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Deep Learning for the Detection and Classification of Diabetic Retinopathy Stages

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***Abstract*—The incidence of diabetic retinopathy (DR), a complication of diabetes leading to severe vision impairment and potential blindness, has surged worldwide in recent years. This condition is considered one of the leading causes of vision loss. To improve diagnostic accuracy for DR and reduce the burden on healthcare professionals, artificial intelligence (AI) methods are increasingly implemented in medical institutions. AI-based models, in particular, are integrating more algorithms to enhance the performance of existing neural network architectures that are commercially used for DR detection. However, these neural network models still exhibit limitations, such as the need for high computational power and lower accuracy in detecting early DR stages. To overcome these challenges, developing more advanced machine learning models for precise DR detection and classification of DR stages is essential, as it would aid ophthalmologists in making accurate diagnoses.**

This article reviews current research on the use of deep learning in diagnosing and classifying DR and related diseases, as well as the challenges ophthalmologists face in detecting this condition and potential solutions for early-stage DR detection. This review provides information on modern approaches to DR detection using deep learning applications and discusses the issues and limitations in this area.

Keywords* — *diabetic retinopathy; ophthalmology; vision loss; artificial intelligence; machine learning; deep learning.

I. INTRODUCTION

The global prevalence of diabetic retinopathy (DR), a complication of diabetes that leads to significant vision impairment and potential blindness, underscores the profound impact of diabetes on eye health. According to the International Diabetes Federation, as of 2019, there were 463 million adults aged 20 to 79 with diabetes worldwide, a number projected to increase to 700 million by 2045 [1]. DR is a common complication among people with diabetes, with a global prevalence of 27%, as shown in a meta-analysis conducted by Yau et al. in 2012 [2]. This comprehensive analysis covered various demographic and geographic groups, providing an extensive overview of DR incidence. These statistics emphasize the urgent need for careful monitoring and implementation of strategies to prevent DR spread, highlighting the importance of international cooperation and resource allocation to mitigate the impact of vision impairments associated with this microvascular complication.

DR is a serious complication of diabetes that affects microcirculation, potentially leading to partial or complete blindness. This condition arises from prolonged hyperglycemia, causing structural and functional changes in the retinal blood vessels. DR progresses over time and can manifest in various stages, beginning with mild, non-proliferative changes, such as microaneurysms and hemorrhages, and advancing to severe non-proliferative and proliferative stages marked by neovascularization. This stage, characterized by the growth of new abnormal blood vessels in the retina, represents further diabetic eye deterioration [3].

The pathophysiological mechanisms include inflammation, oxidative stress, and endothelial dysfunction. DR's impact on vision ranges from mild impairment to irreversible blindness. Fragile new blood vessels formed in the proliferative stage are prone to leakage, leading to macular edema, the main cause of vision loss in affected individuals [4]. Fibrous tissue formed during neovascularization can also result in retinal detachment, further aggravating vision loss. Regular preventive eye exams and timely interventions, such as laser photocoagulation (cauterization of affected retinal tissue) and intravitreal injections (direct drug administration into the vitreous body), play a crucial role in DR control and mitigating its harmful effects on vision.

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As diabetes prevalence continues to rise globally, understanding the mechanisms behind DR becomes increasingly important for developing effective prevention and control strategies. Early diagnosis of DR is essential to prevent blindness and optimize treatment. Timely detection of minor changes at early stages enables prompt intervention, often before irreversible symptoms appear.

Routine preventive screenings, including advanced imaging technologies such as optical coherence tomography (OCT) and fundus photography, have proven effective in detecting minor abnormalities that might go unnoticed with traditional methods. These technologies allow clinicians to visualize and assess retinal microcirculation and macular thickness with high precision, facilitating early diagnosis and personalized treatment plans.

Technological advancements in medical diagnostics have accelerated over recent decades. In particular, the application of artificial intelligence (AI) to support diagnostic decision-making has significantly improved diagnostic accuracy and efficiency. For example, radiological studies use deep learning algorithms for tasks like image interpretation and pathology detection. In a study by Esteva et al. [5], a dataset containing skin tumor images, including melanomas and basal and squamous cell carcinomas, was used. By applying a deep convolutional neural network, researchers achieved highly accurate tumor classification, with the model distinguishing between malignant and benign tumors as accurately as, or even more accurately than, experienced dermatologists. The model correctly classified 95% of malignant tumors and 98% of benign tumors.

