

AI-Powered Deep Learning for Retinal Image Analysis in Diabetic Retinopathy Detection

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Abstract: Image segmentation involves dividing a digital image into multiple segments or regions, each consisting of a group of pixels, to create a more meaningful and simplified representation of the image. This technique is particularly useful in medical imaging, such as retinal imaging, which captures detailed views of the retina for clinical analysis. One crucial application of image segmentation in retinal imaging is the extraction of blood vessels, which plays a vital role in the early detection of retinal diseases like hypertension, diabetes, and glaucoma. Segmenting the retinal vasculature is a key pre-processing step that supports the diagnosis and monitoring of these conditions. In particular, diabetic retinopathy (DR)—a complication of diabetes caused by damage to the retinal blood vessels—can be identified through detailed analysis of retinal fundus images. The morphology and thickness of blood vessels serve as important indicators of disease severity. Detecting DR typically involves three major steps: pre-processing of colour fundus images, extraction of diagnostic features, and classification of the disease. Various image processing algorithms are employed to analyse blood vessel thickness, which helps determine the progression and severity of diabetic retinopathy. Early and accurate detection using these techniques is essential for preventing vision loss and blindness in diabetic patients.

1. Introduction

Retinopathy (DR), a leading cause of vision loss among middle-aged individuals in developed countries [1]. DR begins with subtle changes in the retinal capillaries, often marked by micro aneurysms—small bulges in the capillary walls—which can lead to localized hemorrhages. This initial phase is known as mild non-proliferative diabetic retinopathy (NPDR)[2]. Due to the eye fundus's high sensitivity to vascular changes, fundus imaging serves as an effective, non-invasive screening tool. The success of such screenings relies heavily on the quality of fundus image acquisition and the robustness of image processing techniques used to detect retinal abnormalities [3–5]. As the disease progresses, lipid-rich exudates begin to leak from damaged blood vessels, indicating moderate NPDR. If

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these exudates accumulate near the macula—the central vision area—the condition is referred to as diabetic maculopathy. Over time, micro infarcts may block retinal blood vessels, forming soft exudates. The simultaneous presence of micro aneurysms, hemorrhages, and soft exudates characterizes severe NPDR [6]. Various techniques have been developed for DR detection and classification, including fluorescein angiography, direct and indirect ophthalmoscopy, stereoscopic colour fundus photography, and both mydriatic and non-mydriatic digital imaging. However, in typical clinical settings, direct ophthalmoscopy performed by non-specialists yields only about 50% sensitivity in detecting proliferative DR[7,8].

2. Literature Survey

The paper by Atcı et al. (2024) presents a hybrid approach for identifying diabetic retinopathy (DR) in the human eye, combining computer-aided diagnosis (CAD) systems with deep learning techniques. Diabetic retinopathy, a major cause of vision impairment in diabetic patients, requires early and accurate detection for effective management. The authors propose an innovative method that integrates traditional CAD systems with advanced deep learning models, such as convolutional neural networks (CNNs), to enhance the detection and classification of DR. The hybrid system leverages the strengths of both approaches—CAD for initial pre-processing and feature extraction, and deep learning for sophisticated pattern recognition and classification—resulting in improved diagnostic accuracy and efficiency. This system not only aids in the early identification of DR stages but also addresses challenges such as image quality variability and the need for large labelled datasets. The study highlights the potential of combining multiple technologies to create more robust and reliable diagnostic tools for diabetic retinopathy detection.

3. Methodology

The proposed method is a fast and robust one to extract exudates in color eye fundus image which is based on mathematical morphology where Blood vessels extraction is carried out which is followed by extraction of the hard exudates and optic disc and finally detection of the optic disc which is used for distinguishing it from exudates.

