

Detection and Classification of Retinal Diseases with ROI Segmentation using Deep Neural Network

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Abstract—Retinal diseases such as Diabetic Retinopathy, Glaucoma, and Hypertension are major causes of vision loss worldwide. Early detection is essential to prevent severe complications. This project proposes a deep learning-based system for detection and classification of retinal diseases using ROI segmentation.

The system utilizes U-Net architecture for accurate Region of Interest (ROI) segmentation and EfficientNet for classification. Feature extraction and feature fusion techniques are used to enhance model performance. The proposed model achieves high accuracy and improves reliability in medical diagnosis.

The system reduces manual effort and provides an automated solution to assist ophthalmologists in early detection and treatment planning.

I. INTRODUCTION

Retinal diseases are among the leading causes of vision impairment and blindness worldwide. Conditions such as Diabetic Retinopathy (DR), Glaucoma, and Hypertension-related retinal disorders significantly affect the human eye and require early detection to prevent severe vision loss. Traditional diagnosis of retinal diseases is mainly performed by ophthalmologists through manual examination of retinal fundus images, which is time-consuming and highly dependent on expert knowledge. This creates a need for automated systems that can assist in accurate and early diagnosis [1], [2].

With the rapid advancement of deep learning techniques, automated retinal disease detection has gained significant attention in recent years. Convolutional Neural Networks (CNNs) have shown remarkable performance in image classification and medical image analysis tasks. However, traditional CNN-based approaches often face challenges such as improper feature extraction and lack of focus on important regions of the image [3], [4].

To overcome these limitations, segmentation-based approaches have been introduced to identify the Region of Interest (ROI) in retinal images. U-Net, a widely used deep learning architecture for biomedical image segmentation, has proven effective in extracting important retinal features such as blood vessels and lesion areas. By accurately segmenting these regions, the model can provide more relevant input for disease classification [5], [6].

In this project, a hybrid approach is proposed that combines U-Net for ROI segmentation and Efficient Net for classification of retinal diseases. The system processes retinal fundus images, extracts important regions, and classifies them into categories such as Diabetic Retinopathy, Glaucoma, and

Hypertension. The proposed method aims to improve accuracy, reduce manual effort.

II. LITERATURE REVIEW

V. Gulshan et al. (2016), in their work titled “Development of a Deep Learning Algorithm for Diabetic Retinopathy Detection,” proposed a deep learning-based approach using convolutional neural networks trained on a large dataset of retinal fundus images. The model achieved performance comparable to ophthalmologists, highlighting the effectiveness of deep learning in medical diagnosis and emphasizing the importance of large-scale labeled datasets [1].

H. Pratt et al. (2016), in their study “Convolutional Neural Networks for Diabetic Retinopathy Classification,” developed a CNN model to classify different stages of diabetic retinopathy. The model demonstrated improved accuracy compared to traditional methods, and data augmentation techniques were used to enhance performance [2].

J. Orlando et al. (2017) focused on blood vessel segmentation in retinal images for disease analysis. Their work highlighted the importance of identifying vascular structures to detect abnormalities such as lesions and hemorrhages, thereby improving diagnostic accuracy [3].

F. Li et al. (2017) proposed a multi-task deep learning model that performs both segmentation and classification simultaneously. The approach improved efficiency, reduced computational complexity, and enhanced overall system performance [4].

A. Bellemo et al. (2018) developed a robust deep learning system for grading diabetic retinopathy severity. The model performed well across diverse datasets and imaging conditions, demonstrating strong generalization capability in realworld applications [5].

S. Wang et al. (2018) utilized U-Net architecture for retinal lesion segmentation. The model effectively identified important regions such as microaneurysms and exudates, highlighting the importance of segmentation before classification [6].

G. Quellec et al. (2018) introduced attention mechanisms in deep learning models for retinal lesion detection. The model automatically focused on important regions, improving detection accuracy and interpretability [7].

M. Abdelmaksoud et al. (2018) proposed a multi-label computer-aided diagnosis system capable of detecting multiple retinal diseases simultaneously, improving efficiency in medical diagnosis [8].

