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Convolutional neural networks in diabetic eye disease detection: A survey on retinopathy and macular edema

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Abstract: Diabetic Retinopathy (DR) and Diabetic Macular Edema (DME) are notable eye disorders affecting the retina's inner side. This retina helps a person see and distinguish between colors, which is crucial for performing daily activities. It has been observed in long-term diabetic patients, and the count gradually increases. Manually identifying its presence can be time-consuming and may not yield accurate results, as it can lead to various stages that, if delayed, can cause visual Impairment. Emerging technologies and advancements in medical care have enabled automated mechanisms to perform this task. Machine learning (ML) and Deep learning (DL) are two emerging fields of Artificial Intelligence that help identify grading severity through retinal fundus images at early stages and properly treat patients. The paper reviews convolutional neural networks (CNN) with hybrid models of ML and DL algorithms to implement and achieve it, along with the assets, limitations, and gaps of each mechanism, and helps improve further research.
Keywords: *Deep learning, CNN, Diabetic macular edema, Diabetic retinopathy, Eye disease, Machine learning.*

1. Introduction

Diabetes is one of the most common endocrine disorders in human beings, it is characterized by abnormal levels of blood glucose in the body [1]. Elevated glucose levels characterize this chronic condition. This leads to type 1 diabetes and type 2 diabetes or the inability to use the insulin it makes effectively, which, when not treated properly, affects most of the body's organs, like kidney failure, heart attacks, eyes, and life-threatening issues. One significant issue is DR, a painful eye disease that affects diabetic patients with elevated glucose levels. Around 537 million adults between the ages of 20 and 79 worldwide are currently living with diabetes, and this figure is expected to rise substantially in the coming years.

Vision is crucial to one's life, and when it is impaired or lost, known as blindness, it can restrict one's daily activities, pull back one's independent mobility, and at extreme levels, result in mortality [2].

DR, when not properly diagnosed early can lead to severe complications and potentially result in permanent vision loss. Research indicates that approximately 103.12 million individuals currently suffer from this condition, and this number could rise to 160.50 million. Long-term high blood sugar levels cause gradual vascular disturbances in the retina, a condition that has been prevalent among individuals living with diabetes for over ten years [2]. Diabetic retinopathy, a disorder characterized by hyperglycemia, which damages and injures the ocular blood vessels, causing them to leak and rupture, is among the most prevalent complications of diabetes. Lesions on the retina are the visible manifestation of this condition. These lesions lead to haemorrhages (cottage of blood due to rupture in blood vessels), exudates (fluid inflammation), and microaneurysms (white bulges).

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Microaneurysms: These tiny red dots in the retina, frequently encircled by a ring of yellow lipids, are the first visible indicators of DR [1].
Haemorrhages: The initial visible signs of DR are small red spots in the retina, typically encircled by a ring of yellow lipids [1].
Hard exudates: These are thick yellow retinal lesions, caused by plasma leakage.
Soft exudates: Cotton wool spots, lesions observed on the retina [1].

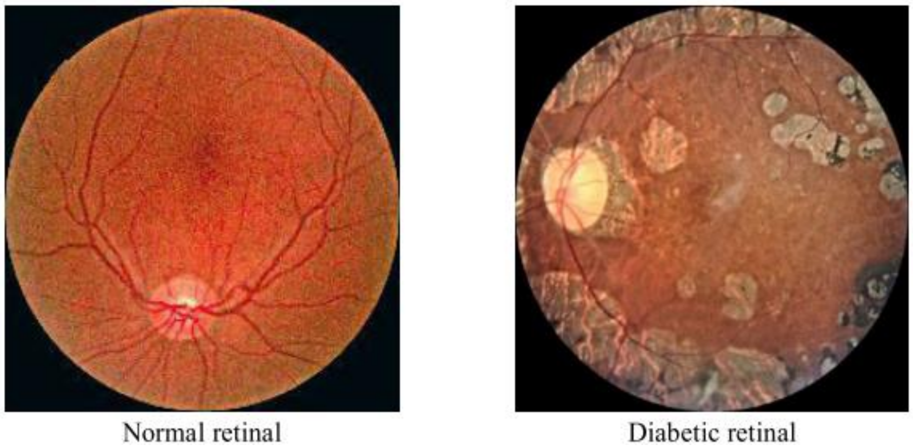


Figure 1.
Difference between a normal retinal and diabetic retinal eye.

