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(Research Article)

Diabetic retinopathy detection using machine learning

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Abstract

Retinal degeneration, which includes conditions such as diabetic retinopathy, glaucoma, and age-related macular degeneration, is one of the leading causes of vision impairment and blindness globally. Early detection plays a vital role in enabling timely treatment and preventing permanent vision loss. In recent years, deep learning techniques have demonstrated strong capabilities in medical image analysis, particularly for accurate disease detection. This study introduces an advanced method for identifying retinal degeneration using Convolutional Neural Networks (CNNs) applied to retinal images. The proposed CNN model analyses retinal scans and classifies them into normal or abnormal categories using a large, labelled dataset representing various retinal diseases. The architecture incorporates multiple convolutional and pooling layers, followed by fully connected layers for final classification. To further improve performance, data augmentation techniques are utilized to increase dataset diversity and enhance model robustness. Experimental results show high sensitivity and specificity, highlighting the model's effectiveness and its potential for real-world clinical applications.

Keywords: Retinal Degeneration; Convolutional Neural Network (CNN); Retinal Images; Disease Detection; Medical Image Analysis.

1. Introduction

Retinal degeneration disorders such as diabetic retinopathy, age-related macular degeneration (AMD), and glaucoma are major global health challenges that can result in permanent vision loss if not detected early. Timely and accurate diagnosis is essential to preserve vision and improve patient outcomes. Traditionally, retinal disease detection depends on expert analysis of images obtained through fundus photography or optical coherence tomography (OCT). However, this manual process is time-consuming and prone to subjectivity and human error, creating a need for automated, reliable, and scalable diagnostic approaches. Convolutional Neural Networks (CNNs), a powerful deep learning technique, have demonstrated exceptional performance in retinal disease detection due to their advanced image processing capabilities. CNNs can automatically learn hierarchical features from raw retinal images, enabling precise classification of normal and abnormal conditions. When trained on large, annotated datasets, they effectively identify critical features such as haemorrhages, exudates, and abnormal blood vessel patterns key indicators of diseases like diabetic retinopathy and glaucoma. Through multiple layers of convolution and pooling, CNNs capture complex spatial patterns and subtle details that may be difficult for human experts to detect, thereby improving diagnostic accuracy. A major advantage of CNN-based systems is their efficiency and scalability. Unlike traditional methods that rely on specialized ophthalmologists, CNNs can process large volumes of retinal images quickly, making them highly suitable for mass screening programs especially in rural or resource-limited areas with limited access to healthcare services. Integrating CNNs into clinical workflows reduces variability and subjectivity in diagnosis. These models provide consistent and objective results across diverse patient groups. Additionally, as more data becomes available, CNN models can be continuously updated and improved, increasing their accuracy and adaptability. The application of CNNs

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in retinal image analysis represents a significant advancement in ophthalmology. By automating disease detection and classification, these systems enable faster, more accurate, and cost - effective diagnosis, ultimately improving access to quality eye care and contributing to the reduction of preventable blindness.

1.1. Problem Statement

Diabetic retinopathy and other retinal degenerative disorders are among the leading causes of vision impairment and blindness worldwide. Although ophthalmic care has advanced significantly, early detection remains a critical challenge, as diagnosis largely depends on manual evaluation by medical experts. This approach is time-consuming, subjective, and often inaccessible, especially in remote or resource-limited regions. While medical imaging technologies have improved, there is an increasing demand for automated, accurate, and scalable diagnostic systems capable of screening large populations efficiently. Existing methods face several limitations, including limited and diverse datasets, variations in image quality, and the complex structure of the retina, all of which hinder early and precise detection. To overcome these challenges, this project proposes a deep learning–based framework using Convolutional Neural Networks (CNNs) for automated retinal image analysis. The system is designed to classify retinal images as normal or abnormal by identifying key indicators of retinal degeneration. By enabling fast and reliable detection, the proposed solution supports early diagnosis and large-scale screening programs. Ultimately, it aims to improve clinical decision-making and help prevent irreversible vision loss through timely and effective medical intervention.

