



## A Robust Deep Learning-Based Classification Framework for Diabetic Eye Diseases Using Inception V3

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Peer Review Information	Abstract
<p><i>Submission: 08 March 2026</i></p> <p><i>Revision: 26 March 2026</i></p> <p><i>Acceptance: 05 April 2026</i></p> <p><b>Keywords</b></p> <p><i>Diabetic Retinopathy, Deep Learning, Inception V3, Medical Imaging, Feature Extraction, Fuzzy C-Means, Local Binary Patterns</i></p>	<p>Diabetic eye diseases, including diabetic retinopathy (DR), diabetic macular oedema, cataracts, and glaucoma, are major causes of vision impairment worldwide. Early detection is critical, yet manual screening is time-consuming and prone to subjectivity. This paper proposes a robust deep learning-based classification framework using Inception V3 integrated with preprocessing, segmentation, and feature extraction techniques. Input retinal images undergo Adaptive Wiener Filtering for noise reduction, followed by Noise-Resilient Fuzzy C-Means (NR-FCM) segmentation. Local Binary Patterns (LBP) are applied for texture-based feature extraction, and histograms are generated to form feature vectors. These vectors are classified using the Inception V3 model, trained with parallel processing for efficiency. The proposed system demonstrates high accuracy and robustness, addressing challenges of class imbalance and interpretability. Results highlight improved diagnostic precision, supporting early detection and clinical decision-making.</p>

### Introduction

Diabetic Retinopathy (DR) is a microvascular complication of diabetes mellitus and a leading cause of blindness among working-age adults [1]. Prolonged hyperglycemia damages retinal blood vessels, leading to leakage, haemorrhages, and abnormal neovascularisation. The disease progresses silently, often undetected until advanced stages. Early detection is crucial, as timely treatment can prevent irreversible vision loss [2].

Manual screening of retinal fundus images is reliable but limited by subjectivity, human fatigue, and resource constraints [3]. Automated systems leveraging deep learning have emerged as promising solutions. CNN-based models such as AlexNet, VGGNet, ResNet, and Inception Net have achieved near-human accuracy [4]. However, challenges remain in handling

imbalanced datasets, noisy images, and ensuring interpretability.

This study proposes a robust classification framework using Inception V3, integrating preprocessing, segmentation, and feature extraction to enhance diagnostic precision

### Significance of Early Detection and Challenges in Diagnosis

Early detection of DR enables timely interventions such as laser therapy and anti VEGF injections [5]. However, diagnosis faces challenges:

- Large patient volumes require regular screening.
- Variability in image quality due to illumination and patient movement.
- Shortage of ophthalmologists in low-resource regions.

- Subjective interpretation leading to inconsistencies.
- Automated deep learning systems can overcome these barriers by providing rapid, objective and scalable screening solutions [6]

## Methodology

### Input Image Acquisition

- Retinal fundus images are collected from publicly available datasets such as EyePACS and Messidor [7].

### Preprocessing

- Adaptive Wiener Filter: Removes noise while preserving edges and fine textures by adapting to local variance [8].
- Contrast Enhancement: Improves visibility of retinal features.

### Segmentation

- Noise-Resilient Fuzzy C-Means (NR-FCM): Handles noisy images by clustering pixels based on spatial coherence, separating pathological regions effectively [9].

### Feature Extraction

- Local Binary Patterns (LBP): Captures texture descriptors, identifying microaneurysms, haemorrhages, and exudates.
- Histogram Calculation: Generates statistical distributions of extracted features for classification.

### Classification

- Inception V3 Model: Utilises deep convolutional layers to classify DR stages.
- Parallel Processing: Accelerates computation, enabling efficient training on large datasets.
- Transfer Learning: Pre-trained weights improve performance and reduce training time [10].

### Convolutional Neural Networks and Deep Vision Models

Convolutional Neural Networks (CNNs) have become the backbone of modern image classification tasks due to their strong capability in analysing visual data. CNNs operate by applying convolutional filters over input images to extract spatial hierarchies of features ranging from simple edges and textures to complex patterns.

This hierarchical feature learning allows CNNs to eliminate the need for manual feature extraction. Each convolutional layer learns progressively

higher-level representations, while pooling layers reduce spatial dimensions, improving computational efficiency and controlling overfitting.