Using deep learning, research by Gulshan et al. [6] demonstrated the feasibility of automatically analyzing retinal images to detect DR signs with 97% accuracy. However, the task of distinguishing intermediate disease stages and detecting early-stage DR remains relevant.

AI algorithms trained on large medical datasets enhance diagnostic accuracy by efficiently analyzing retinal images for DR indicators. The integration of these technologies not only accelerates the diagnostic process but also supports the adoption of telemedicine, allowing remote screening and monitoring for individuals with limited access to specialized healthcare services.

As technology advances, its role in enhancing the accuracy and accessibility of DR diagnosis becomes increasingly critical in the global fight against diabetes-related vision loss. Neural networks and machine learning have initiated a paradigm shift in DR prediction, providing a powerful tool for risk stratification and early intervention.

II. DIABETIC RETINOPATHY

DR is divided into various stages, each characterized by specific changes in the retina (Fig. 1). In the early stages, mild non-proliferative diabetic retinopathy (NPDR) involves the formation of microaneurysms, small hemorrhages, and retinal vein dilation.

As the disease progresses to moderate and severe NPDR, vascular abnormalities become more pronounced, including intraretinal microvascular anomalies and other retinal irregularities. The proliferative stage is marked by neovascularization, leading to the formation of fragile new blood vessels that are prone to leakage and hemorrhaging.

Additionally, fibrous tissue formed during neovascularization presents a risk of retinal detachment and further vision loss. Despite the clear progression of symptoms correlated with DR stages, timely diagnosis of this condition remains challenging. The disease can be asymptomatic, and patients may not notice it until their vision has deteriorated significantly.

Limited access to regular screenings, especially among populations in developing countries, complicates early disease detection. Additionally, reliance on traditional examination methods may delay the identification of retinal changes. The complex pathophysiology of diabetic retinopathy requires specialized imaging techniques, such as optical coherence tomography and fundus photography, to detect early signs of disease progression. The challenges associated with timely diagnosis highlight the critical need to improve screening strategies and integrate advanced technologies to prevent irreversible vision loss in individuals with diabetes.

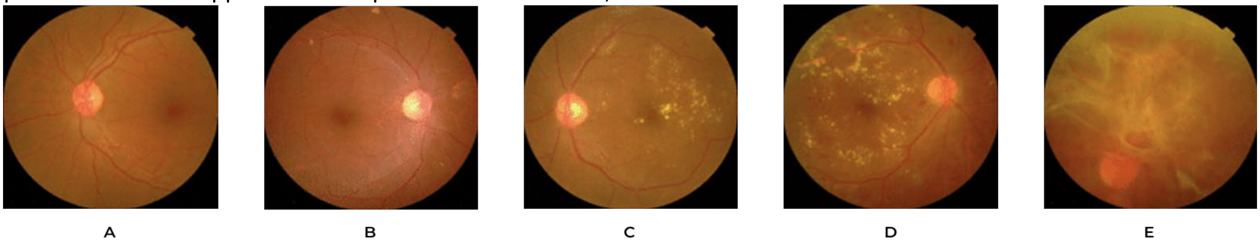

Fig. 1. Stages of DR: A - healthy eye, B - non-proliferative retinopathy, C - pre-proliferative retinopathy, D - proliferative retinopathy, E - diabetic maculopathy.

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III. FUNDAMENTAL PRINCIPLES OF NEURAL NETWORK CONSTRUCTION AND COMPARISON OF COMMON ARCHITECTURES FOR DIABETIC RETINOPATHY CLASSIFICATION

Neural networks are machine learning algorithms composed of interconnected artificial neurons that process and transmit information. Each neuron receives input data, performs a nonlinear operation, and passes the result to the next neuron. These neurons are organized into layers, with data passing from the input layer to the output layer through intermediate hidden layers. Neural networks can learn based on available data by adjusting their parameters and weights to optimally perform specific tasks, such as image recognition, classification, or prediction [7].

