPE: 94%-95%, QWKS: 0.91-0.92.
[45]	Fully CNN	2018	MAs.	E-Ophtha, DiaretDB1, and ROC.	SEN: 0.392 ± 0.157 at 8 false positives per image (FPI) on the DIARETDB1. SEN: 0.562 ± 0.233 at 8 FPI on the E-ophtha. SEN: 0.485 ± 0.109 at 20 FPI in the ROC training dataset.
[46]	Deep CNN (AlexNet, VggNet, GoogleNet and ResNet)	2018	DR stages	Kaggle DR detection	ACC: VggNet-s: 95.68%, AUC: VggNet-s: 97.86%, SEN: VggNet-16: 90.78%, SPE: VggNet-s: 97.43%
[47]	ResNet	2022	MAs, EXs, CWS, HEM.	Local datset	AUC 95.5%, SEN 88.8%, SPE 83.9%.
[48]	CNN, VGG16	2020	DR stages.	APTOS 2019	ACC: 91.32%
[49]	CNN: VggNet	2020	MAs, blood vessel	EyePACS	ACC: 95.41%, precision (PRE): 96.03%, recall (REC): 94.30%, SPE: 97.0%, F1-score: 98.50%
[50]	Ensemble of 5 models deep CNN: Resnet50, Inceptionv3, Xception, Dense121, Dense169	2019	DR stages	Kaggle DR detection	ACC: 80.8%, REC: 51.5%, SPE: 86.7%, PRE: 63.8%, F1-score: 53.7%
[51]	Ensemble: NTS-Net, SBSLayer, ResNet-50, DensNet-201, NASNet	2020	MAs, HEM.	EyePACS, Messidor	EyePACS: AUC: 96.31%, ACC: 83.42%, SEN: 83%, SPE: 73%. Messidor: AUC: 92.99%, ACC: 76.25%, SEN: 76%, SPE: 91%.
[52]	CNN	2018	Exsudats, optic disk	DiaretDB0, DiaretDB1, DrimDB	DiaretDB0: SEN: 100%, SPE: 90.14%, TCC: 94.82% DiaretDB: SEN: 99.2%, SPE: 89.24%, TCC: 93.96% DrimDB: SEN: 100%, SPE: 90.86%, TCC: 95.24%

Briefly, the work using ML and DL has shown promising results in aiding the diagnosis and detection of DR more quickly and accurately. The work conducted with machine learning focuses on extracting relevant features from retinal images and then using supervised learning algorithms to train a classification model. The results obtained with this approach have been encouraging, but determining which features are most important for classification is often challenging. The work carried out with deep learning involves using deep neural networks to learn relevant features from the images automatically. This approach has demonstrated even better results for detecting DR, as it can learn more complex and non-linear features that are often difficult to extract manually.

Based on the proposed works registered in the field of DR and published in PubMed, one of the most significant resources worldwide for accessing scientific articles, medical journals, publication abstracts, and other documents in the fields of life sciences, medicine, health, and biology. Figure 6 below shows the number resulting from searching works published in recent years in the same field.

