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Comparative Analysis Techniques for Early Detection and Staging of Diabetic Retinopathy

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Abstract: The escalating global prevalence of diabetes underscores the urgent need for effective early detection and grading methods to mitigate complications such as Diabetic Retinopathy (DR), which can lead to significant vision impairment. This paper provides a comprehensive review of Deep Learning (DL) based techniques for diagnosing and grading DR from retinal fundus images, emphasizing the importance of accurate and timely diagnosis and classification. This research evaluates various DL models, with a particular focus on convolutional neural networks (CNNs), for detecting and grading DR. The study examines common datasets to assess the performance of these models. By analyzing the efficacy of different DL architectures across diverse datasets, the study aims to highlight their strengths and weaknesses in handling the complexities of both DR detection and severity grading. The findings highlight significant advancements in AI-driven DR detection and grading. The review shows that while some DL models excel in specific aspects, no single model consistently outperforms others across all metrics. There is a promising trend towards improving diagnostic accuracy and grading consistency, demonstrating the potential of these technologies for early diagnosis and DR severity classification. This study emphasizes the need for ongoing development of DL-based methods for DR detection and grading. It highlights AI's potential to improve early and accurate diagnosis, crucial for effective treatment and better patient outcomes. The insights from this review support efforts to create more reliable AI diagnostic tools for DR, addressing a critical need in the global diabetes epidemic.

Keywords: *DR Detection, Deep Learning Models, Convolutional neural networks (CNNs), DR Grading, Retinal fundus images*

1. Introduction

Diabetes mellitus is a metabolic disorder where the body fails to produce insulin and cannot properly retain or utilize glucose for energy [1]. Over the past twenty years, the number of individuals affected by diabetes has risen dramatically, as reported by the IDF Diabetes Atlas [2], Globally, it has been diagnosed in almost 500 million persons of all ages, and by 2045, that number is predicted to rise to 700 million. According to a World Health Organization (WHO) estimate, there were 422 million diabetes patients worldwide in 2014, up from 108 million in 2013. According to estimates, this population might rise to 629 million by 2045. An estimated 1.6 million fatalities were attributed to diabetes in 2016. Diagnosing diabetes at an early age significantly reduces the risk of various conditions, including heart attacks, stroke, kidney failure, blindness, and lower limb amputation. Various medical conditions are treated using different classification strategies. Diabetes comes in various forms, including Type 1, Type 2, and gestational diabetes. When Type 1 occurs, the pancreas is unable to generate enough insulin for the body. Type 2 diabetes, the most prevalent kind, is caused by an improper utilization of insulin by the body. High blood glucose levels in pregnant women are a sign of gestational diabetes. [3].

Additionally, one in three diabetic individuals will experience diabetic retinopathy (DR) by 2040, according to the IDF Diabetes Atlas. Damage to the blood vessels behind the retina is a sign of diabetic retinopathy (DR). It is crucial to address this because, if left untreated for an extended period of time, it could cause major consequences including blindness. Currently, medical professionals manually evaluate fundus photos of the eye to determine the extent of DR. This takes a lot of time, and there aren't enough medical experts to handle the quantity of people that need care[4]. Therefore, developing an automated system to aid in the detection of diabetic retinopathy is highly desirable. Medical diagnostic systems have made extensive use of machine learning techniques. They have demonstrated the ability to diagnose conditions accurately, treat patients effectively, and save money. Within Artificial Intelligence (AI), deep learning is a subset of machine learning that has the ability to learn from data on its own. It can learn without supervision as well. Even a human brain can take years to process the vast amounts of unstructured and unlabeled material that it can learn. Multiple layers are used in deep learning to extract features from unprocessed input. Convolutional Neural Networks (CNNs) are one type of artificial neural network upon which deep learning models are built. Researchers employ a variety of methods, including the Backpropagation Neural Network (BPNN), to diagnose

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diabetes[5].

Fundus pictures, which give visual recordings that capture the current ophthalmic appearance of an individual's retina, are used in the majority of investigations in this discipline. These fundus images can be used to categorize DR based on the existence of DR symptoms using many processes, including retinal blood vessel segmentation, DR detection and lesion segmentation. [6]. The detection and staging of DR can be determined by identifying the presence or absence of various lesions. These lesions include microaneurysms (MAs), superficial retinal hemorrhages (SRHs), exudates (both soft exudates (SEs) and hard exudates (HEs)), intraretinal hemorrhages (IHEs), and cotton wool spots (CWSs). The Small World FANN model demonstrates notable performance in diagnosing diabetes.

