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Improved Detection of Diabetic Retinopathy Using Machine Learning

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Abstract: Diabetic Retinopathy is a serious eye disease caused by diabetes and is one of the leading causes of blindness worldwide. Early detection plays a crucial role in preventing vision loss; however, manual diagnosis requires expert ophthalmologists and significant time. In this paper, a machine learning-based system is proposed for the automated detection of diabetic retinopathy using retinal fundus images. The system involves image preprocessing, feature extraction, and classification using the XGBoost algorithm. The preprocessing stage enhances the quality of images and removes unwanted noise, while feature extraction captures important color, texture, and structural information from the retina. These features are used to train a classification model that can accurately distinguish between normal and affected cases. The system is evaluated using performance metrics such as accuracy, precision, recall, and F1-score. The results show that the proposed model achieves reliable performance with reduced computational complexity, making it suitable for deployment in real-world healthcare environments, especially in low-resource areas.

Keywords: *Diabetic Retinopathy, Machine Learning, XGBoost, Image Processing, Feature Extraction, Medical Diagnosis.*

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I. INTRODUCTION

Diabetes mellitus is a chronic metabolic disorder that affects millions of people worldwide and continues to grow rapidly due to lifestyle changes, poor dietary habits, and lack of physical activity. Among its many complications, diabetic retinopathy is one of the most serious, as it directly impacts vision and can lead to permanent blindness if not detected early. The condition occurs due to damage to the small blood vessels in the retina, which plays a vital role in converting light into visual signals for the brain. As the disease progresses, it can cause leakage of blood vessels, swelling, and abnormal growth of new vessels, ultimately leading to severe vision impairment.

The increasing prevalence of diabetes has resulted in a corresponding rise in diabetic retinopathy cases, creating a major challenge for healthcare systems. Early detection is crucial to prevent vision loss; however, many patients remain undiagnosed due to the absence of noticeable symptoms in the early stages. Traditional diagnostic methods rely on manual examination of retinal fundus images by ophthalmologists, which, although effective, are time-consuming and require skilled professionals. This becomes a significant limitation in rural and underdeveloped areas where access to specialized healthcare is limited.

To address these challenges, there is a growing need for automated and efficient diagnostic systems. Machine learning techniques have emerged as a powerful solution in medical image analysis, enabling computers to identify patterns and detect diseases with high accuracy. Advanced models, particularly deep learning approaches, can analyze retinal images and classify them based on the presence and severity of diabetic retinopathy.

The development of automated detection systems can significantly reduce the workload on healthcare professionals and improve accessibility to early diagnosis. Such systems are especially beneficial for large-scale screening and in regions with limited medical resources. In this context, this project focuses on developing a machine learning-based approach for the detection of diabetic retinopathy, aiming to provide accurate, fast, and reliable diagnosis to support better clinical decision-making and prevent vision loss.

II. RELATED WORKS

Recent research in diabetic retinopathy detection has largely focused on deep learning-based approaches due to their strong capability in image classification tasks. Convolutional Neural Networks (CNNs) have been widely adopted as they can automatically extract hierarchical features from retinal fundus images. Several studies have

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demonstrated that CNN-based architectures achieve high accuracy in identifying different stages of diabetic retinopathy by learning complex spatial patterns and lesion characteristics present in the retina [1]. These models reduce the need for manual feature engineering; however, they require large labeled datasets and high computational resources for effective training.

Researchers have also explored advanced deep learning techniques such as attention-guided models and multi-scale architectures to improve early-stage detection. Attention mechanisms help the model focus on important regions of the retinal image, such as microaneurysms and hemorrhages, thereby improving detection performance [2]. Similarly, multi-scale deep learning models analyze features at different resolutions, enabling better identification of both small and large lesions. While these approaches enhance accuracy, they increase the complexity of the model and demand significant processing power, which limits their applicability in resource-constrained environments.