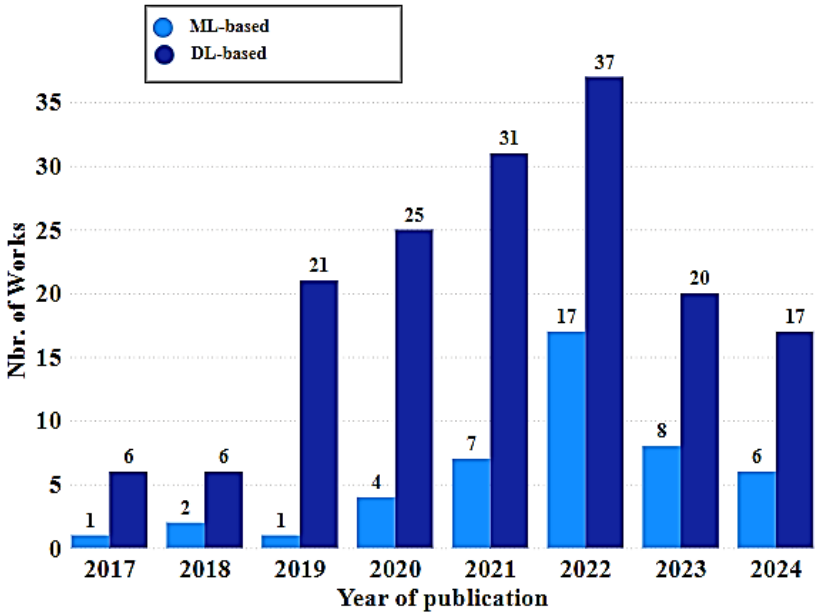

Figure 6. Works published in PubMed: DR using DL and ML

4. RETINA DATASETS

Several retina datasets have been employed to train, validate, and compare algorithms for detecting DR lesions and their classification. These datasets encompass publicly available and smaller datasets utilized in specific studies and private datasets developed by hospitals and clinics.

Among the various databases established in the broader field of ocular diseases, the most extensively used ones, particularly in DR, are listed below. A more detailed summary of these datasets is provided in Table 3. Figure 7 shows a histogram representing the size of different datasets.

a) ImageRet: comprising two datasets, DiaretDB0 [53] created in 2006, and DiaretDB1 [54] created in 2009, annotated with DR lesions aiding classification.
b) FIRE (fundus image registration) [55]: created in 2017 to evaluate image registration algorithms in retinal imaging.
c) Kaggle DR detection [56]: a dataset containing over 10,000 fundus images, sourced from EyePACS (eye picture archiving and communication system). It is used for DR classification.
d) APTOS 2019 (Asia Pacific Tele-Ophthalmology Society) [57]: refers to the purpose of the Kaggle blindness detection competition. It is a dataset for DR classification, including 5,590 retinal images.
e) Messidor [58]: a dataset designed to assist in the early detection and segmentation of retinal lesions, with 1,200 high-quality images.
f) E-Ophtha [59]: proper for DR screening. It is divided into subsets based on lesion presence (exudates and microaneurysms):
   – E-Ophtha-EX: containing 82 fundus images, with 47 images having exudates. This subset of data is useful primarily for assisting researchers in the segmentation of exudates.
   – E-Ophtha-MA: comprising 381 retinal images, with 148 images specifically having microaneurysms and small hemorrhages. This subset is valuable for any research focused on the segmentation of microaneurysms.
g) Indian diabetic retinopathy image dataset (IDRiD) [60]: consists of 516 fundus images used for DR and macular edema classification.
h) Digital retinal images for vessel extraction (DRIVE) [61]: includes 40 retinal fundus images primarily for vessel segmentation studies.
i) Structured analysis of the retina (STARE) [62]: contains 400 images focusing on segmentation of various eye conditions.
j) High-resolution fundus imaging dataset (HRF) [63], [64]: consists of 45 images annotated for lesion distribution.
k) Retinopathy online challenge (ROC) [64]: a dataset of 100 retinal images for microaneurysm detection.

These datasets play a vital role in training and evaluating DR detection and classification algorithms. Detailed summaries of these datasets are provided in Table 3, while Figure 7 depicts a histogram illustrating the size distribution of the datasets.

