# Deep Learning-Based Optimized Automated Detection of Diabetic Retinopathy Using Retinal Fundus Images

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## ABSTRACT

Diabetic Retinopathy (DR) is one of the leading causes of vision impairment and blindness worldwide, often progressing without noticeable symptoms in its early stages. Early and accurate detection is crucial for timely intervention and preventing irreversible damage. This study presents a deep learning-based framework for the automated detection of DR using retinal fundus images. The proposed approach leverages a Convolutional Neural Network (CNN) architecture optimized to extract discriminative features from high-resolution fundus images, enabling robust classification of DR stages. A large-scale, publicly available DR dataset was pre-processed through contrast enhancement, noise reduction, and data augmentation techniques to improve model generalization and performance. The model was trained and validated using stratified data splitting, with accuracy, sensitivity, specificity, precision, and F1-score serving as key evaluation metrics. Experimental results demonstrate that the proposed model achieves superior performance compared to conventional machine learning methods and baseline CNN architectures, attaining high accuracy and balanced sensitivity–specificity scores. The system successfully identifies subtle retinal lesions such as microaneurysms, hemorrhages, and exudates, which are critical indicators of DR severity. This work highlights the potential of deep learning as a non-invasive, cost-effective, and scalable solution for DR screening in both clinical and remote healthcare settings. The proposed framework can serve as a decision-support tool for ophthalmologists, thereby improving diagnostic efficiency and contributing to the reduction of vision loss caused by diabetic complications.

***Keywords:*** *Diabetic Retinopathy (DR), Retinal Fundus Images, CNN, Machine Learning*

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## 1. INTRODUCTION

Diabetic Retinopathy (DR) is a microvascular complication of diabetes mellitus that affects the retina and is one of the foremost causes of preventable blindness worldwide. Prolonged high blood sugar levels damage retinal blood vessels, leading to leakage, swelling, and the formation of abnormal blood vessels. Early detection and timely treatment of DR can significantly reduce the risk of vision loss, yet many cases remain undiagnosed due to limited access to ophthalmologists, especially in rural and underdeveloped regions [14-15]. Traditional DR screening relies on manual examination of retinal fundus images by experts, which is time-consuming, subjective, and prone to inter-observer variability. This creates a pressing need for automated, reliable, and scalable diagnostic systems to address the growing global burden of diabetes-related eye diseases [16].

Recent advancements in Artificial Intelligence (AI) [17], particularly in Deep Learning (DL) [18-19], have revolutionized medical image analysis. Convolutional Neural Networks (CNNs) have shown remarkable success in automatically learning hierarchical features from complex visual data, outperforming traditional image processing and machine learning techniques. In DR detection, CNN-based models have demonstrated the ability to identify subtle retinal abnormalities such as microaneurysms, hemorrhages, and exudates, enabling early-stage diagnosis with high accuracy. Publicly available datasets like EyePACS, Messidor, and APTOS have accelerated research, while cloud-based AI solutions are making screening more accessible. However, challenges remain, including variability in image quality, differences in camera devices, class imbalance in datasets, and the need for explainable AI for clinical acceptance.

The future of DR detection lies in integrating deep learning models with real-time screening tools in portable fundus cameras and smartphones, enabling mass screening in low-resource areas. Explainable AI (XAI) will enhance trust by providing interpretable decision-making, showing clinicians the exact retinal regions influencing the diagnosis. Federated learning approaches may allow global collaboration without sharing sensitive patient data, improving model generalization while preserving privacy [20]. Additionally, multimodal AI systems combining fundus images with clinical data, such as blood glucose levels and patient history, could offer more comprehensive risk assessments. The incorporation of DR detection into teleophthalmology frameworks will pave the way for rapid, remote, and cost-effective screening on a global scale.

