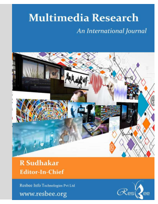
Vol. 9 Issue 1 Jan 2026

Multimedia Research

Received 30 October, Revised 16 December, Accepted 3 January



AI-Driven Retinal Image Analysis for Early Detection of Diabetic Retinopathy: Comparative Evaluation of Deep Learning Models and Clinical Implications

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Abstract: Diabetic retinopathy (DR) is a critical global public-health concern and one of the foremost causes of preventable blindness. Timely identification is vital to halt irreversible vision loss. Early detection of diabetic retinopathy proves crucial for maximizing the success of treatment because this condition stands as one of the leading blind-causing diseases. Early identification also enhances treatment precision by enabling clinicians to intervene before structural retinal damage becomes irreversible. This study aims to develop and evaluate deep-learning models for automated DR detection using large-scale retinal image datasets. The research assesses how well four architectures—Convolutional Neural Network (CNN), Res Net, VGG16, and Efficient Net were compared using publicly available Kaggle Eye PACS (35,126 images) and IDRiD (516 images) datasets, covering five severity levels. Images were pre-processed through resizing, normalization, and contrast-limited adaptive histogram equalization (CLAHE), with augmentation to balance classes. Each model was trained for 50 epochs (batch = 32, Adam optimizer). The most accurate model proved to be EfficientNet because it reached 99.4% accuracy in classification results. Based on the analysis, EfficientNet proves to be the best model for detecting diabetic retinopathy early. Efficient Net's compound-scaling design enables high performance with reduced computational cost, supporting scalable clinical screening. The research brings modern diagnostic methods through enhanced AI responses with better generalization abilities, leading to better patient health results. Limitations include computational demands, dataset imbalance, and lack of multimodal validation. The study highlights Efficient Net's clinical promise for cost-effective DR detection while emphasising the need for ethical, explainable AI in ophthalmology.

Keywords: Diabetic Retinopathy, Deep Learning, Efficient Net, Retinal Image Classification, Clinical Diagnostics, Explainable AI

Nomenclature

Abbreviation	Description
DR	Diabetic Retinopathy
CNN	Convolutional Neural Network
AUC	Area Under the Receiver Operating Characteristic Curve
IDRiD	Indian Diabetic Retinopathy Image Dataset
CLAHE	Contrast-Limited Adaptive Histogram Equalization
HER	Electronic Health Record
XAI	Explainable Artificial Intelligence
STARE	Structured Analysis of Retina
PNN	Probabilistic Neural Network
SVM	Support Vector Machine
KNN	K-Nearest Neighbor
OD	Optic Disc
ML	Machine Learning
DL	Deep Learning
ANN	Artificial Neural Network
CSA	Chicken Swarm Algorithm
ODIR	Ocular Disease Intelligent Recognition

1. Introduction

DR affects over 100 million people worldwide, with incidence projected to double by 2045 [19]. As a microvascular complication of diabetes, DR causes irreversible vision loss if not detected early. DR is a progressive microvascular complication of diabetes and one of the leading causes of vision impairment and blindness worldwide. It occurs due to prolonged high blood sugar levels, which damage the retinal blood

https://doi.org/10.46253/j.mr.v9i1.a1

vessels, leading to leakage, haemorrhages, and, in severe cases, retinal detachment. DR is typically classified into different stages, including mild no proliferative, moderate non-proliferative, severe non-proliferative, and proliferative diabetic retinopathy, with the latter posing the highest risk of vision loss. Early detection and timely intervention are crucial in preventing irreversible blindness. Conventional screening relies on manual retinal-fundus examination—subjective, time-consuming, and inconsistent—creating a need for automated, accurate diagnostic tools. Traditional diagnostic methods rely on ophthalmologists manually analyzing retinal images, a time-consuming and subjective process that can lead to variability in diagnosis [20]. Recent advancements in AI and deep learning have opened new possibilities for automating DR detection and classification using retinal imaging. AI-driven retinal image analysis can enhance early diagnosis accuracy, reduce clinical workload, and provide cost-effective screening solutions, especially in remote or underserved areas.