Table 3. Details of dataset used in DR field

N°	Dataset	Origine		Nbr	Acquisition			Tasks	
		Year	Country	images	Camera	FOV (°)	Resolution	Motivation	Labels
[53]	ImageRet	2006	Finland	130	Digital fundus camera	50	1500x1152	Lesions detection	0-1
[54]	DiaretDB0 DiaretDB1	2009		89					
[55]	FIRE	2017	Greece	134	Nidek AFC 210 fundus caméra	35	2912x2912	Detection of light and dark lesions	-
[56]	EyePACS	2015	USA	+10.000	Centervue DRS, Optovue iCam,	45	2048x1536	Classification of DR	0-4
[65]	Kaggle blindness detection competition (APTOS)	2019	USA	5590	Canon CR1/DGi/CR2, and Topcon NW	45	Réduite to 224x224	Classification of DR	0-4
[58]	Messidor	2014	France	1200	3CCD camera mounted on Topcon TRC NW6 non-Mydriatic rethinograph	45	1440x960, 2240x1488, and 2304x1536	Detection of lesions	0-3
[59]	E-Ophtha-MA	2014	France	381	OPHDIAT	45	1440x960, 2544x1696 and 2048x1360	Detection of MAs	0-1
	E-Ophtha-EXs			82				Detection of exsudats	
[60]	IDRiD	2018	India	516	Kowa VX-10a digital fundus camera	50	4288x2848	Classification of DR/DME	DR: 0-4 DME: 0-1
[61]	DRIVE	2004	Nether-lands	40	Canon CR5 non-Mydriatic 3CCD camera	45	768x584	Segmentation of blood vessels	0-1
[62]	STARE	-	USA	400	Topcon TRV-50 fundus camera	35	605x700	Detection of EXs et HEM.	0-1
[63]	HRF	2013	-	45	Canon CR-1	45	3504x2336	Segmentation of blood vessels	0-1
[64]	ROC	2010	USA	100	Canon CR5-45-NM camera	45	768x576, 1058x1061, 1389x1383	Detection of MAs	0-1
[66]	DRiDB	2013	Croatia	50	Zeiss VISUCAM 200 camera	45	720x576	Detection of lesions	0-1
[67]	HEI-MED	2012	USA	169	Zeiss Visucam PRO fundus camera	45	2196x1958	Detection of EXs	0-1
[68]	REVIEW	2008	UK	16	Canon EOS D30	50-60	3584x2438, 1360x1024, 2160x1440	Segmentation of blood vessels	0-1
[69]	RODREP	-	-	1120	Topcon TRC-NW65 non-Mydriatic	45	2000x1312	Classification of DR	0-4
[70]	DRION-DB	2014	France	110	HP-PhotoSmart-S20 high-resolution scanner	45	600x400	Detection of OD, Segmentation of blood vessels	0-1

The primary goal of incorporating diverse datasets in DR research is to enhance the accuracy, robustness, and generalizability of models and algorithms developed for detecting, diagnosing, and managing the disease. These datasets include various retinal images with variations based on:

- Patient population, ensuring that DR detection models can effectively generalize to new patients.
- The equipment used to capture the images, encompassing factors like resolution, image quality, and field of view, ensures that the models can adapt to different imaging setups.
- The stage of DR, as the datasets encompass a range of disease severities, aids in the detection at different stages.

– Additionally, these retinal images may exhibit diverse DR lesions, such as microaneurysms, exudates, hemorrhages, and neovascularization. This diversity facilitates models' ability to detect various lesion types effectively. Moreover, the images are accompanied by precise annotations, which are crucial for training and evaluating DR detection models and ensuring the models are honed with accuracy.