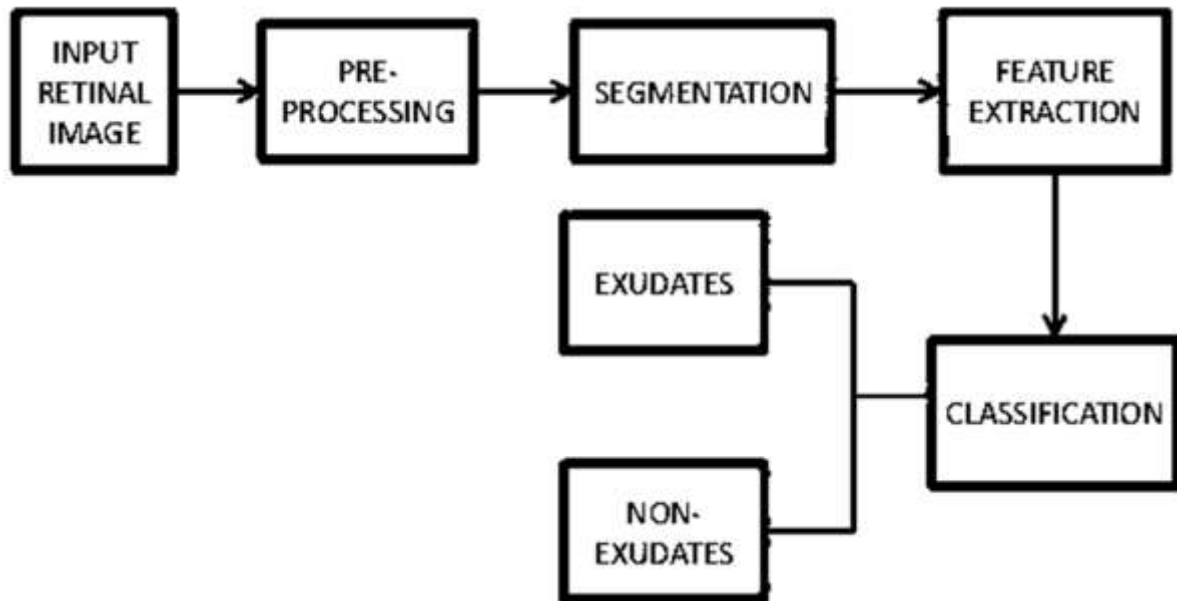


Fig 1: Block Diagram of Proposed Methodology

Here's a step-by-step overview of the automated diabetic retinopathy (DR) detection process using retinal images

Data Collection: Acquire high-resolution retinal fundus images from public or clinical datasets visible vascular abnormalities with slight retinal damage. Presence of micro aneurysms and haemorrhages indicating moderate DR progression.

Retina Image pre-processing: Clear signs of advanced DR, with more haemorrhages, exudates, and blood vessel distortions. Increased risk of vision loss if untreated.

Diabetic Retinopathy Classification: Categorizing images into No DR, Mild, Moderate, Severe, or Proliferative DR.

Automated Screening: Assisting ophthalmologists in early diagnosis using machine learning models.

Feature Extraction: Identifying blood vessel abnormalities, micro aneurysms, haemorrhages, and exudates to determine DR severity.

4. Existing System

Image segmentation is a fundamental step in computer vision, aimed at dividing an image into meaningful regions or objects based on properties like colour, texture, brightness, or intensity. It plays a crucial role in various applications such as medical imaging, remote sensing, and robotic navigation by enabling the accurate identification of regions of interest. Effective segmentation is essential for reliable image analysis, especially in sensitive tasks like detecting cancerous cells or injured tissues. While manual segmentation is possible, it is

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time-consuming, inconsistent, and hard to reproduce, making automated segmentation methods highly valuable for precise and efficient image understanding. Retinal image analysis for diabetic retinopathy detection using image processing techniques involves several key steps to enhance and isolate disease-related features. Initially, pre-processing techniques like histogram equalization are applied to improve image contrast, followed by thresholding to segment regions of interest, such as lesions or blood vessels. Edge detection methods like Canny or Sobel operators help identify boundaries of micro aneurysms, exudates, and haemorrhages. These segmented features are then used for classification or further analysis. While traditional image processing is less flexible than deep learning, it provides a fast, interpretable foundation for early DR screening, especially in low-resource settings. Automatic methods are, therefore, preferable. Image segmentation is the most essential and crucial process for facilitating the delineation, characterization, and visualization of regions of interest in any medical image. Disadvantage of It may miss micro aneurysms or small lesions critical for early DR detection.