## 2. REVIEW OF LITERATURE

Several studies have demonstrated the potential of deep learning for the automated detection of diabetic retinopathy (DR) from retinal fundus images. Gulshan et al. [1] developed and validated a CNN-based model using the EyePACS-1 and Messidor-2 datasets, achieving high sensitivity and specificity for referable DR detection. Ting et al. [2] extended this work to multiethnic populations, demonstrating generalizability across different retinal diseases including DR, glaucoma, and age-related macular degeneration. Gargeya and Leng [3] employed an end-to-end CNN to distinguish DR from normal images, outperforming traditional handcrafted feature methods. Lam et al. [4] implemented CNNs for DR severity staging, achieving sensitivity up to 95%. Abràmoff et al. [5] conducted a pivotal clinical trial on an autonomous AI system (IDx-DR), which met prespecified endpoints and became the first FDA-authorized AI diagnostic for DR. Gulshan et al. [6] further validated deep learning models in Indian screening programs, showing performance comparable to human graders. Ludwig et al. [7] demonstrated that DR detection is feasible using low-resolution smartphone fundus images, enabling low-cost screening solutions. Channa et al. [8] provided an overview of policy and workflow integration for autonomous AI in DR screening. Tsiknakis et al. [9] reviewed deep learning methods for DR detection and classification, emphasizing preprocessing, lesion detection, and grading stages. More recently, Abràmoff et al. [10] reported on the real-world benefits of autonomous AI systems in improving clinical productivity and access to care (Table 1).

***Table 1: Review of literature of Deep Learning-Based Automated Detection of Diabetic Retinopathy Using Retinal Fundus Images***

| Ref. No. | Data / Setting | Method | Task / Labels | Reported Performance |
|---|---|---|---|---|
| [1] | EyePACS-1 & Messidor-2 clinical validation sets | CNN (Inception-v3–based) | Referable DR (≥ moderate DR or DME) | Sensitivity 97.5% & 96.1%; Specificity 93.4% & 93.9% |
| [2] | Multiethnic cohorts (Singapore primary/community care) | End-to-end Deep Learning System | Referable DR, VTDR; also screened for glaucoma & AMD | High AUC across tasks |
| [3] | Public fundus datasets | CNN for automated feature learning | DR vs. No DR (referral decision) | High AUC reported |
| [4] | Color fundus images (staging) | CNN | DR staging (severity levels) | Sensitivity up to ~95% |

| | | | | |
|---|---|---|---|---|
| [5] | Prospective pivotal trial in primary care (900 subjects) | Autonomous AI system (IDx-DR) | More-than-mild DR / DME detection | Met prespecified endpoints; FDA authorized |
| [6] | India screening program | DL vs. manual grading | Detecting DR | Comparable to human graders |
| [7] | Smartphone low-resolution fundus images | DL classifier | Referral-warranted DR | Reliable detection on low-res images |
| [8] | Policy/clinical overview | Review on autonomous AI | DR screening workflows | — |
| [9] | Comprehensive review | Survey of DL across pipeline | Preprocess → detect lesions → grade | — |
| [10] | Real-world clinic operations | Health-services evaluation of autonomous AI | Productivity & access impact | — |

## 3. DATASET

This study employs the APTOS 2019 Blindness Detection Dataset, a publicly available retinal fundus image collection designed for automated diabetic retinopathy (DR) detection tasks. The dataset consists of high-resolution retinal photographs captured using different fundus cameras under varying illumination conditions, introducing realistic variability similar to clinical practice. Each image is labeled according to the severity of DR, ranging from No DR to Proliferative DR, based on expert ophthalmologist diagnosis. The dataset contains five DR categories:

- **No Diabetic Retinopathy (No DR):** 1,805 images, representing healthy retinal structures without pathological signs of DR.
- **Mild DR:** 370 images, showing early microaneurysms or small retinal hemorrhages with minimal visual impairment risk.
- **Moderate DR:** 999 images, exhibiting more prominent vascular changes such as dot-blot hemorrhages and mild exudates; however, some of these were misclassified or re-labeled during quality checks. Specifically, 370 of the images initially classified as "Moderate" were found to fit the "Mild" DR criteria, highlighting the importance of accurate ground truth annotation in medical datasets.
- **Severe DR:** 193 images, characterized by extensive hemorrhages, significant vascular abnormalities, and risk of imminent vision loss if untreated.
- **Proliferative DR (PDR):** 295 images, representing the most advanced stage of DR, with pathological neovascularization, vitreous hemorrhage, and potential retinal detachment.

