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Advanced Deep Learning Approaches for Automated Diabetic Retinopathy Detection and Severity Classification: A Multi-Model Review

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Abstract

Diabetic Retinopathy (DR) is one of the main causes of preventable blindness worldwide, especially in people of working age. Manual assessment of retinal fundus images is labor-intensive and frequently subject to variability, particularly in the early phases of the disease. Advancements in deep learning (DL) methodologies have facilitated automated, high-precision detection and grading of Diabetic Retinopathy severity, providing scalable frameworks for clinical screening applications. This review consolidates pivotal research employing hybrid deep learning (DL) architectures, such as Google Net and ResNet augmented with adaptive particle swarm optimization (APSO), in conjunction with conventional machine learning classifiers like Support Vector Machines, Random Forests, and Decision Trees. Furthermore, the surveyed literature underscores the emergence of advanced paradigms—including supervised, self-supervised, and transformer-based frameworks—and explores the integration of federated learning and generative adversarial networks (GANs) to enhance model resilience and generalizability. The review articulates prospective avenues, including the integration of multi-modal data sources and the development of resource-efficient architectures to facilitate real-world clinical implementation.

Keywords: *Diabetic Retinopathy (DR), Deep Learning (DL), Retinal Fundus Images, Google Net, ResNet, Machine Learning (ML), Support Vector Machine (SVM), Random Forest, Decision Tree, Medical Image Analysis.*

1. Introduction

Diabetic Retinopathy (DR) is a progressive microvascular complication of diabetes, and it remains one of the leading causes of preventable blindness worldwide. The global diabetic population is expected to cross 700 million by 2045, which directly increases the number of individuals at risk for DR-related vision impairment. Early DR detection is crucial because treatment in the initial phases can significantly reduce progression to severe or proliferative stages. The manual examination of fundus images by ophthalmologists is the basis for traditional DR diagnosis; this method is time-consuming, subjective, and inconsistent among graders. Manual reviews are no longer scalable due to the growth of screening programs, particularly in rural and low-resource areas. Although they present a promising answer, computer-aided diagnosis (CAD) systems have historically required large annotated datasets and a significant amount of training time. Although deep learning has revolutionized medical imaging, DR detection is still hampered by its largest drawback, which is its need for massive annotated datasets. To get around this, the reviewed research suggests a transfer learning method that divides DR into five severity levels using a refined ResNet50 architecture. The motivation, technique, results, and implications for medical AI are all covered in further detail in this narrative review. **Figure 1.** illustrates the different DR stages, First Phase (No Diabetic Retinopathy): The retina looks nearly normal at this point, and there is no obvious blood vessel damage. Exudates, hemorrhage's, or microaneurysms are not present. Although the patient has diabetes, there are now no noticeable alterations to the retina. NPDR, or mild non-proliferative diabetic retinopathy. This is the earliest visible stage of diabetic retinopathy, as small red dots termed microaneurysms begin to develop. There are just a few anomalies in these microaneurysms, which are small bulges in the retinal capillaries. Although this stage usually does not result in any discernible vision loss, it NPDR, or moderate

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non-proliferative diabetic retinopathy. There are more microaneurysms and tiny dot-and-blot hemorrhages at this stage. Additionally, the retina may develop cotton-wool spots, which are white patches. Retinal oedema may start when some of the blood vessels in the retina become clogged. This stage is indicative of growing retinal damage and an increased chance of vision issues. Diabetic Retinopathy: Severe Non-Proliferative and Proliferative. At this point, a large number of retinal blood vessels are clogged, depriving the retina of oxygen (a condition called ischemia). There may be more cotton-wool patches and larger hemorrhages. At this stage, neovascularization—the formation of new aberrant blood vessels—may start. Proliferative diabetic retinopathy (PDR), which can cause major consequences such as vitreous rupture, retinal detachment, and severe vision loss, develops from this critical stage.