Diabetic macular edema (DME) is a serious DR indicator. It begins with blurred sight and can progress to partial or complete irreversible vision loss [3]. DME is a complicated disease that starts with blood vessels leaking, the blood-retinal barrier breaking down, and fat building up in the retinal layer [4]. This process causes retinal swelling and exudate formation in the macula—hyperglycaemia cause glycosylation, contributing to the progression of diabetes mellitus (DM). Over time, this process denatures collagen proteins within the vessel walls, resulting in capillary thickening and eventual breakdown. DME detection can be performed directly or indirectly. Assessment of diabetic macular edema (DME) typically involves direct methods like stereoscopy or tomography, or indirectly by identifying hard exudates (HE) in color retinal images. However, despite advancements, evaluating DME remains largely manual and time-consuming, primarily relying on examining color fundus images [5]. How close the hard exudates (HE) are to the center of the macula [3] determines the extremity of DME. It showcases the severity in three different gradings: no DME (no visible HE's), NCSME, and CSME. We categorize the disease as mild or severe DME. The severity of DME is assessed based on whether the distance between the hard exudates (HEs) and the macula center is shorter or longer than the diameter of the optic disc [3]. The central retina plays a critical role in visual acuity. Therefore, vision blurs when edema affects the macula and may disappear completely [6]. When diagnosing and managing eye lesions, ophthalmologists usually perform a comprehensive eye examination, which involves evaluating visual acuity, conducting slit-lamp examinations, and sometimes employing optical coherence tomography (OCT) or fundus photography. Early detection and proper medication can save a person from critical conditions and permanent vision loss. Fig. 2 depicts the DR stage [7] whereas Table 1 outlines the five stages of DR detection [7]. Fig. 3 illustrates the DME grading process, while Table 2 details the importance of each grading stage [7].

Table 1.
Clinical assessment-based DR classification.

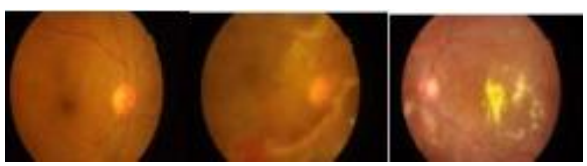
DR stage	Diagnosis	Observable clinical findings
0	No DR	No abnormalities
1	Mild DR	Microaneurysms are present
2	Moderate NPDR	Microaneurysms, Haemorrhages or exudates can have any of two features
3	Severe NPDR	Venous bleeding in two quadrants if found
4	PDR	Neovascularization or/and Vitreous haemorrhage

(a) No DR (b) Mild DR (c) Moderate DR (d) Severe NPDR (d) Proliferative DR

Figure 2.
Stages of diabetic retinopathy.

Table 2.
Diabetic macular edema categorization.

DME grade	Diagnosis	Observable clinical findings
0	Denoting normal	Barely observable arterial narrowing
1	Non-clinically significant macular edema	Irregularities in the arterial narrowing
2	Clinically significant edema	Along with grade 1 wool cotton-like bulges seen



Grade 0 Grade 1 Grade 2

Figure 3.
Grading of diabetic macular edema.

Many individuals affected by DR avoid consulting eye-care professionals until the condition progresses from severe NPDR or PDR stages. Additionally, classic techniques for identifying DR require ophthalmologists for evaluation and diagnosis, which is both laborious and costly. Therefore, it has become essential to introduce efficient DL and ML (ML) methodologies, primarily utilizing retinal images that visually capture the ophthalmic condition of one's retina. The classification task usually involves categorizing the condition into binary classes, referred to as DR detection [8]. In DR, the process involves identifying the affected regions and classifying the types of contamination, ranging from moderate to extreme. Individuals often approach this task as a multiclass classification problem [8].