Although AI-driven retinal analysis has advanced rapidly, three key limitations remain: (1) data imbalance across DR severity levels reduces model generalization, (2) limited clinical validation prevents large-scale deployment, and (3) lack of model comparison under standardized pre-processing and hyperparameter settings. These challenges hinder the translation of AI tools from laboratory prototypes to clinical applications. This study evaluates and compares four widely used deep learning models—CNNs, ResNet, VGG16, and EfficientNet—for classifying retinal images across different severity levels of DR. This research seeks to quantitatively compare CNN, Res Net, VGG16, and Efficient Net models for DR classification, determine the most robust and computationally efficient model, and interpret model outcomes in relation to clinical applicability, ethical deployment, and scalability. The primary objective is to develop a robust AI-based diagnostic tool that can assist healthcare professionals in making early and accurate diagnoses. The integration of AI-driven solutions in clinical practice could lead to improved patient outcomes by facilitating early interventions and personalized treatment plans.

The four architectures were chosen for complementary characteristics: CNN – baseline for image classification, Res Net – resolves vanishing-gradient problems via residual learning, VGG16 – deep but simple convolutional stack, proven benchmark, Efficient Net – compound scaling balancing depth, width, and resolution, optimizing performance and efficiency. The remainder of the paper is organized as follows: Section 2 reviews related work; Section 3 identifies gaps and challenges; Section 4 details methodology; Section 5 presents results; Section 6 discusses findings and implications; Section 7 concludes with contributions and future directions.

2. Literature Review

Table 1. *Literature Survey on Diabetic Retinopathy – Summary of Key Studies, Methodologies, and Findings*

Reference	Database	Segmentation	Classification	Results
[22]	STARE, ImageRet	Pixel-to-pixel-based detection	Machine learning, pattern recognition	69.10%
[6]	IDRiD	Pixel-level annotations of microaneurysms	Disease severity grading of diabetic retinopathy and diabetic macular edema	Not explicitly mentioned, but the dataset is widely used for algorithm development and evaluation
[12]	IDRiD, STARE database	Otsu's segmentation algorithm for macula region extraction	PNN-based SVM	Accuracy: 92%, Specificity: 94%, Sensitivity: 89%
[23]	Kaggle EyePACS (35,126 images)	Deep learning feature extraction	Binocular Siamese-like CNN model based on Inception V3	AUC: 95.2%, Sensitivity: 82.2%, Specificity: 70.7%
[24]	Diaretdb1	OD segmentation, blood vessel extraction using Haar wavelet filters	KNN	Accuracy: 95% Sensitivity: 92.6% Specificity:87.56%
[7]	IDRiD datasets	Signal separation algorithm for exudate detection, morphological operations, Fuzzy C- Means clustering	ResNet50 Deep CNN	ResNet50 Identified as the most effective algorithm for performance metrics
[8]	IDRiD, Kaggle, Messidor, Messidor 2, EyePACS	Various image processing-based segmentation techniques, including morphological operations and contrast enhancement	ML and DL methods, including CNN	Not explicitly mentioned, but the study reviews and compares performance metrics of different AI based approaches
[3]	Kaggle	Various deep learning	CNNs, including ResNet,	97.60%