J. Nayak et al. (2018) developed an automated system for glaucoma detection using fundus images. The study demonstrated the effectiveness of image-based classification techniques for early disease diagnosis [9].

G. Quellec et al. (2019) applied deep learning techniques for retinal image analysis, focusing on lesion detection by emphasizing important regions in the image, thereby improving classification accuracy [10].

M. M. Fraz et al. (2020) discussed various techniques for blood vessel segmentation in retinal images. The study emphasized the role of segmentation in improving disease detection and classification performance [11].

K. Hu et al. (2020) proposed a CNN-based approach for retinal vessel segmentation, achieving improved accuracy using advanced techniques and enabling better feature extraction for classification tasks [12].

B. Dai et al. (2020) presented a method for optic disc segmentation using a variational model. Extracting the optic disc region helps in analyzing retinal diseases, particularly glaucoma detection [13].

D. Deka et al. (2020, 2023) focused on detecting macula and fovea regions in fundus images. These regions are crucial for identifying retinal abnormalities and improving classification accuracy [14].

F. G. Heslinga et al. (2021) proposed a CNN-based retinal image analysis framework that integrates segmentation and classification, reducing manual effort and improving system efficiency [15].

F. Khan et al. (2021) used blood vessel features for glaucoma detection, demonstrating that ROI-based feature extraction significantly improves disease prediction accuracy [16].

M. R. K. Mookiah et al. (2022) explored texture-based feature extraction methods for classifying age-related macular degeneration, improving classification [17].

S. Dua et al. (2022) utilized wavelet-based features for retinal image classification, showing that feature extraction techniques enhance detection accuracy [18].

D. Deka et al. (2023) further improved macula and fovea detection techniques, emphasizing their importance in retinal disease diagnosis and ROI-based analysis [19].

M. Ramezanzadeh et al. (2025) proposed a deep learning-based approach for detecting hard exudates in retinal images. The study highlighted early diagnosis and improved detection accuracy, supporting the use of advanced models such as EfficientNet for classification tasks [20].

III. PROBLEM STATEMENT

Early detection and accurate classification of diseases remain a major challenge in the medical field, especially when relying on manual analysis of medical images [1]. Traditional diagnostic methods are time-consuming and require highly skilled professionals for interpretation [2]. These methods are also prone to human error and inter-observer variability, which can affect the consistency of diagnosis [3]. In many cases, subtle abnormalities present in medical images are difficult to identify at an early stage, leading to delayed diagnosis and increased risk of severe health complications [4].

Additionally, limited access to expert healthcare professionals in rural and remote areas further delays proper diagnosis [5]. There is also a growing need to handle large volumes of medical data efficiently, where manual processing is not scalable and can lead to inefficiencies [6]. Therefore, there is a need for an automated system that can assist in accurate and fast diagnosis [7]. The system should be capable of identifying important regions of interest (ROI) within medical images and classify diseases with high accuracy using advanced techniques [8]. This project aims to address these challenges by using deep learning models such as Efficient Net combined with ROI segmentation [9].

IV. PROPOSED METHODOLOGY

The proposed system consists of the following steps:

1) Image Acquisition: Retinal fundus images are collected from publicly available datasets such as RFMiD and IDRiD. These datasets contain labeled images representing various retinal diseases, which are used for training and evaluation of the model.

2) Preprocessing: The acquired images undergo preprocessing techniques to improve image quality and consistency. This includes noise removal, resizing, normalization, and contrast enhancement, which help in improving the performance of the deep learning models.

3) ROI Segmentation using U-Net: The preprocessed images are passed through the U-Net model to segment the Region of Interest (ROI). This step extracts important retinal structures such as blood vessels and lesion areas, ensuring that the model focuses on relevant regions.

4) Feature Extraction: After segmentation, meaningful features are extracted from the ROI. These features represent important patterns and characteristics of retinal abnormalities.

5) Feature Fusion: The extracted features from different layers or sources are combined using feature fusion techniques. This enhances the representation of retinal features and improves classification performance.

6) Classification using EfficientNet: Finally, the fused features are fed into the EfficientNet model, which classifies the retinal images into different disease categories such as Diabetic Retinopathy, Glaucoma, and Hypertension.