This literature survey aims to compile, analyze, and present the findings of various studies that have employed CNNs (convolutional neural networks) and hybrid models of ML-Projection models to show how diabetic retinopathy will get worse. The aim is to provide fellow researchers with up-to-date research methodologies to develop ML-based prognostic models for assessing the risk of DR progression and its associated complications. Furthermore, it gathers the latest discoveries from these investigations, recognizes research obstacles, constraints, and areas lacking, and aids in selecting predictors and ML techniques for developing groundbreaking prediction models.

Manually detecting diabetic retinopathy through fundus images can be time-consuming and may not accurately distinguish between the severe and proliferative stages. This can cause delays, prevent early detection of the problem, and fail to provide medication at the appropriate time, potentially resulting in severe and permanent vision loss. Advancements in technology and improvements in image processing have made it possible to automatically detect diabetic retinopathy and edema, along with their severity levels, using a range of ML and DL algorithms, providing valuable support to the medical field in addressing diverse image classification challenges. We have conducted a few studies, which are listed below, that demonstrate technology implementation, achievements, and the potential for further research. Utilizing ML and deep convolutional neural networks to construct risk-prognostic models is unavoidable. This is because they are adept at identifying complex patterns within extensive patient datasets and comprehending the nuanced connections among individuals' risk factors over time, gleaned from past cases.

The paper consists of multiple sections. Sections 2, 3, and 4 are titled "Literature Review," “Datasets Used,” and “Discussions”. Section 5 focuses on the “Future Work” that can be implemented for further enhancements, and Section 6 is entitled “Conclusion”.

2. Literature Review

The diagnosis and classification of DR and DME can be made by finding the lesions on the retina. Preprocessing images is an essential step to minimize noise and enhance their quality. The main goals of this review are to find accurate information about diabetic retinopathy using unlabelled and limited annotated data, to compare and look at the different current approaches for DR identification using DL methodologies while taking into account the unique features of DR, and to look into the possible opportunities and problems that future researchers in DR diagnosis will need to confront and address.

Table 3.
DR- DME grading studies.

Literature	Dataset	Method
DR detection and grading approaches		
Nazih, et al. [8]	FGADR	Vision transformer (ViT)
Ali, et al. [9]	MESSIDOR, IDRiD	ResNet-50 inceptionV3
Shaik and Cherukuri [2]	Kaggle APTOS 2019 and ISBI IDRiD	Hinge attention network
Reddy and Gurrala [10]	IDRiD	HGCN with RASCA
Ardiyanto, et al. [11]	APTOS 2019	ResNet-50
Cao, et al. [12]	DIARETDB1	CNN
Aswathi, et al. [13]	APTOS 2019	ResNet-50
Jabbar, et al. [14]	DIARETDB1	GoogleNet ResNet
DME detection and grading approaches		
Yinghua, et al. [15]	MESSIDOR	ResNet50
Gayathri and Subramanian [3]	Kaggle	DenseNet
Tu, et al. [16]	IDRiD	VGGNet
Suchetha, et al. [17]	MESSIDOR, DMED	-
Gadde and Kiran [18]	IDRiD	CNN
Albelaihi and Ibrahim [19]	MESSIDOR DIARETDB0 DIARETDB1 HEI-MED	VGGNet,ResNet
Chaudhary and Pachori [20]	IDRiD MESSIDOR	2DFBSE-FAWT

Among all the approaches the most commonly used is Convolutional Neural Networks. CNN stands as a cornerstone in DL, is renowned for its effectiveness, and is often employed alongside other prominent architectures like ResNet, Inception, and GoogLeNet. These models are widely favored for their prowess in image classification tasks.

A Convolutional Neural Network (CNN) is a specialized deep neural network designed for processing grid-structured data, particularly images. It comprises multiple layers, including convolutional layers, pooling layers, and fully connected layers. CNNs have revolutionized tasks like image categorization, object detection, and image segmentation by independently learning hierarchical features from raw data. Some notable types of CNN models include ResNet, GoogleNet, LeNet, AlexNet, and VGG.

