Journal of Computing & Biomedical Informatics
ISSN: 2710 - 1606
Volume 09 Issue 02
2025

Research Article
https://doi.org/10.56979/902/2025

AI-Based Early Detection of Diabetic Retinopathy to Prevent Severe Visual Impairment

Samina Inayat[1*], Hafiz Muhammad Anwaar Ul Haq[1], Sania Shafqat[1], and Khalid Hamid[1]

[1]Department of Computer Science and IT, Superior University Lahore, 54000, Pakistan.
[*]Corresponding Author: Samina Inayat. Email: sammanwaar@gmail.com

Received: June 27, 2025 **Accepted:** August 07, 2025

Abstract: Diabetic retinopathy (DR) is a leading cause of preventable blindness among working-age adults globally, with a significant economic and social burden. Early detection plays a main role in preventing the progress of the disease to advanced stages that cause irreversible vision loss. Traditional screening methods, although effective, are often resource-intensive and time-consuming. This research introduces an AI-powered deep learning approach using Convolutional Neural Networks (CNN) to find and categorize diabetic retinopathy from retinal fundus images with high accuracy and minimal human intervention. The proposed system is trained and validated on a labeled dataset, incorporating advanced preprocessing technique and data augmentation, and the model achieved promising results in binary classification (DR vs. No DR), with robust evaluation through accuracy, recall, precision, F1-score, and ROC-AUC metrics. Results suggest that the developed CNN model can serve as an effective decision-support system for ophthalmologists, especially in under-resourced regions. Furthermore, the methodology can be extended to other retinal diseases and adapted for mobile diagnostic platforms.

Keywords: Diabetic Retinopathy; Deep Learning; Convolutional Neural Networks; Artificial Intelligence

1. Introduction

1.1. Background

Diabetic Retinopathy is one of the most severe complications of diabetes, affecting nearly one-third of the global diabetic population. It arises from prolonged high blood sugar levels that damage retinal blood vessels, swelling, leakage, or abnormal growth of blood vessels in the retina [1]. If not identified and treated early, this condition may result in permanent vision loss or blindness.

According to the World Health Organization, Diabetic Retinopathy is responsible for 4.8% of the 37 million blindness cases globally. Early detection and intervention are vital in preventing disease progression. However, traditional DR screening methods e.g manual fundus image analysis, angiography, and optical coherence tomography require specialized equipment and expert ophthalmologists—both of which are scarce in many developing countries. Consequently, a large segment of the diabetic population remains undiagnosed until irreversible damage has occurred.

1.2. Problem Statement

Despite advancements in medical imaging and clinical diagnostics, timely screening of diabetic retinopathy remains a challenge due to scarcity of trained ophthalmologists, the high cost of advanced diagnostic equipment, and the logistical challenges of regular screenings in remote or under-resourced settings. These limitations necessitate the development of an automated, intelligent, and scalable solution to assist in early-stage diagnosis and reduce the burden on healthcare systems.

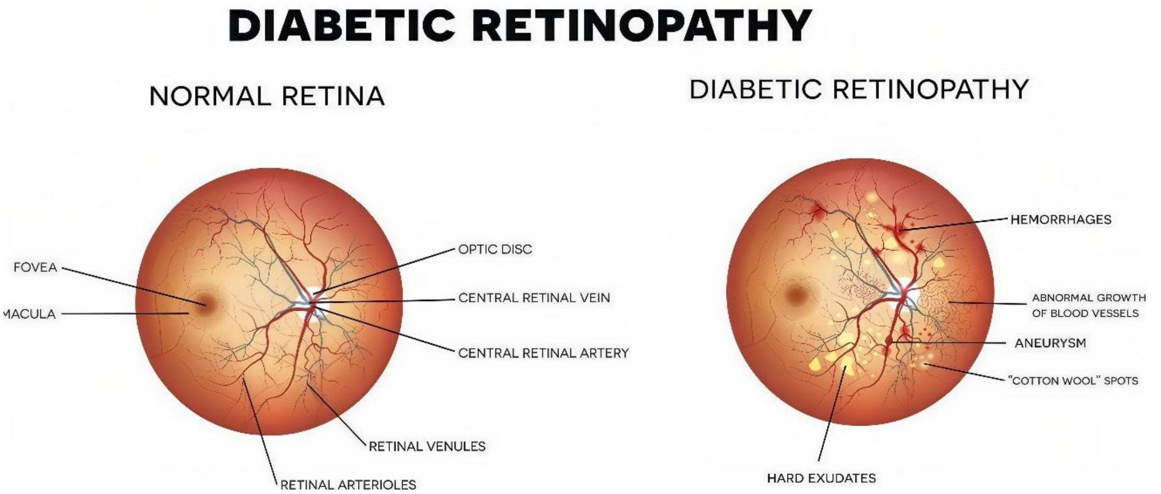

Figure 1. Diabetic Retinopathy

1.3. Role of Artificial Intelligence in DR Detection

Artificial Intelligence (AI), and more specifically deep learning, has arisen as a transformative tool in medical diagnostics. Among various architectures, Convolutional Neural Networks (CNNs) have superior performance in image classification tasks, including detecting retinal diseases [2]. CNNs are accomplished of learning spatial hierarchies of features directly from the data, removing the need for manual feature extraction. In this study, a CNN-based model is developed to classify retinal images into Diabetic Retinopathy and non-Diabetic Retinopathy categories. The model utilizes advanced data preprocessing, augmentation, and an optimized training pipeline using Binary Cross Entropy as Adam and the loss function as optimizer. Its performance is assessed using a set of evaluation metrics to determine its clinical applicability. While existing models have shown promise, many suffer from issues related to low accuracy in early-stage detection, lack of robustness to diverse datasets, or reliance on complex architectures. Our study addresses these limitations by proposing a novel convolutional neural network (CNN) architecture designed for high-accuracy binary classification of diabetic retinopathy on a large, publicly available dataset.

The objective of this experiment is to find out the advancement of a deep neural network-based early detection system for diabetic retinopathy through convolutional neural networks (CNNs). The system is trained using the public retinal fundus image datasets, and the end goal is to classify the different stages of DR from the absence of Diabetic Retinopathy to proliferative Diabetic Retinopathy. The proposed model basically works on CNN architecture, which efficiently extracts the spatial Artificial Intelligence (AI)". Importantly, deep learning has shown enormous promise in the dispensation of medical images, even ophthalmic imaging [3]. The use of Convolutional Neural Networks (CNNs) has started showing success at detecting and classifying diabetes retinopathy stages with retinal fundus images with high accuracy. However, deep learning models are able to reduce the amount of human intervention by training on large data sets to learn complex patterns and features that can be quite subtle for human experts to discern.

Using AI aims to improve not only the Speed and accuracy of DR detection but also to build a more practical implementation that aids in early intervention strategies geared toward preventing diabetic patients from going into severe visual impairment.