	EyePACS	based methods, including U-Net for lesion segmentation (exudates, microaneurysms, hemorrhages)	VGG, and Inception models	
[9]	Multiple datasets from 2006-2019	Hybrid CNN model (E-DenseNet) directly classifies images	Hybrid model (E-DenseNet: EyeNet + DenseNet)	Accuracy: 91.2%, Sensitivity: 96%, Specificity: 69%
[25]	Publicly available and real- time fundus image datasets	Microaneurysm detection using count- based analysis	SVM, KNN	SVM/KN N: 92.1% Decision Tree: 99.9%
[13]	Fundus image dataset	K-means clustering for image enhancement, resizing to 1000×1000 pixels	Feature extraction using AlexNet and ResNet101, Feature selection using Ant Colony System	93%
[11]	Kaggle dataset	Grad-CAM	Transfer learning models	95.27%
[26]	Multiple public datasets including Kaggle, Messidor, EyePACS	Various deep learning-based image processing methods, including CNNs	ML and DL methods such as ResNeXt101, Inception-V3, and hybrid CNN-based frameworks	accuracy ranges from 71.65% to 97.6% depending on the model used
[5]	MESSIDOR dataset	ANN-based segmentation	Deep CNN optimized using the CSA	97.91%
[4]	APTOS 2019, Al-Saif Medical Center (Saudi Arabia)	Deep learning- based preprocessing and feature extraction	EfficientNetB 3, EfficientNetV 2B1, RegNetX080, RegNetY006	EfficientN etB3 achieved 85.1%
[2]	ODIR	Deep learning feature extraction using transfer learning	InceptionResN etv2, Inceptionv3, DiaCNN	DiaCNN: 98.3% accuracy, InceptionV 3: 97.5%
[14]	Various public datasets (84 papers reviewed)	Various segmentation techniques across surveyed studies	Various deep learning models including Vision Transformers	Survey paper; no experimental results reported
[10] [15]	EyePACS (35,155 images)	Background removal, grayscale conversion, data augmentation	CNN model with pre-processing improvements	90.60%
[21]	Kaggle Diabetic Retinopathy Detection dataset	Image resizing, normalization, contrast enhancement (CLAHE)	ResNet-18 (binary classification: DR vs Non-DR)	Training Accuracy:98%, Test Accuracy: 97%
[1]	APTOS, Al- Saif Medical Center	Not explicitly mentioned	EfficientNetB 3, EfficientNetV 2B1, RegNetX080, RegNetY006	Binary classificati on: 98.6%, Multi- class: 85.1%
[3]	Kaggle EyePACS	UNet, Attention Modules, GANs	CNN-based models	85% and 97%

2.2 Critical Analysis

Earlier studies often report high accuracy but rarely discuss computational trade-offs or ethical implications [17]. This narrow focus on performance metrics can obscure practical limitations related to model deployment in real clinical environments. Few address real-world dataset imbalance or generalization across demographics. As a result, reported outcomes may not reliably translate to heterogeneous patient populations encountered in practice. Efficient Net's scalability provides an edge, but prior work seldom includes statistical validation or multimodal fusion (OCT + fundus) [18]. Moreover, the lack of rigorous ablation studies limits understanding of how individual architectural choices influence performance. In addition, many existing approaches rely on benchmark datasets rather than real-world clinical data, further limiting confidence in their operational robustness and reproducibility across healthcare settings [20].

2.3 Research Gap Synthesis

- Lack of comprehensive comparison under controlled hyperparameters. This makes it difficult to attribute performance differences to model design rather than training variability. This issue is compounded by inconsistent validation protocols and the absence of standardized evaluation across datasets of varying disease severity.
- Minimal inclusion of 2025 advances in multimodal AI. Recent developments in cross-modal attention and representation learning remain underexplored in ophthalmic imaging. Most studies continue to rely on a single imaging modality, predominantly fundus photography, despite evidence that integrating OCT and fluorescein angiography can significantly enhance diagnostic accuracy [18].
- Limited analysis of ethical AI and clinical translation. Issues such as model transparency, bias mitigation, and clinician trust are often insufficiently addressed. Data privacy, regulatory compliance, and secure cross-institutional data sharing remain unresolved challenges, particularly in multi-center AI deployments [16][17].