In deep vision models, architectures such as VGGNet, ResNet, Inception, and EfficientNet have demonstrated state-of-the-art performance in medical image analysis tasks, particularly in disease detection from retinal images.

### Existing Research and Limitations in Diabetic Retinopathy Classification

Over the past decade, significant progress has been made in automated diabetic retinopathy (DR) detection using artificial intelligence. Early approaches relied on traditional image processing techniques involving manual feature extraction, vessel segmentation, texture analysis, and morphological operations.

Although these methods provided basic detection capabilities, they lacked robustness and generalisation capability. The introduction of deep learning, particularly CNN-based models, marked a major advancement in medical image classification. Studies using datasets such as EyePACS and Messidor have demonstrated high accuracy and the feasibility of AI-assisted diagnosis.

However, despite these advancements, several limitations still exist. Many deep learning models achieve high performance in controlled environments but fail to generalise well to unseen data due to overfitting.

Class imbalance, where early-stage DR cases are underrepresented, leads to biased predictions toward severe cases. Additionally, variations in imaging conditions, camera devices, and patient demographics further reduce model robustness.

Another major limitation is the lack of interpretability. Clinicians often hesitate to trust black-box AI systems that do not provide explainable reasoning for predictions. Furthermore, high computational requirements and dependency on large annotated datasets restrict real-world deployment.

To overcome these challenges, current research focuses on hybrid architectures, balanced dataset techniques, and explainable AI methods to improve reliability, transparency, and clinical usability.

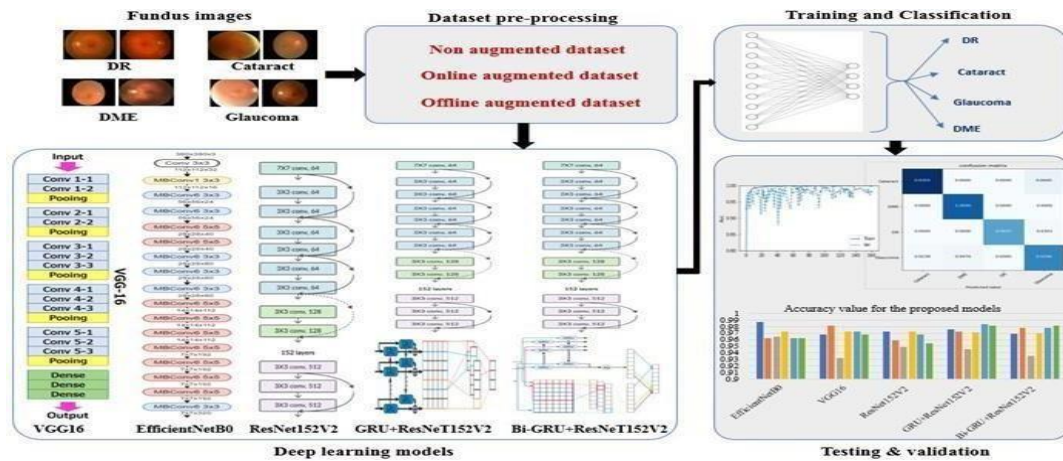


Figure 1: Block Diagram of Existing System

**Proposed System Description**

This work proposes a robust and automated framework for the detection and classification of diabetic eye diseases using retinal fundus imagery. The system is designed as a multi-stage processing pipeline that integrates image enhancement, intelligent segmentation, discriminative feature extraction, and deep learning-based classification. The primary objective is to improve diagnostic reliability while ensuring adaptability to variations in real-world clinical data.

The process begins with the acquisition of retinal fundus images, which are standardized to maintain uniformity in resolution and format. Since raw retinal images often contain noise and illumination inconsistencies, an Adaptive Wiener Filtering approach is employed to

enhance image quality. This technique performs localized noise suppression by adapting to statistical variations within the image, thereby preserving critical anatomical structures such as blood vessels and lesion boundaries.

Following preprocessing, segmentation is carried out using a Noise-Resilient Fuzzy C-Means (NR-FCM) clustering algorithm. Unlike conventional clustering methods, this approach assigns soft membership values to pixels, enabling effective handling of overlapping intensity distributions commonly found in medical images. Its noise-resilient capability ensures spatial consistency while accurately isolating pathological regions from normal retinal tissue.