2. Literature review

Diabetic Retinopathy remains an important cause loss of vision globally, necessitating early detection to prevent permanent damage and improve patient outcomes. Traditional screening methods, such as dilated eye examinations and fundus photography, face inherent limits including the need for time-intensive nature, trained personnel and specialized equipment leading to suboptimal screening rates, particularly in resource-limited settings [4]

Artificial intelligence offers a transformative opportunity to overcome these barriers, enhancing both the efficiency of ongoing care management and accuracy of screening Recent advancements, particularly in deep learning (DL) and convolutional neural networks (CNNs), this system provides a low-cost solution, its performance metrics are based on a smaller dataset. AI systems examine retinal images with expert-level accuracy for detection and grading. Studies demonstrate high performance, with AI models achieving sensitivity ranging from 83.3% to 100% and specificity from 85% to 92.5% in detecting referable DR or more than mild DR [5]. FDA-approved systems like IDx-DR (LumineticsCore) and EyeArt exemplify this progress.

The integration of AI significantly improves accessibility and efficiency by enabling screenings in primary care, remote locations, and even via smartphone-based cameras, thereby reducing the burden on healthcare providers and systems. However, challenges persist, including ensuring generalizability across various populations, standard image acquisition, and enhancing the interpretability of AI models through techniques like Explainable AI (XAI) to build clinician trust. Continued research and validation are crucial to optimize AI application ensure its supportable influence on public health.

Table 1. Comparative Analysis of AI-Driven Approaches for Diabetic Retinopathy Detection

Paper/Authors (Year)	**Study Type/ Objective**	**AI Techniques Used**	**Dataset(s) Used**	**Key Findings/ Performance Metrics (for DR)**	**Limitations/ Challenges**
Sacchini et al. (2025)	Systematic Review focusing on AI in Diabetic Retinopathy screening in Type 1 Diabetes (T1D).	AI (general), Autonomous AI, ML, DL (Inception-V3, DenseNet-121, VGG16, Xception)	8 studies, 2,717 participants (1,470 with T1D)	AI enhances DR screening in T1D, rapid analysis, positive provider feedback.	No European studies; temporal filter to 5 years
Wolf et al. (2024)	RCT on AI's effect on DR screening participation in youth with T1D.	Autonomous AI system	EG: 81 (T1D=59), CG: 82 (T1D=12)	85.7% sensitivity, 79.3% specificity; 30.1% increased adherence.	Limited to T1D youth
Alsadoun et al. (2024)	Narrative Review on AI-enhanced DR detection from fundus images.	AI (general)	Not applicable	Discusses technologies, benefits, and clinical adoption challenges.	Review only; no new data
Low-Cost AI System (Undated)	Proposed system for DR detection	Custom CNN (3.5M params), Transfer	Undisclosed	98.2% DR accuracy, edge-cloud	AlexNet slightly better for Glaucoma

	in low-resource settings.	Learning (MATLAB-Retrained AlexNet)		mode, 70% hardware cost reduction.	
Asif et al. (2025)	Systematic Review on AI evolution/performance for DR detection.	ML (SVM, RF), DL, FL, XAI	EyePACS, Kaggle DR, MESSIDOR, IDRiD, DRIVE, etc.	Fuzzy-SVM: 98% acc, 96% sens, 97% spec. DL AUC > 0.90.	High risk of bias, inadequate reporting
Selvi et al. (2024)	Comprehensive Review on AI for DR diagnosis/classification.	CNNs, U-Net, ResNet50, DITL, etc.	OCTA, EyePACS, MESSIDOR, etc.	DL: 98–99% accuracy, high AUC on various datasets.	Dataset quality, interpretability, generalization issues
Samad et al. (Undated)	Enhancing DR early detection with DL and XAI.	Proposed CNN, Transfer Learning, RNN, SVM	Kaggle Aptos, Messidor2, IDRiD	95.27% accuracy multiclass, 100% binary; robust external testing.	Needs balanced datasets in high-diabetes regions
Zhang et al. (2020)	Real-world multicenter AI-based DR screening in China.	DL five-stage DR classification	47,269 patients; validated on 15,805	83.3% sensitivity, 92.5% specificity; autonomous decision support.	Low-quality image issues in clinics
Qian et al. (2022)	Evaluating AI grading system for DR.	AI-based automated grading	2,766 images	0.965 acc/sens/spec, 0.980 AUC; better PPV/NPV, lower FP/FN.	Not specified
Natarajan et al. (2019)	Offline AI algorithm for DR on smartphone retinal images.	Offline AI	Images from Mumbai dispensaries	100% sensitivity, ~82–88% specificity (varied by quality).	Small sample, no severity grading

Channa et al. (2023)	Policy Model comparing AI vs ECP-based screening.	Autonomous AI vs Eye Care Provider (ECP)	Derived from prevalence and diagnostic data	AI prevents 27,000+ vision loss cases in 5 yrs; higher sensitivity.	Modeling assumptions; not empirically tested
Ting et al. (2019)	Review of AI in DR screening.	DL (AlexNet, VGGNet, Inception-V3/4)	EyePACS-1, Messidor-2, etc.	DL: AUC up to 0.991, 97.5% sensitivity, 93.4% specificity.	Barriers in clinical implementation
Abdalla & Mohanraj (Undated)	Review on AI/ML in DR detection.	DL (CNNs), ML (SVM, RF, LR)	Not applicable	DL more scalable, ML needs pre-extracted features.	Review only
Sobhi et al. (2025)	Review on AI in DR and related diabetes complications.	AI, ML, DL (Sandhu et al.)	OCT/OCTA, 111 patients	98.7% accuracy, 100% sens, 0.981 AUC (Sandhu).	Image quality, labeling cost, bias/privacy issues
Yao et al. (2024)	Overview of AI for DR and DME.	AI, DL	SMART India, smartphone images	AUC ~0.98–0.99; 89% sens, 83% spec on smartphone.	Low resolution in handheld images

3. Methodology

The methodology of this research outlines the complete pipeline used to develop and evaluate a Convolutional Neural Network based system for the early detection of Diabetic Retinopathy from fundus images of retina. This section is broken down into distinct phases, including data preparation, model architecture, training procedure, evaluation metrics, and visual analytics. Every term and process has been explained in detail for clarity and academic completeness.

