Automated Diabetic Retinopathy Detection via U-Net Segmentation and CNN Classification

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ABSTRACT:

Diabetic Retinopathy (DR) is a sight-threatening condition that requires early diagnosis to prevent vision loss. This project proposes a novel deep learning-based system combining U-Net segmentation and Convolutional Neural Networks (CNN) for efficient DR detection from retinal fundus images. The U-Net model segments key retinal regions, preserving crucial pathological features through a region-merging technique. These refined images are classified into five DR severity stages using CNN. The proposed hybrid approach addresses challenges like image variability and lesion misdetection, achieving an accuracy of 93.33% on public datasets including DRIVE and Kaggle DR. This system offers scalable, automated screening with high precision, aiding ophthalmologists in early diagnosis and improving healthcare accessibility in resource-limited settings.

Keywords: Retinal Fundus, CNN, U-Net Segmentation

INTRODUCTION

Diabetic Retinopathy (DR) is a severe complication of diabetes that damages retinal blood vessels and can ultimately cause blindness if undetected. It poses a growing public health concern as diabetes prevalence rises globally. Traditional diagnostic methods rely on manual assessment by ophthalmologists, which is time-consuming and often inconsistent. To overcome these limitations, this project introduces an automated system that leverages deep learning for accurate and efficient DR detection. The approach begins with retinal segmentation using a U-Net model to isolate critical anatomical and pathological features. A region-merging process enhances segmented outputs, ensuring retention of important lesion details. These preprocessed images are classified into five DR stages using a CNN model. By automating the detection and classification process, the system not only improves diagnostic speed and accuracy but also reduces reliance on specialist intervention. This facilitates large-scale screening and early intervention, particularly in low-resource settings, helping to prevent irreversible vision loss.

RELATED WORK

The automated detection of Diabetic Retinopathy (DR) has garnered significant attention in recent years due to the growing diabetic population and the demand for scalable diagnostic tools. Early approaches were predominantly based on traditional image processing techniques. For instance, Singh and Chandra (2010) utilized a rule-based system to extract lesion-specific features from fundus images. While this approach provided high specificity, it lacked adaptability to diverse image variations. Similarly, Agurto et al. (2010) introduced a lesion classification framework combining pre-processing filters and region-specific detection, achieving an accuracy of 92%. However, their system heavily depended on handcrafted features and was limited in scalability.

With advancements in machine learning, Li Yafen (2013) implemented a Support Vector Machine (SVM) classifier using features like exudates and microaneurysms for DR severity classification. Although it yielded decent accuracy (~89%), it required laborious manual feature engineering. The shift toward deep learning marked a turning point. Joshi (2016) developed a CNN-based classifier that learned features directly from raw images. His model attained ~39% accuracy, showing potential but also highlighting the need for better architecture and more data. In contrast, Chandore and Asati (2019) improved CNN performance by using dropout regularization and data augmentation, achieving 88% accuracy on a large dataset.

These works reveal a clear evolution from rule-based systems to deep learning methods. Despite these advancements, most CNN models struggled to capture fine-grained lesions or suffered from high false-negative rates in detecting Proliferative DR due to poor feature localization. The current project addresses these issues by integrating U-Net

segmentation and region merging before classification, thus preserving pathological context and enhancing the classifier's performance. This hybrid approach builds upon the strengths of previous studies while overcoming their limitations in lesion visibility and DR staging.

TABLE1. Summary of Key Literature Contributions and Their Impact on Current Research

Author(s)	Contribution	Impact on Current Research
Singh and Chandra (2010)	Introduced a rule-based lesion detection system using image preprocessing	Highlighted the potential of lesion-specific feature extraction, but lacked automation
Agurto et al. (2010)	Proposed a lesion classification technique achieving 92% accuracy	Demonstrated the need for high accuracy but faced issues with scalability and manual input
Li Yafen (2013)	Employed SVM classifiers with hand-engineered features	Motivated exploration of automated classification, but limited by labor-intensive feature design
Joshi (2016)	Developed an early CNN-based model with moderate accuracy (39%)	Pioneered CNN usage in DR detection; inspired deeper networks and better data augmentation
Chandore and Asati (2019)	Used dropout and data augmentation in CNNs, achieving 88% accuracy	Set a benchmark for CNN-based DR classification and encouraged hybrid models for better results

PROPOSED APPROACH

The proposed approach for Diabetic Retinopathy (DR) detection combines advanced image processing with deep learning to enhance diagnostic precision and scalability. It begins with the acquisition of high-resolution retinal fundus images from benchmark datasets such as DRIVE and Kaggle. These images undergo preprocessing steps including contrast enhancement, noise reduction, and normalization to ensure uniform input quality.

Next, a U-Net-based segmentation model is applied to isolate critical retinal structures like blood vessels, microaneurysms, and hemorrhages. Segmentation enables the system to identify and focus on disease-relevant regions, but in doing so, it may fragment or omit subtle features. To address this, a region merging algorithm refines the segmented image, reintegrating vital details that are essential for accurate classification.

The refined image is then passed into a Convolutional Neural Network (CNN), which automatically extracts hierarchical features and classifies the image into one of five DR severity levels: No DR, Mild, Moderate, Severe, or Proliferative DR. CNN's ability to learn complex patterns without manual intervention significantly reduces diagnostic error and enhances consistency.