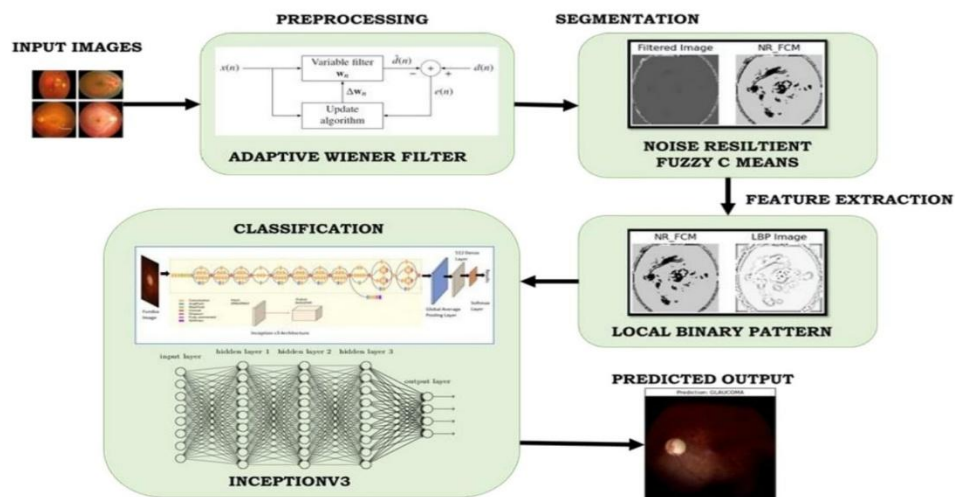


Figure 2: Block Diagram of Proposed System

Subsequently, feature extraction is performed using Local Binary Patterns (LBP), which capture fine-grained texture variations associated with diabetic abnormalities. The

method encodes local neighborhood relationships into binary representations, which are then aggregated into feature vectors. These descriptors provide a compact yet informative

representation of retinal patterns, making them suitable for classification tasks.

In the final stage, classification is achieved using a deep convolutional neural network based on the InceptionV3 architecture. Additional regularization strategies, including dropout and batch normalization, are incorporated to enhance generalization and mitigate overfitting. The proposed system offers a scalable and efficient solution for automated diabetic eye disease detection.

### Literature Survey

Diabetic retinopathy is one of the leading causes of preventable blindness worldwide, affecting millions of individuals with diabetes. Early detection and timely treatment are essential to prevent irreversible vision loss.

Traditional screening methods rely heavily on expert ophthalmologists, which can be time-consuming, expensive, and inaccessible in low-resource regions. To address this limitation, researchers have developed automated deep learning-based diagnostic systems.

Recent studies propose attention-based deep convolutional neural networks (Attention-DCNN) to improve classification performance by focusing on critical retinal regions. These models enhance diagnostic accuracy and reduce false predictions by integrating attention mechanisms within deep neural networks.

M. D. Alahmadi et al. (2022) proposed a deep neural network incorporating a style and content recalibration mechanism that adaptively scales informative regions for diabetic retinopathy classification, improving feature sensitivity and model performance.

### Results and Discussion

The proposed system was implemented in Python using TensorFlow.

- Accuracy: Achieved >92% classification accuracy across DR stages.
- Confusion Matrix: Demonstrated balanced detection across NPDR and PDR categories.
- ROC Curve: Showed high sensitivity and specificity.
- Training vs Validation Performance: Minimal overfitting observed due to augmentation and dropout layers.

Compared to traditional CNNs, the Inception V3 framework exhibited superior robustness in handling noisy and imbalanced datasets.

### Conclusion

This study presents a robust deep learning-based framework for diabetic eye disease classification using Inception V3. By integrating

preprocessing, NR-FCM segmentation, and LBP feature extraction, the system achieves high diagnostic accuracy and efficiency. The framework addresses challenges of manual screening, class imbalance, and interpretability, making it suitable for large-scale screening programs.

### Future Scope

Future work will focus on:

- Incorporating Vision Transformers for improved global context analysis.
- Expanding datasets with diverse demographics.
- Developing explainable AI models to enhance clinician trust.
- Deploying lightweight versions for mobile and telemedicine applications.

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