3.1. Dataset Description

In this study data set used retinal fundus images labeled according to the presence or absence of Diabetic Retinopathy [6]. Each image belongs to one of the following categories:

- Class 0 – Normal
- Class 1 – Diabetic Retinopathy Present (Mild to severe signs of DR)

	image_path	category_encoded
0	/kaggle/input/diagnosis-of-diabetic-retinopath...	0
1	/kaggle/input/diagnosis-of-diabetic-retinopath...	0
2	/kaggle/input/diagnosis-of-diabetic-retinopath...	0
3	/kaggle/input/diagnosis-of-diabetic-retinopath...	0
4	/kaggle/input/diagnosis-of-diabetic-retinopath...	0
...	...	...
2095	/kaggle/input/diagnosis-of-diabetic-retinopath...	1
2096	/kaggle/input/diagnosis-of-diabetic-retinopath...	1
2097	/kaggle/input/diagnosis-of-diabetic-retinopath...	1
2098	/kaggle/input/diagnosis-of-diabetic-retinopath...	1
2099	/kaggle/input/diagnosis-of-diabetic-retinopath...	1

Figure 2. Dataset Image Paths

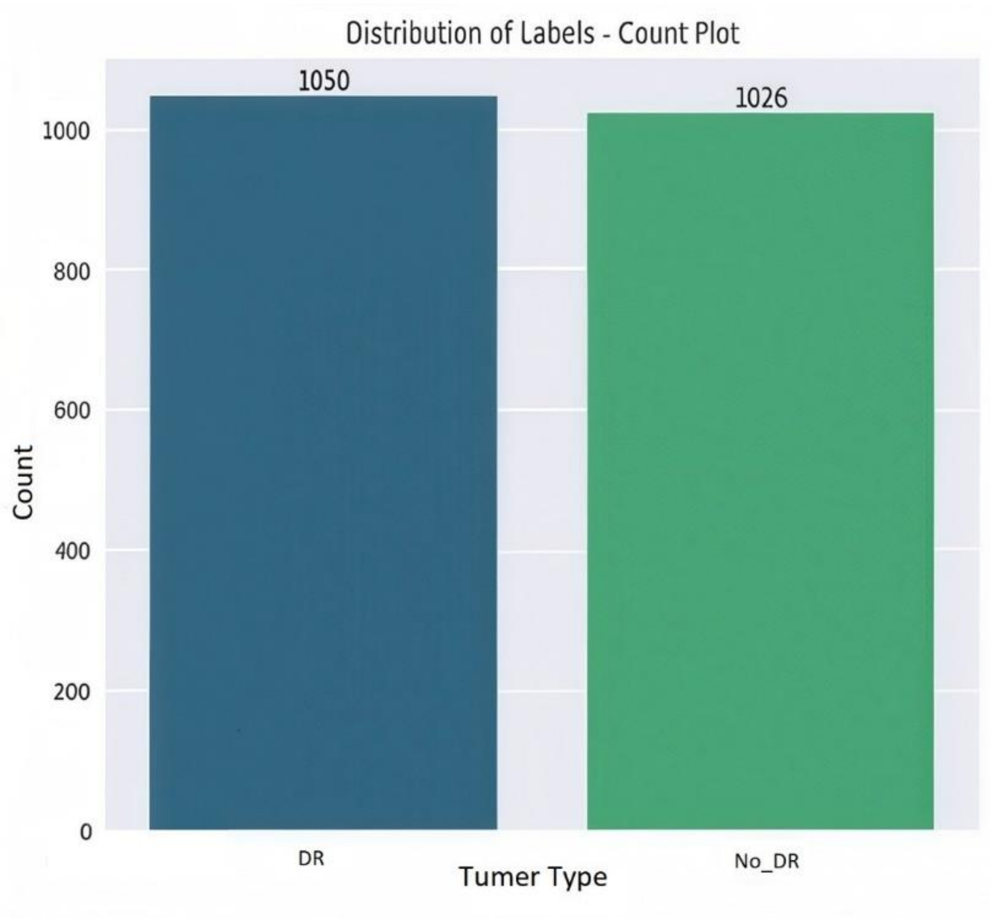

Figure 3. Distribution of Labels

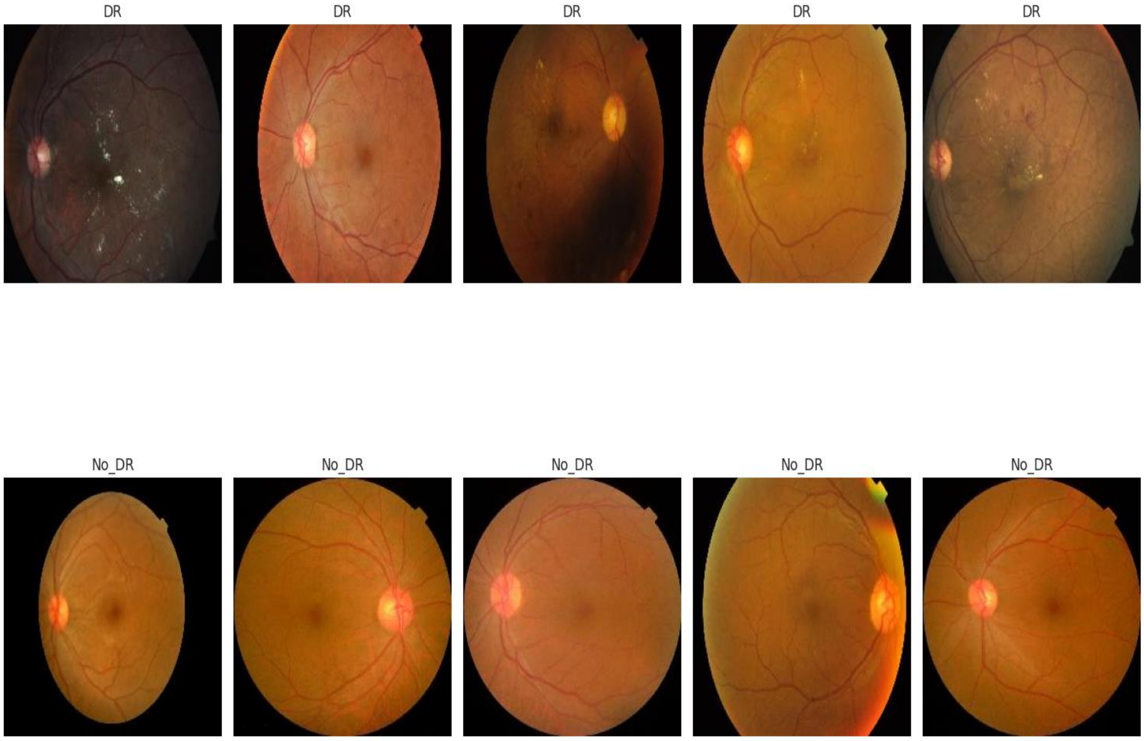

Figure 4. Images side-by-side with 0 1 classification

These labels form the ground truth, serving as the reference usual against the model's predictions are compared during evaluation. The dataset is structured for training and testing subsets to enable both model learning and unbiased performance evaluation.

3.2. Data Preprocessing

Preprocessing is essential to standardize inputs, improve performance, and increase the generalizability of the model. The following steps were applied:

3.2.1. Image Resizing

Retinal images are typically of high and varying resolutions. For uniformity and computational feasibility, all images are resized to 224 × 224 pixels, the standard input size for many CNN architectures.