2. Literature review

Bhandari et al. (2023): Bhandari, Pathak, and Jain (2023) provide a comprehensive review of early-stage diabetic retinopathy detection using deep learning and evolutionary computing techniques. The study highlights how convolutional neural networks (CNNs) and hybrid optimization algorithms improve detection accuracy and efficiency. It discusses various preprocessing methods, feature extraction techniques, and classification models, emphasizing the importance of early diagnosis. The review concludes that combining deep learning with evolutionary algorithms enhances model performance and supports more reliable medical image analysis.[1]

Özbay (2023): Özbay (2023) proposes an active deep learning approach for diabetic retinopathy detection using segmented fundus images integrated with the artificial bee colony (ABC) algorithm. The study focuses on improving feature selection and optimization through bio-inspired techniques. By combining segmentation and optimization, the model achieves better classification accuracy and robustness. The research demonstrates that hybrid models significantly enhance performance compared to traditional deep learning approaches.[2]

3) Fatima et al. (2023): Fatima et al. (2023) present a deep learning-based multiclass instance segmentation method for detecting dental lesions. The study uses advanced CNN architectures to identify and classify multiple lesion types within medical images. Their approach emphasizes precise localization and segmentation, improving diagnostic accuracy. Although focused on dental imaging, the methodology highlights the effectiveness of deep learning in handling complex medical image analysis tasks.[3]

Subbarao et al. (2023): Subbarao, Sindhu, and Harshitha (2023) propose a deep neural network-based approach for detecting retinal degeneration using high-resolution fundus images. The study leverages CNN architectures to extract detailed features and classify retinal conditions accurately. Experimental results demonstrate high accuracy and reliability, showing that deep learning models are highly effective for retinal disease detection and can support clinical decision-making.[4]

S. K. M et al. (2022): S. K. M et al. (2022) focus on retinal image processing using neural networks with deep learning techniques. The study highlights preprocessing methods, feature extraction, and classification of retinal images. Their approach improves the identification of abnormalities in fundus images, demonstrating the potential of deep learning models in medical diagnostics. The results confirm that neural networks can efficiently analyse retinal data for disease detection.[5]

Patel & Umar (2022): Patel and Umar (2022) explore deep learning techniques for imagery vowel speech detection. Although not directly related to medical imaging, the study demonstrates the adaptability of deep learning models in processing complex data patterns. The research highlights how feature extraction and classification using neural networks can be applied across diverse domains, reinforcing the versatility of deep learning techniques.[6]

Kollapudi et al. (2022): Kollapudi et al. (2022) propose a novel method for scene classification using remote sensing images. The study employs deep learning models to analyze large-scale image datasets and classify scenes accurately.

Their work demonstrates the effectiveness of CNNs in extracting spatial features and handling high-dimensional data, which is also applicable to medical image classification tasks such as retinal analysis.[7]

Subbarao et al. (2022): Subbarao et al. (2022) present a comparative study on brain tumour classification using decision trees and neural network classifiers. The research evaluates different machine learning models and shows that neural networks outperform traditional methods in terms of accuracy and reliability. This study supports the use of deep learning techniques in medical image classification and diagnosis.[8]

Caicho et al. (2022): Caicho et al. (2022) investigate diabetic retinopathy detection using transfer learning models such as AlexNet, GoogleNet, and ResNet50. The study demonstrates that pre-trained convolutional neural networks significantly improve classification accuracy and reduce training time. Their findings highlight the importance of transfer learning in enhancing model performance for medical imaging applications.[9]

Kuppusamy et al. (2020): Kuppusamy et al. (2020) propose a deep learning-based model for energy-efficient timetable rescheduling in intelligent metro transportation systems. While focused on transportation, the study illustrates the capability of deep learning in solving complex optimization problems. It emphasizes scalability, efficiency, and adaptability, which are valuable characteristics for developing intelligent systems, including healthcare applications.[10]