Neurons are the primary building blocks of neural networks. They receive input data, multiply it by weights, and pass the result to an activation function. Each neuron typically has its activation value, determining the signal passed to the next neuron. Weights are numerical values that connect neurons to each other, with each connection having its weight, which signifies the importance of that connection for output. Weight coefficients affect each neuron’s contribution to the overall network output and can be adjusted during training.

Activation functions determine a neuron’s output signal based on input data received from previous neurons. They introduce nonlinearity into neural networks, enabling them to model complex relationships between data. Neural networks learn by adjusting weights based on available data. This process involves feeding input data into the network, calculating the error between predicted and actual results, and adjusting the weights to minimize this error.

The process of data transmission from the input layer through hidden layers to the output layer is called forward propagation. Input data is multiplied by weights and processed through activation functions to obtain the network's output. Backpropagation is used to update neuron weights based on the obtained error. The error propagates from the output layer back to the input, adjusting weights according to the error gradient. This process is repeated until optimal learning results are achieved.

Neural networks and machine learning algorithms accelerate the analysis of medical data, which typically requires significant time and resources. Convolutional models demonstrate an accuracy of approximately 87% in detecting mild to moderate stages of diabetic retinopathy, greatly speeding up patient screening and DR detection, saving time, and increasing the chances of successful treatment [6].

Various types of neural networks are widely used for medical image recognition tasks. Convolutional neural networks (CNNs) are among the most commonly used networks for image recognition (Fig. 2). They are applied to image processing through specialized convolutional layers, enabling the identification of local hierarchical features.

Recurrent neural networks (RNNs) are a type of neural network that uses feedback loops to process sequential data, retaining information about previous steps for contextual analysis. They are well-suited for analyzing sequential data, such as text or time series. In the context of image recognition, these networks can be used to process sequences of image regions.

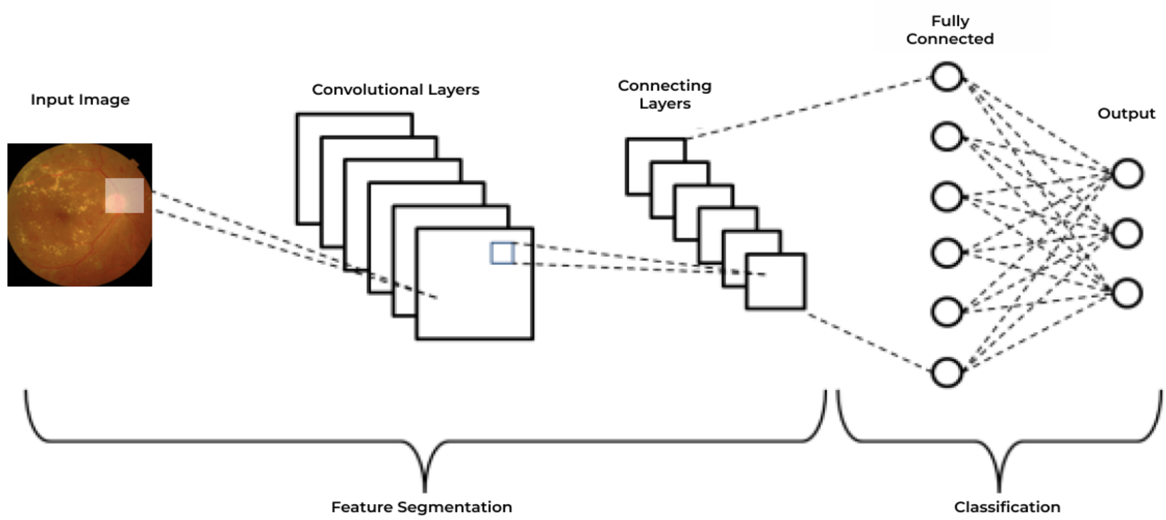

Fig. 2. Diagram of a Convolutional Neural Network Architecture for Diabetic Retinopathy Classification.

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Table 1. Open source DR datasets.