3.2.2. Normalization

To speed up learning and ensure numerical stability, pixel values were scaled to the range [0, 1] by dividing each pixel by 255. This ensures that all input data is on the same scale.

3.2.3. Data Augmentation

Data augmentation reduce overfitting by artificially increase the diversity of the training dataset. Techniques used include:

- Rotation (±15 degrees): Simulates camera angle variability
- Horizontal/Vertical Flipping: Simulates left/right or top/bottom eye capture
- Zooming: Introduces scale variance
- Brightness/Contrast Adjustments

These transformations ensure the model learns robust features invariant to orientation and lighting conditions.

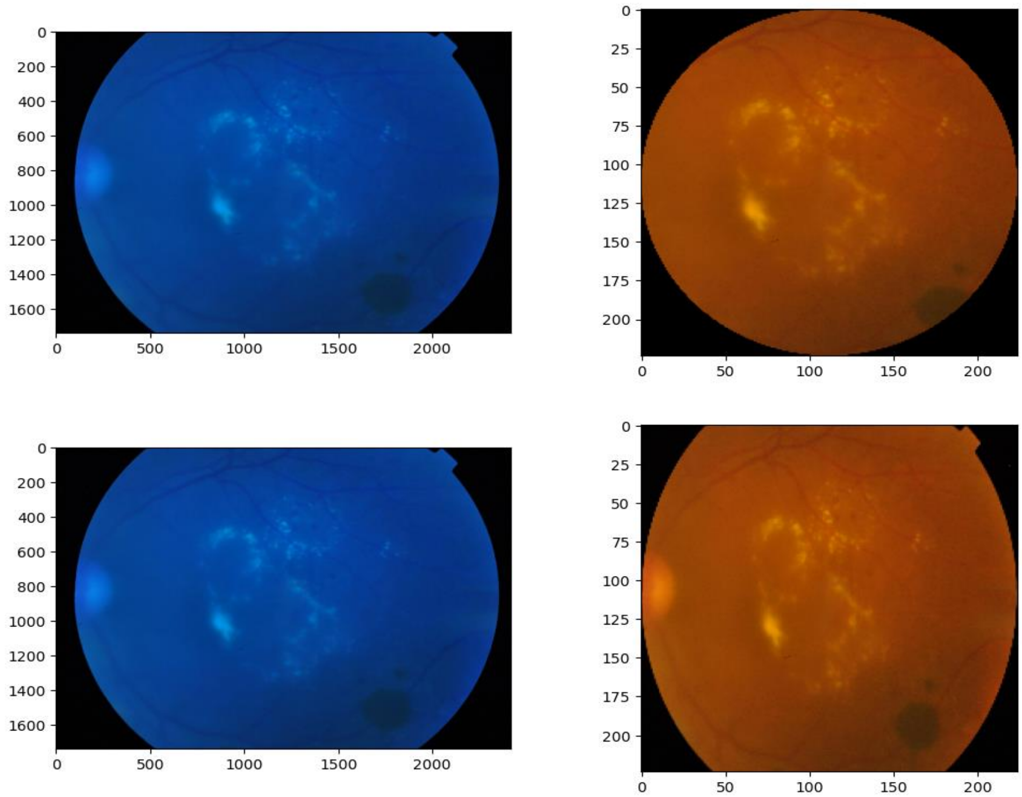

Figure 5. Images resizing

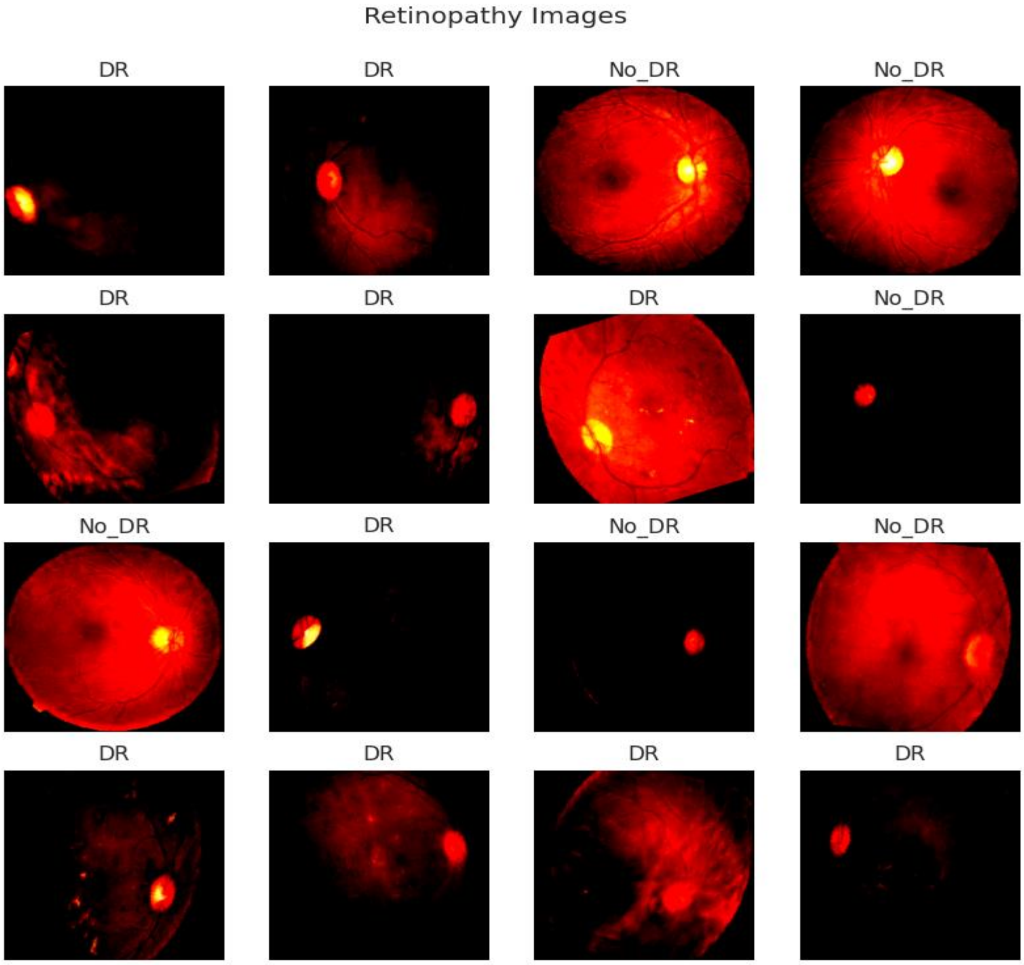

Figure 6. Retinopathy Images

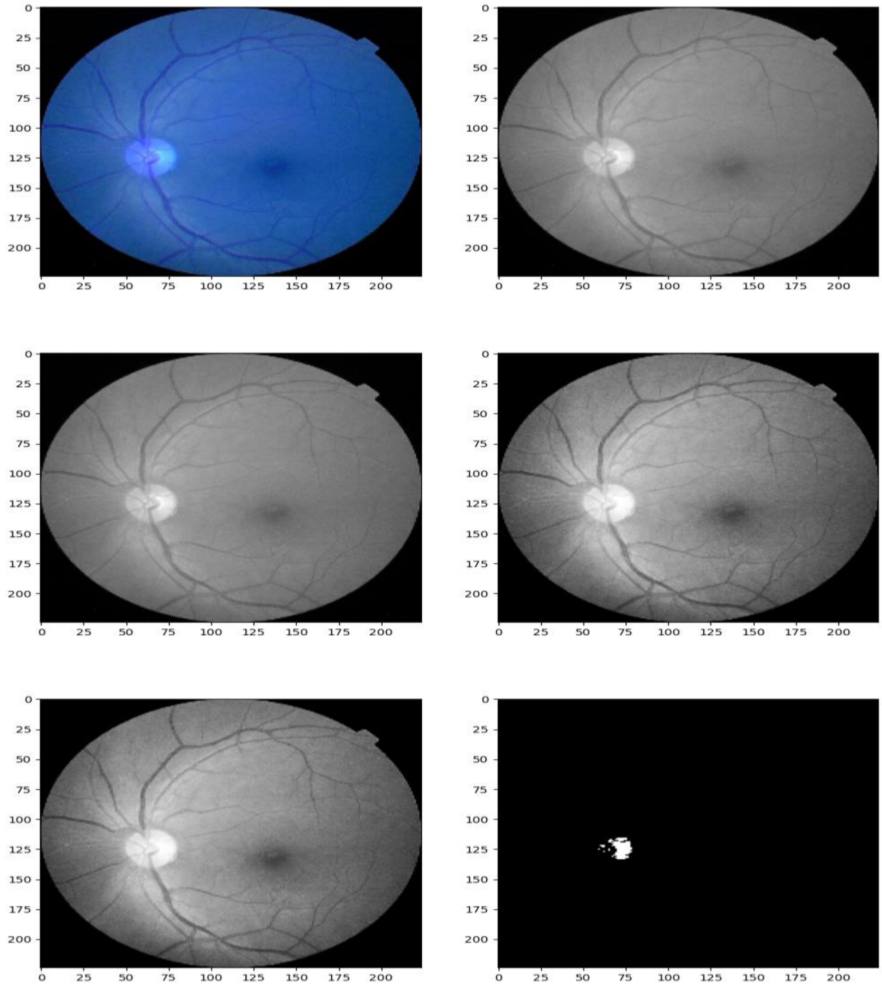

Figure 7. Sample of augmented images side-by-side with original versions.

3.3. Convolutional Neural Network Architecture

CNNs are a specialized class of neural networks designed for visual pattern recognition. Our custom architecture contains many layers, each responsible for extracting and interpreting different levels of features from the input image.

3.3.1. Input Layer

Accepts input of shape 224x224x3, where:

- 224 × 224 = image height and width
- 3 = RGB channels (color image)

3.3.2. Convolutional Layers

Each convolutional layer applies filters (kernels) to extract features such as edges, curves, and textures.

- First Convolutional Layer: 32 filters (3x3), followed by ReLU
- Second Convolutional Layer: 64 filters, deeper texture extraction
- Third Convolutional Layer: 128 filters, complex patterns (e.g., vessels, hemorrhages)

Mathematically, convolution is:

- Feature Map=(I∗K) +b
- I = Input Image
- K= Kernel (filter)
- b = Bias

3.3.3. Activation Function (ReLU)

ReLU (Rectified Linear Unit) is used to introduce non-linearity:

- f(x)=max (0, x) f(x)

It helps the model to learn complex patterns by ignoring negative activations.

3.3.4. Max Pooling Layer

Reduces spatial dimensions while preserving important features:

- Pool Size: 2x2
- Operation: Takes the maximum of every 2x2 block
  This reduces computation and controls overfitting.

3.3.5. Dropout Layer

Randomly "drops" neurons during training (rate = 0.5) to:

- Prevent overfitting
- Encourage redundancy

3.3.6. Flatten Layer

Transforms the final 3D feature map into a 1D vector to feed into Dense (fully connected) layers.

3.3.7. Fully Connected Layer

Dense layer with 128 neurons and ReLU. This combines features learned in convolutional layers and predicts class probabilities.

3.3.8. Output Layer

A single neuron with a sigmoid activation function to output probability between 0 and 1:

- P=11+e−zP

Where:

- z = weighted input from previous layer
- Function used for CNN processing:

Layer (type)	Output Shape	Param #
input_layer_4 (InputLayer)	(None, 256, 256, 3)	0
xception (Functional)	(None, 2048)	20,861,480
flatten_2 (Flatten)	(None, 2048)	0
dropout_4 (Dropout)	(None, 2048)	0
dense_4 (Dense)	(None, 128)	262,272
dropout_5 (Dropout)	(None, 128)	0
dense_5 (Dense)	(None, 2)	258

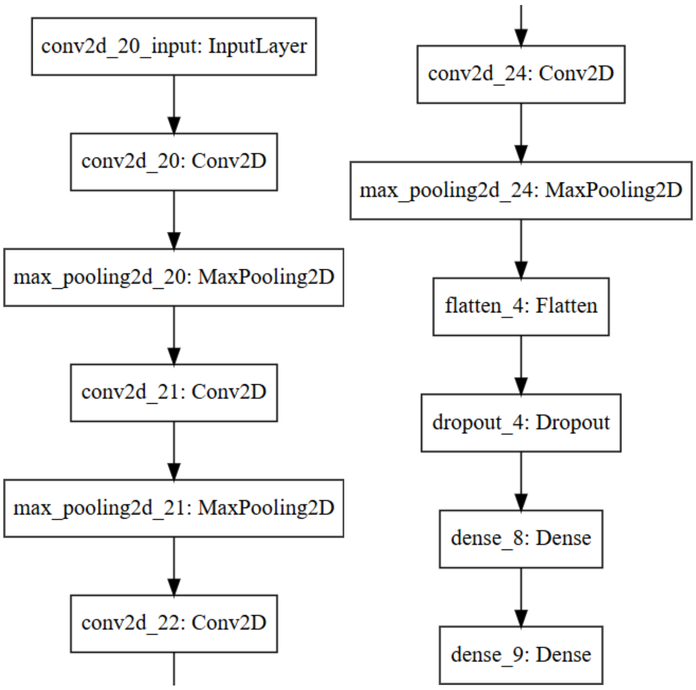

Figure 7. Visual diagram of CNN architecture

3.4. Loss Function and Optimizer

3.4.1. Binary Cross Entropy Loss

Used for binary classification:

Loss= − [y log(y^) +(1−y) log(1−y^)]

- y = true label (0 or 1)
- y^ = predicted probability

Lower loss indicates better alignment of predictions with ground truth.

