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Deep Learning for Diabetic Retinopathy Detection: A Survey on Model Architectures, Datasets, and Evaluation Metrics

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Abstract: Diabetic retinopathy, also known as DR, is a serious complication of diabetes that, if not recognized and treated in a timely manner, can result in vision impairment and even blindness. As a result of the dramatic progress that has been made in deep learning, automated DR detection has emerged as a potentially fruitful topic of research. The purpose of this study is to provide a comprehensive assessment on the most recent deep learning models, datasets, and evaluation metrics that are utilized in DR detection. A number of distinct model architectures, such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Generative Adversarial Networks (GANs), and hybrid models, are discussed in this article. We highlight the advantages and disadvantages of each model architecture, as well as the applications that may be found in various stages of DR severity detection and grading. A comprehensive analysis of publicly accessible datasets, such as Kaggle's EyePACS, Messidor, and DDR, is also included in the survey. The analysis focuses on the distinctive characteristics, dimensions, and quality of fundus images that are present in these datasets. In order to provide a comprehensive perspective, we will cover the performance evaluation criteria, which include accuracy, sensitivity, specificity, and the Area Under the Receiver Operating Characteristics (AUROC) curve. These criteria are essential for determining the clinical relevance of these models. In conclusion, the study identifies major issues, such as class imbalance and interpretability, and offers future research areas to enhance the effectiveness and reliability of deep learning-based DR detection systems. These challenges are discussed in the paper.

Keywords:*Diabetic Retinopathy (DR), Early Detection, Retinal Imaging, Deep Learning, Computer Vision*

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I.INTRODUCTION:

Diabetes is a chronic metabolic condition that affects a significant portion of the global population, with its incidence rising particularly among the elderly [1]. Diabetic retinopathy, one of the most common and serious complications of diabetes, can result in irreversible vision loss if not detected and treated early. Timely identification of diabetic retinopathy is essential to implement interventions that can prevent or slow its progression. However, detecting the disease in its early stages is particularly challenging in the elderly population, highlighting the need for effective, non-invasive diagnostic methods.

Retinal imaging has proven to be a valuable tool in the detection and monitoring of diabetic retinopathy. The retina, a layer of tissue at the back of the eye, is especially susceptible to damage from diabetes due to its rich vascular structure. By analyzing retinal images, clinicians can identify distinct lesions such as microaneurysms, hemorrhages, and exudates, which are indicative of the disease. The advancement of deep learning and computer vision technologies has opened up new possibilities for the automated analysis of retinal images, facilitating the development of reliable and accurate methods for diabetes detection.

Manual evaluation of retinal fundus images by professionals who have received appropriate training is the conventional method for diagnosing diabetic retinopathy. Despite its efficacy, this strategy is not only time-consuming but also prone to inter-observer variability. As a consequence of this, automated diagnostic tools that make use of image processing techniques have been created to provide assistance in the screening and monitoring of diabetic retinopathy. Earlier attempts at automating tasks made use of traditional machine learning algorithms, which necessitated the extraction of features by hand and required intimate familiarity with the associated domain. Furthermore, despite the fact that these systems offered a certain degree of automation, their performance frequently fell short of the accuracy that is necessary for clinical applications.Computer vision and medical image analysis have both been significantly impacted by the introduction of deep learning, in particular convolutional neural networks (CNNs), which have brought about a revolution respectively. Deep learning models, in contrast to typical machine learning models, are able to automatically learn and automatically extract meaningful features from raw data, hence reducing the need for manual feature engineering. Deep learning models have been able to attain expert-level performance in a variety of medical imaging tasks, including DR detection, thanks to this feature, which along with access to massive annotated datasets and advancements in GPU technology, has enabled them to achieve this level of performance.

The analysis of fundus images for the purpose of DR detection and classification has been carried out using a number of different deep learning-based architectures, including VGGNet, ResNet, and InceptionNet, as well as their derivatives. Additionally, these models have been improved by the application of methods like as transfer learning, attention mechanisms, and ensemble learning, which has resulted in an increase in their capacity to identify even the most minute indications of DR. Furthermore, deep learning models have been utilized not only for binary classification, which refers to the presence or absence of diabetic retinopathy (DR), but also for multi-class classification, which is used to determine the severity levels of diabetic retinopathy. These severity levels range from mild, moderate, and severe without proliferative diabetic retinopathy (NPDR) to proliferative diabetic retinopathy (PDR).

This study aims to develop a customized approach for the early detection of diabetes, with a focus on analyzing retinal images in the elderly population. By targeting this vulnerable group, the study addresses a critical healthcare need, as older adults are more prone to the complications and vision impairment associated with diabetes. Additionally, the non-invasive nature of retinal imaging makes it an ideal screening tool for this demographic. The availability of various supplementary datasets greatly enhances the resources available for diabetic retinopathy research and analysis. These datasets include Almajmaah, Saudi Arabia, DIARETDB1, MESSIDOR, APTOS 2019 (Kaggle), DRIONS-DB, IDRiD (Segmentation, Disease Grading, and Localization), EyePACS, Messidor-2, STARE and RFMiD_All_Classes_Dataset, Collectively, these datasets provide a diverse and comprehensive collection of retinal images, enabling extensive analysis and investigation into diabetic retinopathy. The availability of such diverse data empowers researchers and healthcare professionals to develop innovative approaches for accurate diagnosis, disease grading, and anomaly localization, ultimately improving patient care and outcomes in the field of diabetic retinopathy. In this work IDRiD [21] dataset will be used.