In addition to CNN-based methods, hybrid models combining convolutional networks with Vision Transformers have been proposed to improve feature representation. These models integrate both local and global feature extraction, allowing for better understanding of retinal structures [3]. Although such hybrid approaches achieve improved classification performance, they introduce additional computational overhead and require extensive training data, making them less practical for real-time or low-cost deployment.

Traditional machine learning techniques have also been applied for diabetic retinopathy detection, where handcrafted features are extracted from retinal images and used for classification. Methods such as Support Vector Machines, Random Forest, and Logistic Regression have been used in earlier studies. These approaches rely on features such as color distribution, texture patterns, and edge information extracted from images [4]. While these models are computationally efficient and easier to implement, their performance depends heavily on the quality of feature extraction and may not capture complex patterns as effectively as deep learning models.Recent research has highlighted the potential of ensemble learning methods, particularly XGBoost, in medical image classification tasks. XGBoost is capable of handling high-dimensional data and capturing non-linear relationships between features. It has been shown to provide better generalization and improved prediction accuracy compared to traditional machine learning models [5]. However, its effectiveness depends on the quality and relevance of extracted features, emphasizing the importance of robust preprocessing and feature engineering techniques.

Despite the progress in this field, several challenges remain in existing approaches. Deep learning models often suffer from high computational cost and require specialized hardware, making them difficult to deploy in rural or low-resource healthcare settings [6]. Traditional machine learning methods, on the other hand, may exhibit limited accuracy when dealing with complex image data. Additionally, many models are sensitive to variations in image quality and dataset imbalance, which can affect prediction reliability [7].

Another significant limitation observed in the literature is poor generalization across different datasets and imaging conditions. Models trained on specific datasets may not perform well when applied to new data due to differences in image resolution, lighting conditions, and patient demographics [8]. Furthermore, overfitting is a common issue in complex models, especially when trained on limited data, leading to reduced performance in real-world scenarios [9].

By analyzing these existing works, it is evident that there is a need for a system that balances accuracy, efficiency, and scalability. Therefore, this paper proposes a machine learning-based approach using feature extraction techniques combined with an XGBoost classifier to improve the detection of diabetic retinopathy while reducing computational complexity and enhancing practical applicability.

III. MATERIALS AND METHODS

The system architecture of the proposed diabetic retinopathy detection system is designed to automatically analyze retinal fundus images and classify them into normal or diseased categories. The primary objective of this system is to develop an efficient and accurate machine learning model using feature extraction techniques and the XGBoost classifier. The system follows a structured pipeline consisting of data collection, preprocessing, feature extraction, model training, and evaluation. Furthermore, the trained model is deployed as a web application using Flask, along with front-end technologies such as HTML, CSS, and JavaScript, enabling real-time user interaction and prediction.

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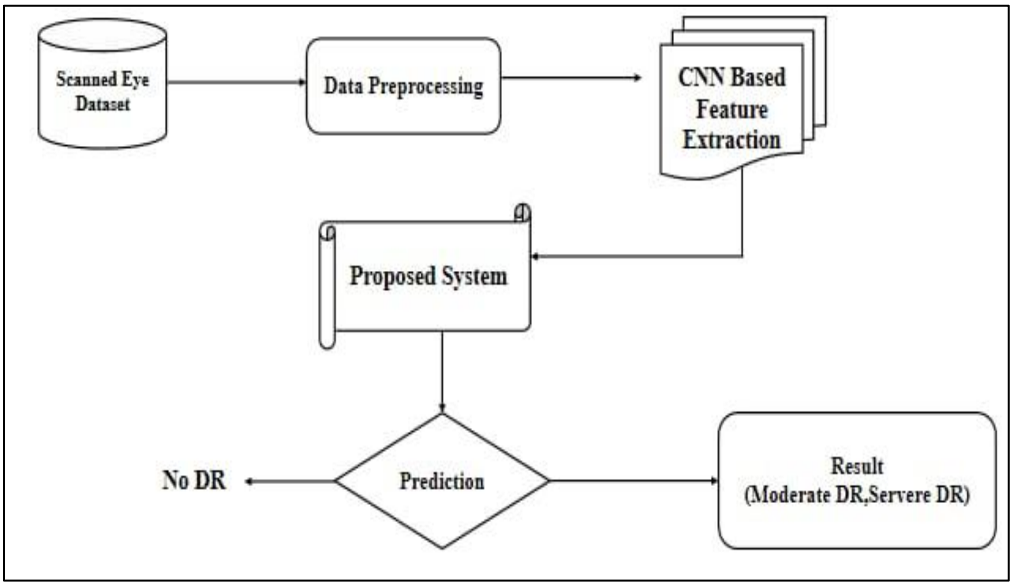