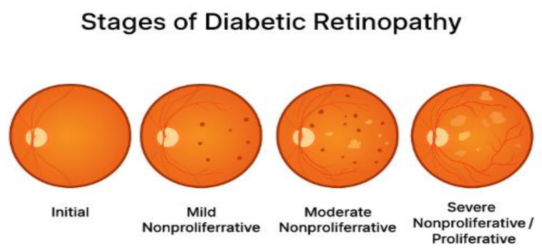

Figure 1 Stages of Diabetic Retinopathy

2. Literature Survey

Ahmad et al.[1] review highlights that green-channel preprocessing and SVM-based classifiers are the most widely used and effective approaches in recent studies. Ahmed Al-Tayeb.[2] reviews how smartphone-based retinal imaging combined with machine-learning (GLCM + SVM) can provide a low-cost, accessible solution for early detection of diabetic retinopathy. Muthusamy et al.[3] proposes a new deep-learning model called MAPCRCI-DMPLC that improves diabetic retinopathy detection by using advanced preprocessing, ROI extraction, and feature extraction techniques. Al-Farooqi et al.[4] compares ML, DL, hybrid, and optimization methods for diabetic retinopathy detection and concludes that despite DL's higher accuracy, issues like dataset quality, computation cost, and generalization still limit overall performance. Mannan Uddin et al.[5] paper presents an ensemble-learning framework that combines multiple classifiers to improve diabetic retinopathy prediction, showing that linear SVM achieves the highest accuracy among the tested models. Siddarth et al.[5][6] demonstrates that DenseNet-121 can automatically extract rich retinal features and achieve high-accuracy diabetic retinopathy classification, making it an effective deep-learning framework for early disease detection. Sumadithya et al.[6] proposes a deep-learning approach using Capsule Networks and GANs to improve automated detection of diabetic retinopathy and macular edema, achieving promising results on Messidor and IDRiD datasets. Kotambkar et al.[7] introduces a cascaded learning framework that improves diabetic retinopathy severity prediction by combining multi-stage feature extraction and classification for more accurate grading. Mangal et al.[8] develops a CNN-based system that accurately

Table 1 Datasets Used for Training DR Detection & Classification Models

S. No	Paper / Model	Algorithm / Architecture	Dataset Used	Output / Accuracy / Metrics
1	Transfer Learning Approach for DR Classification (ResNet50)	Fine-Tuned ResNet50	APTOS 2019 (3,662 images)	Accuracy: 90%, Kappa: 0.94
2	Efficient Net for Diabetic Retinopathy Diagnosis	Efficient Net (B0/B3 variants)	APTOS 2019 (Kaggle)	Train Accuracy: 98%, Validation: 96.14%
3	Hybrid Deep Learning Approach	Combined DenseNet121 + Xception + EfficientNetB3	APTOS 2019	Accuracy: 86%, Balanced Precision/Recall
4	DenseNet-121 Framework for DR Feature Extraction	DenseNet-121 (transfer learning)	APTOS Dataset	Accuracy: 96–97%, High precision & recall
5	Ensemble Stacking Approach (VGG16 + ML classifiers)	VGG16 features + 9 ML Models + Logistic Regression meta-learner	APTOS 2019	Accuracy: 99.50%, High class sensitivity
6	CBAM-Enhanced InceptionV3 for DR Classification	InceptionV3 + CBAM (Attention Module)	APTOS 2019	Accuracy: 95.37%, Precision/Recall > 93%
7	Deep Learning Approaches for DR – Comparative Review	VGG, ResNet, AlexNet, GANs, Ensembles	Kaggle, MESSIDOR-2, e-Ophtha	Many models ≈ 93–97% accuracy
8	Deep Learning Techniques for Retinopathy Detection	CNNs, RNNs, GANs, Transfer Learning	EyePACS, IDRiD, STARE, DRIVE, UK Biobank	90–97% accuracy depending on architecture
9	DR Prediction Using Hybrid ML Techniques	SVM, KNN, ANN, Random Forest	Local hospital datasets, Kaggle DR	Accuracy: 85–95% depending on feature design
10	Optimization-Based DR Detection (Grey Wolf Optimization)	CNN + GWO optimizer	Kaggle/EyePACS	Accuracy typically around 92–95%

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classifies diabetic retinopathy severity levels using retinal images, demonstrating strong performance compared to existing machine-learning models. Arunasakthi et al.[9] proposes an Efficient Net-based deep-learning framework that achieves high-accuracy early detection of diabetic retinopathy, offering a fast, reliable, and scalable solution for automated retinal screening. Dasari et al.[10] demonstrates that a fine-tuned ResNet50 transfer-learning model can accurately classify diabetic retinopathy severity, achieving high accuracy even with limited labeled data. Tibari et al.[11] presents a hybrid deep-learning and ensemble-stacking model using VGG16 features and multiple ML classifiers, achieving fast and highly accurate diabetic retinopathy detection with 99.5% accuracy. Vohra et al.[12] presents a low-cost AI-enabled system combining affordable imaging hardware, a custom CNN model, and cloud-based analysis to accurately detect diabetic retinopathy, glaucoma, and AMD, making early eye-disease screening accessible in resource-limited settings. Hossain et al.[13] CBAM-enhanced InceptionV3 model that improves multiclass diabetic retinopathy classification accuracy to 95.37% by focusing on important retinal regions and handling class imbalance effectively. Romeo et al.[14] reviews recent deep-learning methods for detecting and classifying eye diseases from retinal images, highlighting that models like DenseNet and ResNet achieve high accuracy but face challenges such as limited datasets, lack of multi-label capability, and poor generalization in real clinical settings.