№	Database	Description
1	*Kaggle Diabetic Retinopathy Detection* [9]	This dataset from Kaggle contains high-resolution retinal images, categorized by stages of diabetic retinopathy. It is one of the most commonly used datasets for training and testing deep learning models in this field.
2	*Messidor Dataset* [10]	The Messidor dataset consists of 1,200 retinal images, including 700 normal and 500 pathological images with diabetic retinopathy. It is frequently used for comparative analysis and evaluating machine learning algorithms for detecting diabetic retinopathy.
3	*DRIVE Database* [11]	DRIVE (Digital Retinal Images for Vessel Extraction) is a database containing 40 color images for training and 20 images for testing. It is primarily used for blood vessel segmentation but can also be applied to diabetic retinopathy detection.
4	*STARE Dataset* [12]	The STARE (Structured Analysis of the Retina) dataset contains 400 retinal images, 81 of which show signs of diabetic retinopathy. It is commonly used for research on diabetic retinopathy detection and related tasks.
5	*DIARETDB1* [13]	DIARETDB1 is a publicly available dataset containing 89 color images of various stages of diabetic retinopathy.
6	*E-ophtha* [14]	The e-ophtha dataset comprises retinal images collected in real clinical settings, including cases of diabetic retinopathy.
7	*APTOS 2019 Blindness Detection* [15]	The APTOS 2019 dataset contains over 14,000 retinal images. It is used for Kaggle competitions and provides a diverse set of images for training and evaluation.
8	*IDRiD (Indian Diabetic Retinopathy Image Dataset)* [16]	IDRID consists of 516 retinal images, including 413 images for training and 103 images for testing. It is used for diabetic retinopathy detection among the Indian population.
9	*MESSIDOR-2 Dataset* [17]	MESSIDOR-2 is an extension of the original MESSIDOR dataset, containing a larger collection of retinal images with diabetic retinopathy.
10	*HRF (High-Resolution Fundus) Image Database* [18]	The HRF database contains 45 retinal images with signs of diabetic retinopathy. These high-resolution images are suitable for training deep-learning models for detecting diabetic retinopathy and related tasks.

Deep neural networks (DNNs) are networks with a large number of layers, used to recognize high-level features in images. They may consist of convolutional layers, pooling layers, and fully connected layers, although the number and type of layers vary depending on the specific task. While these types of networks are commonly applied to image recognition, other architectures and layer combinations are used to achieve optimal results depending on the task and data. For example, CapsNet is an architecture designed to better understand spatial relationships in images, while Fully Convolutional Networks (FCNs) are employed in medical diagnostics for the automatic detection and delineation of pathological structures in images [8].

Machine learning models trained on diverse datasets covering various disease stages are used to predict the likelihood of DR development or progression in patients. By identifying changes that may not be noticeable to clinicians using traditional screening methods, these models allow for proactive intervention, thereby reducing the risk of vision loss. The continuous enhancement of deep learning-based predictive models has the potential to improve approaches to personalized medicine, enabling targeted interventions and resource allocation based on individual risk assessments.

Examples of open retinal image datasets frequently used in the research on DR detection through deep learning, along with brief descriptions of these datasets, are presented in Table 1.

The need for a reliable and accurate solution for early-stage DR detection has led to the active use of various neural network models, with potential applications in clinical practice given an optimal balance of computational and time resources and high detection and classification accuracy.

One of the most widely used architectures is Inception-v3 and its modifications. In the study by Kermany et al. [19], Inception-v3 and ResNet models were employed to avoid information loss during training. These deep CNNs consist of deep convolutional layers with connection blocks. Inception-v3 stands out with its architecture, incorporating convolutional layers of different kernel sizes and Inception modules to perform both convolution and pooling operations (the process of reducing input data dimensionality by aggregating values in certain subregions while retaining key features for further analysis) within a single layer. The number of layers in these models can range from several dozen to hundreds, depending on the specific implementation and task, with different parameters and characteristics adapted for medical image analysis.

Another example of this model's application is in the study by Lee et al. [20], published in the *American Journal of Ophthalmology*, which evaluated deep learning's effectiveness in detecting diabetic retinopathy and diabetic macular edema in retinal images. The study used an Inception-Net model with cluster bootstrap and tested it in six countries with four types of retinal cameras. The model demonstrated high accuracy and reliability, with sensitivity at 98%, specificity at 96%, and accuracy at 97%. These metrics indicate the model's strong capability to accurately detect both diabetic retinopathy and diabetic macular edema across differ-

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ent types of retinal images worldwide. The results suggest the potential benefits of specialized deep learning systems in diagnosing and monitoring diabetic eye complications.