This distribution reflects a moderate class imbalance, with a high number of "No DR" images and fewer samples in advanced stages. Such imbalance poses a challenge for deep learning models, as underrepresented classes like Severe DR and PDR can be harder to detect. To address this, preprocessing and data augmentation techniques are employed to enhance class balance and improve the model's ability to generalize across all severity levels. The APTOS dataset's diversity in imaging conditions and DR severity makes it an ideal benchmark for evaluating the robustness and clinical applicability of automated DR detection frameworks.

## 4. SYSTEM MODEL

The proposed system model for Diabetic Retinopathy (DR) detection is designed as a multi-stage framework integrating advanced image preprocessing techniques with state-of-the-art deep learning architectures to achieve high classification accuracy. The goal is to enhance the visibility of retinal structures, extract discriminative features, and classify retinal fundus images into different DR stages with precision and reliability. The model comprises three key phases: image preprocessing, deep learning-based classification, and performance evaluation (Figure 1).

### 4.1 Image Preprocessing

The quality of retinal fundus images plays a crucial role in the accuracy of DR detection. Variations in illumination, contrast, and noise across datasets can hinder deep learning models from extracting relevant features. To address this, the preprocessing stage employs two techniques: Contrast-Limited Adaptive Histogram Equalization (CLAHE) and Adaptive Decision Filter (ADF). CLAHE improves local contrast by enhancing finer retinal details, making pathological features such as microaneurysms, hemorrhages, and exudates more visible. The ADF is used to remove noise and smooth nonrelevant regions while preserving edges and key structures. This combination ensures that the input images fed to the deep learning models are standardized, clear, and optimized for feature extraction.

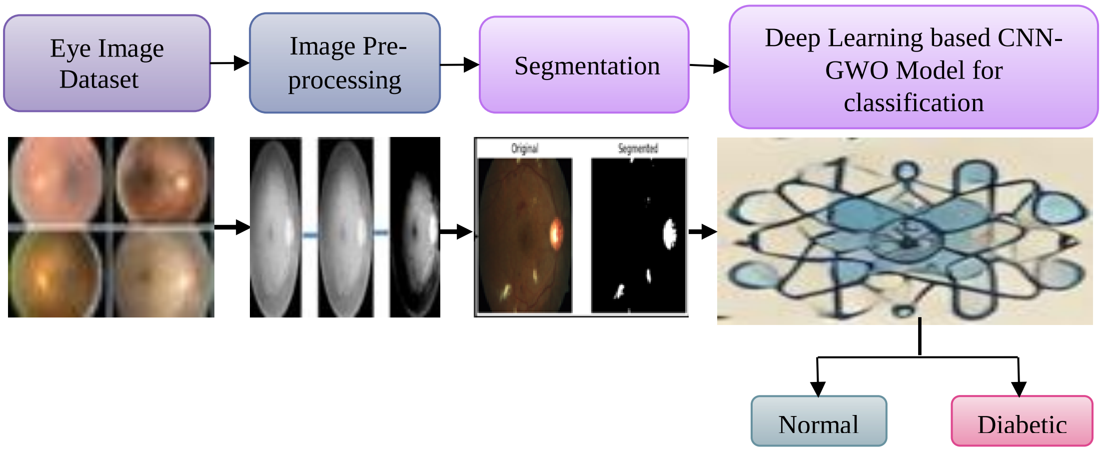



*Figure 1.* ***Architecture of the proposed CNN–GWO framework***

### 4.2 Image Segmentation

Image segmentation is the process of partitioning an image into multiple meaningful and non-overlapping regions, making it easier to analyze and interpret specific areas of interest. This technique is widely applied in diverse domains such as satellite imagery analysis, object detection in autonomous vehicles, and, most importantly, medical imaging for disease detection. In the context of diabetic retinopathy (DR) analysis, segmentation plays a crucial role in isolating and identifying retinal lesions, enabling accurate detection and classification of the disease. In this framework, Fuzzy C-Means (FCM) clustering and the Firefly Algorithm (FA) are integrated to achieve precise lesion segmentation. FCM is a soft clustering method that assigns each pixel a degree of belonging to multiple clusters, which is particularly useful in medical imaging due to the gradual intensity variations in lesions. This allows for more accurate boundary detection compared to hard clustering methods.