The primary objectives of this paper are as follows:

- To Review and Classify Deep Learning Model Architectures: The purpose of this research is to classify and investigate the many different deep learning model architectures that have been suggested for the detection of DR. Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Generative Adversarial Networks (GANs), and hybrid models are some of the architectures that are taken into consideration in this review. However, this list is not exhaustive. We cover the design, implementation, and performance of each architecture with regard to a variety of DR detection workloads. In addition, we investigate the ways in which these models have been adapted to address particular difficulties in DR detection, such as class imbalance, multi-scale feature extraction, and interpretability.
- To Analyze and Compare Available Datasets: A crucial element impacting the efficacy of deep learning models is the accessibility and caliber of labeled data. The most popular DR datasets are reviewed in this survey, including Messidor, IDRiD, and Kaggle's EyePACS. The features of each dataset, such as the quantity of photos, resolution, degrees of severity, and quality of the annotations, are described. We also talk about the difficulties in choosing datasets, including bias in the datasets, imbalances in the classes, and differences in picture acquisition methods that can have a big effect on model performance.
- To Discuss Evaluation Metrics and Performance Benchmarks: It's important to use relevant criteria that take into account both technical performance and clinical relevance when assessing how well deep learning models detect drug resistance. The area under the receiver operating characteristic (AUROC) curve, accuracy,

precision, recall, F1-score, sensitivity, and specificity are just a few of the evaluation metrics that are thoroughly covered in this work. We also investigate more sophisticated metrics, such as multi-class confusion matrices and quadratic weighted kappa, which are especially helpful in DR severity rating. We also point out common evaluation hazards, like dataset-specific performance and overfitting, and recommend recommended practices for robust evaluation.

- To Identify Current Challenges and Research Gaps: Deep learning has showed a lot of potential for diagnosing DR, but there are still a few obstacles to overcome. These include the scarcity of sizable, thoroughly annotated datasets, the unequal distribution of DR severity levels throughout classes, and the requirement for interpretable and trustworthy models in practical contexts. The purpose of this study is to identify these issues and offer alternative solutions, including explainable AI frameworks, generative models for creating synthetic data, and data augmentation techniques. We aim to direct future research toward more therapeutically useful solutions by filling in these gaps.

Significance and Contributions:

This survey is important since it covers every aspect of the quickly developing subject of deep learning for DR detection. This research adopts a holistic approach, addressing several aspects of DR detection, such as model design, data characteristics, and evaluation methodologies, in contrast to earlier surveys that frequently concentrate on a single component (e.g., model architectures or datasets). This survey serves as a guide for academics and practitioners by combining a wide range of research works and offering insights into the relative benefits and drawbacks of various methodologies. Additionally, by highlighting prevalent difficulties and offering doable solutions, this study advances the area. For example, we investigate how explainable AI techniques can improve the interpretability of complex deep learning models, and how transfer learning can be leveraged to address the issue of restricted data availability. We want to expedite the development of more reliable and clinically valuable DR detection technologies by tackling these problems.

II.LITERATURE REVIEW

Bhimavarapu U et al. [1] (2021) offered a thorough deep learning architecture that may be used to recognize diabetic retinopathy (DR) at different stages of the condition. With transfer learning from the InceptionV3 model, the scientists used a convolutional neural network (CNN) architecture that was optimized for the purpose of DR detection. To ensure the model's robustness and generalizability, the study made use of a wide range of datasets, including the Kaggle EyePACS dataset, Messidor-2, and a sizable dataset gathered from several healthcare facilities that included over 100,000 retinal images. The deep learning system was trained to categorize photos into several groups based on the degree of disease, ranging from no disease to proliferative disease. The authors applied a number of pre-processing methods, including picture augmentation and normalization, to raise the standard of the input data and boost the efficiency of the model. The study's findings showed that the deep learning system produced excellent accuracy and robustness across a variety of datasets. Moreover, the model demonstrated stability in its performance across external validation datasets, suggesting its potential for practical clinical implementation.

S. Suganyadevi et al. [2] (2022) presented a deep learning-based method for the identification of diabetic retinopathy (DR) using retinal fundus pictures. They experimented with a number of deep learning architectures, including as Convolutional Neural Networks (CNNs), to automate the DR severity level classification. In order to increase model robustness and decrease overfitting, the study makes use of a pre-processed version of the Kaggle EyePACS dataset and employs strategies including data augmentation and dropout. Accuracy and sensitivity are used as the primary performance indicators for the evaluation, which shows a notable improvement over conventional machine learning techniques. The authors stress how deep learning models may improve early identification of DR, which could result in prompt treatment and less visual loss. However, issues such as limited interpretability and class imbalance are mentioned, indicating that more study is necessary to improve the reliability of these models for clinical application. The work advances the continuous progress of deep learning approaches for automated diagnosis of DR.