AI approaches such as machine learning and deep learning have made it possible to detect and segment the affected areas of the retina with high performance through retinal grading and detection. Machine learning techniques are frequently applied to the grading and classification of DR data. Nazir et al. [7] employed a novel method known as the "tetragonal local octa pattern (T-LOP) features" to represent fundus images. Later, an extreme learning machine was used to carry out this classification [8]. This work suggests a neural-network-based resampling technique that significantly enhances diabetes detection.This study suggested a resampling technique based on neural networks to enhance SVM classifiers' capacity to identify diabetic patients.

Researchers have recently used a variety of deep learning techniques to accomplish these goals. This work offers a survey of the current research in this field, emphasizing the application of DL for fundus image-based DR detection and grading. In deep learning (DL), artificial neural networks with multiple processing layers are employed to gradually extract high-level features from the data.

The organization of the paper is as follows: Section 1 presents the introduction, followed by Section 2 covering the literature review. Section 3 outlines the discussion, while Section 4 encompasses the conclusion. Finally, Section 5 includes the references.

2. Literature Review

Diabetic retinopathy diagnosis involves two key processes: detection and grading. Detection distinguishes between diabetic retinopathy and normal retinas, employing binary classification. Grading, on the other hand, identifies and labels affected areas, categorizing the severity of infection as mild, moderate, or severe shown in Fig., 1. Timely detection of diabetes is crucial for preserving human health and mitigating the potentially fatal consequences of the condition. Over recent years, diverse methods employing various models and methodologies have emerged for diagnosing diabetes. These encompass neural network-based methods, deep learning strategies, machine learning techniques, decision-making approaches, the k-NN method, diagnostic methodologies based on retinal images, and diagnosis techniques utilizing facial images.

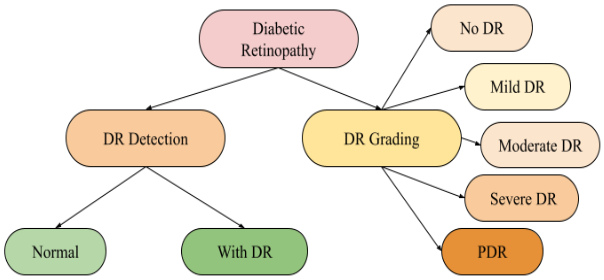


Fig 1. Diabetic Retinopathy Study methods

2.1 DR Detection

Studies on diabetic retinopathy detection commonly utilize binary classification to differentiate input images as either healthy or showing signs of diabetic retinopathy (DR). In this context, our focus centers on deep learning methodologies, which have demonstrated superior effectiveness when contrasted with alternative machine learning or conventional techniques. The authors [9] study focuses on diabetic retinopathy (DR), a diabetes complication affecting the eye's back due to high blood sugar levels, potentially leading to blindness if untreated. To aid early detection and treatment, researchers devised a Convolutional Neural Network (CNN) model to classify DR stages based on retinal images. Achieving a remarkable 96% accuracy, the model effectively distinguishes between DR presence and absence, facilitating easier screening and timely intervention. The authors in [10] study addresses diabetic retinopathy (DR), a condition stemming from prolonged high blood sugar levels in diabetic patients, which can lead to vision loss if not detected early. The research proposes an automated system utilizing high-resolution fundus images to classify patients as having DR or not. Through image preprocessing and a Convolutional Neural Network (CNN) model, the system achieves remarkable results: 100% predictive accuracy and sensitivity. This automated approach has clinical significance, offering efficient classification of retinal images, relieving doctors of review burdens and providing immediate predictions without external assistance.