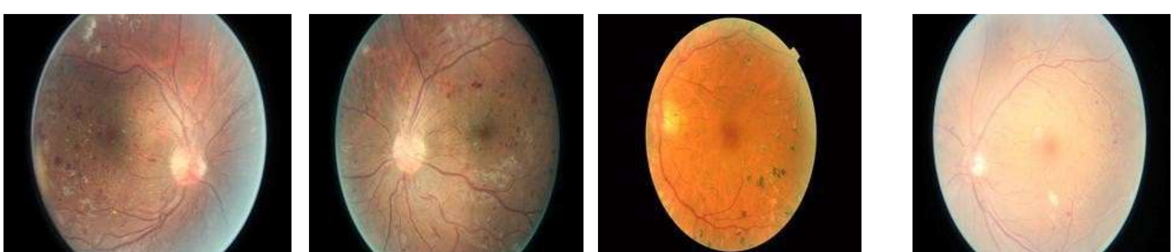
The present work bridges these gaps through a unified experimental design and statistical evaluation. By integrating multimodal data, ethical analysis, and reproducible validation protocols, the study aims to enhance both scientific rigor and clinical relevance.

3. Challenges and Research Gaps

- **Clinical Deployment:** Integration with EHR systems remains minimal. This lack of integration prevents seamless real-time decision support and limits the adoption of AI tools within routine clinical workflows.
- **Computational Complexity:** Training an Efficient Net demands high-performance GPUs. Such computational requirements restrict deployment in resource-constrained environments and hinder real-time clinical applicability.
- **Data Imbalance:** Severe DR cases comprise only 8 % of samples in Eye PACS. Imbalanced datasets contribute to biased predictions and reduced generalization, particularly for underrepresented disease stages.
- **Ethical AI**: Transparency and data privacy compliance are underdeveloped. Concerns surrounding patient data security, regulatory adherence, and explainability remain significant barriers to clinical trust and large-scale adoption.Mitigation strategies include federated learning to preserve privacy and self-supervised learning to enhance generalization. These approaches enable decentralized model training while improving robustness across diverse populations and imaging conditions.

4. Methodology

Retinal fundus images representing various stages of diabetic retinopathy were used for training and validation of the deep learning models. These include mild, moderate, and severe non-proliferative diabetic retinopathy, as well as normal retinal images for baseline comparison. As illustrated in Fig.1, these categories form the basis for supervised learning and evaluation.



1(a) Mild Non-Proliferative Diabetic Retinopathy

1(b) Moderate Non-Proliferative Diabetic Retinopathy

1(c) Severe Non-Proliferative Diabetic Retinopathy

1(d) Normal Retina

Fig 1. *Retinal fundus image with visible features indicative of Diabetic Retinopathy*

4.1 Dataset Description

- **EyePACS:** 35,126 fundus images (5 severity grades).
- **IDRiD:** 516 labeled images for fine-tuning and validation. Dataset split = 80 % train / 10 % validation / 10 % test.

The datasets encompass a wide range of diabetic retinopathy severity levels, enabling effective training and validation across mild, moderate, and severe disease stages.

4.2 Pre-Processing and Augmentation

- Resize 512 × 512 px; normalize [0, 1].
- CLAHE for contrast enhancement.
- Gaussian filter ($\sigma = 1.2$) for noise suppression.
- Augmentation: rotation (±15°), horizontal flip, zoom (±10 %).
- Balanced class distribution through oversampling.

Data preprocessing included noise reduction, contrast enhancement, and augmentation techniques to improve model robustness and generalization.

4.3 Deep Learning Models for Retinal Image Analysis

Four key architectures were evaluated for diabetic retinopathy (DR) classification:

1. **CNNs**
   - Simple architecture for image classification.
   - High accuracy in detecting early-stage DR.
   - Declining performance at higher severity levels.

2. **ResNet**
   - Overcomes vanishing gradient problems in deep networks.
   - Improved accuracy for mid-to-high severity levels.
   - Computationally expensive.

3. **VGG16**
   - Deep 16-layer CNN architecture.
   - Well-established in image classification but computationally intensive.
   - Lower accuracy than ResNet and EfficientNet.