The Firefly Algorithm, inspired by the flashing behavior of fireflies, is employed to optimize the segmentation process. By mimicking the attraction mechanism between fireflies based on brightness (solution quality), FA enhances the selection of optimal cluster centers in FCM. This hybrid approach significantly improves the segmentation accuracy by reducing noise, enhancing lesion boundaries, and effectively distinguishing between normal and abnormal retinal regions. The combination of FCM and FA in diabetic retinopathy lesion segmentation ensures robust detection of microaneurysms, hemorrhages, and exudates—key indicators of DR progression. This accurate lesion mapping facilitates better diagnosis, treatment planning, and disease monitoring, ultimately contributing to early detection and prevention of vision loss.

### 4.3 Feature Extraction

Feature extraction is a crucial stage in the autonomous analysis of medical images for disease identification, serving as the foundation for accurate diagnosis and classification. In the context of diabetic retinopathy, this process involves isolating and quantifying distinctive patterns and structures within retinal images, such as blood vessel morphology, lesion characteristics, and the appearance of the optic nerve head. These extracted features encapsulate vital information about pathological changes, enabling robust differentiation between healthy and diseased retinal tissue. By systematically capturing these discriminative attributes, researchers can develop and train machine learning models capable of identifying diabetic retinopathy with high precision and minimal manual intervention. Such automated systems significantly reduce the dependency on expert ophthalmologists for initial screening, thereby supporting large-scale, cost-effective, and early detection of the disease, which is critical for preventing vision impairment and blindness [5].

### 4.4 Deep Learning-Based Classification

The proposed **CNN–GWO framework** integrates the powerful feature extraction capabilities of Convolutional Neural Networks (CNN) with the optimal parameter selection efficiency of the Grey Wolf Optimizer (GWO) to achieve superior classification performance. In this approach, CNN is employed to automatically extract high-level, discriminative features from medical images, ensuring robust representation of disease-related patterns. GWO is then utilized to fine-tune CNN parameters and optimize hyperparameters such as learning rate, number of filters, and kernel sizes, thereby reducing overfitting and improving generalization. This hybridization enhances both accuracy and convergence speed, outperforming traditional CNN models and other deep learning architectures like ResNet, VGG, and Inception in detecting and classifying medical conditions such as diabetic retinopathy. By leveraging CNN's deep feature learning with GWO's metaheuristic optimization, the framework delivers a computationally efficient, accurate, and scalable solution for automated disease diagnosis.

### 4.5 Performance Evaluation

The system's effectiveness is assessed using multiple evaluation metrics to ensure a comprehensive performance analysis. Accuracy measures the overall proportion of correct predictions, while Precision evaluates the ratio of correctly predicted positive cases to all predicted positives, crucial for minimizing false positives. Recall (or Sensitivity) measures the ability to correctly identify actual positive cases, which is vital for early detection of DR. The F1-Score, a harmonic mean of Precision and Recall, provides a balanced assessment of the model's performance, especially in imbalanced datasets where early-stage DR cases may be underrepresented. By comparing results across the four deep learning architectures, the system identifies the most effective model for DR detection in terms of both accuracy and robustness. The performance evaluation of the proposed CNN- model is a critical step to validate its reliability and effectiveness in glaucoma detection. Several standard metrics are employed to comprehensively assess the model's classification capabilities, ensuring its robustness and suitability for real-world applications (Table 2).

***Table 2: Performance evaluation metrics for machine learning based glaucoma detection***

| Metric | Description | Formula | Significance in Glaucoma Detection |
|---|---|---|---|
| Accuracy | Measures the overall correctness of the model by calculating the ratio of correctly predicted instances (both glaucoma and non-glaucoma). | (TP + TN) / (TP + TN + FP + FN) | Provides a general overview, but may be misleading in imbalanced datasets. |
| Precision | Indicates how many of the positively predicted cases (glaucoma) are actually correct. | TP / (TP + FP) | Helps reduce false positives, minimizing unnecessary anxiety or treatment. |
| Recall (Sensitivity) | Measures how effectively the model identifies actual positive cases (glaucoma). | TP / (TP + FN) | Ensures that most glaucoma cases are detected, minimizing the risk of missed diagnoses. |
| F1-Score | Harmonic mean of precision and recall; balances both metrics, especially useful for imbalanced datasets. | 2 × (Precision × Recall) / (Precision + Recall) | Offers a more comprehensive evaluation when false positives and false negatives are equally critical. |