Authors have opted for pre-trained models, referred to as backbones, in lieu of basic convolutional neural networks, employing them for transfer learning or feature extraction in their methodologies. For instance, researchers in [11] utilized InceptionV3 to categorize diabetic retinopathy (DR) based on RGB and texture features. Diabetic retinopathy (DR) poses a significant threat to vision if not detected early. Addressing this, the authors [12] propose a solution using Binary Convolutional Neural Networks (BCNN), known for their memory efficiency. By augmenting the dataset, they enhance model performance. Their approach surpasses existing methods, particularly in memory-restricted environments, offering promise for efficient DR detection and management. Diabetes, a widespread chronic ailment, demands early detection and management to avert complications, especially for Type 2 Diabetes Mellitus (T2DM). The authors [13] proposes a semi-automated framework utilizing machine learning to identify T2DM cases from Electronic Health Records (EHRs). The authors introduce a data-driven framework leveraging feature engineering and machine learning to refine filtering criteria, striving to enhance recall while maintaining low false-positive rates. Various machine learning models such as k-Nearest-Neighbors, Naïve Bayes, Decision Tree, Random Forest, Support Vector Machine, and Logistic Regression are assessed for their effectiveness.

This authors [14] introduces MobileNetV2, a convolutional neural network architecture tailored for resource-constrained environments like mobile devices, for diabetic retinopathy detection. Key points include its design for accuracy and computational efficiency, its utilization in a mobile application for capturing retinal images, and its high accuracy in analyzing these images for signs of diabetic retinopathy. The proposed technique [15] began with image enhancement to improve clarity, followed by edge detection to extract blood vessels from retinal images. Canny edge detection and the Kirsch template were employed for this purpose. Graph-based techniques were subsequently employed for the classification of retinal vessels, where graphs are utilized to represent connections and nodes. Object detection was performed on images using unique features, and the MSER algorithm identified damaged areas. Classification was based on comparing row and column-wise values, with maximum values indicating diabetes. The methodology achieved an accuracy of 88%. The authors [16] introduces a deep learning approach using convolutional neural networks (CNNs) to classify various stages of diabetic retinopathy (DR) from fundus photography. The dataset, sourced from Xiangya No. 2 Hospital Ophthalmology in Changsha, China, is extensive but unbalanced. To address this, preprocessing, regularization, and augmentation techniques are employed to enhance dataset quality and balance. Different ResNet structures, including ResNet-101, ResNet-50, and VggNet-16, are utilized, with ResNet-101 achieving the highest accuracy of 98.88% during testing. The authors [17] propose an automated system for diabetic retinopathy (DR) detection using transfer learning, aiming to prevent vision loss by early detection. They fine-tune five pre-trained deep learning models for DR classification: Xception, InceptionResNetV2, MobileNetV2, DenseNet121, and NASNetMobile. The validation accuracy achieved by each model varies, with InceptionResNetV2 demonstrating the highest accuracy at 96.25%.In another study [18], researchers assessed the performance of three deep learning architectures—Transformer-based networks, CNNs, and multi-layered perceptrons (MLPs)—for diabetic retinopathy (DR) classification. They evaluated models including EfficientNet, ResNet, Swin-Transformer, Vision-Transformer (ViT), and MLP-Mixer, finding that transformer-based models achieved the highest accuracy.For the task, the authors of [19] utilized AlexNet, ResNet-50, and VGG-16. They empirically assessed the performance of 28 deep hybrid architectures in binary classifying diabetic retinopathy into referable DR and non-referable DR, contrasting these results with those obtained from end-to-end deep learning (DL) architectures.

Among the evaluated architectures, the hybrid model integrating the SVM classifier with MobileNetV2 for feature extraction demonstrated superior performance.In another study [20], the authors performed a three-class classification of fundus images, categorizing them into normal, glaucomatous, and diabetic retinopathy eyes. They utilized various CNN models for this task, including MobileNetV2, DenseNet-121, InceptionV3, InceptionResNetV2, ResNet-50, and VGG-16. In their study, the authors [21] introduced a basic convolutional neural network (CNN) for the automated classification of diabetic retinopathy (DR). They experimented with both original images and the images processed with an anisotropic diffusion filter. The findings revealed that employing the anisotropic diffusion filter enhanced the model's performance.