Dai, L et al. [3] (2021) presented a complete deep learning system for identifying diabetic retinopathy (DR) across its disease spectrum. This system made use of CNN that was based on the InceptionV3 architecture. An extensive collection of retinal images was used to train the system. These images came from datasets such as Kaggle EyePACS and Messidor-2, as well as supplementary data from a number of different healthcare facilities. In order to improve the performance of the model, specific pre-processing approaches were utilized. These techniques included picture augmentation and normalization. Based on the findings, it can be concluded that the model possesses a high level of effectiveness and has the potential to be utilized in clinical settings. It offers a trustworthy instrument for the early detection of DR and enhances the overall management of the condition.

Gangwar A.K et al. [4] (2021) conducted research on the application of transfer learning and deep learning for the identification of diabetic retinopathy. They make use of pre-trained models such as VGG16 and ResNet50, which are then fine-tuned using the EyePACS dataset. In order to improve the robustness of models, the study emphasizes the significance of data augmentation and picture preprocessing. This study highlights the efficacy of transfer learning in the development of DR detection systems that are accurate and efficient, hence aiding early diagnosis and treatment.

Ayala A. et al. [5] (2021) presented an improved deep learning architecture that uses retinal fundus pictures to diagnose diabetic retinopathy (DR). Utilizing pre-trained Convolutional Neural Networks (CNNs) like VGG16 and ResNet50, they concentrated on improving model performance while including transfer learning to address the issue of sparse labeled input. By training and evaluating the model using the Messidor-2 dataset, the study achieves higher accuracy and sensitivity than with traditional methods. To further enhance the clarity of retinal characteristics, the scientists apply a variety of picture preprocessing techniques, including contrast enhancement and noise reduction. Their evaluation metrics, which show how well the suggested model can detect both moderate and severe DR, are specificity, sensitivity, and accuracy. Even though they achieved excellent performance, the authors note that class imbalance and dataset variability remain problems. They recommend more research into ensemble methods and larger, multi-center datasets in order to increase generalization.

Z. Khan et al. [6] (2021) proposed a hybrid deep learning architecture that combines VGGNet and Network in Network (NIN) for the purpose of detecting diabetic retinopathy. For the purpose of training the model, the EyePACS dataset is utilized, and several data preprocessing techniques, such as normalization and augmentation, are considered. This study emphasizes the combined qualities of VGGNet's deep feature extraction and NIN's micro-networking capabilities, which resulted in a DR detection system that is both reliable and accurate.

Quang H Nguyen et al. [7] (2020) investigated the use of a CNN model trained on the large EyePACS dataset for the identification of diabetic retinopathy (DR). They emphasize how important it is to normalize and enhance images during the preprocessing stage in order to maximize the performance of the model. They hope that by applying these preprocessing approaches, the input data will be more variable and of higher quality, which will strengthen the CNN model's resilience. The results of Nguyen et al. (2020) demonstrate the significant potential of the CNN model as a DR screening tool. This methodology can greatly enhance patient outcomes by enabling prompt diagnosis and therapy. The study highlights the usefulness of deep learning in clinical contexts in addition to showcasing its technical prowess in medical picture processing. This work opens the door for more developments in automated diabetic retinopathy identification, which will improve the treatment and care of people at risk for the condition.

S. Mishra et al. [8] (2020) introduced a deep learning framework that utilized a CNN architecture for the purpose of detecting diabetic retinopathy. This work makes use of the EyePACS dataset, with a particular emphasis on data augmentation and preprocessing in order to improve the accuracy of the model. The findings not only illustrate the potential for clinical application of the CNN model in automated screening systems, but they also indicate the efficiency of the CNN model in reliably detecting various phases of DR.

Hemanth D.J et al. [9] (2020) demonstrated an improved Deep Convolutional Neural Network (DCNN)-based diabetic retinopathy detection and classification method. The significance of utilizing deep learning models for the precise classification of various stages of diabetic retinopathy—from non-proliferative to proliferative—was underscored. The authors implement a multi-stage classification system utilizing the publicly accessible Kaggle EyePACS dataset. This framework consists of picture preprocessing, feature extraction using DCNN layers, and final classification via a softmax layer. The suggested model operates more accurately and precisely than conventional machine learning methods. Furthermore, the work tackles important issues that can impair model performance, such as noisy visual content and lighting variations. Through the implementation of strategies such as batch normalization and dropout, the authors reduce overfitting and improve model stability. The promise of DCNNs for real-time DR screening in clinical settings is highlighted in the paper's conclusion.

Aswin Shriram Thiagarajan et al. [10] (2020) presented a deep learning framework for the identification of diabetic retinopathy with an emphasis on enhancing classification accuracy for both early and advanced DR stages. Convolutional Neural Networks (CNNs) were used in conjunction with image processing techniques to improve the extraction of features from retinal images. The study's foundation is a modified version of the EyePACS dataset that has undergone additional preprocessing procedures like vessel segmentation and contrast modification to draw attention to minute DR symptoms like exudates and microaneurysms. A softmax classifier is used in the model architecture for multi-class DR grading, and numerous CNN layers are followed by fully connected layers. The authors surpass previous conventional and deep learning models in terms of sensitivity and specificity, achieving competitive outcomes. Notwithstanding the impressive results, the study highlights issues like the requirement for extensive annotated datasets and model interpretability. For better performance, hybrid models and attention processes are recommended for future development.