Similarly, Sayres et al. [21] achieved comparable accuracy metrics, showing high speed and ability to accurately detect various diabetic eye pathologies in primary care settings. Their study used an Inception-v4 model with heatmap grading, trained on a large retinal image dataset, achieving a sensitivity of 97%, specificity of 94%, and accuracy of 96%.

In another study by Abràmoff MD et al. [22], this architecture opened new perspectives for early DR diagnosis. This study involved diabetic patients in primary care offices, and the model used was based on deep learning, autonomously analyzing retinal images to detect DR signs. It employed a deep convolutional neural network similar to Inception-v3, trained on a large dataset of retinal images.

The ResNet-50 model includes 50 convolutional layers, with connection blocks that prevent information loss and vanishing gradient issues during training. In the study [23], the model was trained to detect and classify various lesion types, such as exudates, hemorrhages, and microaneurysms, with high accuracy. ResNet-50 is also mentioned in another study on retinal lesion detection and classification [24], where different neural network architectures, including CNN, ResNet, and DenseNet, were compared for their effectiveness in identifying DR features. Each model had unique parameters, such as layer count, filter quantity per layer, and activation functions. For example, CNN used three layers with 3x3 filters, while ResNet had 50 layers with variable weight coefficients. DenseNet with 121 layers proved optimal, with parameters tailored to the collected data's characteristics.

It is important to note that different architectures and parameters can influence model performance in DR detection. Exploring these options can improve the accuracy and reliability of deep learning-based diagnostic systems. These models are particularly useful for studies with unbalanced retinal image datasets [25], where various CNN configurations with different layer counts and parameters were compared. Specifically, models with 10 convolutional layers, where the size and number of filters progressively decreased to highlight critical image features, were examined. Additionally, an architecture with 5 convolutional and 3 fully connected layers was used for further feature analysis and DR presence determination.

Deeper, more complex models using more convolutional layers generally achieve better results in DR detection on retinal images. In cases where class imbalance is unavoidable, data augmentation is used. The study [26] explores the effectiveness of deep learning data augmentation techniques for DR classification, addressing low multi-class classification accuracy and dataset imbalance across DR stages through image preprocessing and augmentation, followed by deep learning with ResNet-50.

The use of deep convolutional neural networks in the study [27] allowed automation of image assessment and improved results compared to traditional macular edema evaluation methods on retinal images. The authors enhanced the variety of training image samples through data augmentation, including cropping, random angle rotation, vertical and horizontal stretching, shifting, and mirroring.

In comparing the aforementioned types of neural networks for DR classification, each architecture has distinct advantages and drawbacks:

ResNet: Due to its depth, ResNet effectively addresses the vanishing gradient problem, allowing the training of deep networks with more layers. This helps avoid accuracy degradation as network depth increases. The vanishing gradient problem occurs when the gradient diminishes through multiple layers during backpropagation, limiting learning efficiency, especially for layers closer to the input.

DenseNet: Unlike ResNet, DenseNet connects each layer directly to all previous and subsequent layers. This enhances information and gradient flow, increasing classification accuracy while requiring fewer parameters than other architectures.

InceptionNet: Known for its complex structure, InceptionNet uses modules with parallel filters of different sizes, enabling efficient information extraction at various image detail levels. However, this approach can increase model complexity and computational costs during training and may present challenges when deploying the model on resource-limited devices.

In conclusion, selecting a neural network architecture for DR classification should consider the specific task requirements, available resources, and the need for accuracy and computational efficiency.

IV. CHALLENGES AND LIMITATIONS OF APPLYING DEEP LEARNING FOR DIABETIC RETINOPATHY DIAGNOSIS AND FUTURE DEVELOPMENT

The application of neural networks for predicting DR faces several challenges that require attention. Firstly, obtaining large and diverse retinal image datasets with expert annotations can be challenging due to the need for ophthalmologists' assessments, a time-consuming and costly process [28]. Secondly, the quality of retinal images, captured with different camera types and shooting protocols, can vary, leading to inconsistencies in model accuracy across datasets [29].