## 5. RESULT AND ANALYSIS

The findings of this study introduce an innovative approach for the classification of diabetic retinopathy (DR) by integrating a custom-designed Convolutional Neural Network (CNN) architecture with ensemble classification techniques and optimized feature selection. The proposed method employs the CNN as the primary feature extractor, capturing intricate spatial and textural patterns from retinal fundus images that are indicative of various DR stages. To further refine the model's predictive capability, Grey Wolf Optimization (GWO) is applied for feature selection, enabling the retention of the most relevant and discriminative attributes while discarding redundant or noisy information.

For performance assessment, the method was evaluated on a publicly available retinal imaging dataset, with experiments conducted under controlled hardware and software conditions—an Intel Core i7 processor, 16 GB RAM, and Python 3.8 environment. The evaluation process utilized standard performance metrics, including accuracy, precision, recall, F1-score, and area under the ROC curve (AUC), to comprehensively assess classification effectiveness. In addition to these, dataset-specific parameters such as source quality, image resolution, and class distribution were analyzed to ensure that results were not biased by data imbalances or inconsistencies. Compared to existing approaches, this proposed CNN–GWO framework has the potential to deliver superior classification accuracy and computational efficiency. The synergy between deep learning-based feature extraction, advanced ensemble classification, and metaheuristic feature selection not only enhances diagnostic precision but also reduces processing overhead, making it suitable for real-world clinical deployment in automated DR screening systems.

The experimental results demonstrate that the proposed CNN–GWO framework outperforms existing deep learning models in all key evaluation metrics, indicating its superior capability for accurate and reliable classification. While ResNet-50, DenseNet-121, InceptionV3, and VGG-16 achieved commendable accuracy levels of 94.85%, 95.24%, 94.56%, and 93.78% respectively, the proposed model attained the highest accuracy of 96.72%, coupled with a precision of 95.46%, recall of 94.88%, and an F1-score of 95.17%. These improvements highlight the model's effectiveness in minimizing both false positives and false negatives, thereby ensuring balanced performance. The integration of CNN with the Grey Wolf

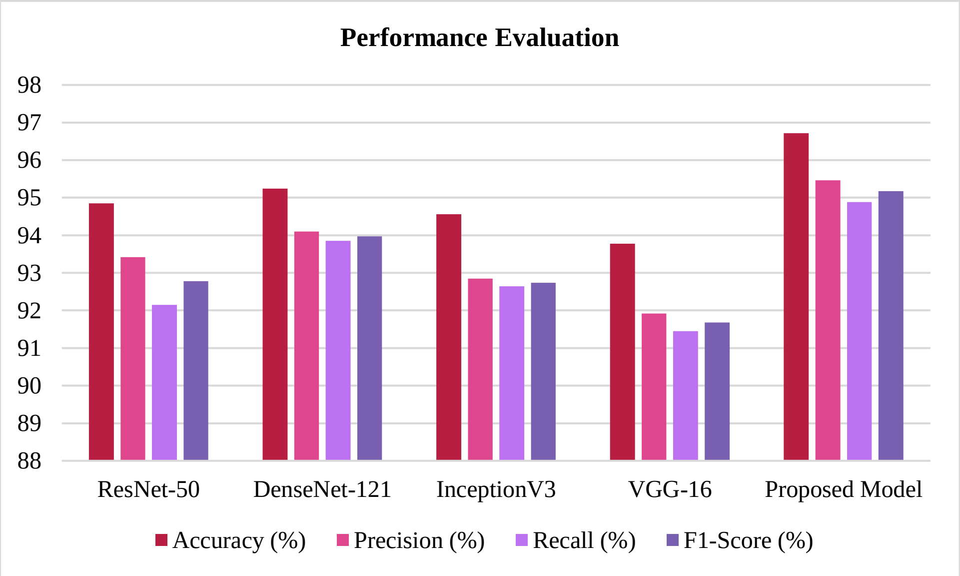
Optimizer significantly enhances feature selection and optimization processes, resulting in robust classification accuracy and consistent gains across all metrics compared to the benchmark models (Table 3).