The authors, [22] introduces a deep learning framework for predicting diabetic retinopathy progression from fundus photos, crucial for early detection and prevention of vision loss. Using recurrent neural networks, it identifies relevant features from eye blood vessels. While showing advanced diabetic state identification, it stresses the need for validation and replication studies in healthcare image processing. The authors in [23] two methods for detecting diabetic retinopathy (DR) are proposed. The first approach involves feature extraction using image processing techniques and textural features, followed by classification using a Decision Tree model, achieving an accuracy of 94.4. The second approach utilizes transfer learning with pre-trained deep learning models, resulting in an accuracy of 88.8%. The study also developed an end-to-end web application for DR prediction based on these methods, which can be integrated into screening centers.This study by [24] proposes two deep learning architectures for DR detection and classification: a hybrid network combining VGG16 and XGBoost Classifier, and the DenseNet 121 network. The models were evaluated using the APTOS 2019 Blindness Detection Kaggle Dataset. The DenseNet

121 model achieved superior performance with an accuracy of 97.30%, highlighting its potential for effective DR diagnosis. The Models description of DR detection is provided in table 1.

Table 1. DR Detection Models

Reference	Model Name	Model Description
Zheng Tao et al. (2017)[13]	EHR-based DR Detection	Machine learning on electronic health records to identify diabetes.
Mangrulkar, R.S. (2017) [15]	Retinal Image Classifier	Image processing and machine learning for diabetes detection.
Chakrabarty, N. (2018)[10]	Chakrabarty DR Detection	CNN-based method for detecting diabetic retinopathy.
Kazakh-British, N.P. et al. (2018)[21]	Blood Vessel Classification CNN	CNN for blood vessel detection and retinal image classification.
Umapathy, A. et al. (2019)[23]	Transfer Learning DR Detection	Transfer learning with image processing for DR detection.
Kolla, M. & Venugopal, T. (2021)[12]	Binary CNN	Efficient CNN for diabetic retinopathy classification.
Rêgo, S. et al. (2021)[11]	Automated Diagnostic System	Deep learning for automated DR screening.
Sanjana, S. et al. (2021)[17]	Transfer Learning DR Detection	Pre-trained models fine-tuned for DR detection.
Kumar, N.S. & Karthikeyan, B.R. (2021)[18]	CNN-Transformer-MLP	Combination of CNN, Transformer, and MLP for DR detection.
Nasir, N. et al. (2022)[9]	Deep DR	CNN-based model for DR detection with preprocessing.
Pamadi, A.M. et al. (2022)[14]	MobileNetV2 DR Detection	MobileNetV2 for efficient DR detection on mobile devices.
Saranya, P. et al. (2022)[16]	DenseNet DR Detection	DenseNet for detecting DR in retinal images.
Lahmar, C. & Idri, A. (2022)[19]	Deep Hybrid Architecture	Hybrid deep learning architecture for DR classification.
Dwivedi, S.A. et al. (2022)[20]	Real-Time DR Detection	Real-time deep learning system for classifying eye conditions.
Gunasekaran, K. et al. (2022)[22]	Early Prediction DR Framework	Framework for early prediction of DR from fundus images.
Mohanty et al. (2023)[24]	Hybrid Network	Combines VGG16 with XGBoost for robust DR detection on imbalanced datasets.

2.2 DR Grading

Diabetic retinopathy (DR) is categorized into various stages based on the International Clinical Diabetic Retinopathy (ICDR) scale: no apparent retinopathy, mild non-proliferative diabetic retinopathy (NPDR), moderate NPDR, severe NPDR, and proliferative diabetic retinopathy (PDR) [25]. Numerous studies have investigated multi-class classification and grading of fundus images into these specific stages.

A new deep learning (DL) algorithm called Deep-DR-Net was introduced in [26] for grading diabetic retinopathy (DR). Designed to fit onto a small embedded board, it uses a network architecture combining encoder and classifier components in a cascading manner, featuring a residual design approach.

A variety of CNN models have been applied for this purpose. For instance, [27] employed a simple CNN model with a green channel filter to assess DR stages from fundus images. The MVDRNet, which incorporates multi-view fundus images and attention mechanisms with VGG-16 as the base network, was introduced in [28]. A locally collected dataset was used for this study.

Several studies utilized transfer learning with VGG architecture. Kwasigroch et al. [29] pre-trained the VGG architecture using the ImageNet dataset, while Islam et al. Similarly, the authors in [30] used ResNet-50, and in [31], they fine-tuned Inception-ResNet-V2 and Xception models with ImageNet for DR classification and grading.