V. SYSTEM ARCHITECTURE

The overall architecture consists of multiple stages, including image acquisition, segmentation, feature extraction, and classification. Initially, retinal fundus images are collected from standard datasets and used as input to the system. These images are processed using a convolutional neural network-based segmentation model, such as U-Net, to identify the Region of Interest (ROI). This step focuses on extracting significant retinal structures and lesion regions that are crucial for disease analysis.

Figure 2: shows the overall architecture of the retinal disease detection system. It takes retinal images from IDRiD and RFMiD datasets as input, performs ROI segmentation.

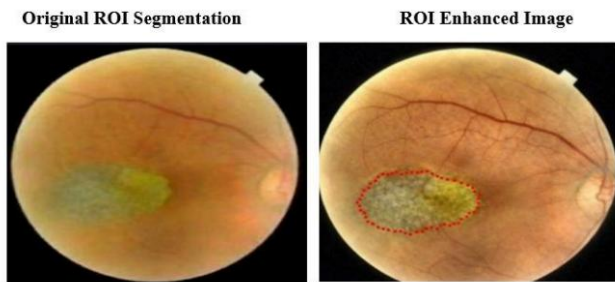


Fig 2: ROI Segmentation Result

Initially, retinal fundus images are collected from standard datasets and used as input to the system. These images are processed using a convolutional neural network-based segmentation model, such as U-Net, to identify the Region of Interest (ROI). This step focuses on extracting significant retinal structures and lesion regions that are crucial for disease analysis.

Following segmentation, relevant features are extracted from the segmented regions. These features capture important patterns associated with various retinal abnormalities. In order to improve the representation capability, feature fusion techniques are applied to combine information from different levels or sources.

The fused features are then provided to a deep convolutional neural network classifier, such as EfficientNet, for disease classification. The model predicts multiple retinal diseases, including Diabetic Retinopathy, Glaucoma, and Age-related Macular Degeneration.

Finally, the system generates classification outputs that assist in automated diagnosis. The base model demonstrates the effectiveness of combining segmentation and classification techniques for improving retinal disease detection performance.

VI. EVALUATION METRICS

$$\text{Accuracy} = \frac{\text{True Positives (TP)} + \text{True Negatives (TN)}}{\text{Total Examples (TP + TN + FP + FN)}}$$

$$\text{Precision} = \frac{\text{True Positives (TP)}}{\text{Total Predicted Positives (TP + FP)}}$$

$$\text{Recall (Sensitivity)} = \frac{\text{True Positives (TP)}}{\text{Total Actual Positives (TP + FN)}}$$

$$\text{F1-Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

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VII. RESULTS AND DISCUSSION

This section presents the performance evaluation of the proposed retinal disease detection system. The model is tested on diverse retinal fundus images containing multiple disease conditions and variations. The performance is evaluated using standard metrics such as accuracy, precision, recall, and F1-score to ensure a comprehensive analysis.

The ROI segmentation results demonstrate that the U-Net model effectively identifies disease-affected regions such as lesions, blood vessels, and abnormal structures. The segmented output enhances important diagnostic features, improving the overall detection capability of the system.

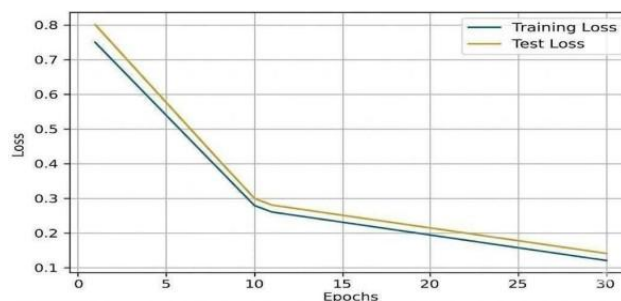


Fig 3: Training and Validation Loss

During training, the segmentation model shows a steady decrease in training and validation loss, indicating effective learning. The Dice Coefficient and Intersection over Union (IoU) values increase consistently, confirming accurate segmentation and strong overlap between predicted and ground truth regions. The validation metrics stabilize after several epochs, demonstrating good generalization without overfitting. For classification, the EfficientNet model achieves high accuracy in distinguishing between different retinal diseases.