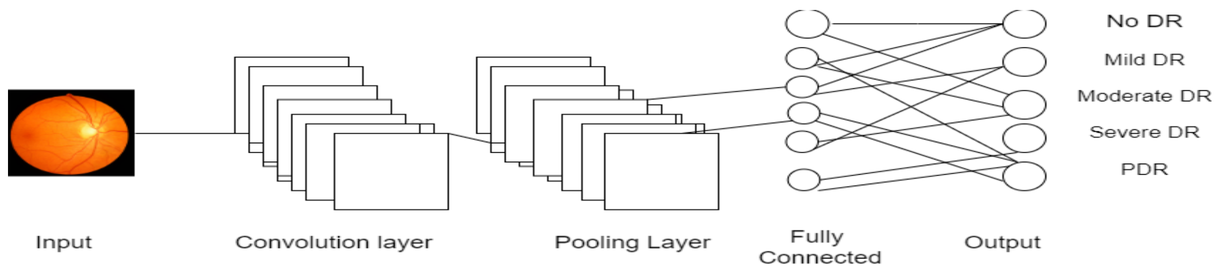


Figure 4.
CNN Architecture.

ResNet (Residual Learning) is characterized by the incorporation of skip connections, enabling the bypassing of one or more layers. The skip connections function to mitigate the vanishing gradient issue and aid in the training of neural networks that are exceptionally deep. ResNet architectures typically comprise a sequence of residual blocks, each incorporating convolutional layers and capturing mappings.

GoogleNet, also known as InceptionNet, is designed for image recognition and processing, notable for its fidelity and computational resources. Its key component, the Inception module, enhances the network learns features at multiple scales concurrently, enhancing image classification performance. GoogleNet employs global average pooling and factorized convolutions to optimize both performance and resource usage.

LeNet, pioneering CNN architecture designed for handwritten digit recognition. Trained on the MNIST dataset, LeNet achieved high recognition accuracy and laid the groundwork for many subsequent CNN architectures.

AlexNet, self-possessed of five convolutional layers, three pooling layers, and fully connected layers, demonstrated superior performance compared to conventional ML techniques. Its success laid the foundation for the develop ent of deeper architectures.

2.1. DR-Based Detection Methodologies

Shaik and Cherukuri [2] used one of the emerging technologies DL with various attention stages called the Hinge Attention Network (HAN) model, integrating spatial attention autoencoder, channel attention-based hinge neural network, and Convolutional LSTM layer to grade diabetic retinopathy severity. The implementation through the Hinge Attention Network model HA-Net integrates both spatial and channel attention mechanisms, effectively boosting feature extraction capabilities and improving classification accuracy. It has demonstrated impressive performance, achieving accuracy rates of 85.54% on Kaggle APTOS and 66.41% on IDRiD datasets, surpassing several existing models [21]. HA-Net employs transfer learning methods with deep convolutional neural network architectures, enhancing its feature extraction prowess and boosting overall model performance. Atteia, et al. [22] have implemented a model that retrieves features from two DL models, Resnet50 and Inceptionv3. The model follows feature extraction by using Resnet50 – ResNet50 incorporates a range of convolutional filter sizes to expedite training and counteract the degradation challenge stemming from deeper network architectures. The Inception-v3 architecture is specifically tailored to visual classification to train fundus images. Incorporating [22] ResNet50 and Inceptionv3 models amplifies accuracy and performance when detecting diabetic retinopathy [23]. DL models benefit significantly from data augmentation techniques, leading to notable enhancements in performance [24]. Detecting diabetic retinopathy early through these methods can mitigate visual loss and facilitate prompt treatment, underscoring their clinical significance Decenciere, et al. [25] and Saeedi, et al. [26]. Reddy and Gurrala [10] and Zhang, et al. [27] introduced a customized deer hunting optimization algorithm (MDHOA) to select pertinent features effectively. By combining a hybrid graph convolutional network (HGCN) with relation-aware channel-spatial attention (RACSA), the proposed OHGCNet model enhances feature extraction performance. By amalgamating attention mechanisms, dilated convolution, and optimal feature selection, the OHGC-Net model achieves superior classification performance. Nazih, et al. [8] and Patil, et al. [28] employed the Vision Transformer (ViT) model to predict the severity of DR. This model employed a transformer encoder architecture, which integrated Multi-head Self-Attention (MSA) and MLP modules, to handle image patches. The proposed ViT model adeptly captures crucial features from retinal images. Enhancing comprehension of DR severity, thereby providing valuable assistance to physicians for making precise, personalized, and prompt decisions in real medical situations Farag, et al. [29]. Cao, et al. [12] implemented a system that utilizes a compact DL algorithm called Deep-DR-Net, designed to fit on an embedded development board. Deep-DR-Net enhances diabetic retinopathy diagnosis accuracy through DL algorithms, ensuring precise assessment. Incorporating diverse convolutional layers and compact model size, it enriches feature differentiation while remaining suitable for resource-constrained devices. Aswathi, et al. [13] utilized ML methods such as RF, neural networks, and SVM for microaneurysm (MA) detection. PCA was employed as a technique for reducing input dimensionality in the classification process. Through dimensionality reduction techniques like PCA and RF feature importance, it effectively mitigates the curse of dimensionality, leading to more efficient classifier training and heightened performance. Additionally, its demonstrated generalizability across diverse datasets underscores its adaptability and robustness, while the comparative analysis against traditional and DL methods offers comprehensive insights, particularly valuable in scenarios with limited dataset sizes.