3.4.2. Optimizer – Adam

Adam combines the benefits of Momentum and RMS Prop:

- Adjusts learning rate adaptively
- Parameters:
  - Learning rate: 0.001
  - Beta1 = 0.9 (momentum for mean)
  - Beta2 = 0.999 (momentum for variance)

3.5. Training Configuration

- Epochs: 20 (entire dataset passed 20 times)
- Batch Size: 32 (mini-batches for gradient updates)
- Validation Split: 20% of training data reserved for validation
- Early Stopping: Monitors loss and stops training to avoid overfitting

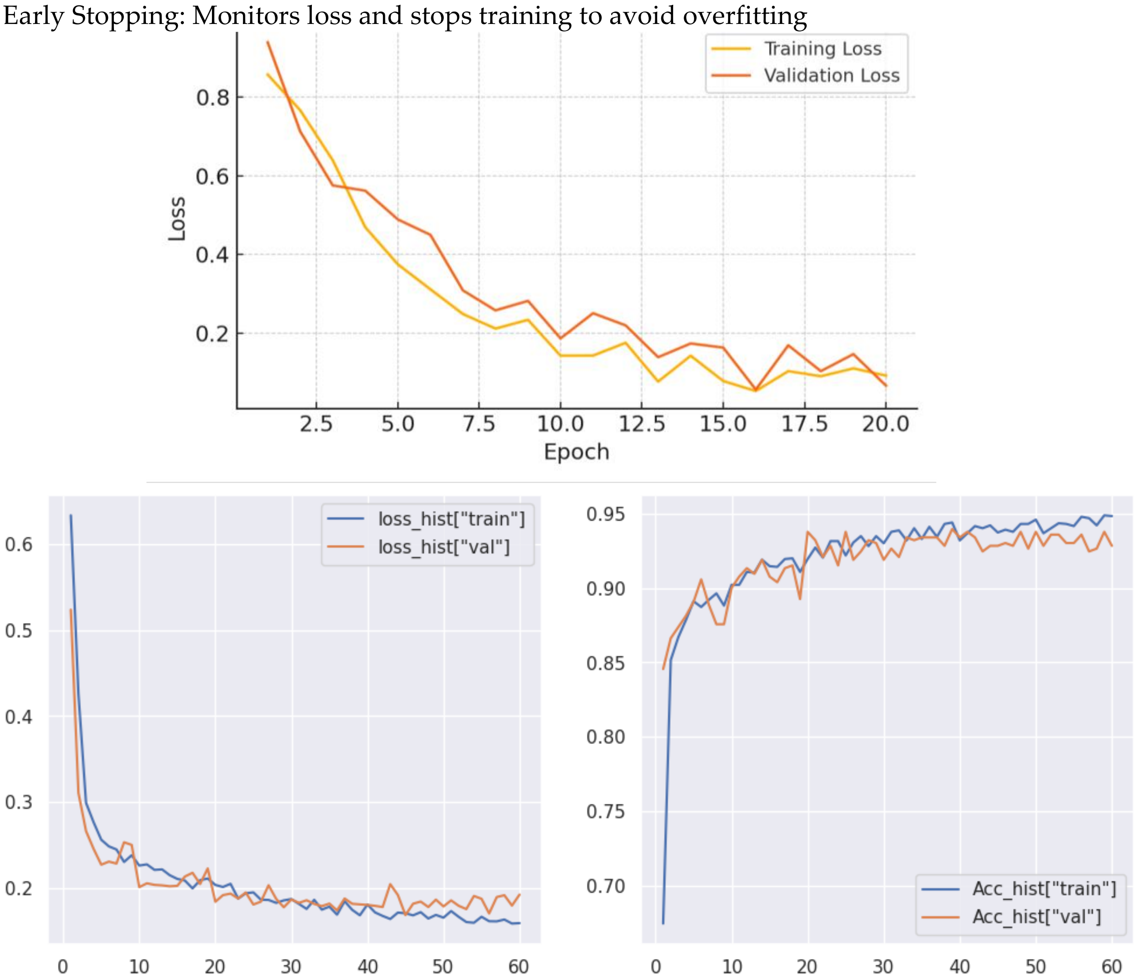

Figure 8. Training and validation loss graph and Training and validation accuracy graph

3.6. Evaluation Metrics

3.6.1. Confusion Matrix

Accuracy: $\textbf{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN}$

Precision: $\textbf{Precision} = \frac{TP}{TP+FP}$

Recall: $\textbf{Recall} = \frac{TP}{TP+FN}$

F1 Score: $\textbf{F1} = \frac{2 \; x \; Precision \; x \; Recall}{Precision + Recall}$