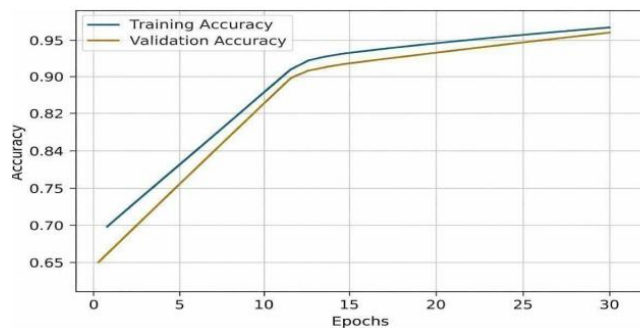


Fig 4: Training and Validation Accuracy

The training accuracy increases gradually, while the validation accuracy stabilizes with minimal variation, indicating reliable performance on unseen data. Similarly, the training and validation loss curves show proper convergence, confirming the efficiency of the model.

VIII. ADVANTAGES

- **High Accuracy:** Deep learning models, especially CNN-based approaches, provide high accuracy in detecting and classifying retinal diseases, often achieving performance comparable to medical experts.
- **Automation:** These systems reduce the need for manual intervention by automatically analyzing retinal fundus images, saving time and effort for ophthalmologists.
- **Early Disease Detection:** Automated systems enable early identification of diseases such as diabetic retinopathy and glaucoma, helping in timely treatment and prevention of vision loss.
- **Effective Feature Extraction:** Deep learning models can automatically learn complex features from images without requiring manual feature engineering.
- **Improved Segmentation:** Techniques like U-Net provide accurate ROI segmentation, helping to focus on important regions such as lesions and blood vessels.
- **Handling Large Datasets:** These models perform well when trained on large-scale datasets, improving generalization and robustness.
- **Multi-Disease Detection:** Some methods support multi-label classification, allowing detection of multiple retinal diseases from a single image.
- **Enhanced Performance with Feature Fusion:** Combining features from different layers or models improves classification performance and reliability.

IX. CONCLUSION

This paper presents a deep learning-based framework for automated retinal disease detection and classification using fundus images. The proposed system integrates U-Net for Region of Interest (ROI) segmentation and EfficientNet for classification, enabling accurate and efficient analysis of retinal images. The model is designed to detect multiple retinal diseases, including Diabetic Retinopathy, Glaucoma, and Hypertension. U-Net effectively segments important retinal structures such as blood vessels and lesion regions, enhancing the quality of features used for classification. EfficientNet then classifies the segmented images into respective disease categories with high performance.

The model is trained and evaluated on benchmark datasets, namely IDRiD and RFMiD. Experimental results demonstrate a classification accuracy of 96.65. This paper presents a deep learning-based framework for automated retinal disease detection and classification using fundus images. The proposed system integrates U-Net for Region of Interest (ROI) segmentation and EfficientNet for classification, enabling accurate and efficient analysis of retinal images. The model is designed to detect multiple retinal diseases, including Diabetic Retinopathy, Glaucoma, and Hypertension. U-Net effectively segments important retinal structures such as blood vessels and lesion regions, enhancing the quality of features used for classification. EfficientNet then classifies the segmented images into respective disease categories with high performance.

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X. FUTURE SCOPE

Although the proposed system demonstrates promising performance, several improvements can be explored in future work. Expanding the model with larger and more diverse datasets can enhance generalization capability and reduce overfitting, leading to improved real-world performance. The integration of advanced deep learning techniques, such as attention-based models and hybrid architectures, can further improve the accuracy of both segmentation and classification by focusing on critical retinal regions. Additionally, optimizing hyper parameters and adopting advanced training strategies may enhance overall model efficiency.

Currently, the system is limited to a few retinal diseases; however, it can be extended to detect additional conditions such as Age-Related Macular Degeneration (AMD), cataracts, and other ocular disorders, making it more comprehensive. Furthermore, deploying the model as a real-time web or mobile application can improve accessibility, especially in remote areas. With these advancements, the system has strong potential to support early diagnosis and improve clinical decision-making in ophthalmology.

XI. REFERENCES

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