3. Review of Methodology

Diabetic retinopathy classification can be divided into two categories: multi-class classification, which identifies the precise stage of DR, and binary classification, which seeks to identify the presence or absence of DR. As a result, further techniques were created with an emphasis on lesion-based classification. The subsequent sections of the study review those classification tasks under supervised and self-supervised learning. This architecture outlines the entire process of an AI system intended for the interpretation of medical images. Images are gathered, arranged, and examined for security and compliance in the first step, Data Ingestion and Governance, Figure 2. The images are next cleaned by preprocessing and quality control, which eliminates noise, adjusts brightness, and makes sure only high-quality images are fed into the pipeline. Data augmentation and balancing employ both conventional approaches and GAN-based strategies to provide more varied samples in order to address class imbalance. Experts annotate illness features in Labelling, Consensus, and Lesion Annotation; numerous annotations can be pooled for accuracy.

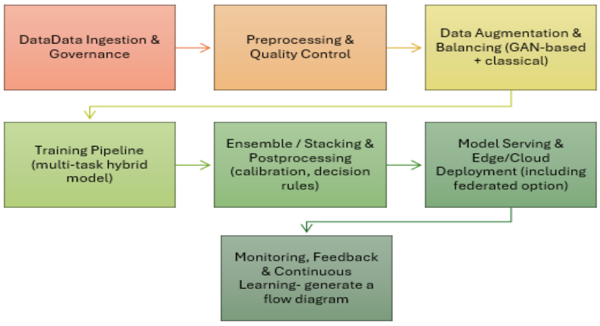

Figure 2 Workflow of AI System

The Training Pipeline is a multi-task hybrid model that includes an Explainability Module (e.g., attention maps, Grad-CAM) to demonstrate how the model makes decisions, a Classification Head that predicts the 5-class ICDR diabetic retinopathy stage, a Segmentation Head that detects and outlines lesions, and an Uncertainty & Calibration Module that gauges model confidence. The Ensemble/Stacking & Postprocessing stage applies final calibration or criteria for trustworthy decision-making after combining model outputs after training. With the option for federated learning to protect data privacy, the final model is implemented via Edge/Cloud Serving. Monitoring, feedback, and continuous learning are the final steps in the process. Here, model performance is monitored, user input is gathered, and the system is updated often to increase accuracy over time.

3.1. Traditional Machine-Learning (Handcrafted Features) Approaches

Conventional methods of machine learning (handcrafted features) Early DR systems used hand-crafted features (texture, color histogram, vascular morphology, lesion counts) and explicit image

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processing. Classical classifiers like SVM, KNN, Random Forest, and logistic regression came next. When datasets were modest and photos were carefully pre-processed, several research studies reported decent accuracy; these methods are generally interpretable and computationally light. However, they frequently have trouble with noisy, heterogeneous clinical images and require careful feature design. These techniques continue to be useful in low-resource environments and as parts of hybrid pipelines.

3.2. Rise of Deep Learning (end-to-end CNNs).

By directly learning hierarchical picture properties from pixels, convolutional neural networks (CNNs) transformed retinal image analysis. DR categorization and lesion detection have made extensive use of architectures including VGG, ResNet, Dense Network, Inception, and Efficient Net. On big, well-annotated datasets, sophisticated models always perform better than handcrafted feature systems. Numerous effective CNN applications and high claimed accuracies (typically >90%) for binary referable DR detection and, occasionally, multiclass grading are summarized in the reviews and experimental articles you supplied.