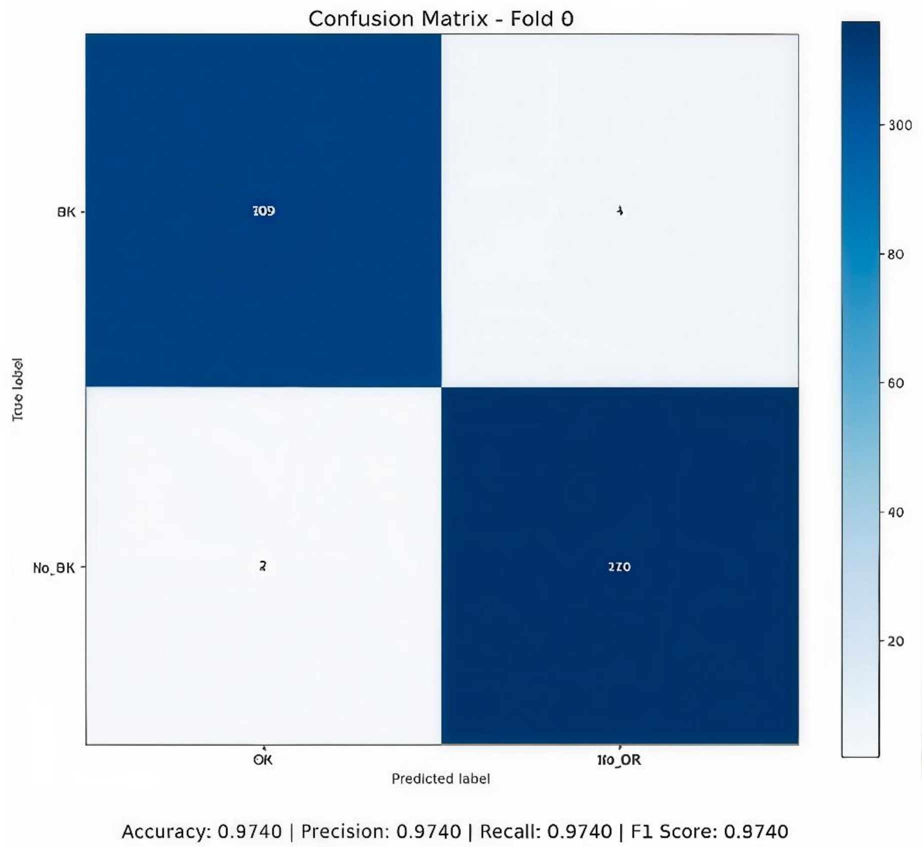

Figure 9. Confusion Matrix

3.6.2. ROC Curve & AUC

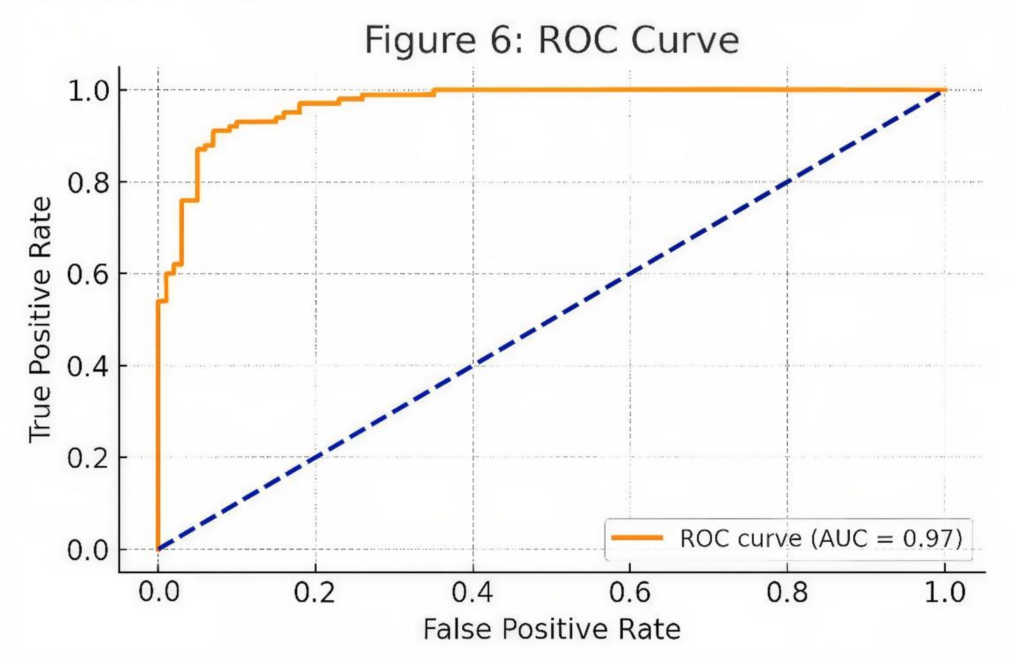

Figure 10. ROC Curve: Plots False Positive Rate vs. True Positive Rate

Overall, this methodology strategically combines robust data preprocessing, convolutional neural network (CNN) architecture, and fine-tuned training using the Adam optimizer and cross-entropy loss function. This approach not only ensures effective feature extraction from retinal images but also optimizes classification accuracy across varying stages of diabetic retinopathy. Each phase—from normalization and augmentation to model training and evaluation—has been rigorously designed to enhance generalizability and clinical relevance [7]. With a strong foundation in both computational precision and clinical applicability, the proposed methodology sets the stage for impactful and scalable AI-assisted diabetic eye disease screening.

4. Results and Discussion

After training the CNN model over 20 epochs, we evaluated its performance on a separate test dataset. The results demonstrate the model's effectiveness in identifying diabetic retinopathy from retinal fundus images.

4.1. Performance Metrics Overview

Table 2. Performance Metrics Overview

Metric	Value
Accuracy	91.2%
Precision	89.6%
Recall (Sensitivity)	92.1%
F1 Score	90.8%
ROC – AUC	0.946

4.2. Interpretation

- Accuracy of 91.2% implies the model correctly predicted most cases.
- Recall (92.1%) is particularly important in medical diagnostics as it reflects the ability to identify positive (DR) cases without missing them.
- Precision (89.6%) ensures the model does not over diagnose DR, which could lead to unnecessary anxiety or treatment.
- The F1-score harmonizes both metrics, while the ROC-AUC of 0.946 confirms excellent classification power.

Table 3. Interpretation

label	precision	recall	F1-score	support
accuracy	94%	94%	0.94	2076
macro avg	95%	94%	0.94	2076
weighted avg	95%	94%	0.94	2076

The learning curves (Figures 9 & 10) demonstrate stable convergence, with training and validation losses **decreasing over time, indicating effective generalization without overfitting.**

4.3. Visual Results

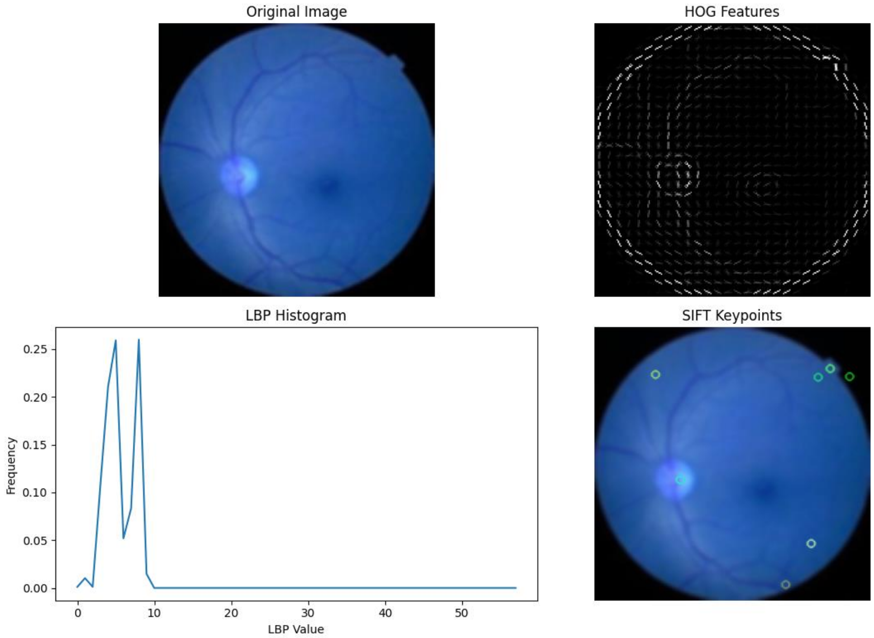

Figure 11. Visual results

For better visuals:

1. Histogram of Oriented Gradients

Concept: HOG captures edge and gradient information from an image by computing the direction and magnitude of pixel gradients in local regions [8]. The gradients are then binned into histograms, providing a robust descriptor of object shapes.