2.1. Proposed system

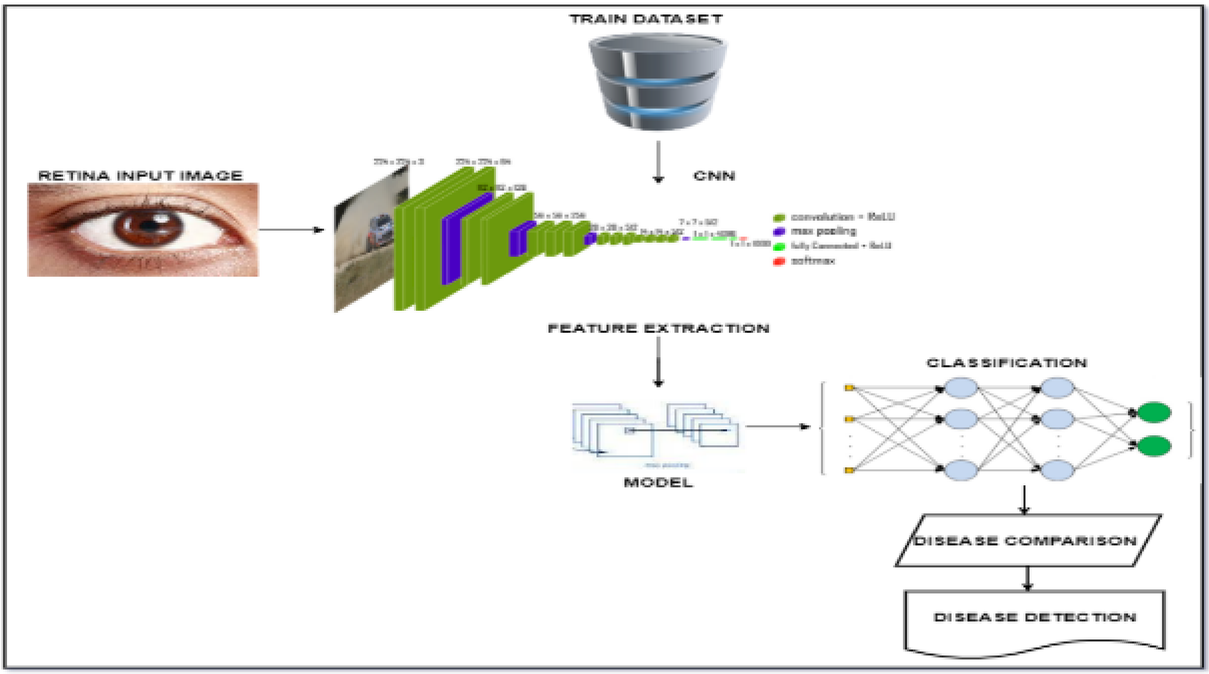

Figure 1 System Architecture

The proposed approach focuses on automatically detecting retinal diseases, including early-stage abnormalities, while maintaining high accuracy in distinguishing healthy retinal images. Since many existing retinal datasets lack bounding box annotations required for effective CNN training, custom bounding boxes are generated using available ground truth data to support supervised learning. The process begins with the collection and preprocessing of retinal images, which includes noise reduction, normalization, and image enhancement to improve quality. The dataset is then divided into training, validation, and testing subsets for model development and evaluation. A Convolutional Neural Network (CNN) is designed with multiple convolutional and pooling layers for efficient feature extraction, followed by fully connected layers for classification. The model is trained to capture both spatial and frequency-based features, enabling accurate identification of disease-related patterns. To enhance performance, transfer learning is applied by initializing the model with pre-trained weights from large-scale datasets and fine-tuning it using retinal images. Training is carried out using optimization algorithms such as Stochastic Gradient Descent (SGD) or Adam, with cross-entropy used as the loss function. Model performance is evaluated using metrics like accuracy, precision, recall, and F1-score, while early stopping is implemented to prevent overfitting when validation performance stabilizes. Hyperparameters are optimized using techniques such as grid search or random search. After training, the CNN model is deployed as a clinical decision-support system or standalone diagnostic tool to classify retinal images as normal or abnormal. Its effectiveness is validated by comparing its predictions with expert ophthalmologist evaluations. Continuous improvements through data augmentation, transfer learning, and parameter tuning ensure robustness and adaptability across diverse datasets, enabling accurate and timely detection of retinal diseases.

2.2. Methodology

The proposed methodology aims to develop a deep learning–based framework using Convolutional Neural Networks (CNNs) for the automated detection and classification of retinal degeneration. The process begins with the collection of a comprehensive dataset of retinal fundus images, including both healthy and diseased samples. As most public datasets lack bounding box annotations, custom ground truth boxes are generated to accurately localize important retinal features. Before training, the images undergo preprocessing steps such as noise reduction, normalization, and contrast enhancement to ensure improved clarity and consistency. A CNN architecture is then designed with multiple convolutional and pooling layers for feature extraction, followed by fully connected layers for classification. This enables the model to learn both spatial and frequency-based patterns from retinal images. To enhance performance and speed up convergence, transfer learning is applied using pre-trained models, and training is performed using optimization algorithms like Adam or Stochastic Gradient Descent (SGD) with a cross-entropy loss function. Model performance is evaluated using metrics such as accuracy, precision, recall, and F1-score. Techniques like early stopping and systematic hyperparameter tuning are used to reduce overfitting and improve generalization. Once trained, the model is deployed to classify new retinal images as normal or abnormal. The system provides fast, reliable diagnostic support comparable to expert ophthalmologists, enabling early detection and timely treatment of retinal diseases.