3.3. Transfer Learning, Label-Efficiency and Data Augmentation

Transfer learning (pretraining on ImageNet/fine-tuning) is a popular approach because medical datasets are smaller and noisier than natural-image corpora. Fine-tuned networks (ResNet50, InceptionV3, and EfficientNet) achieve near state-of-the-art performance while using fewer labelled instances, according to several studies. To correct imbalance and improve generalization, data augmentations (rotations, flips, color jitter, CLAHE) and synthetic sample generation (GANs, SMOTE-like oversampling) are frequently employed. Even when trained with subsets of labels, the refined ResNet50 study you supplied shows strong label efficiency—maintaining respectable accuracy

4. Challenges

Despite quick progress, machine learning and deep learning-based diabetic retinopathy (DR) detection still face a number of significant obstacles. The primary problem, particularly for early-stage and proliferative DR, is the scarcity of high-quality, annotated datasets, which causes significant class imbalance and skewed model predictions. In real-world clinical settings, domain shifts caused by variations in fundus picture quality, light, noise, and heterogeneous imaging devices greatly impair model stability and generalization. When trained on tiny datasets, deep learning models frequently experience overfitting and demand a significant amount of processing power. Furthermore, a lot of deep models function as "black boxes", which are difficult to understand and don't reveal which retinal characteristics influence the classification choice. This lack of openness hinders regulatory approval and erodes clinician trust. Furthermore, the comparability of study results is restricted by inconsistent grading criteria (ICDR, ETDRS, national screening guidelines). When combined, these obstacles prevent the widespread use of automated DR screening systems.

5. Research Gap

Despite significant advancements in automated DR detection, there are still a number of unanswered research questions. The lack of standardized, multi-Centre datasets that reflect a variety of demographics, camera types, and imaging settings represents a significant gap. As a result, models that do well on controlled datasets, such as APTOS and Eyepatch, are unable to generalize in actual clinical settings. The creation of explainable and clinically interpretable models is hampered by the absence of lesion-level annotation, which is another significant gap.

Conclusion

In summary, the application of deep learning, transfer learning, hybrid architectures, ensemble models, and attention mechanisms has significantly advanced automated diabetic retinopathy detection, exhibiting great accuracy across several benchmark datasets. Early DR screening has demonstrated great promise for models like ResNet50, DenseNet121, Efficient Net, CBAM-enhanced networks, and ensemble stacking techniques. However, limitations, including dataset imbalances, poor generalization across devices, limited interpretability, and a lack of real-world validation, continue to constrain widespread adoption. Standardized datasets, explainable and clinically interpretable models, training frameworks

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that protect privacy, and comprehensive prospective assessments are all necessary to address these issues. The incorporation of reliable, scalable DR screening systems into healthcare can significantly improve patient outcomes and prevent blindness with ongoing advances in AI and medical imaging, particularly in underprivileged areas with limited access to ophthalmologists.

Future Purpose

In order to increase model reliability, future automated DR detection research can concentrate on creating bigger, more varied datasets with consistent grading. Clinical integration will be supported and clinician trust will be reinforced by explainable AI techniques like Grad-CAM and attention mapping. Advanced architectures, such as multi-branch networks, hybrid CNN-Transformer models, and Vision Transformers, can improve lesion detection and comprehension of the global environment. Hospitals will be able to jointly train models while maintaining patient privacy thanks to federated learning. In low-resource environments, real-time screening can be supported by lightweight models tailored for mobile devices.
In order to provide a more thorough evaluation of the retina, future systems might also use multimodal techniques that integrate fundus photos, OCT scans, and clinical data.

References

[1]. A. Ahmad, A. B. Mansoor, R. Mumtaz, M. Khan, and S. H. Mirza, “Image processing and classification in diabetic retinopathy: A review,” in 2014 5th European Workshop on Visual Information Processing (EUVIP), Paris, France: IEEE, Dec. 2014, pp. 1–6. doi: 10.1109/EUVIP.2014.7018362.

[2]. K. Ahmed Al-Tayeb, A. Jarndal, H. Dahrouj, and K. Dautov, “Diabetic Retinopathy Detection Through Smartphonebased Retinal Imaging Approach: A Brief Review,” in 2024 Advances in Science and Engineering Technology International Conferences (ASET), Abu Dhabi, United Arab Emirates: IEEE, June 2024, pp. 1–5. doi: 10.1109/ASET60340.2024.10708654.

[3]. M. Al-Farouni, B. Panduri, M. A. Alkhafaij, R. Rana Veer Samara Sihman Bharattej, and Y. Chanti, “Comparative Approach on Machine Learning and Deep Learning Techniques based Diabetic Retinopathy Detection,” in 2024 Second International Conference on Networks, Multimedia and Information Technology (NMITCON), Bengaluru, India: IEEE, Aug. 2024, pp. 1–5. doi: 10.1109/NMITCON62075.2024.10698758.

