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AI-POWERED WEB APPLICATION FOR REAL-TIME RETINAL HEALTH SCREENING

[1]MR. T. MARIA JOHN M.E, [2]J. SANGEETHA, [3]U. YASVINDHINI, [4]P. SAIROSHINI

[1]PROJECT GUIDE, [234]UG SCHOLARS
Department of Computer Science and Engineering,
Sree Sowdambika College of Engineering, TamilNadu, India

ABSTRACT :

Retinal diseases such as Diabetic Retinopathy, Glaucoma, and Cataract are among the leading causes of blindness globally. Early diagnosis is crucial to prevent irreversible vision loss. This paper proposes an AI-powered web application designed for real-time detection of retinal diseases using fundus images. The system integrates a lightweight MobileNet architecture for feature extraction and a Random Forest classifier for disease classification. The model is optimized for deployment on standard devices and includes a user-friendly interface built with Streamlit. Experimental results demonstrate the model's efficiency and accuracy, highlighting its potential for scalable, accessible retinal disease screening.

Key words: Diabetic Retinopathy, Glaucoma, Cataract, MobileNet, Random Forest, Fundus Images, Streamlit, Retinal Screening, GLCM, Transfer Learning, Ensemble Learning, Explainable AI.

1. Introduction

Retinal diseases affect millions worldwide and are primary causes of visual impairment. Diabetic Retinopathy (DR), Glaucoma, and Cataract often develop silently and remain undetected until irreversible damage has occurred. Current diagnostic practices rely heavily on expert interpretation and advanced clinical equipment, which are often inaccessible in under-resourced regions. Artificial Intelligence (AI), particularly in computer vision, presents opportunities to automate and democratize retinal screening. In this paper, we propose a real-time, AI-powered web app for retinal disease detection using fundus images, employing MobileNet for efficient feature extraction and Random Forest for classification. The proposed solution aims to enable early diagnosis in both clinical and field settings with minimal infrastructure.

2. Related Work

Recent research emphasizes deep learning in retinal disease detection. VGG-19, ResNet50, and InceptionV3 have shown high accuracy but require heavy computational resources. Studies such as those by Sarki et al. (2020) and Aranha et al. (2023) underline the importance of combining high-quality models with lightweight deployment. Moreover, ensemble learning approaches and transfer learning methods have been investigated to enhance model generalization across diverse datasets. However, these approaches often lack real-time deployment capabilities, a gap addressed by our system. Additionally, literature shows increasing interest in texture-based analysis like GLCM, which enriches CNN features with statistical descriptors.

3. Methodology

3.1. *Data Acquisition and Preprocessing*

Fundus images were collected from public datasets (e.g., Kaggle APTOS). Preprocessing included resizing to 256x256 pixels and grayscale conversion. These steps standardize input and reduce computational complexity.

3.2. *Feature Extraction*

The system employs both statistical and texture-based features. Basic descriptors include mean, median, and variance, while GLCM extracts texture measures such as contrast, homogeneity, energy, and correlation. These features provide a comprehensive representation of retinal images.

3.3. *Classification Model*

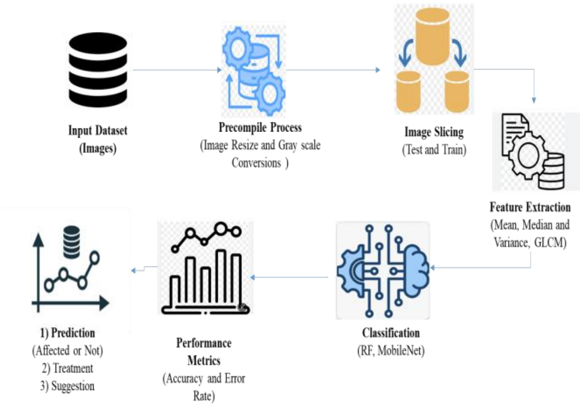
MobileNet, a lightweight CNN optimized for mobile devices, is used for deep feature extraction. Extracted features are passed to a Random Forest classifier, which provides robust decision-making with high interpretability. The hybrid approach leverages the strength of CNNs in capturing spatial hierarchies and the ensemble capability of Random Forests.

