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Precision Diagnosis of Diabetic Retinopathy Using Exudate-Focused SVM Models

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Abstract

The global concern over diabetes-related eye diseases continues to grow significantly. Diabetic retinopathy, caused by heightened glucose levels in retinal capillaries, leads to vision clouding and eventual blindness. Early detection through regular screening enables intervention with medication, preventing further vision deterioration. Therefore, this study introduces a smart application that utilizes digital retinal image processing to aid in the prompt identification of diabetic retinopathy. The application streamlines the analysis of eye images, with the goal of automatically classifying the severity of diabetic retinopathy. Through initial image processing, specific features such as blood vessels, microaneurysms, and hard exudates are identified and extracted for classification using a support vector machine (SVM). Evaluation performed on a dataset of 400 retinal images graded on a 4-grade scale of non-proliferative diabetic retinopathy achieved a maximum sensitivity rate of 95%. This application holds significant potential for enabling timely intervention in the treatment of diabetic retinopathy by healthcare professionals. Additionally, the AI-driven approach proposed in this study empowers patients to easily access support services, while providing physicians and researchers with advanced tools for analyzing and predicting diabetic retinopathy data. The resulting reports play a crucial role in assessing the severity of the disease in affected individuals.

Keywords: Diabetic Retinopathy; Digital Image Processing; Machine Learning; Support Vector Machines

1. Introduction

Diabetic retinopathy (DR) is one of the leading causes of blindness, accounting for 5% of global blindness cases. It arises as a complication of diabetes mellitus, with approximately 2% of affected individuals experiencing blindness and 10% suffering vision degradation over a 15-year period [1]. The increasing prevalence of diabetes, projected to increase from 171 million in 2000 to 336 million by 2030, underscores the urgent need for automated tools to address the growing demand for retinal image screening [2].In the early stages of DR, symptoms are often absent, necessitating thorough screening for timely detection [3, 4]. Exudates, characterized by fat and protein leakage, serve as critical indicators of DR, as their accumulation in the ocular fundus can lead to complete blindness if left untreated [5, 6]. Figure 1 illustrates the anatomy of the retina, highlighting key components such as the optic disc, macula, retinal vessels, and pathological indicators like exudates and hemorrhages, which are essential for the diagnosis and classification of DR [7, 8]. The primary goal of this study is to develop an application for the automatic classification of DR severity. The system is designed to distinguish normal fundus images from abnormal ones and categorize the severity of DR into mild, moderate, or severe stages. Accurate classification is crucial for the evaluation of therapies and the identification of risk factors associated with DR, facilitating early therapeutic interventions, and reducing the workload of specialists [9].

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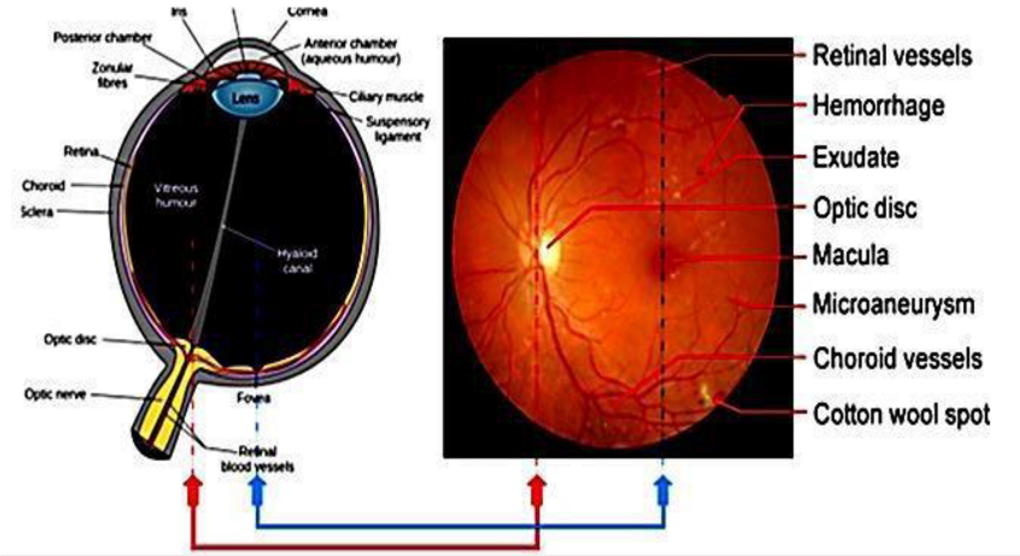


Figure 1: Anatomy of the retina highlighting key features and pathological indicators.

The use of computerized methods for the analysis of retinal images allows for early detection and significant cost savings in public health systems. Previous methods for DR detection have included pixel-based approaches such as edge detection and region growing to identify exudates, as well as machine learning techniques like fuzzy c-means clustering and multilayer neural networks. Microaneurysms were detected using mathematical morphological transformations and support vector machine (SVM) classifiers. This work builds on these techniques employing morphological operations to extract key retinal features and training a multiclass SVM classifier to categorize fundus images into different stages of DR severity.