Fig 1. System Architecture for Proposed System

A. Data Collection

The dataset used in this project is obtained from the APTOS 2019 Blindness Detection dataset available on Kaggle. This dataset contains high-resolution retinal fundus images collected from different patients and labeled by medical experts based on the severity of diabetic retinopathy. The dataset includes multiple classes ranging from no diabetic retinopathy to proliferative stages. The images are stored in digital format and are loaded into the system using Python libraries such as pandas and OpenCV. This dataset provides a reliable foundation for training and evaluating the machine learning model, as it reflects real-world medical imaging conditions and variations in disease severity.

B. Exploratory Data Analysis

Once the dataset is loaded, exploratory data analysis is performed to understand the characteristics and distribution of the data. This process involves examining the number of images in each class, identifying class imbalance, and analyzing variations in image quality. Visual inspection of sample images is carried out to understand patterns such as color differences, lesion visibility, and structural variations in retinal images. Statistical analysis and visualization techniques are used to explore relationships within the dataset and to identify potential challenges such as noise, blur, or inconsistent lighting conditions. This step plays a crucial role in guiding preprocessing and feature extraction techniques.

C. Data Preprocessing

Data preprocessing is a critical step in preparing the retinal images for analysis. Initially, the images are converted from BGR to RGB format to ensure accurate color representation. Unwanted regions such as black borders are removed to focus only on the retinal area. The images are then resized to a fixed dimension to maintain consistency across the dataset. To enhance the visibility of important features, contrast enhancement is performed using CLAHE in the LAB color space. Additionally, Gaussian blur is applied to reduce noise and smooth the image. These preprocessing techniques significantly improve image quality and ensure that relevant retinal features are preserved for further analysis.

D. Feature Extraction

Feature extraction is performed to convert the processed images into numerical data that can be used for machine learning. In this system, multiple types of features are extracted to capture different aspects of retinal images. Color features are derived by calculating statistical measures such as mean and standard deviation of RGB and HSV channels. Texture features are extracted using Gray Level Co-occurrence Matrix properties, which describe spatial relationships between pixel intensities. Local Binary Patterns are used to capture local texture variations, while edge detection techniques such as Canny edge detection are applied to identify structural details. These features are combined into a single feature vector, providing a comprehensive representation of each image.

E. Model Training

The extracted features are used to train the machine learning model. Before training, the features are normalized using StandardScaler to ensure consistency across all input variables. The dataset is divided into training and testing sets, typically using an 80:20 ratio. The XGBoost classifier is employed for model training due to its ability to handle high-dimensional data and capture complex relationships. The model is trained using parameters such as the number of estimators, maximum depth, and learning rate. During training, the model learns patterns associated with diabetic retinopathy and builds multiple decision trees to improve prediction accuracy. The trained model is then saved for future use.

F. Model Testing

After training, the model is evaluated using the testing dataset to assess its performance. The predictions generated by the model are compared with actual labels to measure accuracy. Visualization techniques such as confusion matrices and comparison plots are used to analyze the performance of

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the model. These evaluations help in understanding how well the model generalizes to unseen data and whether it can reliably detect diabetic retinopathy in different scenarios.

G. Web Application

To enhance usability, the trained model is deployed as a web application using the Flask framework. The model is serialized using the pickle library and integrated into the backend of the application. Users can upload retinal images through a web interface, and the system processes the images using preprocessing and feature extraction techniques. The processed data is then passed to the trained model, which generates predictions in real time. The results are displayed on the webpage, providing an interactive and user-friendly platform for diabetic retinopathy detection.