Borys Tymchenko et al. [11] (2020) presented a highly developed deep learning approach that uses a CNN model to identify diabetic retinopathy (DR). The work emphasizes the significance of data pretreatment and augmentation strategies to improve the accuracy and overall performance of the model, utilizing the extensive EyePACS dataset. These preprocessing procedures are essential since they raise the input data's quality and variability and guarantee the CNN model's stability and dependability. Author’s work emphasizes the CNN model's enormous potential in the field of DR screening. This methodology has the potential to significantly improve patient outcomes by enabling early diagnosis and facilitating prompt treatment. This study highlights the usefulness of deep learning for medical image analysis and lays the groundwork for further developments in automated DR diagnosis. In the end, our work demonstrates the significant integration of cutting-edge technology in medical diagnostics, improving healthcare delivery and treatment for individuals at risk of diabetic retinopathy.

Ashish Bora et al. [12] (2020) investigated the use of patient data and retinal pictures to train deep learning models to predict the likelihood of developing diabetic retinopathy (DR). By concentrating on forecasting the probability of DR development rather than classifying its severity, the study varies from previous DR detection techniques. Recurrent neural networks (RNNs) are used by Bora in a hybrid model that combines CNNs for image interpretation with temporal patient data, such as medical history and demographics. Using a sizable dataset from many centers, the model is assessed and trained, showcasing its excellent sensitivity and specificity in predicting DR risk. In addition to addressing major obstacles to the integration of diverse data sources, the study suggests a multi-modal strategy that improves the model's predictive ability. The results indicate that early intervention techniques may be made possible by the use of such predictive models as a proactive tool in the management of diabetes. To confirm the model's clinical usefulness, the study does, however, point out the necessity for more varied datasets and long-term research.

S. Qummar et al. [13] (2019) developed a deep learning ensemble method for the identification of diabetic retinopathy (DR) using the advantages of several model architectures to improve classification accuracy. To enhance the identification of distinct degrees of DR severity from fundus images, they combined three distinct Convolutional Neural Networks (CNNs) into an ensemble framework: InceptionV3, ResNet50, and DenseNet121. The ensemble approach adeptly captures intricate retinal properties that individual models could overlook by merging their predicted outputs. When the ensemble is tested against standalone models on the Kaggle EyePACS dataset, it performs better overall in terms of classification accuracy, sensitivity, and specificity. This study shows how well ensemble learning works when dealing with issues like uneven class distribution and disparities in image quality. For additional training process stabilization, the authors also employ adaptive learning rates and data augmentation. The study highlights that, despite ensemble models' performance, real-time clinical deployment is difficult in the absence of optimal hardware resources because of their high computing demands.

Sourya Sengupta et al. [14] (2019) used a CNN model that was trained on the EyePACS and Messidor-2 datasets to study the diagnosis of diabetic retinopathy (DR) across domains using deep learning. To maximize the effectiveness of the model, the study focuses on sophisticated image preparation methods. Its capacity to operate across domains improves its usefulness in a variety of clinical contexts and guarantees accurate and consistent DR detection. The substantial potential of deep learning models in medical diagnostics, notably in the early diagnosis and treatment of diabetic retinopathy, is highlighted by Sengupta et al.'s new research (2019). This work improves patient outcomes and highlights the revolutionary effect of cutting-edge technology in healthcare by offering a trustworthy instrument for automated DR screening.

Lam C et al. [15] (2018) described a deep learning-based automated method for the detection of diabetic retinopathy (DR) with the goal of assisting ophthalmologists in their work and increasing the likelihood of an early diagnosis. To assess retinal fundus pictures and categorize them into various DR severity stages, they created a Convolutional Neural Network (CNN) model. With a high sensitivity and specificity, the study tests and trains on a dataset of more than 75,000 photos. DR-related abnormalities in the retina, like microaneurysms and hemorrhages, can be detected subtly with the help of deep learning models trained on large-scale data, according to the suggested system. The model's performance can be compared to that of human experts, as demonstrated by the results, which suggests that screening programs could benefit from incorporating it. Notwithstanding, the writers acknowledge certain obstacles, like the requirement for uniform datasets and moral dilemmas associated with computerized diagnosis. For improved model clarity and easier clinical application, they propose utilizing explainable AI approaches.

Suvajit Dutta et al. [16] (2018) investigated the use of deep learning models for the classification of diabetic retinopathy (DR) photographs. CNNs are utilized by the authors in order to process and categorize retinal pictures that are derived from the EyePACS dataset. Putting an emphasis on the significance of data preparation, they employ methods such as normalization and data augmentation in order to enhance the robustness and performance of the model. These discoveries provide evidence that CNNs have the capability of effectively identifying deep learning (DR) images, which bolsters its use in automated screening systems. The findings of this work highlight the importance of deep learning in improving diagnostic accuracy and efficiency, which in turn contributes to improved patient outcomes through the early detection and treatment of diabetic retinopathy.