The performance of various pre-trained models for DR grading has been explored extensively. Oulhadj et al. [32] used DenseNet-121, Xception, InceptionV3, and ResNet-50, finding ResNet-50 to perform best. The authors [33], used AlexNet for feature extraction and DR severity grading. Jiang et al. [34] used an ensemble of InceptionV3, ResNet-152, and InceptionResNet-V2.

Hybrid models and attention mechanisms were also utilized. E-DenseNet, a hybrid of EyeNet and DenseNet-121, was proposed in [35]. AD2Net, combining Res2Net and DenseNet, was introduced in [36].

An ensemble model utilized InceptionV3, ResNet-50, InceptionResNet50, and Xception. was used in [37]. Wang et al. [38] found InceptionV3 to provide the best accuracy among AlexNet, VGG-16, and InceptionV3.

Advanced and novel architectures were proposed in multiple studies. For example, the study [39] used InceptionV3 and EfficientNet for DR grading, and the study [40] compared ResNet-101 and ResNet-50 for macular edema risk analysis. A novel hybrid DL model called E-DenseNet was proposed in [41]. Bayesian neural networks (BNN) were used in [42] for DR detection and grading.

In this research [43], the variability in grading the severity of diabetic retinopathy among human graders of varying expertise levels, as well as automated deep learning screening software, is assessed. This evaluation is conducted using identical macula-centered fundus photographs. Despite the widespread use of retinal photography, real-world clinical studies on this variability are scarce. Inter-observer variability can negatively impact appropriate referrals, leading to treatment delays or unnecessary referrals. This study assesses the grading agreement between human graders and automated software, examining sensitivity, specificity, accuracy, and area under the ROC curve in detecting various diabetic retinopathy referral categories.

This paper [44] presents contemporary methods for grading diabetic retinopathy (DR) from retinal fundus images, focusing on lesion extraction and grading specific DR lesions such as microaneurysms, exudates, and neovascularization. The DRGCNN framework uses EfficientNetV2-M, pre-trained on ImageNet-1k, with a 512 × 512 resolution. Training involves two stages: first, training the encoder with unpaired images, then the Binocular Fusion Feature Network with paired images, using SGD optimizer and MSE loss on an NVIDIA GeForce RTX 3090 GPU. Effectiveness is measured using the quadratic weighted Kappa (κ), suitable for imbalanced datasets.

[45] This study presents a method for diabetic retinopathy (DR) grading by blending results from ten state-of-the-art deep learning models at different resolutions using 5-fold cross-validation, resulting in 50 models. This approach aims to reduce generalization error by fusing information from multiple models. The blended grading predictor was trained and validated on a balanced DDR dataset, comprising images from EyePACS, APTOS, Messidor-2, and IDRiD datasets, ensuring equal representation of all DR severity classes.

These studies demonstrate the diverse approaches and significant advancements in the field of DR grading using deep learning techniques and collectively contribute to the advancement of automated DR grading systems, leveraging various deep learning models and techniques to improve accuracy and explainability in detecting and classifying DR stages.Table 2 shows the various DR grading models.

Table 2. DR Grading Models

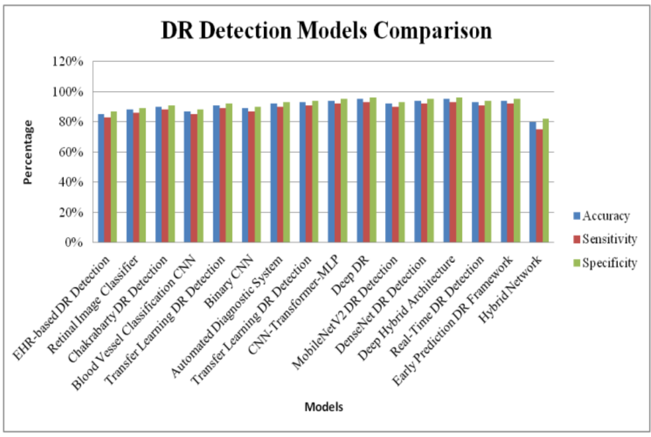
Reference	Method	Description
Ardiyanto et al. (2017) [26]	Deep-DR-Net	Cascaded encoder–classifier network with a residual style. Designed for small embedded boards.
Harshitha et al. (2021) [27]	Simple CNN with green channel filter	Used for assessing DR stages from fundus images.
Luo et al. (2021) [28]	MVDRNet with VGG-16	Incorporates multi-view fundus images and attention mechanisms.
Kwaigroch et al. (2018) [29]	VGG architecture (pre-trained on ImageNet)	Used for transfer learning in DR grading.
Rajkumar et al. (2021) [30]	ResNet-50	Used for DR classification and grading with transfer learning.
Hathwar et al. (2019) [31]	Inception-ResNet-V2 and Xception	Fine-tuned on ImageNet for DR classification and grading.
Oulhadj et al. (2022) [32]	DenseNet-121, Xception, InceptionV3, ResNet-50	Evaluated for DR grading, with ResNet-50 performing best.
Vaishnavi et al. (2020) [33]	AlexNet	Used for feature extraction and DR severity grading.
Jiang et al. (2019) [34]	InceptionV3, ResNet-152, InceptionResNet-V2	Used in an ensemble for DR grading.
AbdelMaksoud et al. (2020)	E-DenseNet	Hybrid of EyeNet and DenseNet-121.