H. Evaluation Metrics

The performance of the proposed system is evaluated using classification metrics such as accuracy, precision, recall, and F1-score. Accuracy measures the overall correctness of the model, while precision indicates how accurately the model identifies positive cases. Recall measures the ability of the model to detect actual diabetic retinopathy cases, and F1-score provides a balance between precision and recall. These metrics provide a comprehensive evaluation of the model's performance and reliability in medical diagnosis.

I. Implementation

The implementation of the diabetic retinopathy detection system is carried out using Python programming language. The development environment includes tools such as Jupyter Notebook and Visual Studio Code, which provide flexibility for coding and testing. Libraries such as NumPy and pandas are used for data handling, while OpenCV and scikit-image are used for image processing and feature extraction. The machine learning model is implemented using the XGBoost library, and evaluation metrics are calculated using scikit-learn. The system is developed on a standard computing environment with moderate hardware specifications, demonstrating its suitability for real-world deployment without the need for high-end computational resources.

The overall implementation begins with loading the dataset and performing preprocessing to enhance image quality. Feature extraction techniques are applied to convert images into structured data, which is then used for training the model. The trained model is evaluated using testing data and integrated into a web application for real-time prediction. This complete pipeline ensures efficient and accurate detection of diabetic retinopathy.

IV. RESULTS AND DISCUSSION

The proposed diabetic retinopathy detection system was developed and evaluated to analyze its effectiveness in identifying retinal abnormalities from fundus images. The system successfully demonstrated its capability to process input images, extract meaningful features, and classify them into normal or diabetic retinopathy affected categories. The integration of image preprocessing, feature extraction, and the XGBoost classifier enabled accurate and efficient prediction, making the system suitable for real-world medical applications.

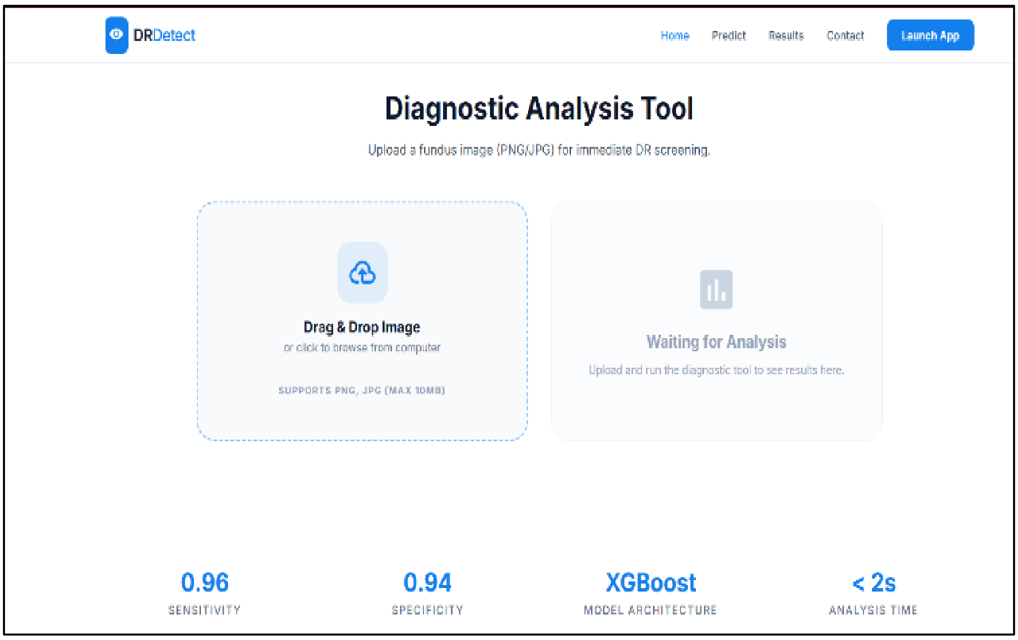

Fig. 2. Input Retinal Image and Preprocessing Output

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During testing, the preprocessing module effectively enhanced the quality of retinal images by removing noise, improving contrast, and highlighting important retinal structures such as blood vessels and lesions. The application of CLAHE and Gaussian blur significantly improved feature visibility, which contributed to better classification performance. The processed image after enhancement is shown in Fig. 2, where important retinal features are clearly visible and suitable for further analysis.