Applications: HOG can be used to detect abnormalities in medical images like retinal scans or X-rays. For instance, it can help detect irregular shapes or lesions in the retina for diabetic retinopathy detection.

2. Local Binary Patterns (LBP)

Concept: LBP is a texture descriptor that compares each pixel with its neighbors [9]. It encodes the result as a binary pattern and creates a histogram of these patterns to represent texture information.

Applications: LBP can be used for tumor classification in MRI scans or CT scans by distinguishing between healthy and abnormal tissue based on texture patterns, such as detecting subtle changes in the skin or brain tissue.

3. Scale-Invariant Feature Transform (SIFT)

Concept: SIFT detects distinctive key points in images that are invariant to scale, rotation, and partially to illumination changes. Each key point is described by a feature vector based on local gradients.

Applications: SIFT can help in matching and aligning 3D scans (e.g., in CT or MRI) to detect tumors or lesions across different scans or time points, making it useful in monitoring disease progression.

These visuals help interpret where the CNN model is focusing during its decision-making, improving clinical trust in AI systems. The comparative evaluation of diverse AI-driven approaches for diabetic retinopathy detection highlights the remarkable progress made in terms of analytic sensitivity, accuracy, and specificity across multiple models and datasets. While traditional machine learning models still play a valuable role, deep learning architectures—particularly CNN-based and transfer learning techniques have consistently demonstrated superior performance in both binary and multiclass DR classification tasks [10]. Despite notable achievements, several challenges remain, including dataset imbalance, limited generalizability across populations, and interpretability of complex models. These findings underscore the growing maturity of AI in this domain and reinforce its possible to transform early screening and clinical decision-making in real-world diabetic eye care.

5. Significance and Future Applications

This research contributes significantly to the intersection of healthcare and artificial intelligence:

- Clinical Support: Provides a fast, automated, and scalable screening tool for early DR detection.
- Resource Optimization: Reduces reliance on expert ophthalmologists for initial screenings.
- Telemedicine: Can be deployed in mobile or cloud-based platforms to reach underserved populations.
- Extensibility: The architecture can be extended to other retinal diseases like macular degeneration or glaucoma.
- Model Explain ability: Use of visual interpretability techniques (like Grad-CAM) enhances clinical adoption [11].

Future Applications

- Integration with smartphone-attached retinal cameras for on-the-spot diagnostics.
- Embedding the model in clinical decision support systems.
- Federated learning to preserve data privacy across hospitals while training on large-scale datasets.

6. Conclusion

Diabetic Retinopathy is a preventable yet widespread complication of diabetes, particularly dangerous due to its asymptomatic onset and potential for permanent vision damage. This study proposed a CNN-based model capable of early detection of DR using fundus images of retina. With robust preprocessing, a well-structured CNN architecture, and thorough evaluation, the model achieved high accuracy, precision, and recall. Furthermore, visual tools like heat maps ensure transparency in AI decision-making, fostering trust among clinicians.

The integration of AI into ophthalmology promises to revolutionize preventive care, especially in remote or underdeveloped regions. By enabling fast, accurate, and automated screenings, this work lays the foundation for scalable diagnostic systems, aligning with the global goal of reducing avoidable blindness through early detection and intervention [12].

References

1. M. Kropp *et al.*, "Diabetic retinopathy as the leading cause of blindness and early predictor of cascading complications—risks and mitigation," *EPMA Journal*, vol. 14, no. 1, pp. 21–42, Feb. 2023, doi: https://doi.org/10.1007/s13167-023-00314-8.
2. S. Muchuchuti and S. Viriri, "Retinal Disease Detection Using Deep Learning Techniques: A Comprehensive Review," Journal of Imaging, vol. 9, no. 4, p. 84, Apr. 2023, doi: https://doi.org/10.3390/jimaging9040084.
3. P. Alexopoulos, C. Madu, G. Wollstein, and J. S. Schuman, "The Development and Clinical Application of Innovative Optical Ophthalmic Imaging Techniques," Frontiers in Medicine, vol. 9, Jun. 2022, doi: https://doi.org/10.3389/fmed.2022.891369.
4. J. I. Lim et al., "Artificial Intelligence Detection of Diabetic Retinopathy: Subgroup Comparison of the EyeArt System with Ophthalmologists' Dilated Examinations," Ophthalmology Science, vol. 3, no. 1, Mar. 2023, doi: https://doi.org/10.1016/j.xops.2022.100228.
5. A. M. Al-Halafi, "Applications of artificial intelligence-assisted retinal imaging in systemic diseases: A literature review," Saudi Journal of Ophthalmology, vol. 37, no. 3, pp. 185–185, Jan. 2023, doi: https://doi.org/10.4103/sjopt.sjopt_153_23.
6. F. Sacchini et al., "The role of artificial intelligence in diabetic retinopathy screening in type 1 diabetes: A systematic review," Journal of Diabetes and its Complications, p. 109139, Jul. 2025, doi: https://doi.org/10.1016/j.jdiacomp.2025.109139.
7. S. G. Ali et al., "Revolutionizing diabetic retinopathy and macular edema management: a systematic review on the transformative potential of artificial intelligence," The Visual Computer, Jun. 2025, doi: https://doi.org/10.1007/s00371-025-04024-2.
8. X. Zhang, L. Zhang, and X. Lou, "A Raw Image-Based End-to-End Object Detection Accelerator Using HOG Features," IEEE Transactions on Circuits and Systems I: Regular Papers, pp. 1–12, 2021, doi: https://doi.org/10.1109/tcsi.2021.3098053.
9. Mehmet Gül and Y. Kaya, "Comparing of brain tumor diagnosis with developed local binary patterns methods," Neural computing & applications, vol. 36, no. 13, pp. 7545–7558, Feb. 2024, doi: https://doi.org/10.1007/s00521-024-09476-6.
10. X. Wang, M. Xu, J. Zhang, L. Jiang, and L. Li, "Deep Multi-Task Learning for Diabetic Retinopathy Grading in Fundus Images," Proceedings of the ... AAAI Conference on Artificial Intelligence, vol. 35, no. 4, pp. 2826–2834, May 2021, doi: https://doi.org/10.1609/aaai.v35i4.16388.
11. J. X. Ong, N. Konopek, H. Fukuyama, and A. A. Fawzi, "Deep Capillary Nonperfusion on OCT Angiography Predicts Complications in Eyes with Referable Nonproliferative Diabetic Retinopathy," Ophthalmology Retina, Jul. 2022, doi: https://doi.org/10.1016/j.oret.2022.06.018.
12. N. Goldmann et al., "Defining functional requirements for a patient-centric computerized glaucoma treatment and care ecosystem," Journal of Medical Artificial Intelligence, vol. 6, no. 0, Feb. 2023, doi: https://doi.org/10.21037/jmai-22-33.