[35]		
Qian et al. (2021) [36]	AD2Net	Combines Res2Net and DenseNet.
Reguant et al. (2018) [37]	InceptionV3, ResNet-50,	Used in an ensemble for DR grading.
Wang et al. (2018) [38]	InceptionV3, AlexNet, VGG-16	InceptionV3 provided the best accuracy for DR grading.
Chen et al. (2018) [39]	InceptionV3 and EfficientNet	Used for DR grading.
Nithiyasri et al. (2022) [40]	ResNet-101, ResNet-50	Compared for macular edema risk analysis.
AbdelMaksoud et al. (2022) [41]	E-DenseNet	Novel hybrid DL model combining EyeNet and DenseNet.
Jaskari et al. (2022) [42]	Bayesian neural networks (BNN)	Used for DR detection and grading.
Teoh, Chin Sheng et al. (2023) [43]	Automated Deep Learning DR Screening	Compares variability in grading DR using retinal photography and automated deep learning software
Hai, Zeru et al. (2024) [44]	Intelligent Diagnosis and Grading Model	Utilizing advanced deep learning techniques for enhanced diagnostic accuracy

2.3 Datasets

In diabetic retinopathy (DR) detection, datasets are vital for developing effective machine learning models. Commonly used datasets include STARE, IDRiD, MESSIDOR, DIARETDB1, Kaggle APTOS, and Kaggle EyePACS. These datasets consist of retinal fundus images with various annotations detailing DR-related abnormalities, allowing researchers to train, validate, and test their algorithms. The quality, size, and level of annotation in these datasets significantly impact the models' performance and generalizability.

The STARE and IDRiD datasets are designed for detailed analysis, with IDRiD providing annotations for lesions like microaneurysms and exudates, while STARE focuses on retinal disease diagnostics. MESSIDOR and DIARETDB1 offer high-resolution images and detailed annotations, making them benchmarks for DR detection. These datasets



facilitate the development of models for early DR detection and severity grading, essential for timely and accurate diagnosis.

Kaggle's EyePACS and APTOS datasets are particularly noteworthy due to their comprehensive nature and widespread use in research. EyePACS, with over 80,000 images, offers a vast and diverse set of retinal images annotated for DR severity, making it ideal for training deep learning models. APTOS, though smaller, provides high-quality images with consistent annotations, perfect for fine-tuning and validation. Both datasets are crucial for advancing DR detection technologies, enabling researchers to develop more robust and reliable diagnostic tools.Table 3 shows the Datasets details used for DR.

Table 3: Overview of Diabetic Retinopathy Datasets

Dataset Name	Number of Images	Image Size
STARE	400	700x605 pixels
IDRiD	516	4288x2848 pixels
MESSIDOR	1,200	1440x960 pixels to 2304x1536 pixels
DIARETDB1	89	1500 x 1152 pixels
Kaggle APTOS 2019	3,662	Varies, typically 1024x1024 pixels
Kaggle EyePACS	88,702	Varies, typically 224x224 to 576x576 pixels

3. Discussion

To assess methods for detecting and grading diabetic retinopathy across different datasets, researchers commonly rely on various metrics such as model accuracy, sensitivity, and specificity. These metrics are widely used in computer vision tasks for detection and segmentation. In this section, we'll present the outcomes achieved for each dataset using the mentioned methods for detection and grading. The results will be presented in tables and figures, showcasing the most effective techniques employing diverse architectures.