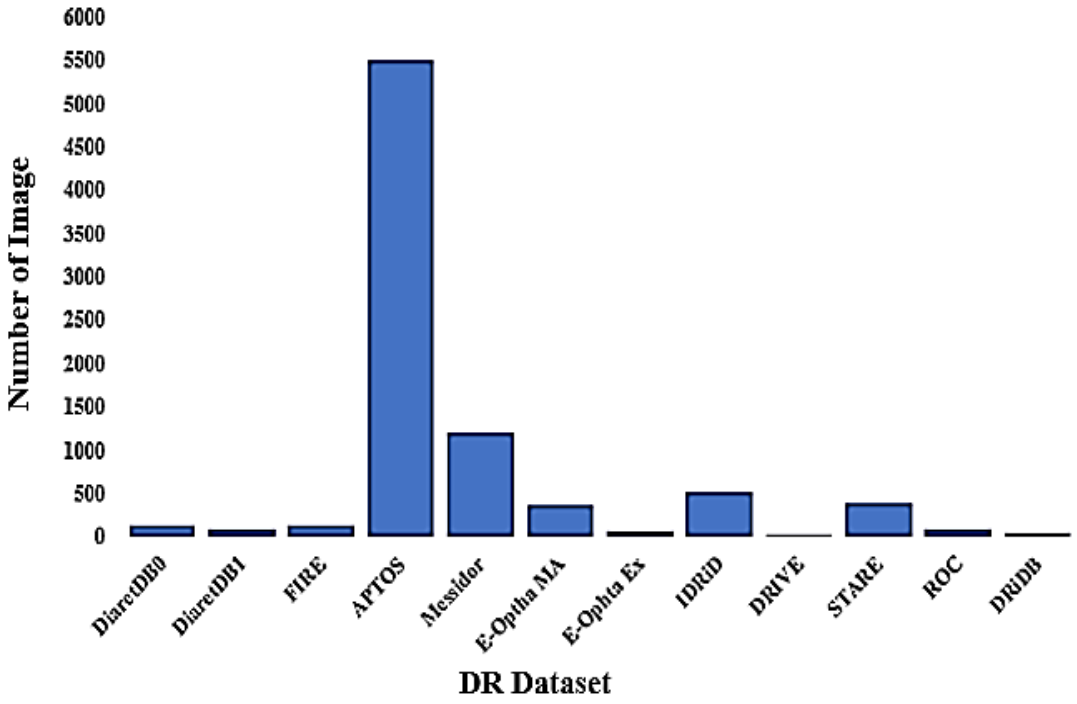

Figure 7. Number of images in each dataset (size of dataset)

5. CONCLUSION

In conclusion, DR is a severe complication of diabetes, and its early and accurate diagnosis is crucial to prevent irreversible eye damage. This article provided a comprehensive overview of DR, including its definition, signs, and classification. Recognizing the potential of ML and DL in medical image analysis, this review explored their integration in DR diagnosis to replace manual assessment.

Numerous works in the field were analyzed, showcasing various proposed ML and DL models and their performance values. These models demonstrated promising results in automating DR detection, highlighting the potential to enhance the efficiency and accessibility of healthcare services. Researchers leveraged large and diverse datasets to train these models, ensuring robustness and generalization. Despite progress, some challenges remain, such as more extensive and standardized datasets, addressing model interpretability, and ensuring seamless integration into clinical practice. Further research is warranted to refine existing approaches and develop novel techniques to advance the field of DR diagnosis.

In summary, integrating ML and DL techniques in DR diagnosis represents a significant step towards revolutionizing the field of ophthalmology, empowering healthcare professionals with efficient tools for early and accurate detection, ultimately improving patient outcomes and reducing the burden of this sight-threatening condition.

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AUTHOR CONTRIBUTIONS STATEMENT

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Chaouki Makhlouf	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		✓	✓
Mohamed Ridda Laouar		✓		✓	✓	✓	✓			✓	✓	✓	✓	✓
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Bourougaa Salima		✓		✓	✓	✓	✓			✓	✓			
Sean Eom		✓			✓	✓	✓			✓	✓	✓		✓

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

This study is a survey and does not generate new experimental data. The datasets reviewed and discussed in this paper are publicly available and referenced in the REFERENCES section. Detailed descriptions, including the sources, characteristics, and purposes of these datasets, are provided in Table [3] of the manuscript. Readers interested in accessing these datasets should refer to the original sources cited in the references.

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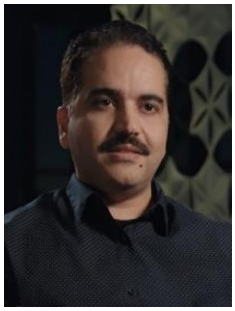

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