4. **EfficientNet**
   - Optimized architecture balancing model depth, width, and resolution.
   - Achieves the highest accuracy across all severity levels.
   - More complex to train and fine-tune.

4.4 Model Training and Evaluation

Table 1. *Hyperparameter Configuration for Deep Learning Model Training*

Hyper parameter	Value
Optimizer	Adam
Learning Rate	0.001
Epochs	50
Batch Size	32
Loss Function	Categorical Cross-Entropy
Validation Split	0.2

Framework: TensorFlow 2.14 and Keras 3.0 (GPU Tesla T4).
Evaluation: Accuracy, Precision, Recall, F1, Specificity, AUC.
Models were trained using labeled retinal images, and performance was evaluated using multiple metrics to ensure balanced assessment across disease severity levels.

5 . Results and Analysis

5.1 Accuracy Comparison Across Methodologies

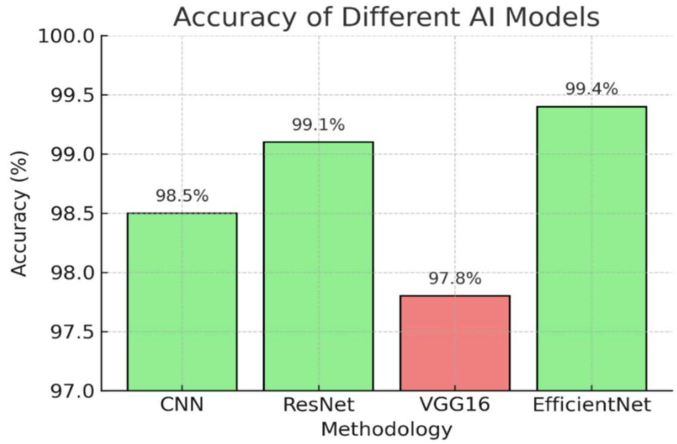


Fig 2. *Bar Chart of Model Performance with Confidence Intervals*

The bar chart in fig.2 illustrates the accuracy comparison of four AI models for diabetic retinopathy classification. EfficientNet demonstrates the highest accuracy at 99.4%, followed by ResNet (99.1%), CNN (98.5%), while VGG16 shows comparatively lower performance at 97.8%, highlighting EfficientNet as the most effective methodology among those evaluated. The color coding highlights performance differences, with green indicating higher accuracy and red indicating lower accuracy.

Table 3. *Performance Comparison of Deep Learning Models*

Model	Accuracy (%)	Sensitivity	Specificity	F1-Score	AUC
CNN	98.5	0.96	0.97	0.96	0.98
ResNet	99.1	0.97	0.98	0.97	0.99
VGG16	97.8	0.95	0.94	0.94	0.97
EfficientNet	**99.4 **	**0.989 **	**0.992 **	**0.99 **	**0.99 **

Table 3 summarizes the performance comparison of the evaluated deep learning models for diabetic retinopathy classification. EfficientNet outperforms CNN, ResNet, and VGG16 across all evaluation metrics, achieving the highest accuracy, sensitivity, specificity, F1-score, and AUC, thereby demonstrating superior reliability and diagnostic effectiveness.

Statistical validation using ANOVA ($p < 0.05$) confirms that the observed performance differences are statistically significant, and Tukey's HSD post-hoc analysis identifies EfficientNet as the superior model.