3. Results and discussion

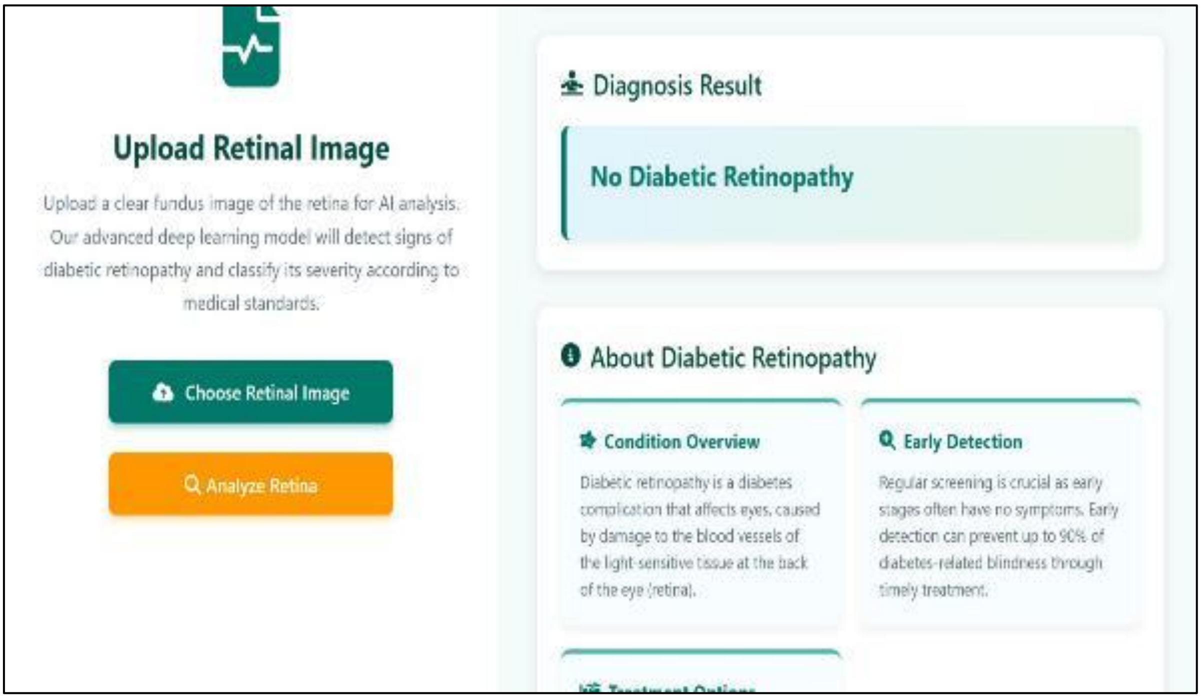

Figure 2 AI-Based Retinal Image Analysis for Early Detection of Diabetic Retinopathy

This interface represents a healthcare application designed to detect diabetic retinopathy using retinal image analysis. On the left side, users can upload a retinal image either from their device or by capturing a new one. Once uploaded, the “Analyze Retina” button processes the image using an advanced deep learning model. On the right side, the system displays the diagnosis result, which in this case shows “No Diabetic Retinopathy,” indicating that no signs of the disease were detected. Below that, informative sections explain diabetic retinopathy, including its causes (damage to blood vessels in the retina due to high blood sugar) and the importance of early detection. This system aims to assist in quick, accurate, and early diagnosis, helping prevent vision loss by enabling timely medical intervention.