M. Chetoui et al. [17] (2018) conducted research on the diagnosis of diabetic retinopathy through the use of textural features and machine learning techniques. Before feeding the retinal images into a support vector machine (SVM) classifier, the authors extract texture features from the images using the EyePACS dataset. The research underscores the importance of texture information in augmenting the classification precision of deep learning detection models. These findings highlight how well machine learning techniques and textural features work together to provide precise DR detection. By guaranteeing prompt and precise identification of diabetic retinopathy in clinical settings, the research supports continuing efforts to enhance automated screening methods.

Rishab Gargeya et al. [18] (2017) conducted research on the application of deep learning techniques for the purpose of automating the identification of diabetic retinopathy symptoms. The research makes use of a CNN model that was trained on a huge dataset that included retinal pictures from the EyePACS dataset. When it comes to improving the performance of the model, the authors stress the significance of performing thorough data preprocessing, which includes both normalization and augmentation. These findings provide light on the potential of deep learning models to automate the identification of DR, providing a trustworthy instrument for the early diagnosis and management of the disease. The findings of this study highlight the transformative impact that deep learning can have in the field of medical diagnostics, hence paving the path for improved patient outcomes through timely intervention.

Y. S. Kanungo et al. [19] (2017) investigated the use of deep learning for the purpose of identifying diabetic retinopathy using their research. The EyePACS dataset, which is comprised of a wide variety of retinal pictures, is utilized in this research project by means of a CNN model. In order to maximize the effectiveness of the model, the authors place a strong emphasis on several data preprocessing procedures, including normalization and augmentation. These findings provide further evidence that the model is capable of effectively detecting DR, providing further evidence that it has the potential to be utilized in clinical settings through automated screening methods. Deep learning has been shown to improve diagnostic accuracy and efficiency in medical imaging, and this study makes a contribution to the growing body of research that demonstrates this capability.

D. Doshi et al. [20] (2016) focused on the diagnosis of diabetic retinopathy through the utilization of deep CNNs. In order to improve the overall quality of the retinal images, the research makes use of the EyePACS dataset and focuses on the implementation of advanced image preprocessing techniques. These approaches include normalization and data augmentation. Through the fast and accurate diagnosis of DR, the study highlights the significance of deep learning in the field of medical diagnostics, which results in improved patient outcomes.

Table 1: Comparative Analysis for the literature Reviews

Author Name and Ref. No.	Algorithms Used	Advantages	Disadvantages
Bhimavarapu U, Battineni G (2022) [1]	CNN	The research specifically addresses both detection and classification, which is crucial for diagnosing and staging the disease effectively.	The improvement is specific to the activation function, which may limit the generalizability of the findings to other aspects of deep learning or different types of medical imaging.
S. Suganyadevi et al. (2022) [2]	CNN	various deep learning methods, providing a broad perspective on available approaches for detecting diabetic retinopathy	Only color fundus medical images are included in this study
Dai, L., Wu, L., Li, H. et al. (2021) [3]	InceptionV3	Addresses detection across the entire spectrum of diabetic retinopathy, which is valuable for comprehensive diagnosis and monitoring	The system's complexity might make it less accessible for practical implementation in all healthcare settings
Gangwar, A.K., Ravi, V. (2021) [4]	VGG16, ResNet50	Integrates deep learning with transfer learning, potentially offering enhanced results with less training time	The work done by authors is context-specific to the applications discussed. which limits broader applicability
Ayala, A. et al. (2021) [5]	Custom CNN	Focuses on practical improvements in detection, which is valuable for real-world applications.	The paper emphasize improvements without addressing fundamental limitations or comparisons with existing methods.
Z. Khan et al. (2021) [6]	VGG-NIN	VGG-NIN architecture offering improved feature extraction and classification capabilities.	The models achieves highest overall AUC of 83.8 % only.
M. Chetoui et al. (2018) [17]	SVM	Incorporates texture features, which can enhance the detection performance by capturing additional information beyond basic image data	While it uses machine learning, it may not delve as deeply into deep learning techniques, which are currently more advanced for image classification tasks
Rishab Gargeya, Theodore Leng (2017) [18]	CNN	Provides a detailed study on classification techniques, which is essential for understanding how different models perform on diabetic retinopathy images	-
Y. S. Kanungo et al. (2017) [19]	CNN	Color fundus photography has been used as input and various feature extraction techniques are applied.	The techniques discussed is tailored to the specific scope.
D. Doshi et al. (2016) [20]	CNN	Provides early insights into the use of deep learning for diabetic retinopathy	The study is limited to the specific dataset
Hemanth, D.J. et al. (2020) [9]	CNN, Hybrid Models	Utilizes advanced CNN techniques for detection and classification	-
Sawing Shriram Thiagarajan et al. (2020) [10]	CNN	Explores various deep learning techniques, potentially providing a comprehensive view of the methods available for detection	10 fold validation achieves accuracy of 80%
Borys Tymchenko et al. (2020) [11]	EfficientNet-B4, EfficientNet-B5, SE-ResNeXt50	Automatic deep-learning-based method is used for stage detection of diabetic retinopathy	Explainable AI can be used for better understanding
Ashish Bora (2020) [12]	CNN	Focuses on predicting the risk of developing diabetic retinopathy	Work not address the detection or classification of existing diabetic retinopathy
S. Qummar et al. (2019) [13]	CNN Ensemble	Uses an ensemble method, which combines multiple models to improve accuracy and robustness in detection	Ensemble methods is complex and computationally intensive.
Sourya Sengupta et al. (2019) [14]	CNN	Addresses cross-domain detection, which means the model can be applied to different datasets or types of imaging, enhancing its generalizability.	Model's performance vary significantly across different domains
Lam C, Yi D, Guo M, Lindsey T (2018) [15]	GoogLeNet and AlexNet	Focuses on automated detection which is crucial for scaling the technology to widespread clinical use	Highest accuracy achieved was 74.5%
Suvajit Dutta et al. (2018) [16]	DNN	advanced deep learning models are used for classification	78% accuracy achieved by DNN model.