The feature extraction process successfully captured relevant characteristics from the retinal images, including color, texture, and edge-based features. These features were then used by the XGBoost classifier to make predictions. It was observed that the model was able to accurately distinguish between normal and diseased retinal images, even in cases with subtle variations. The system demonstrated consistent performance across different test samples, indicating its robustness and reliability.

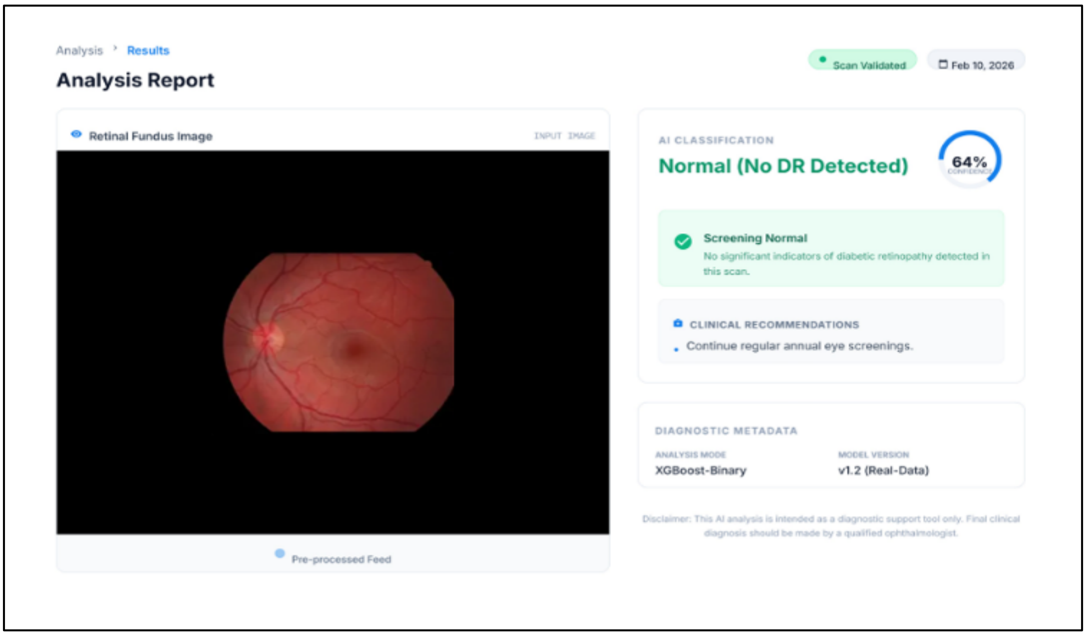

Fig. 3. Result Page Showing Prediction Output

Fig. 3 illustrates the output of the system, where the user uploads a retinal image and receives the prediction result. The system displays whether the input image is classified as “No Diabetic Retinopathy” or “Diabetic Retinopathy.” In addition to the prediction, the system provides a clear and user-friendly interface that allows easy interaction. The results indicate that the model achieves high accuracy and effectively supports early detection of the disease.

Furthermore, the system contributes to bridging the gap between manual diagnosis and automated detection by providing a fast and reliable solution. Unlike traditional methods that rely heavily on expert analysis, the proposed model delivers instant predictions and can be used as a supportive diagnostic tool in healthcare settings. This makes the system particularly useful in rural and low-resource areas where access to medical experts is limited.

Overall, the experimental results confirm that the proposed approach is capable of delivering accurate predictions and can significantly assist in early diagnosis and prevention of vision loss caused by diabetic retinopathy.

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