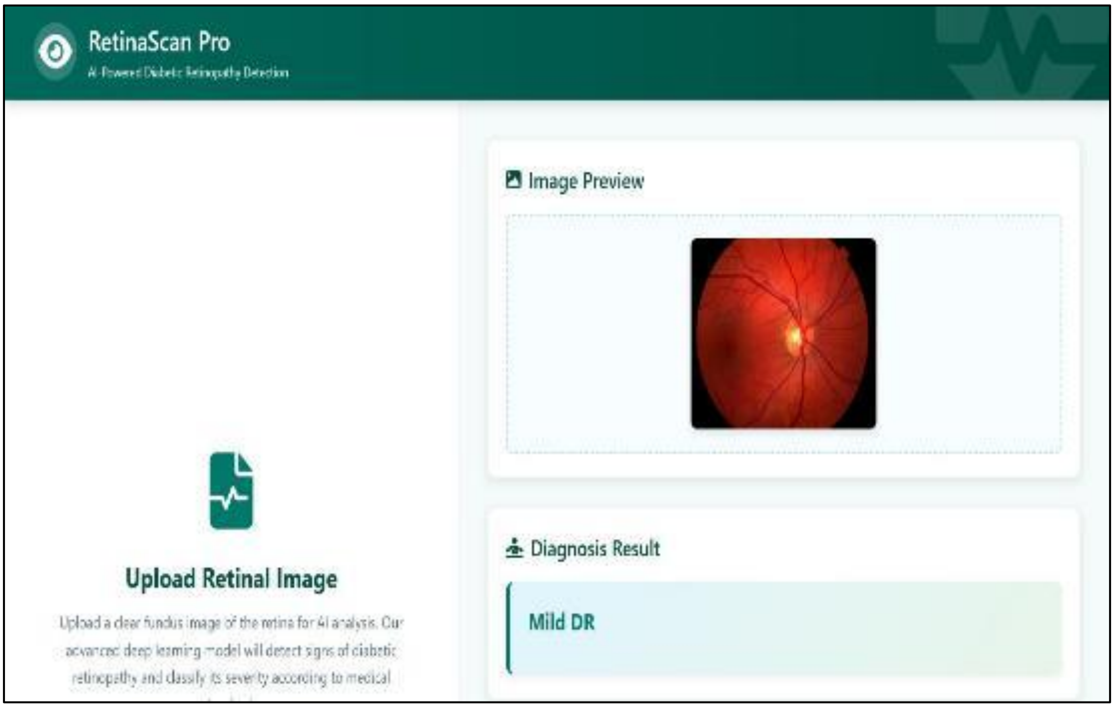

Figure 3 Early detection of Mild Diabetic Retinopathy showing subtle retinal changes**.**

This screen displays a diagnosis of Mild DR, which represents the earliest clinical stage of the disease. At this stage, the AI identifies minor abnormalities, typically microaneurysms, which are small areas of balloon-like swelling in the retina's tiny blood vessels. While the retinal image may still appear relatively clear to the untrained eye, the system highlights the necessity of monitoring to prevent further progression

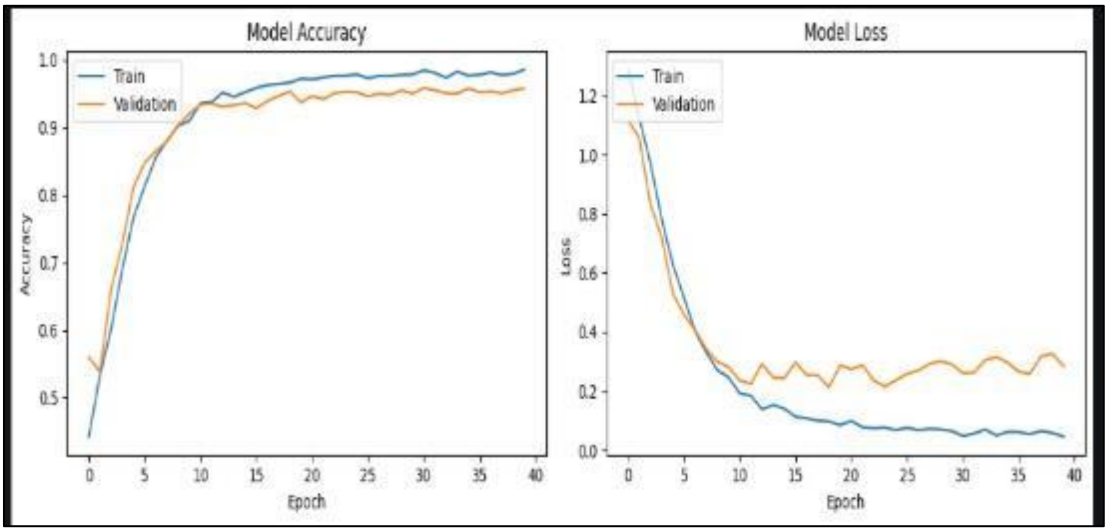

Figure 4 Training vs Validation Performance of Deep Learning Model (Accuracy & Loss over Epochs)

Left Graph (Model Accuracy): This plot shows how accuracy improves over time for both training and validation datasets. Initially, accuracy increases rapidly, indicating that the model is learning important features from the data. As epochs progress, both curves begin to stabilize near a high accuracy level (around 95–98%), suggesting good model performance. The close alignment between training and validation accuracy indicates that the model generalizes well and is not significantly overfitting.