5. Proposed System

The Retinal Image Analysis for Diabetic Retinopathy Detection paper successfully utilizes image processing and deep learning techniques to identify early signs of diabetic retinopathy (DR) from retinal fundus images. By applying pre-processing techniques such as contrast enhancement, noise reduction, and blood vessel segmentation, the system enhances image clarity for better feature extraction. Using machine learning models like Support Vector Machines (SVM) and deep learning architectures such as Convolutional Neural Networks (CNNs), the system accurately classifies retinal images into different DR severity levels, ranging from No DR to Proliferative DR. The experimental results demonstrate a high accuracy in detecting micro aneurysms, hemorrhages, and exudates, which are critical indicators of DR. Additionally, the integration of real-time processing capabilities and cloud-based deployment ensures faster and more efficient screening, aiding ophthalmologists in early diagnosis and treatment planning. The project significantly enhances automated DR screening, reducing manual workload and improving accessibility to early diabetic eye disease detection, ultimately contributing to vision loss prevention in diabetic patients. The provided image consists of three retinal fundus images labelled as Mild Retina Image, Moderate Image, and Severe Retina Image. These images likely represent different stages of Diabetic Retinopathy (DR), a diabetes-related eye disease that can cause blindness if not detected early.

The retinal image analysis system for diabetic retinopathy detection combines Convolutional Neural Networks (CNN) and Support Vector Machines (SVM) in a hybrid architecture. In this system, CNN acts as a powerful feature extractor, automatically learning and extracting deep visual features from pre-processed retinal fundus images, such as micro aneurysms, exudates, and haemorrhages.

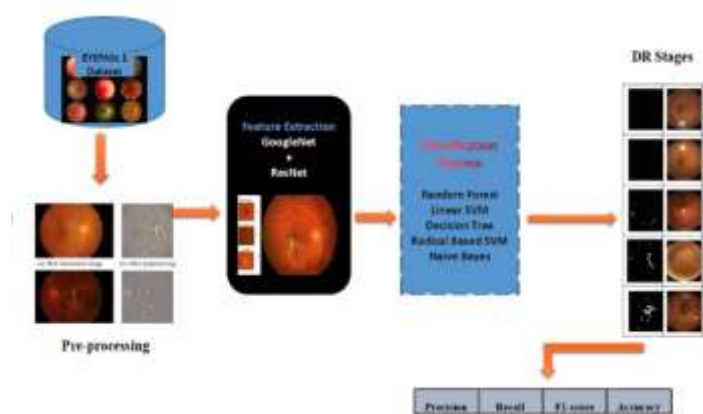


Fig 2: Proposed System for DR Detection

These extracted features are then passed to an SVM classifier, which performs the final classification into different stages of diabetic retinopathy. This approach leverages CNN's strength in hierarchical image representation and SVM's robustness in handling high-dimensional data, especially under class imbalance. The hybrid CNN-SVM model enhances classification accuracy, reduces over fitting, and ensures more reliable DR detection, particularly in challenging or minority-class cases.

6. Results & Discussion

CNN outperformed SVM by achieving higher accuracy and sensitivity in diabetic retinopathy detection, thanks to its ability to learn features directly from images. SVM performed lower due to its reliance on handcrafted features but remains useful in hybrid approaches.