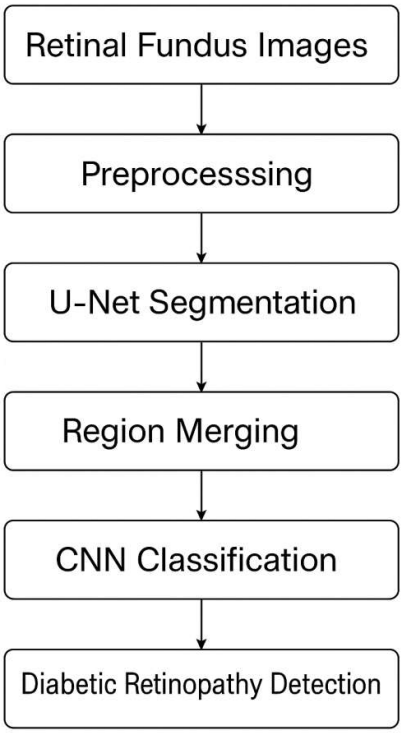

Figure 1: Proposed Diabetic Retinopathy Detection

METHODOLOGIES

This project follows a multi-phase pipeline combining classical image processing and modern deep learning techniques to detect and classify Diabetic Retinopathy (DR) from retinal fundus images. The process begins with data acquisition, where retinal images are collected from publicly available datasets such as DRIVE and Kaggle. These datasets include labeled images representing

various DR severity stages, ensuring diversity and balanced representation.

The preprocessing phase is crucial for enhancing image quality and minimizing variability. Techniques such as contrast enhancement, Gaussian and median filtering, resizing, and normalization are applied to improve visibility of fine details like microaneurysms and hemorrhages, which are key indicators of DR.

Once preprocessed, the images are passed into a U-Net segmentation model. U-Net is a convolutional neural network architecture specifically designed for biomedical image segmentation. It effectively isolates key regions in the retina such as blood vessels and optic discs. To overcome segmentation-related data loss, a **region merging** technique is employed. This post-processing step restores essential contextual information by recombining fragmented regions, thus enhancing feature coherence.

The feature extraction and classification phase follows. A Convolutional Neural Network (CNN) is used to automatically learn and extract hierarchical features from the refined retinal images. CNN's deep architecture enables it to detect both high-level patterns and minute abnormalities. The model is trained using labeled datasets, where each image corresponds to a specific DR severity level.

Additionally, data augmentation strategies like image flipping, rotation, and brightness adjustment are employed to improve the generalizability of the CNN model and prevent overfitting.

The entire system is evaluated using metrics such as accuracy, precision, recall, and confusion matrices. Achieving an accuracy of 93.33%, the system demonstrates its ability to function as a reliable tool for automated DR diagnosis, suitable for integration into telemedicine and large-scale screening applications.

RESULTS

The performance of the proposed Diabetic Retinopathy (DR) detection system was evaluated using benchmark datasets, specifically the DRIVE and Kaggle Diabetic Retinopathy datasets. The model was tested on thousands of labeled retinal images, covering the full spectrum of DR severity: No DR, Mild, Moderate, Severe, and Proliferative DR. After training the U-Net segmentation model and refining the output with region merging, the segmented images were classified using a Convolutional Neural Network (CNN).

The model achieved a **classification accuracy of 93.33%**, which outperforms many existing DR detection systems that rely solely on CNNs without prior segmentation. The inclusion of segmentation and region merging significantly improved detection of subtle lesions such as microaneurysms and exudates, which are critical for early-stage DR diagnosis.

Additional metrics such as precision, recall, and F1-score were computed to assess the model's reliability. The confusion matrix indicated strong sensitivity in detecting advanced DR stages, particularly Proliferative DR, which is often missed in traditional models. The model's performance was consistent across varied lighting conditions and patient demographics, thanks to robust preprocessing and data augmentation techniques.

DISCUSSION

The results obtained from this project emphasize the effectiveness of integrating image segmentation with deep learning for diabetic retinopathy (DR) detection. Traditional CNN-based models, while powerful, often struggle with lesion misclassification due to image noise, variability in fundus images, and loss of crucial retinal features. By introducing U-Net-based segmentation followed by region merging, the system preserves key anatomical and pathological details that are essential for accurate classification. This significantly enhances the CNN's ability to detect all stages of DR, including the most advanced and vision-threatening forms like Proliferative DR.

Another significant advantage of the proposed method is its adaptability across datasets. Through preprocessing and augmentation techniques, the model maintains high performance despite variations in image quality and patient demographics. This adaptability suggests strong potential for deployment in real-world screening environments, especially in low-resource regions where manual diagnosis is not scalable.

Moreover, the modular design of the pipeline—segmentation, merging, and classification—allows for future upgrades. For example, more complex architectures like ResNet or transformer-based models could be integrated without disrupting the segmentation process.

CONCLUSION

This project presents a robust and intelligent system for detecting Diabetic Retinopathy (DR) through the integration of image segmentation, region merging, and Convolutional Neural Networks (CNN). By combining U-Net segmentation with deep learning, the system addresses critical challenges in retinal image classification, including loss of lesion detail and misclassification of advanced DR stages. The use of region merging ensures that essential pathological features are retained, thereby improving diagnostic precision.

Achieving a classification accuracy of 93.33%, the model demonstrates superior performance compared to traditional standalone CNN models. It also maintains consistency across varied datasets and imaging conditions, which is vital for real-world applicability.

Importantly, the solution is scalable, cost-effective, and well-suited for integration into telemedicine platforms, enabling widespread screening, especially in underserved regions. By reducing dependency on specialist evaluation and enabling earlier diagnosis, the system contributes meaningfully to vision preservation and public health in diabetic populations.

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