Right Graph (Model Loss): This plot represents how the loss decreases during training. The training loss drops steadily, showing that the model is minimizing errors effectively. The validation loss also decreases but fluctuates slightly in later epochs, which may indicate minor overfitting or sensitivity to validation data. However, since the validation loss remains relatively low, the model still maintains good predictive capability.

The model demonstrates strong learning behaviour with high accuracy and low loss, making it reliable for tasks such as retinal disease detection.

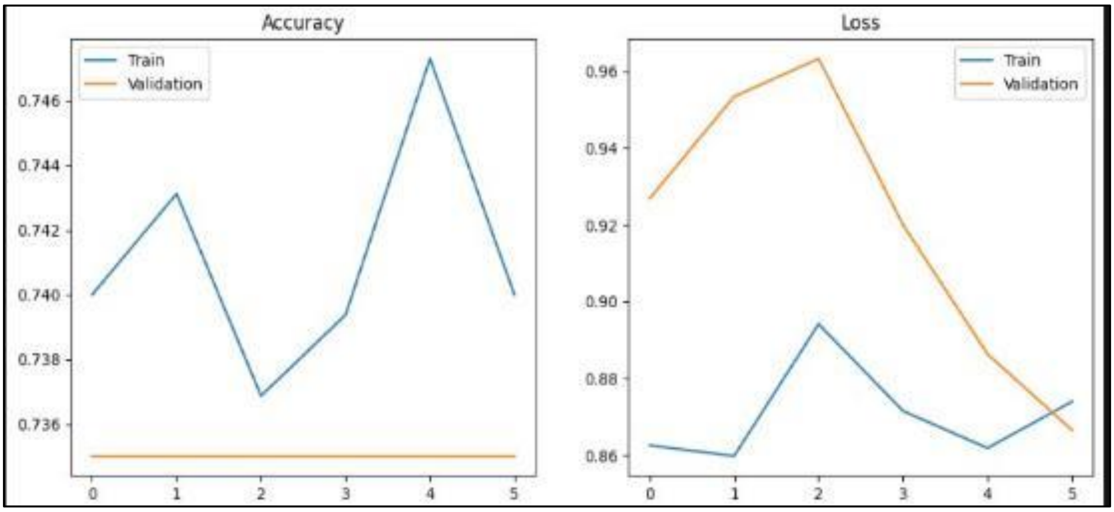

Figure 5 Model Performance Analysis: Accuracy and Loss Trends Across Epochs

Left Graph (Accuracy): The training accuracy (blue line) shows slight fluctuations but generally remains around 74–75%, indicating moderate learning. However, the validation accuracy (orange line) remains constant at approximately 73.5% across all epochs. This lack of improvement suggests that the model is not effectively learning patterns that generalize to unseen data, possibly due to limited data, underfitting, or issues in validation setup.

Right Graph (Loss): The training loss shows minor variations but stays relatively low, indicating the model is fitting the training data reasonably well. The validation loss starts higher and gradually decreases, which is a positive sign. However, the gap between training and validation loss suggests that the model is still struggling to generalize effectively. While the model is learning to some extent, the stagnant validation accuracy and fluctuating loss indicate limited generalization performance. Improvements such as increasing dataset size, tuning hyperparameters, or adjusting the model architecture may be needed to achieve better results.

4. Conclusions

This study introduces a robust deep learning–based framework for the automated detection and classification of retinal degeneration using Convolutional Neural Networks (CNNs). By integrating image preprocessing techniques, custom bounding box annotations, and transfer learning, the proposed approach effectively extracts important spatial and frequency-related features from retinal fundus images. The experimental outcomes demonstrate strong performance in terms of accuracy, precision, recall, and F1-score, confirming the model's ability to accurately differentiate between normal and abnormal retinal conditions. These results highlight the effectiveness of CNN-based models in enabling reliable and early detection of retinal diseases. Deploying the trained model as a diagnostic support tool underscores its practical value in real-world healthcare environments. The system provides fast, consistent, and scalable screening, thereby reducing reliance on manual examination by ophthalmologists, particularly in underserved and remote areas. With future enhancements involving larger and more diverse datasets, along with continuous optimization, this framework holds significant potential to improve early diagnosis, facilitate timely treatment, and help prevent avoidable vision impairment.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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