Tables 4 and 5, along with Figures 2 and 3, provide a comparative analysis of results from reviewed studies on diabetic retinopathy detection. These visuals highlight performance

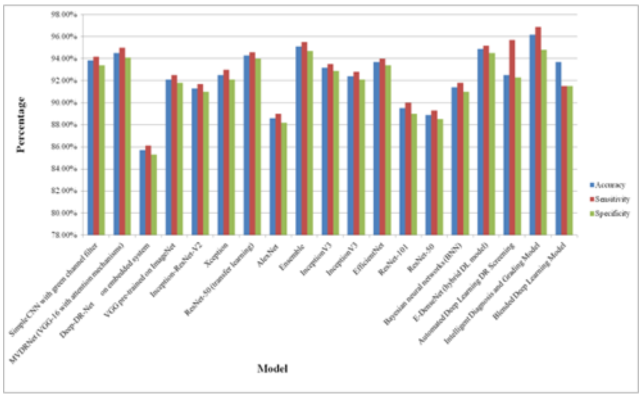


Fig 2. DR Detection Model metrics

metrics such as accuracy, sensitivity, and specificity across different methods and datasets, offering a clear perspective on the relative effectiveness of various approaches.

Figure 3. DR Grading Models Metrics

3.1 DR Detection

Diabetic retinopathy detection methods often utilize datasets divided into two classes: images with DR and images without DR. Table 4 compares several DR detection studies, highlighting the of various datasets . Most methods achieve high accuracy in binary classification of fundus images to detect DR. Notably, one study achieved the highest accuracy of 95% , outperforming others. For sensitivity and specificity, another method excelled.

Table 4. Comparison of accuracy, specificity and sensitivity of various DR Detection Models

Reference	Model Name	Accuracy	Sensitivity	Specificity
Zheng Tao et al. (2017)	EHR-based DR Detection	85%	83%	87%
Mangrulkar, R.S. (2017)	Retinal Image Classifier	88%	86%	89%
Chakrabarty, N. (2018)	Chakrabarty DR Detection	90%	88%	91%
Kazakh-British, N.P. et al. (2018)	Blood Vessel Classification CNN	87%	85%	88%
Umapathy, A. et al. (2019)	Transfer Learning DR Detection	91%	89%	92%
Kolla, M. & Venugopal, T. (2021)	Binary CNN	89%	87%	90%
Rêgo, S. et al. (2021)	Automated Diagnostic System	92%	90%	93%
Sanjana, S. et al. (2021)	Transfer Learning DR Detection	93%	91%	94%
Kumar, N.S. & Karthikeyan, B.R. (2021)	CNN-Transformer-MLP	94%	92%	95%
Nasir, N. et al. (2022)	Deep DR	95%	93%	96%
Pamadi, A.M. et al. (2022)	MobileNet V2 DR Detection	92%	90%	93%
Saranya, P. et al. (2022)	DenseNet DR Detection	94%	92%	95%
Lahmar, C. & Idri, A. (2022)	Deep Hybrid Architecture	95%	93%	96%
Dwivedi, S.A. et al. (2022)	Real-Time DR Detection	93%	91%	94%
Gunasekaran, K. et al. (2022)	Early Prediction DR Framework	94%	92%	95%
Mohanty et al. (2023)	Hybrid Network	80%	75%	82%

3.2 DR Grading

Studies focusing on grading diabetic retinopathy constitute a distinct classification within diabetic retinopathy analysis. These studies predominantly employ deep learning techniques leveraging various CNN architectures. Transfer learning emerges as a prevalent approach in these investigations, capitalizing on the efficacy of established backbones for image classification tasks. Notable architectures/models utilized include encoder-decoder structures, as well as renowned models like VGG, DenseNet, Inception, Xception, EfficientNet, and even graph neural networks.