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Another challenge in applying neural networks in ophthalmology is interpreting the workings of deep learning models, as these architectures often function as "black boxes," making the decision-making process difficult to understand. This lack of interpretability may hinder the acceptance of neural models by medical professionals, limiting their use in clinical practice. Additionally, implementing neural network models in resource-constrained environments, such as medical facilities with limited resources or in regions with restricted internet access, presents logistical and technical challenges. Using complex architectures like ResNet, InceptionNet, and DenseNet also brings computational complexity, particularly when processing large data volumes.

In cases where there is an insufficient number of images at various DR stages for neural network training, data augmentation is employed. Collaborative efforts between medical institutions and researchers support the sharing of annotated datasets, aiding in the development of more robust models. Furthermore, standardizing image acquisition protocols and quality control can help ensure consistent image quality across datasets [30].

Improving the interpretability of neural network models is essential for building trust and understanding among clinicians and patients. Interdisciplinary collaboration between scientists, clinicians, and medical imaging experts fosters the development of interpretable models tailored to clinical needs. Efforts should focus on developing lightweight and efficient neural network architectures suitable for low-power devices like smartphones or portable diagnostic tools. Integrating multimodal data, such as genetic information or patient demographics, into predictive models could enhance accuracy and enable personalized treatment strategies.

CONCLUSION

The studies reviewed highlight the high effectiveness of deep learning systems, particularly deep convolutional neural networks, in detecting and classifying various eye diseases, including DR, through retinal image analysis.

An overview of existing work on DR detection and stage classification reveals challenges directly related to insufficient accuracy in early DR detection, limitations in training neural networks on small datasets, and issues with implementing machine learning models in clinical practice. Many studies aim to achieve better overall accuracy in binary classification (normal/pathological) than for multi-class classification of intermediate disease stages. The image datasets used in these studies are often class-imbalanced, necessitating preprocessing and data augmentation techniques for effective deep learning.

Given these limitations, there is a need for a reliable, automated, and computerized DR diagnostic system that can accurately detect and classify DR stages in less time.

This literature review covers research on DR detection and classification conducted from 2016 to 2023 and examines the latest architectures used by researchers, including InceptionNet, DenseNet, and ResNet. The use of InceptionNet, DenseNet, and ResNet in DR diagnosis is justified due to their power and efficiency. InceptionNet, with its branched structure, effectively leverages information at multiple levels of image detail. DenseNet facilitates efficient information transfer between layers, improving classification accuracy. ResNet addresses the vanishing gradient problem with its "skip connections" concept, easing the training of deep models. These neural network architectures are crucial tools for enhancing the quality of DR diagnosis and stage classification due to their ability to optimally utilize high-resolution image data.

Applying image preprocessing methods, edge detectors, and advanced feature extraction techniques to retinal images can significantly improve the effectiveness of machine learning models for DR detection and stage classification. Hybrid edge detection algorithms, such as combining the Sobel operator with the Canny edge detector, can outline retinal structures, enhancing the visibility of blood vessels, microaneurysms, and hemorrhages.

The analyzed studies reflect a growing interest in applying deep learning in the medical field, particularly in detecting eye diseases like DR. As the number of DR patients continues to rise, delayed diagnosis and ineffective treatment can lead to vision loss. Thus, developing and implementing machine learning methods in clinical practice supports rapid and effective DR diagnosis and improves treatment outcomes for this condition.

REFERENCES

[1] G. D. Ogle, “Global estimates of incidence of type 1 diabetes in children and adolescents: Results from the International Diabetes Federation Atlas, 10th edition”, Diabetes Research and Clinical Practice, vol. 183, p. 109083, Jan. 2022. **DOI:** 10.1016/j.diabres.2021.109083

[2] J. W. Yau, “Global Prevalence and Major Risk Factors of Diabetic Retinopathy”, Diabetes Care, vol. 35, no. 3, pp. 556–564, Feb. 2012. **DOI:** 10.2337/dc11-1909

[3] P. Ansari, “Diabetic Retinopathy: An Overview on Mechanisms, Pathophysiology and Pharmacotherapy”, Diabetology, vol. 3, no. 1, pp. 159–175, Feb. 2022. **DOI:** 10.3390/diabetology3010011