Jabbar, et al. [14] utilize the ResNet-50 DL model for grading DR. A transfer learning approach is applied for the optimization of the ResNet-50 model for improved classification accuracy. Pre-trained on ImageNet, ResNet-50's architecture, including residual blocks and skip connections, optimizes computational efficiency while maintaining high performance, showcasing its effectiveness in medical image classification and outperforming existing methods.

Yinghua, et al. [15] focus on utilizing a hybrid DL model for DR detection. The technology used in the study includes GoogleNet and ResNet models for feature extraction, Adaptive Particle Swarm Optimizer (APSO) was employed for optimization, alongside ML models for classification tasks. It achieves a notable 94% accuracy on benchmark datasets, surpassing advanced methods, while also enhancing various performance parameters across different DR severity levels. Future endeavors include further development of ML algorithms for diagnosis, refining data augmentation and preprocessing strategies for improved system efficacy, and addressing biases in datasets to bolster model robustness and generalizability.

The proposed architecture [7] features a hierarchical multi-task neural network with a squeeze-and-excitation (SE) network as the backbone for extracting image features at multiple scales. It includes two independent forward neural network heads: one dedicated to detecting DR-related features and another focused on diagnosing DR severity. A squeeze-and-excitation (SE) network backbone extracts multi-scale image features, while skip connections transfer these features within the network to improve DR severity diagnosis. The balanced binomial logistic loss function effectively manages data imbalance, ensuring robust detection of specific DR-related features. The process might need considerable computational resources for training and inference, and its effectiveness depends on the volume and quality of the data available. The architecture's effectiveness can vary based on the diversity and distribution of DR-related features in different datasets.

2.2. DME Detection and Grading Methodologies

Yinghua, et al. [15] propose the integration of ResNet50 with channel attention (SENet) in the proposed end-to-end architecture significantly enhances feature extraction, thereby improving grading accuracy and efficiency. However, the complexity of diabetic macular edema (DME) presents challenges for grading accuracy, underscoring the necessity for automated systems to support healthcare professionals. The end-to-end architecture combining ResNet50 and SENet enhances feature extraction, thereby improving grading accuracy and efficiency, which resulted in acquiring an accuracy of 97.06% and specificity of 98.97%. Data augmentation techniques boost network performance and address class imbalance, with ablation experiments validating the robustness and reliability of each module. The complexity of diabetic macular edema (DME) and the dependency on high-quality training data affect grading system accuracy, underscoring the need for continuous data improvement and advanced network training. Additionally, manual grading's time-consuming nature and the scarcity of medical image datasets highlight the necessity for further automation and research to enhance DME grading performance, including the development of new loss functions to address class imbalance and data limitations.