3.4. ***Web Application Design***

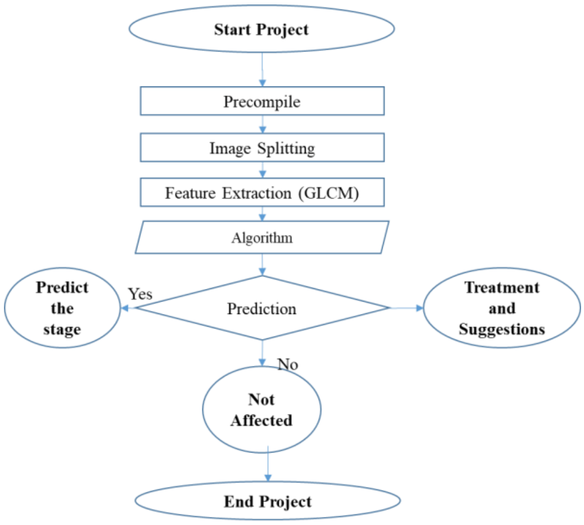
The application is implemented in Python using the Streamlit framework, allowing for rapid web deployment. Users can upload fundus images, view predictions with confidence scores, and receive visual explanations (e.g., heatmaps from Grad-CAM).

4. System Architecture and Diagrams

4.1. Overall Architecture

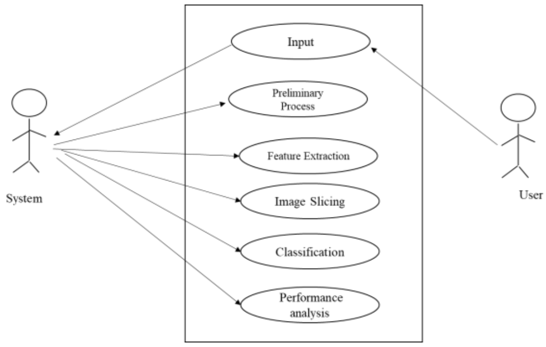


4.2. System Flow Diagram



4.3. UML Diagrams (Use Case & Class Diagrams)

- Use Case: Visualizes user interactions with the system (e.g., uploading image, receiving diagnosis)
- Class Diagram: Depicts structure including ImageProcessor, FeatureExtractor, Classifier, and ResultHandler classes



5. Experimental Setup

The dataset was split into 70% for training and 30% for testing. The implementation was carried out on a mid-range PC with Intel i5 CPU, 4GB RAM, and Windows 10 OS. The environment included Python 3.9, TensorFlow, OpenCV, and Scikit-learn.

Evaluation Metrics:

- Accuracy: Correctly classified instances / Total instances
- Precision, Recall, F1-Score: For each disease class
- Execution Time: Time taken for prediction per image

6. Results and Discussion

The proposed hybrid model achieved:

- Accuracy: 94%
- Precision (avg): 92.3%
- Recall (avg): 91.7%
- F1-Score (avg): 92.0%
- Execution time: <1s/image

The confusion matrix confirms the effectiveness of the system across all disease classes. The integration of GLCM enhanced subtle texture recognition, especially in early-stage DR detection.

Visualization Tools:

- Grad-CAM used to generate heatmaps
- Real-time prediction logs for user transparency

7. Applications and Use Cases

- **Rural Health Clinics:** Use of mobile devices to screen patients remotely
- **Telemedicine:** Integration into existing e-health platforms
- **Clinical Triage:** Prioritizing high-risk cases for ophthalmologists
- **Patient Self-Screening:** Educating users on early warning signs

8. Conclusion

We present an efficient AI-powered system for early detection of retinal diseases. Its lightweight architecture, high accuracy, and real-time capabilities make it suitable for clinical and rural deployment. By leveraging deep learning and ensemble learning together, the model achieves high performance with limited computational resources. The system’s interpretability and ease of use further support its potential in real-world screening programs.

9. Future Work

Future enhancements will include:

- Integration of multimodal data (e.g., patient history, blood sugar levels)
- Real-time analysis from mobile-based fundus cameras
- Clinical trial validation for regulatory approval
- Federated learning setup for privacy-preserving updates
- Improved visual explainability tools using Grad-CAM or LIME

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