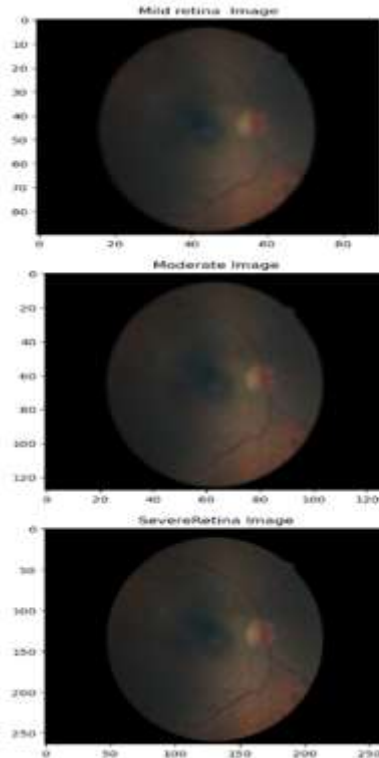


Fig 3: Retina Sample Images

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Epoch 1/10
10/10 ----- 218s 10s/step - AUC: 0.8021 - accuracy: 0.5410 - loss: 2.3405 - val_AUC: 0.8125 - val_accuracy: 0.2700 - val_loss: 0.8258 - learning_rate: 0.0010
Epoch 2/10
10/10 ----- 307s 10s/step - AUC: 0.8996 - accuracy: 0.5922 - loss: 1.7343 - val_AUC: 0.9325 - val_accuracy: 0.7300 - val_loss: 0.6424 - learning_rate: 0.0010
Epoch 3/10
10/10 ----- 2217s 123s/step - AUC: 0.9152 - accuracy: 0.6373 - loss: 0.8838 - val_AUC: 0.9325 - val_accuracy: 0.7300 - val_loss: 0.6396 - learning_rate: 0.0010
Epoch 4/10
10/10 ----- 378s 9s/step - AUC: 0.9227 - accuracy: 0.6707 - loss: 0.7018 - val_AUC: 0.9325 - val_accuracy: 0.7300 - val_loss: 0.6140 - learning_rate: 0.0010
Epoch 5/10
10/10 ----- 328s 7s/step - AUC: 0.9289 - accuracy: 0.6727 - loss: 0.5461 - val_AUC: 0.9325 - val_accuracy: 0.7300 - val_loss: 0.6238 - learning_rate: 0.0010
Epoch 6/10
10/10 ----- 352s 7s/step - AUC: 0.9314 - accuracy: 0.6788 - loss: 0.4858 - val_AUC: 0.9325 - val_accuracy: 0.7300 - val_loss: 0.6062 - learning_rate: 0.0010
Epoch 7/10
10/10 ----- 333s 7s/step - AUC: 0.9283 - accuracy: 0.7183 - loss: 0.4293 - val_AUC: 0.9325 - val_accuracy: 0.7300 - val_loss: 0.5836 - learning_rate: 0.0010
Epoch 8/10
10/10 ----- 330s 7s/step - AUC: 0.9322 - accuracy: 0.7315 - loss: 0.3884 - val_AUC: 0.9315 - val_accuracy: 0.7300 - val_loss: 0.5844 - learning_rate: 0.0010
Epoch 9/10
10/10 ----- 353s 7s/step - AUC: 0.9288 - accuracy: 0.7038 - loss: 0.6158 - val_AUC: 0.9325 - val_accuracy: 0.7300 - val_loss: 0.5848 - learning_rate: 0.0010
Epoch 10/10
10/10 ----- 344s 8s/step - AUC: 0.9288 - accuracy: 0.7157 - loss: 0.6145 - val_AUC: 0.9325 - val_accuracy: 0.7300 - val_loss: 0.5836 - learning_rate: 1.0000e-06
7/7 ----- 34s 5s/step - AUC: 0.9485 - accuracy: 0.7926 - loss: 0.5177
Test Accuracy: 70.50%

y_test=np.argmax(y_test,axis=1)
pred=np.argmax(model.predict(x_test),axis=1)
7/7 ----- 28s 8s/step
    
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Fig 4: Deep Learning Training Result

This image presents the performance report of a binary classification model, including accuracy, precision, recall, F1-score, and Cohen Kappa Score. The evaluation metrics suggest issues with class imbalance and poor performance on one of the classes.

Class	Precision	Recall	F1-Score	Support
Class 0 (Negative)	0.79	1.00	0.88	157

Table 1: Classification Report Performance

The model achieved high performance for Class 0 (Negative), with a precision indicating excellent ability to correctly identify negative cases.