[4] A. R. Khyts, “Diabetic Macular Edema: Patient Management in Light of Modern Recommendations”, Ukrainian Medical Journal, Aug. 2021. [Online Publication] **URL:** https://umj.com.ua/uk/publikatsia-212799-diabetichnij-makulyarnij-nabryak-menedzhment-patsiyentiv-u-svitli-suchasnih-rekomendatsij

[5] A. Esteva, “Dermatologist-level classification of skin cancer with deep neural networks”, Nature, vol. 542, no. 7639, pp. 115–118, Jan. 2017. **DOI:** 10.1038/nature21056

[6] V. Gulshan, “Development and Validation of a Deep Learning Algorithm for Detection of Diabetic Retinopathy in Retinal Fundus Photographs”, JAMA, vol. 316, no. 22, p. 2402, Dec. 2016. **DOI:** 10.1001/jama.2016.17216

[7] I. Goodfellow, Y. Bengio, and A. Courville, "Deep Learning.," MIT Press, 2016. **ISBN:** 9780262035613. **URL:** https://mitpress.mit.edu/9780262035613/deep-learning/

[8] S. K. Zhou, H. Greenspan, and D. Shen, "Deep Learning in Medical Image Analysis," Academic Press, 2017. **URL:** https://www.sciencedirect.com/book/9780128104088/deep-learning-in-medical-image-analysis

[9] Diabetic Retinopathy Detection. Kaggle. **URL:** https://www.kaggle.com/c/diabetic-retinopathy-detection/data

[10] Messidor-1 Dataset. Methods to Evaluate Segmentation and Indexing Techniques in the field of Retinal Ophthalmology. **URL:** https://www.adcis.net/en/third-party/messidor/

[11] DRIVE: Digital Retinal Images for Vessel Extraction **URL:** https://drive.grand-challenge.org/

[12] STARE Dataset. Structured Analysis of the Retina. **URL:** https://cecas.clemson.edu/~ahoover/stare/

[13] DIARETDB1 Dataset. Standard Diabetic Retinopathy Database. **URL:** https://www.kaggle.com/datasets/nguyenhung1903/diaretdb1-standard-diabetic-retinopathy-database

[14] ADCIS. E-ophtha Dataset. **URL:** https://www.adcis.net/en/third-party/e-ophtha

[15] Kaggle. APTOS 2019 Blindness Detection. **URL:** https://www.kaggle.com/competitions/aptos2019-blindness-detection

[16] Indian Diabetic Retinopathy Image Dataset (IDRID). **URL:** https://ieee-dataport.org/open-access/indian-diabetic-retinopathy-image-dataset-idrid

[17] ADCIS. MESSIDOR-2 Dataset. **URL:** https://www.adcis.net/en/third-party/messidor2/

[18] High-Resolution Fundus (HRF) Image Database. **URL:** https://www5.cs.fau.de/research/data/fundus-images/

[19] D. S. Kermany, “Identifying Medical Diagnoses and Treatable Diseases by Image-Based Deep Learning”, Cell, vol. 172, no. 5, pp. 1122–1131.e9, Feb. 2018. **DOI:** 10.1016/j.cell.2018.02.010

[20] D. S. W. Ting, “Development and Validation of a Deep Learning System for Diabetic Retinopathy and Related Eye Diseases Using Retinal Images From Multiethnic Populations With Diabetes”, JAMA, vol. 318, no. 22, p. 2211, Dec. 2017. **DOI:** 10.1001/jama.2017.18152

[21] R. Sayres, “Using a Deep Learning Algorithm and Integrated Gradients Explanation to Assist Grading for Diabetic Retinopathy”, Ophthalmology, vol. 126, no. 4, pp. 552–564, Apr. 2019. **DOI:** 10.1016/j.ophtha.2018.11.016

[22] M. D. Abràmoff, P. T. Lavin, M. Birch, N. Shah, and J. C. Folk, “Pivotal trial of an autonomous AI-based diagnostic system for detection of diabetic retinopathy in primary care offices”, npj Digital Medicine, vol. 1, no. 1, Aug. 2018. **DOI:** 10.1038/s41746-018-0040-6