Gayathri and Subramanian [3] introduces the Soft Attention-based Densenet (SA-Densenet), a CNN variant designed to accurately predict Diabetic Macular Edema (DME) severity from fundoscopic images. Using the Kaggle fundus dataset, SA-Densenet achieved high accuracy, precision, and recall. Key challenges noted include the slow adoption of new technologies in healthcare, concerns about medical data privacy, and the importance of managing false positives and negatives. Future research aims to reduce model parameters, optimize time consumption, and further enhance the predictive capabilities of SA-Densenet for DME severity grading.

Tu, et al. [16] introduce the Feature Separation and Union Network (SUNet) for simultaneous grading. Within SUNet, a feature integration block is utilized, performing iterative feature separation and union steps to extract domain-specific features, thereby improving performance by removing irrelevant features and focusing on relevant ones and providing an exactness of 65.06 and 81.55% in the detection of DR, DME. A lesion regularizer improves interpretability by emphasizing lesions for disease grading. Potential challenges may include network complexity, computational demands, and the need for extensive training data. SUNet's approach could be applied to other multi-task learning scenarios, with future research focusing on optimizing its architecture for scalability and efficiency, exploring real-time clinical applications, and integrating additional diagnostic tasks to enhance its utility in medical imaging analysis.

Suchetha, et al. [17] employ digital fundus images and image processing techniques to detect macula swelling, involving steps like dataset collection, pre-processing, feature selection, and categorization. It can focus on enhancing the algorithm to handle diverse image qualities and artifacts, integrating DL techniques for more accurate feature extraction and classification, and extending dynamic detection and monitoring of macula swelling for proactive healthcare management.

Gadde and Kiran [18] utilized CNNs, to accurately label the risk of DME and assess the grading of DR. CNNs are proficient in image classification tasks as they autonomously learn features through their convolutional layers. The model employed the 'Adam' optimizer, renowned for its impact in minimizing loss through adaptive gradient and root-mean-square propagation algorithms. Adam optimizes learning rates for each parameter individually, resulting in faster convergence during training. Rectified Linear Unit (ReLU) and Linear activation functions were utilized in the model. ReLU introduces non-linearity and aids in faster convergence during gradient descent by facilitating backpropagation. It is demonstrated by the DMERCNET model achieving 87.38% accuracy in classifying Diabetic Macular Edema (DME) risk. DL models indeed demand extensive labeled data, presenting challenges stemming from data privacy and availability concerns. Additionally, they necessitate substantial computational resources, which may not always be accessible in various healthcare settings.

Albelaihi and Ibrahim [19] DL frameworks like EfficientNetB0, VGG16, ResNet152V2, GRUResNet152V2, and Bi-GRUResNet152V2 are utilized for identifying diabetic eye diseases, leveraging various image augmentation methods for training. The algorithm excels in diagnosing medical imaging, effectively identifying and classifying diabetic eye infections, glaucoma, and cataracts, with the EfficientNetB0 model achieving an impressive 98.76% accuracy. While various pre-trained models and geometric augmentation methods enhance performance, limitations include the need for image format conversion and the scarcity of datasets, which necessitate additional preprocessing and augmentation steps to improve model evaluation.

Chaudhary and Pachori [20] explores the use of 2-D-FBSE-FAWT, which leverages FBSE for the efficient implementation of FAWT. This technology employs filter banks for image analysis, aiding in the digital diagnosis of various grades of DR and DME, utilizing key mathematical parameters like QF, RDY, and DF. It provides a comprehensive feature set for analysis, supported by normalization, resampling, and PCA for enhanced preprocessing and dimensionality reduction. The method achieves high performance with ACYavg values of 0.955 for DR 0.965 for DME in the IDRiD database, and 0.975 for DR and 0.985 for DME in the Messidor database. It relies on a constant QF decomposition approach, which may not be suitable for adaptive signal analysis, limiting its applicability in certain scenarios.