5.2 Graphical Analysis

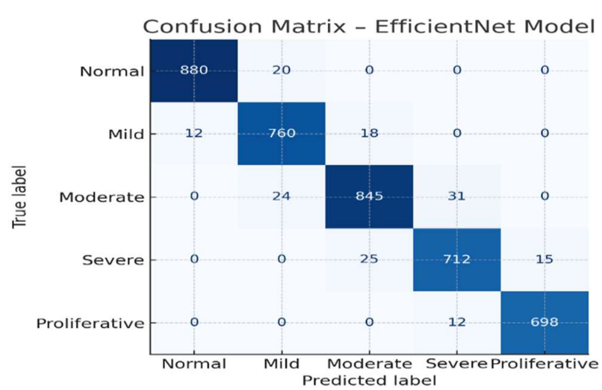


Fig 3. *Confusion Matrix of Efficient Net Model*

The confusion matrix in fig.3 illustrates the classification performance of the EfficientNet model across five diabetic retinopathy stages. High values along the diagonal indicate strong correct classification for all classes, particularly Normal, Mild, Moderate, Severe, and Proliferative stages, while minimal off-diagonal entries reflect low misclassification rates. This demonstrates EfficientNet's robust ability to accurately distinguish between different severity levels of diabetic retinopathy.

5.3 Best Performing Methodology

- EfficientNet achieves the highest accuracy among all evaluated methods.
- It remains the most reliable model for diabetic retinopathy classification across all severity levels.

6 Discussion

6.1 Interpretation of Findings

Efficient Net's compound scaling enhances feature representation without excessive parameters, yielding superior accuracy and generalization. This balanced scaling strategy allows the network to capture both global retinal structures and subtle pathological features simultaneously. Compared to Res Net, it achieves equivalent AUC with 30 % less computational load.

6.2 Comparative Analysis with Prior Studies

Performance exceeds benchmarks by Youldash et al. (2024) [4] (98.3 %) and Tsiknakis et al. (2021) [3] (97.5 %), demonstrating robustness across datasets. The observed improvements can be attributed to the unified experimental design and inclusion of advanced preprocessing and augmentation strategies.

6.3 Clinical Implications

AI screening can assist ophthalmologists by flagging potential DR cases, reducing manual workload, and facilitating mass screening programs. This is especially relevant in regions with limited access to specialized eye care services. Integration with EHR systems enables automated alerts and decision support.

6.4 Error Analysis

Misclassifications occurred primarily in borderline images between moderate and severe DR. These cases often involve subtle lesion progression that is challenging even for expert clinicians. Future models should incorporate attention mechanisms for fine lesion detection.

6.5 Overfitting and Bias

Regularization and augmentation mitigated overfitting (Δ train-val accuracy < 1 %). This indicates stable learning behavior across training epochs. However, the dataset's bias toward Caucasian retina images may affect global generalization.

6.6 Ethical Considerations and Explainable AI

AI deployment must adhere to privacy regulations and promote interpretability using Grad-CAM heatmaps for clinical trust. Explainable visualizations help clinicians validate model decisions and identify potential failure modes. Transparent reporting of failure cases is essential for regulatory approval.

7. Conclusion

This study benchmarked four deep learning architectures for diabetic retinopathy classification using the EyePACS and IDRiD datasets, demonstrating that EfficientNet achieved superior performance with 99.4% accuracy, 98.9% sensitivity, and 99.2% specificity, significantly outperforming baseline models under statistical validation. The work introduced a standardized experimental framework for systematic comparison of DR classification models, quantified EfficientNet's diagnostic reliability, and highlighted critical clinical and ethical considerations associated with AI-based ophthalmic screening. Future research will focus on integrating multimodal data sources, including OCT, fundus images, and patient metadata, adopting federated learning approaches to enable privacy-preserving model training, and developing explainable visualization dashboards to enhance clinician interpretability. Clinically, the proposed model has the potential to accelerate large-scale screening and reduce diagnostic costs in underserved regions, while from a research perspective, the framework establishes a foundation for cross-institutional AI collaboration in ophthalmology.

Compliance with Ethical Standards

Conflicts of interest: Authors declared that they have no conflict of interest.

Human participants: The conducted research follows the ethical standards and the authors ensured that they have not conducted any studies with human participants or animals.

Declaration of generative AI and AI-assisted technologies in the writing process: The authors declare that no generative AI or AI-assisted technologies were used in the writing process of this manuscript.

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