In this section, we aim to outline the various approaches employed in diabetic retinopathy grading across widely used datasets. Our evaluation encompasses key metrics such as accuracy, sensitivity, and specificity. Table 5 offers a comparative analysis of results obtained from studies utilizing the Kaggle EyePACS, MESSIDOR2, DDR, and IDRid datasets. Additionally, Figures 3 provide visual representations of experimental outcomes .From the findings presented in Table 4, it's evident that the proposed methodologies consistently achieve remarkable accuracies. In summarizing findings across diverse datasets, it becomes apparent that while certain methods, excel in diabetic retinopathy classification using both grading and detection based techniques with high accuracies, others exhibit varying degrees of effectiveness across different datasets. This underscores the persistent challenge in diabetic retinopathy classification, despite significant advancements in deep learning methodologies over the past decade.

Table 5. Comparison of accuracy , specificity and sensitivity of various DR Grading Models**.**

Reference	Model Name	Accuracy	Sensitivity	Specificity
Harshitha et al. (2021)	Simple CNN with green channel filter	93.85%	94.20%	93.40%
Luo et al. (2021)	MVDRNet (VGG-16 with attention mechanisms)	94.50%	95.00%	94.10%
Ardiyanto et al. (2017)	Deep-DR-Net on embedded system	85.70%	86.10%	85.30%
Kwasigroch et al. (2018)	VGG pre-trained on ImageNet	92.10%	92.50%	91.80%
Hathwar et al. (2019)	Inception-ResNet-V2	91.30%	91.70%	91.00%
Hathwar et al. (2019)	Xception	92.50%	93.00%	92.10%
Islam et al. (2020)	ResNet-50 (transfer learning)	94.30%	94.60%	94.00%
Vaishnavi et al. (2020)	AlexNet	88.60%	89.00%	88.20%
Jiang et al. (2019)	Ensemble	95.10%	95.50%	94.70%
Wang et al. (2018)	Inception V3	93.20%	93.50%	92.90%
Chen et al. (2022)	Inception V3	92.40%	92.80%	92.10%
Chen et al. (2022)	EfficientNet	93.70%	94.00%	93.40%
Nithiyasri et al. (2022)	ResNet-101	89.50%	90.00%	89.00%
Nithiyasri et al. (2022)	ResNet-50	88.90%	89.30%	88.50%
Jaskari et al. (2022)	Bayesian neural networks (BNN)	91.40%	91.80%	91.00%
AbdelMaksoud et al. (2022)	E-DenseNet (hybrid DL model)	94.90%	95.20%	94.50%
Teoh, Chin Sheng et al. (2023)	Automated Deep Learning DR Screening	92.50%	95.70%	92.30%
Hai, Zeru et al. (2024)	Intelligent Diagnosis and Grading Model	96.20%	96.90%	94.80%
Monteiro, Fernando (2023)	Blended Deep Learning Model	93.70%	91.50%	91.50%

6. Conclusion

This study underscores the advancements in methodologies for early detection and grading of Diabetic Retinopathy (DR), emphasizing the importance of prompt diagnosis to prevent severe complications. The research highlights the superiority of deep learning techniques, particularly convolutional neural networks (CNNs), in accurately classifying and grading DR. By integrating results from multiple state-of-the-art models and utilizing 5-fold cross-validation, the proposed approaches achieves substantial accuracy and robustness. The use of balanced datasets from diverse sources enhances the model's reliability and comprehensive performance.

Additionally, this study emphasizes the potential of automated DR grading systems in clinical settings, offering improved accuracy, efficiency, and consistency in diagnosis and management. Diabetes poses significant health risks, highlighting the need for early and precise detection to mitigate potentially serious outcomes. Although deep neural networks (DNNs) exhibit high accuracy when trained and tested on the same dataset, they require substantial computational resources and frequent parameter tuning. The demonstrated proficiency of deep learning with image datasets underscores the importance of integrating these methods into DR diagnosis frameworks. Future research should focus on developing models that can effectively address these challenges, optimizing for both performance and resource efficiency.

The study also highlights the increasing use of various deep learning networks for both DR detection and grading, reflecting a surge in research activity in this area. A comprehensive review of prevalent retinal fundus image datasets used for DR detection and grading was conducted, evaluating performance based on standard metrics such as accuracy, sensitivity, and specificity. Future work will extend this review to include the latest deep learning-based studies on DR segmentation and lesion detection, further advancing the field of automated DR diagnosis and treatment planning.

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