A brief review of the above-mentioned papers includes the various datasets used the method implemented and various performance analysis features. It highlights the limitations of each mechanism implemented which gives a neat view to understand the effectiveness of the various algorithms used.

3. DR DME Datasets

The most prominent datasets, the technologies used, and the implementation procedures of the prior research on the detection of DR. Early diagnosis methods for DR typically utilize databases comprising images obtained through pupil dilation using a fundus camera that produces digital fundus imaging. The prevalent early-stage detection methods for diabetic retinopathy (DR) typically utilize databases comprising images captured after pupil dilation. For this study, we exclusively examined publicly accessible databases that facilitate early diabetic retinopathy (DR) diagnosis. These databases were selected based on their inclusion of MA masks and support for DR grading, ensuring a comprehensive evaluation of diagnostic capabilities for early-stage DR detection. More than 1000 MA segmentation masks are available, providing valuable resources for the researchers to enhance the development of a highly reliable computer-aided system for early DR diagnosis.

The Kaggle EyePACS [25, 30] dataset stands as the largest and most widely accessed public dataset for DR classification, consisting of over 80,000 fundus images. These images were obtained from the EyePACS platform for the DR Detection competition, which is sponsored by the California Healthcare Foundation [31]. They encompass high-resolution retinal images from both eyes, captured across diverse imaging conditions and beyond. Trained professionals graded the images based on the ICDRDSS scale [32].

The Messidor [21] dataset, consisting of 1,200 retina fundus images, was gathered by three ophthalmic departments in France from 2005 to 2006. Among these images, 800 were acquired after pupil dilation, while the remaining 400 were captured without dilation. The Messidor 2 [21] dataset expands upon the original Messidor dataset, incorporating data types from it along with an extra 690 images.

DRIVE [33] data set includes a total of 40 images with DR detection of 20 where 10 are taken for the testing sets and 10 for the training sets with the image resolution of 768 x 584

The IDRiD [5] dataset comprises 516 high-quality images collected at an ophthalmology clinic in Nanded, India, using a Kowa VX - 10α fundus camera. Before image capture, both eyes of all participants were dilated. This dataset includes image-level grading of Diabetic Retinopathy severity based on the ICDRS scale and assesses the risk of Diabetic Macular Edema (DME) for all 516 images.

HRF [34] dataset consists of images related to blood vessel segmentation and exudates which consists of 45 images in total and 15 identified as images with DR, with an image resolution of 2334 x 3506.

Table 4 outlines the comprehensive datasets utilized in previous research endeavours, accompanied by detailed descriptions [32].

Table 4.
Specifications of frequently utilized datasets.

S.no	Dataset	Total images	Images with DR	Data utilizing	Training sets	Training sets	Image size
1	Kaggle	88702	23359	All features	35126	53576	Different resolutions
2	MESSIDOR	1200	660	EXs and HEMs	-	-	Different resolutions 2304 × 1536,2240 × 1488
3	MESSIDOR 2	1748	-	EXs and HEMs	-	-	Different resolutions
4	DRIVE	40	7	Blood vessels and EXs	20	20	768 × 584
5	STARE	20	10	Blood vessels	-	-	700×605
6	HRF	45	15	Blood vessels and EXs	8	7	2334×3506
7	DDR	13673	6256	All features	6835	4105	Different resolutions
8	DR	435	-	All features	-	-	857×569
9	IDRid	516	348	Mas, EXs and HEMs	413	103	4288848

4. Discussions

The comparisons among all the different types of datasets used and the methods implemented are analyzed and evaluated through the performance metrics achieved are considered and the best results and the best methodologists are considered for further approaches in enhancing the upgrading mechanism for the early detection and severity levels. Table 5 and Table 6 give a comparison overview of the performances of the above-discussed methods. Kaggle, MESSIDOR, and IDRiD are the large datasets that have provided the researchers with effective data for the performance.