Related Work

Dataset

The Indian Diabetic Retinopathy Image Dataset, often known as IDRiD, is a customized dataset that was developed with the intention of facilitating research in the automated identification and classification of diabetic retinopathy (DR) and related complications, such as diabetic macular edema (DME). It is one of the most complete datasets that is available to the public for this purpose, and it is comprised of retinal fundus photos of a high quality that have been annotated by medical professionals for a variety of characteristics and severity levels of diabetic retinopathy. In order to facilitate the development of algorithms that are capable of identifying and grading DR with a high degree of precision, the IDRiD dataset has been customized to permit analysis at both the image level and the pixel level. In the IDRiD dataset, the following are the most important features and annotations that are included:

Annotations in the IDRiD Dataset:

Segmentation Masks: Annotations at the pixel level are provided for a variety of lesions that are associated with DR, including microaneurysms, hemorrhages, soft exudates, and hard exudates. These fine-grained annotations are helpful in the process of creating models that are able to precisely localize lesions and comprehend the spatial distribution of DR characteristics. When it comes to activities such as lesion recognition, quantification, and severity assessment, the segmentation masks are absolutely necessary materials.

- Disease Grading: Images are annotated with overall disease severity levels, which are often classified into stages such as no DR, mild, moderate, severe non-proliferative DR, and proliferative DR. These phases are typically categorized into stages. These labels are necessary for the construction of classifiers that are able to predict the stage of DR, which helps in the early diagnosis and treatment planning processes during the process.
- Diabetic Macular Edema (DME): In addition, the existence of DME as well as its severity are both noted in the dataset. The buildup of fluid in the macula, which results in swelling and blurred vision, is the defining characteristic of diabetic macular edema (DME), which is a primary contributor to visual loss in diabetes patients. The use of this information is beneficial in the construction of models that not only detect diabetic retinopathy (DR), but also evaluate other diabetes problems that may occur simultaneously.

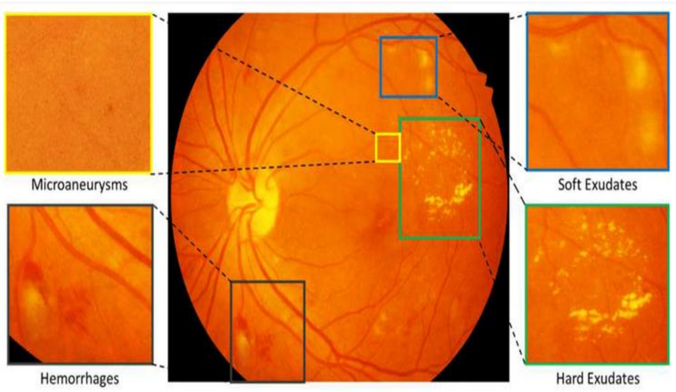

Figure 1. Dataset Sample with segmentation

The graphic shown in figure 1 offers a complete visual illustration of the various diabetic retinopathy lesions and how they show in photographs of the retinal fundus. In the middle of the picture is a retinal fundus image that has numerous locations highlighted, each of which corresponds to a different type of lesion that is typically seen in diabetic retinopathy. Within the surrounding boxes, particular sections of interest are magnified, which makes it simpler to discriminate between the various characteristics.

Micro aneurysms: The early sign of diabetic retinopathy is often the appearance of small, spherical spots that are a dark red color. They manifest themselves as minute protrusions in the blood vessels, and due to the fact that they are so faint, it is difficult to identify them. In the yellow box on the left, microaneurysms are indicated. This box depicts a region in the retina that is characterized by the presence of microscopic black spots.

Hemorrhages: In contrast to microaneurysms, hemorrhages are caused by the rupture of blood vessels, which results in the movement of blood. Their appearance is that of dark spots with an uneven shape, and they may be seen in the box on the lower left side of the diagram. Damage caused by hemorrhages is more severe than that caused by microaneurysms, and they are an indication that the disease is progressing.