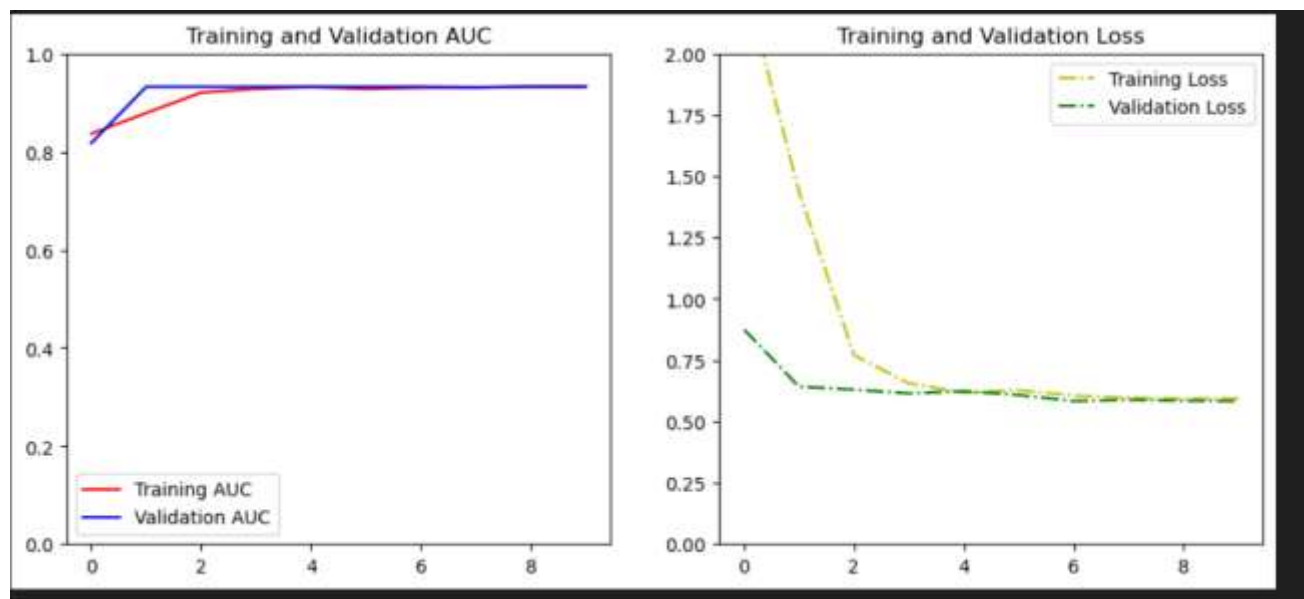


Fig 5: Model Performance Metrics

The deep learning-based model for diabetic retinopathy detection achieved strong results with an AUC of ~ 0.9 and 78.5% test accuracy, indicating effective classification. Despite high performance, it struggles with class imbalance, especially in detecting severe cases. Improvements can include data augmentation, class weight adjustments. Future work may focus on integrating more datasets, advanced CNNs, real-time deployment, telemedicine, and multi-modal analysis (OCT + fundus) to boost accuracy and accessibility in early DR diagnosis.

7. Conclusion & Future Scope

The retinal image analysis project for diabetic retinopathy detection successfully utilizes deep learning and image processing techniques to classify retinal images into different severity levels. The model demonstrates high AUC (~ 0.9) and stable loss reduction, indicating strong classification performance. The absence of significant over fitting, as seen in the aligned training and validation curves, confirms that the model generalizes well to unseen data.

However, the results also highlight the class imbalance issue, where the model struggles with minority class predictions.

Future Scope: The future of retinal image analysis for diabetic retinopathy detection lies in advancing deep learning models like ResNet, Efficient Net, and Vision Transformers to boost accuracy and robustness. Integrating multi-modal data, including OCT scans and patient records, can lead to more comprehensive diagnoses. Real-time deployment through edge AI in portable fundus cameras and cloud-based telemedicine platforms can expand access to early DR screening, especially in remote or underserved regions, enhancing overall disease management and prevention.