Table 5.
Comparison of the different methods for DR Detection.

Literature	Dataset	Method	Performance
Nazih, et al. [8]	FGADR	Vision Transformer (ViT)	F1 score=82.5% Accuracy = 82.5% Precision=96.4% Recall=82.5% Sensitivity=95.6%
Ali, et al. [9]	MESSIDOR, IDRiD	ResNet-50 InceptionV3	F1 score=98.65% Accuracy = 96.85% Sensitivity=99.28% Specificity=98.92% Precision=96.46%
Shaik and Cherukuri [2]	Kaggle APTOS 2019 and ISBI IDRiD	Hinge attention network	Accuracy = 85.54%
Reddy and Gurrala [10]	IDRiD	HGCN with RASCA	Accuracy = 99.03% Precision=99.56% F1 score=99.49% Recall=99.43
Ardiyanto, et al. [11]	APTOS 2019	ResNet-50	Accuracy = 93.2%
Cao, et al. [12]	DIARETDB1	CNN	AUC=98.5% F1 Score=92.6%
Aswathi, et al. [13]	APTOS 2019	ResNet-50	Accuracy =90% Kappa Score= 94%
Jabbar, et al. [14]	DIARETDB1	GoogleNet ResNet	Accuracy= 94% Precision=97% F1 score=96% Recall=89%

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Table 6.
Comarison among the different methods for DME Detection.

Literature	Dataset	Method	Performance
Yinghua, et al. [15]	MESSIDOR	ResNet50	Accuracy= 97.06% Specificity=98.97% F1 score=91.77% Sensitivity=88.64%
Gayathri and Subramanian [3]	Kaggle	DenseNet	Accuracy= 98.37% Precision = 97% Recall = 96%
Tu, et al. [16]	IDRiD	VGGNet	Accuracy = 65.06% Accuracy = 81.55%
Suchetha, et al. [17]	MESSIDOR, DMED	-	Accuracy = 96.07% Sensitivity = 93.74 Specificity = 97.32%
Gadde and Kiran [18]	IDRiD	CNN	Accuracy = 87.38%
Albelaihi and Ibrahim [19]	MESSIDOR DIARETDB0 DIARETDB1 HEI-MED	VGGNet ResNet	Accuracy = 98.7% Recall = 98.7% Precision = 99.7%
Chaudhary and Pachori [20]	IDRiD MESSIDOR	2DFBSE-FAWT	Accuracy = 96.5%

5. Future Directions

Our study has identified several potential avenues for future research. The major implementations for diagnosing of DR and DME is done through CNN. The research in the papers [2, 8, 13] has used Hinge Attention Networks, Vision Transformers, and ResNet-50 algorithms for better results and also have some limitation issues like restriction towards the limited data availability which imparted the overall data, and optimization problems which can, even more, provide better results which with RNN, Capsule Networks, and Transformers which can handle large dependencies and parallel processing, which improve interpretability in spatial hierarchies. The research in papers like [16, 18] provides effective results in detecting DME but with that of Kaggle datasets. Hybrid models along CNN can be implemented by RNN and Attention Mechanism and tested for effective results using other datasets like Messidor and IDRiD datasets. Where we can now work on the Collaborative detection of DR and DME grading with advanced algorithms and achieve effective results, which helps the patients to know about their condition clearly and opt for the required treatment.

6. Conclusion

This work reviewed recent CNN-frameworks for detecting and grading DR and DME using fundus images. We categorized the studies into two groups: those focused on DR detection and DME intensity grading. Most studies classified retinal images according to their complication levels. Various studies have effectively used nearly all recent deep-learning networks for detecting and grading DR and DME. We also assembled a list of frequently utilized Ophthalmic image datasets for DR diagnosing and classification. Furthermore, we compared similar studies based on their performance metrics. Our goal is to inspire researchers to develop innovative strategies for optimizing and hybridizing DL algorithms, and to advance future research on the joint identification and detection of severe grading in DR and DME.

Transparency:

The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

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