[23] Y. Jiang, J. Liang, T. Cheng, X. Lin, Y. Zhang, and J. Dong, “MTPA_Unet: Multi-Scale Transformer-Position Attention Retinal Vessel Segmentation Network Joint Transformer and CNN”, Sensors, vol. 22, no. 12, p. 4592, Jun. 2022. **DOI:** 10.3390/s22124592

[24] L. Wewetzer, L. A. Held, J. Steinhäuser, and D. A. Worthy, “Diagnostic performance of deep-learning-based screening methods for diabetic retinopathy in primary care—A meta-analysis”, PLOS ONE, vol. 16, no. 8, p. e0255034, Aug. 2021. **DOI:** 10.1371/journal.pone.0255034

[25] N. Tsiknakis, “Deep learning for diabetic retinopathy detection and classification based on fundus images: A review”, Computers in Biology and Medicine, vol. 135, p. 104599, Aug. 2021. **DOI:** 10.1016/j.compbiomed.2021.104599

[26] M. S. Patil, S. Chickerur, C. Abhimalya, A. Naik, N. Kumari, and S. Maurya, “Effective Deep Learning Data Augmentation Techniques for Diabetic Retinopathy Classification”, Procedia Computer Science, vol. 218, pp. 1156–1165, Jan. 2023. **DOI:** 10.1016/j.procs.2023.01.094

[27] X. Guo, X. Lu, B. Zhang, X. Hu, and S. Che, “AUTOMATIC DETECTION AND GRADING OF DIABETIC MACULAR EDEMA BASED ON A DEEP NEURAL NETWORK”, Retina, vol. 42, no. 6, pp. 1095–1102, Jun. 2022. **DOI:** 10.1097/IAE.0000000000003434

[28] M. Kim and H.-J. Bae, “Data Augmentation Techniques for Deep Learning-Based Medical Image Analyses”, Journal of the Korean Society of Radiology, vol. 81, no. 6, p. 1290, Jan. 2020. **DOI:** 10.3348/jksr.2020.0158

[29] J.-G. Lee, “Deep Learning in Medical Imaging: General Overview”, Korean Journal of Radiology, vol. 18, no. 4, p. 570, Jan. 2017. **DOI:** 10.3348/kjr.2017.18.4.570

[30] A. M. Mutawa, K. Al-Sabti, S. Raizada, and S. Sruthi, “A Deep Learning Model for Detecting Diabetic Retinopathy Stages with Discrete Wavelet Transform”, Applied Sciences, vol. 14, no. 11, p. 4428, May 2024. **DOI:** 10.3390/app14114428

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***Анотація*—Рівень захворюваності на діабетичну ретинопатію (ДР), яка є ускладненням цукрового діабету і призводить до серйозного погіршення зору та потенційної сліпоти, в останні роки стрімко зріс в усьому світі. Ця патологія вважається однією з найпоширеніших причин втрати зору серед людей. Для покращення точності діагностики ДР, а також зменшення навантаження на медичних працівників, активно впроваджується використання методів штучного інтелекту в медичних установах. Зокрема, моделі на основі штучного інтелекту поєднують все більше алгоритмів для покращення продуктивності наявних архітектур нейронних мереж, які комерційно використовуються для виявлення ДР. Однак, ці моделі з використанням нейронних мереж все ще демонструють деякі обмеження, такі як необхідність високої обчислювальної потужності та низька точність виявлення початкових стадій ДР. Щоб подолати ці обмеження, актуальною є розробка досконаліших моделей машинного навчання для більш точного виявлення ДР на початкових етапах розвитку захворювання та класифікації проміжних стадій ДР, що, зокрема, допоможе офтальмологам поставити точний діагноз.**

У цій статті проведено огляд сучасних досліджень з використання глибокого навчання для вирішення задачі діагностики та класифікації ДР та суміжних захворювань, а також проблем, з якими стикаються офтальмологи при виявленні цього захворювання і можливих рішень для виявлення ДР на початкових стадіях. Цей огляд надає інформацію про сучасні підходи, що використовуються для виявлення ДР на основі застосування глибокого навчання, а також про проблеми та обмеження у цій області.

Ключові слова — діабетична ретинопатія; офтальмологія; втрата зору; штучний інтелект; машинне навчання; глибоке навчання.