References

1. Mutawa, A.M.; Al-Sabti, K.; Raizada, S.; Sruthi, S. A Deep Learning Model for Detecting Diabetic Retinopathy Stages with Discrete Wavelet Transform. *Appl. Sci.* 2024, 14, 4428. [CrossRef].
2. American Academy of Ophthalmology. Diabetic Retinopathy Symptoms. Available online: <https://www.aao.org/eye-health/diseases/diabetic-retinopathy-symptoms> (accessed on 10 September 2024).
3. Khudair, A.H.; Radhi, A.M. Diabetes Diagnosis Using Deep Learning. *Iraqi J. Sci.* 2024, 65, 443–454.
4. Atcı, S.Y.; Güneş, A.; Zontul, M.; Arslan, Z. Identifying Diabetic Retinopathy in the Human Eye: A Hybrid Approach Based on a Computer-Aided Diagnosis System Combined with Deep Learning. *Tomography*.
5. Dhouibi, M.; Salem, A.K.; Saidi, A.; Saoud, S. Acceleration of convolutional neural network based diabetic retinopathy diagnosis system on field programmable gate array. *IJ-ICT 2023*, 12, 214–224. [CrossRef].
6. Tham, Y.-C.; Anees, A.; Zhang, L.; Goh, J.H.L.; Rim, T.H.; Nusinovici, S.; Hamzah, H.; Chee, M.-L.; Tjio, G.; Li, S.; et al. Referral for disease-related visual impairment using retinal photograph-based deep learning: A proof-of-concept, model development study. *Lancet Digit. Health* 2021, 3, e29–e40. [CrossRef].
7. Bora, A.; Balasubramanian, S.; Babenko, B.; Virmani, S.; Venugopalan, S.; Mitani, A.; de Oliveira Marinho, G.; Cuadros, J.; Ruamviboonsuk, P.; Corrado, G.S.; et al. Predicting the risk of developing diabetic retinopathy using deep learning. *Lancet Digit. Health* 2021, 3, e10–e19. [CrossRef].

10.48047/jocaaa.2025.34.06.11

8. Xie, Y.; Nguyen, Q.D.; Hamzah, H.; Lim, G.; Bellemo, V.; Gunasekeran, D.V.; Yip, M.Y.T.; Lee, X.Q.; Hsu, W.; Lee, M.L.; et al. Artificial intelligence for teleophthalmology-based diabetic retinopathy screening in a national programme: An economic analysis modelling study. *Lancet Digit. Health*.
9. Abdelsalam, M.M. Effective blood vessels reconstruction methodology for early detection and classification of diabetic retinopathy using OCTA images by artificial neural network. *Inform. Med. Unlocked* 2020, 20, 100390. [CrossRef].
10. Rim, T.H.; Lee, G.; Kim, Y.; Tham, Y.-C.; Lee, C.J.; Baik, S.J.; Kim, Y.A.; Yu, M.; Deshmukh, M.; Lee, B.K.; et al. Prediction of systemic biomarkers from retinal photographs: Development and validation of deep-learning algorithms. *Lancet Digit. Health* 2020, 2, e526–e536. [CrossRef] [PubMed].
11. Hsieh, Y.-T.; Chuang, L.-M.; Jiang, Y.-D.; Chang, T.-J.; Yang, C.-M.; Yang, C.-H.; Chan, L.-W.; Kao, T.-Y.; Chen, T.-C.; Lin, H.-C.; et al. Application of deep learning image assessment software VeriSee™ for diabetic retinopathy screening. *J. Formos. Med. Assoc.* 2020, 120, 165–171. [CrossRef] [PubMed].
12. rivastava, N.; Hinton, G.; Krizhevsky, A.; Sutskever, I.; Salakhutdinov, R. Dropout: A simple way to prevent neural networks from overfitting. *J. Mach. Learn. Res.* 2014, 15, 1929–1958.
13. LeCun, Y.; Bengio, Y.; Hinton, G. Deep learning. *Nature* 2015, 521, 436–444. [CrossRef] [PubMed].
14. LeCun, Y.; Boser, B.E.; Denker, J.S.; Henderson, D.; Howard, R.E.; Hubbard, W.E.; Jackel, L.D. Handwritten digit recognition with a back-propagation network. In *Advances in Neural Information Processing Systems 2*; Morgan Kaufmann Publishers Inc.: San Francisco, CA, USA, 1990; pp. 396–404.
15. LeCun, Y.; Boser, B.; Denker, J.S.; Henderson, D.; Howard, R.E.; Hubbard, W.; Jackel, L.D. Backpropagation Applied to Handwritten Zip Code Recognition. *Neural Comput.* 1989, 1, 541–551.