[4]. K. Mannanuddin, L. Dhavamani, V. Selvakumar, B. R. Praveen, T. G. Sakthivel, and P. Saranya, “An Ensemble Learning Approach Towards Prediction of Diabetic Retinopathy,” in2023 Seventh International Conference on Image Information Processing (ICIIP), Solan, India: IEEE, Nov. 2023, pp. 464–468.doi:10.1109/ ICIIP61524. 2023. 10537626.

[5]. S. G. Siddarth and S. Chokkalingam, “DenseNet 121 Framework For Automatic Feature Extraction Of Diabetic Retinopathy Images,” in 2024 International Conference on Emerging Systems and Intelligent Computing (ESIC), Bhubaneswar, India: IEEE, Feb. 2024, pp. 338–342. doi: 10.1109/ ESIC60604. 2024. 10481664.

[6]. S. Sumadithya, F. N. Latheef, M. Sameer, and R. M. Lincy G, “Detecting Diabetic Retinopathy Using Deep Learning Techniques,” in 2023 3rd International Conference on Intelligent Technologies (CONIT), Hubli, India: IEEE, June 2023, pp. 1–6. doi: 10.1109/ CONIT59222.2 023. 10205793.

[7]. D. M. Kotambkar and P. M. Wankhede, “Cascaded Learning Approach for Evaluating Diabetic Retinopathy Severity,” in 2023 OITS International Conference on Information Technology (OCIT), Raipur, India: IEEE, Dec. 2023, pp. 254–259. doi: 10.1109/ OCIT59427. 2023.10430987.

[8]. M. Mangal, S. Pandey, S. Parit, D. Pawar, and D. Vekhande, “Design and Development of Diabetic Retinopathy by Using Convolutional Neural Network Classifier,” in 2024 International Conference on Advances in Computing Research on Science Engineering and Technology (ACROSET), Indore, India:

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https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2025.0637

IEEE, Sept. 2024, pp. 1–7. doi: 10.1109/ACROSET62108.2024.10743682.

[9]. K. Arunasakthi, S. S, A. T S S, S. P, R. A P S, and V. Akilandeswari, "EfficientNet-based Deep Learning Framework for Early Detection of Diabetic Retinopathy in Retinal Fundus Images," in 2025 5th International Conference on Pervasive Computing and Social Networking (ICPCSN), Salem, India: IEEE, May 2025, pp. 1173–1179. doi: 10.1109/ ICPCSN65854.2025.11035600.

[10]. S. Dasari, Boo. Poonguzhali, and M. Rayudu, "Transfer Learning Approach for Classification of Diabetic Retinopathy using Fine-Tuned ResNet50 Deep Learning Model," in 2023 International Conference on Sustainable Communication Networks and Application (ICSCNA), Theni, India: IEEE, Nov. 2023, pp. 1361–1367. doi: 10.1109/ ICSCNA58489.2023.10370255.

[11]. A. Tibari and M. Ridouani, "The Combination Between Deep Learning and Ensemble Stacking for a Fast and Accurate Detection of Diabetic Retinopathy Using Fundus Images," in 2024 Sixth International Conference on Intelligent Computing in Data Sciences (ICDS), Marrakech, Morocco: IEEE, Oct. 2024, pp. 1–7. doi: 10.1109 /ICDS62089. 2024.10756405.

[12]. H. Vohra et al., "A Low-Cost AI-Powered System for Early Detection of Diabetic Retinopathy and Ocular Diseases in Resource Limited Settings," IEEE Access, vol. 13, pp. 97322–97336, 2025, doi: 10.1109/ ACCESS. 2025.3572471.

[13]. S. Hossain and A. B. M. A. Hossain, "Improving Diabetic Retinopathy Classification by Employing Convolutional Block Attention Mechanism in Modified InceptionV3 Model," in 2024 IEEE International Women in Engineering (WIE) Conference on Electrical and Computer Engineering (WIECON-ECE), Chennai, India: IEEE, Dec. 2024, pp. 427–431. doi: 10.1109/WIECON-ECE64149.2024.10914921.

[14]. N. K. Romeo, M. Chhabra, and S. Chaturvedi, "Eye Disease Detection and Classification using Deep Learning: A Review," in 2025 International Conference on Cognitive Computing in Engineering, Communications, Sciences and Biomedical Health Informatics (IC3ECSBHI), Greater Noida, India: IEEE, Jan. 2025, pp. 313–318. doi: 10.1109/ IC3ECSBHI63591.2025.10991328.