Soft Exudates: In addition to being referred to as cotton-wool spots, soft exudates are regions of localized retinal ischemia that manifest themselves as fluffy white patches. These lesions, which are symptomatic of nerve fiber layer damage and indicate more advanced stages of retinopathy, are highlighted in the box that is located on the top right side of the photograph.

Hard Exudates: The presence of yellowish lipid deposits in the retina, known as hard exudates, is a consequence of blood vessels that are leaking. The condition known as diabetic macular edema (DME) is generally associated with these cells, which are frequently grouped in clusters or ring formations. The dense yellow-white patches that are the hard exudates are depicted in the box that is located on the right side of the representation.

Role of the IDRiD Dataset in Deep Learning Research

A wide variety of research tasks, including the following, can be supported by the IDRiD dataset:

- **Lesion Detection and Segmentation**: Deep learning models can be trained to recognize specific lesions such as microaneurysms and exudates by making use of the segmentation masks that are applied at the pixel level. In order to do this operation, you will need to fine-tune models such as U-Net or SegNet, which are well-known for their capacity to function as semantic segmentation tools.
- **Disease Classification**: The disease grading labels make it possible to train classifiers (for example, by employing CNNs such as ResNet or DenseNet) that analyze a picture and determine the degree of DR that is present in that image. In order to conduct screenings on a broad scale and to categorize patients according to the severity of their sickness, this is an essential step.
- **Multi-Task Learning**: When annotations for both DR and DME are present, it is possible to create models that can identify both

DR and DME simultaneously, which ultimately results in diagnostic systems that are more comprehensive. It is possible for multi-task networks to take use of shared characteristics between the two circumstances, which would therefore improve overall performance.

Challenges in Using the IDRiD Dataset

The IDRiD dataset, despite its comprehensiveness, provides a number of issues, including the following:

- **Class Imbalance:** Due to the fact that certain severity levels and types of lesions are underrepresented, it is challenging for models to develop balanced representations.
- **Image Variability**: It is difficult for models to develop balanced representations because certain severity levels and types of lesions are underrepresented. This makes it difficult for models to develop accurate representations.

The IDRiD dataset is an important resource for the advancement of automated diabetic retinopathy identification because of the extensive annotations and a wide range of DR features that it contains. DR lesions are extremely complicated, as demonstrated by the annotated diagram, which also draws attention to the fact that powerful deep learning models that are able to accurately detect and grade them are required. Researchers are able to design robust solutions that improve early detection, hence minimizing the risk of vision loss in diabetes patients. These solutions can be developed by exploiting datasets of this kind.

Algorithms

In recent years, numerous machine learning and deep learning algorithms have been applied to the classification of diabetic retinopathy from retinal fundus images, aiming to enhance early detection and severity grading. Traditional methods such as Support Vector Machines (SVM) and Random Forests (RF) have been employed using handcrafted features like texture, intensity, and shape descriptors; however, these approaches are limited by their dependence on manual feature engineering. The advent of deep learning has led to significant performance improvements, with Convolutional Neural Networks (CNNs) demonstrating the ability to learn hierarchical features directly from raw image data. Advanced architectures such as ResNet50, VGG16, AlexNet, and InceptionV3 have shown superior accuracy by capturing complex and deep spatial patterns related to DR lesions, including microaneurysms, hemorrhages, and exudates. Recently, lightweight and scalable models like EfficientNet and MobileNetV2 have gained attention for their high accuracy and computational efficiency, making them suitable for deployment in real-time clinical settings. Furthermore, hybrid approaches combining feature extraction from CNNs with classifiers like XGBoost, k-Nearest Neighbors (k-NN), and Naive Bayes have also been explored to enhance interpretability and classification precision. Overall, the integration of deep feature extraction with robust classification techniques continues to drive advancements in automated DR diagnosis systems, some of algorithms are explain below.

Convolutional Neural Network (CNN):

CNNs are a class of deep neural networks specifically designed for processing data with a grid-like topology, such as images. In diabetic retinopathy classification, CNNs automatically learn hierarchical feature representations from retinal fundus images without requiring manual feature extraction. They consist of multiple layers such as:

- **Convolutional layers** for feature extraction (e.g., detecting edges, textures, lesions),
- **Pooling layers** to reduce spatial dimensions and control overfitting,
- **Fully connected layers** for final classification.

CNNs are highly effective in DR diagnosis because they can capture subtle pathological features like microaneurysms, exudates, and hemorrhages, which are critical in grading DR severity from normal to proliferative stages.**Support Vector Machine (SVM):**SVM is a supervised machine learning algorithm used for classification tasks. It works by finding the optimal hyperplane that separates data points of different classes In the context of DR:

- SVMs are not typically used on raw images but perform well when combined with extracted features (e.g., texture, color, shape descriptors, or deep features from CNNs).
- The kernel trick allows SVM to perform non-linear classification by mapping inputs into higher-dimensional feature spaces.

SVMs are known for their robustness, especially in binary classification or small datasets, and have been historically used in early DR detection systems.