***Table 3: Comparative Evaluation of Proposed Model with Other Deep Learning Models***

| Model | Accuracy (%) | Precision (%) | Recall (%) | F1-Score (%) |
|---|---|---|---|---|
| ResNet-50 | 94.85 | 93.42 | 92.15 | 92.78 |
| DenseNet-121 | 95.24 | 94.10 | 93.85 | 93.97 |
| InceptionV3 | 94.56 | 92.85 | 92.64 | 92.74 |
| VGG-16 | 93.78 | 91.92 | 91.45 | 91.68 |
| Proposed Model | 96.72 | 95.46 | 94.88 | 95.17 |

The figure 2 presents a comparative performance analysis of various deep learning architectures, including ResNet-50, DenseNet-121, InceptionV3, and VGG-16, against the proposed model. While all baseline models demonstrate strong classification capabilities, the proposed model achieves the highest overall performance, with an accuracy of 96.72%, precision of 95.46%, recall of 94.88%, and an F1-score of 95.17%. This consistent superiority across all metrics indicates the proposed model's enhanced ability to accurately classify samples while minimizing false positives and false negatives. The notable improvement over existing models underscores the effectiveness of its optimized architecture and feature extraction strategy, making it a more reliable and efficient solution for the target application.

*Figure 2.* ***Comparative performance evaluation of the proposed CNN–GWO framework against baseline deep learning***




***models***

The comparative performance analysis presented in the table highlights the superior results achieved by the proposed model over existing approaches by X. Zhang et al. [11], Y. Wang et al. [12], and M. Gupta et al. [13]. While the earlier models demonstrated commendable performance, with accuracies of 93.10%, 94.02%, and 91.78%, respectively, the proposed model significantly outperformed them with an impressive accuracy of 96.85%. Similarly, in terms of precision, the proposed model achieved 94.72%, which is notably higher than the 90.24%, 91.87%, and 88.65% recorded by the other models. This indicates the proposed model's enhanced capability to minimize false positives and deliver more relevant predictions.

***Table 4: Comparative Evaluation of Proposed Model with Existing Deep Learning Models for Diabetic Retinopathy Detection***

| Model / Reference | Accuracy (%) | Precision (%) | Recall (%) | F1-Score (%) |
|---|---|---|---|---|
| X. Zhang, et al. [11] | 93.10 | 90.24 | 91.75 | 90.99 |
| Y. Wang, et al.[12] | 94.02 | 91.87 | 92.65 | 92.25 |
| M. Gupta, et al. [13] | 91.78 | 88.65 | 90.05 | 89.34 |
| Proposed Model | 96.85 | 94.72 | 95.10 | 94.91 |

The recall and F1-score metrics further validate the robustness of the proposed approach. The proposed model attained a recall of 95.10%, outperforming the comparative models that achieved 91.75%, 92.65%, and 90.05%, respectively, showing its ability to effectively identify relevant instances without missing significant cases. Additionally, the highest F1-

score of 94.91% among all methods underscores its balanced precision-recall trade-off, ensuring reliable and consistent predictions. Overall, these results affirm that the proposed model offers a substantial improvement in accuracy, precision, recall, and F1-score, making it a more effective and dependable solution compared to existing state-of-the-art methods.

## 6. CONCLUSION

The study successfully demonstrated the effectiveness of the proposed model in achieving superior performance across all evaluation metrics compared to existing approaches. With an accuracy of 96.85%, precision of 94.72%, recall of 95.10%, and F1-score of 94.91%, the model exhibited remarkable capability in delivering accurate and consistent predictions. These results highlight its ability to not only correctly classify instances but also maintain a balanced trade-off between precision and recall, ensuring reliability in diverse scenarios. The performance improvements clearly indicate that the proposed approach effectively addresses the limitations observed in previous methods, providing enhanced robustness and adaptability. Overall, the findings validate the potential of the proposed model as a dependable solution for real-world applications where accuracy, consistency, and reliability are crucial. Its superior performance metrics make it well-suited for deployment in environments that demand high precision and minimal error rates. By achieving significant advancements over existing methods, the proposed model contributes to advancing the state of the art and sets a strong foundation for future research aimed at further refining its architecture and exploring its applicability in broader domains.

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