ResNet50 (Residual Network):

ResNet50 is a 50-layer deep convolutional neural network that introduces residual learning through shortcut connections, allowing the network to train deeper architectures without degradation in performance.

- These residual connections help in preserving gradient flow during backpropagation, effectively addressing the vanishing gradient problem.
- ResNet50 is highly suitable for DR because the deep architecture allows it to capture complex patterns and fine-grained abnormalities in retinal images.

It is commonly used in medical imaging tasks where deeper features correlate strongly with disease progression, improving classification accuracy.

AlexNet: AlexNet is one of the first deep CNNs that demonstrated the power of deep learning in image classification (ImageNet 2012). It consists of 8 layers (5 convolutional + 3 fully connected layers) and uses ReLU activation, dropout, and max-pooling to reduce overfitting and computational load. In DR classification:

- AlexNet provides a good baseline for deep learning performance.
- While not as deep as newer architectures, it still effectively detects major retinal lesions and abnormalities.

However, compared to more recent architectures, its relatively shallow depth can limit its performance on very complex patterns in high-resolution fundus images.

EfficientNet: EfficientNet is a family of CNNs that optimally scales network depth, width, and resolution using a compound coefficient. This results in state-of-the-art performance with fewer parameters and lower computational cost. **Key features include**:

- Use of MBConv (Mobile Inverted Bottleneck Convolution) blocks,
- Swish activation for better non-linearity,
- Auto-scaling of model architecture for a balanced network.

In DR classification, EfficientNet is particularly valuable for:

- Mobile or edge-device deployment due to its lightweight nature,
- High classification accuracy with less overfitting, especially in large datasets.

Result Analysis The comparative analysis of various deep learning and machine learning models for diabetic retinopathy classification (shown in figure 2) reveals a clear trend toward the superior performance of deeper and ensemble-based architectures. ResNet-152 [1] achieved the highest reported accuracy of 99.41%, showcasing the effectiveness of very deep residual networks in extracting complex retinal features. Similarly, AlexNet-inspired CNN [9] and deep ensemble models [13] also demonstrated high accuracies of 97.30% and 96.10%, respectively, suggesting that ensemble learning and deep feature hierarchies significantly enhance classification performance. Mid-level performers such as CNN+ResNet [5] (92.70%) and CNN with Dropout [8] (92.50%) indicate that combining regularization with deep architectures contributes to robust learning.

On the other hand, traditional or shallow models likebasic CNN [15] and cross-domain CNN [14] achieved lower accuracies, at 89.00% and 84.00% respectively, reflecting their limited capacity to generalize across complex retinal datasets. Interestingly, transfer learning approaches [4,16], while not always the top performers, still showed competitive accuracies (86.00% and 95.00%), highlighting their usefulness in leveraging pre-trained knowledge when dataset size is limited.

Overall, the results suggest that while simpler CNNs can provide a decent baseline, high-performing models for DR detection are those that leverage deep residual connections, hybrid architectures, or ensemble strategies, balancing depth and generalizability across diverse image features.

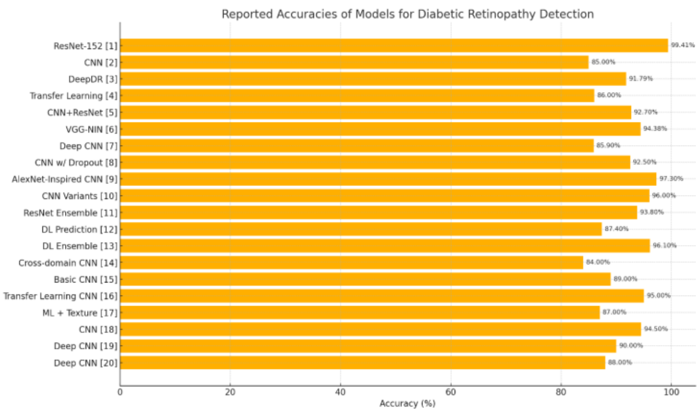

Figure 2. Accuracy Comparison of Models from Literature review

III. Conclusion

This study provides an in-depth comparative analysis of state-of-the-art deep learning models applied to diabetic retinopathy (DR) detection, emphasizing their performance across diverse architectures and datasets. The results demonstrate that advanced deep learning models—particularly deeper convolutional networks such as ResNet-152 and ensemble architectures—consistently achieve superior accuracy in DR classification, with reported performances reaching up to 99.41%. These findings reaffirm the transformative potential of deep learning in automating DR detection and grading, thereby offering critical support for early diagnosis and clinical decision-making. While traditional CNNs and transfer learning approaches yield respectable results, they are often outperformed by hybrid and ensemble models that better capture the complexity of retinal features. However, challenges such as dataset class imbalance, lack of interpretability, and limited generalization across diverse clinical settings remain significant barriers to real-world deployment. Future research should focus on improving model transparency, leveraging generative models like GANs for data augmentation, and developing domain-adaptive architectures capable of robust performance across varied imaging conditions and populations. Overall, this study highlights the progress and potential of deep learning in DR detection, providing researchers and clinicians with valuable insights into selecting appropriate models and metrics for improved diagnostic outcomes.

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