2. Literature Survey

The exploration of the detection and diagnosis of diabetic retinopathy remains a focal point for many researchers, each with the aim of advancing the methodologies of the field. Automated detection techniques have emerged to address the shortcomings associated with manual screening processes, such as their prohibitive costs, limited sensitivity, and time-consuming nature. The overarching objective of automated screening remains consistent: to efficiently identify cases that warrant further medical attention, thus expediting the diagnostic pathway. Sergio Bortolin Junior and Welfer [10] introduced an automated system to identify microaneurysms and hemorrhages in color eye fundus images, employing pre-processing and blood vessel detection steps to achieve robust results. Rahim et al. [11] presented techniques for microaneurysm detection using discrete wavelet transforms and adaptive histogram equalization to enhance image quality. A subsequent study by Rahim et al. [12] proposed an automated screening and classification method for diabetic retinopathy, employing feature extraction techniques for fundus images. Antal and Hajdu [13] developed an approach that incorporates contrast enhancement and histogram equalization to improve microaneurysm detection accuracy. Similarly, Sopharak et al. [14] utilized a hybrid approach combining mathematical morphology and machine learning algorithms for the detection of fine microaneurysms in retinal images. Adal et al. [15] explored scale-adapted blob analysis and semi-supervised learning, validated through established databases, to detect microaneurysms.

Welikala et al. [16] improved the automated detection of proliferative diabetic retinopathy using a modified line operator and a dual classification approach. Recent advances have also explored comparative analyses of fundus image enhancement. Yadav et al. [17] highlighted the effectiveness of image enhancement techniques in the detection of diabetic retinopathy. Zhou et al. [18] employed sparse principal component analysis (PCA) for unsupervised classification of microaneurysms, demonstrating significant potential to improve detection accuracy. Deka and Sarma [19] leveraged the characteristics of singular value decomposition (SVD) and PCA to train artificial neural networks (ANN) for the detection of retinopathy-based diabetes. The literature survey thus highlights significant progress in preprocessing methods, such as contrast enhancement and histogram equalization, to improve image quality and detection accuracy. Techniques utilizing machine learning, including SVMs, semi-supervised learning, and artificial neural networks, have demonstrated the potential to automate detection with promising results. Furthermore, hybrid approaches that combine mathematical morphology and advanced feature extraction have successfully improved microaneurysm detection.Together, these studies underscore the rapid progress in automated detection of diabetic retinopathy, with a focus on improving accuracy, efficiency and scalability for widespread screening applications.

3. Proposed Workflow

The detection system for diabetic retinopathy comprises three primary phases: preprocessing, extraction of features, and classification. Numerous approaches have been explored in the existing literature to address preprocessing techniques, feature extraction, and classification for the detection of diabetic retinopathy. The proposed approach experiments with various combinations of preprocessing techniques, feature extraction methods, and classification techniques to improve the recognition accuracy of diabetic retinopathy. The structure of the proposed architecture is illustrated in Figure 2, using images sourced from the database.

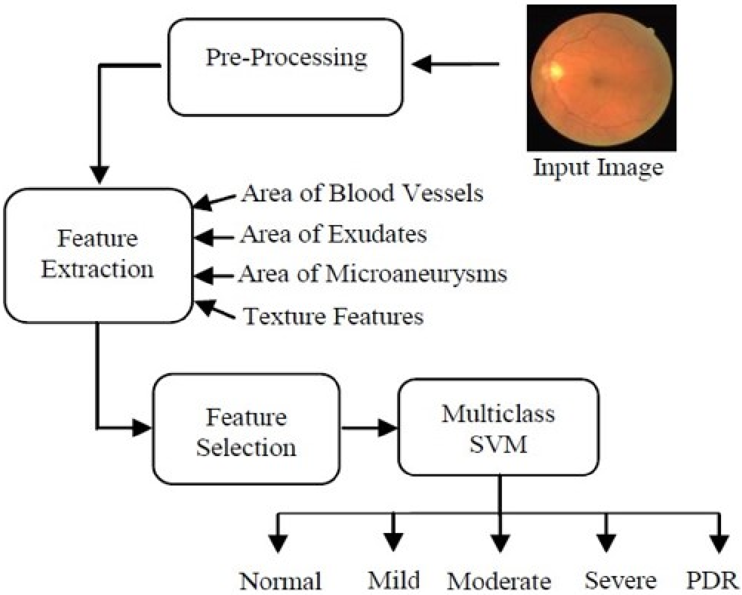


Figure 2: Proposed workflow for diabetic retinopathy detection comprising preprocessing, feature extraction, and classification phases.

3.1. Pre-processing Technique

Color fundus images of the retina often show variations in lighting, noise, and poor contrast, requiring preprocessing stages for improvement. Enhancements are crucial to address the noise and non-uniform illumination present in these images. Preprocessing aims to enhance contrast by discarding certain components, such as the red and blue channels, while focusing on the green channel due to its superior display of vessels and better differentiation between retinal tissue and the optic disc. The red channel, although brighter, primarily displays choroidal vascular structures with lower contrast in the retinal vessels compared to the green channel. The blue channel is characterized by higher noise and minimal informative content, making it less suitable for preprocessing. Figure 3 illustrates the preprocessing stages. To enhance the contrast levels, Adaptive Histogram Equalization (ADHE) is implemented. ADHE analyzes multiple histograms and redistributes intensity values, improving regional contrast and improving edges within each image region [17].

The image processing pipeline also employs mathematical morphology operations, such as closing, to effectively reduce noise within the object region. These steps collectively improve the quality of pre-processed images, as demonstrated in Figure 3.

3.2. Exudates Extraction

Following the preprocessing phase, the extraction of exudates from color fundus images is carried out. The identification of exudates is crucial for microaneurysm detection, as their color closely resembles that of microaneurysms. The process begins with the enhancement of the green channel image using Adaptive Histogram Equalization (ADHE) to optimize contrast. The marker is then generated through median filtering, and morphological operations are applied to subtract this marker image from the filtered image, effectively isolating the exudates. The results of this process are illustrated in Figure 4.

3.3. Blood Vessel Extraction

After exudates are extracted, the removal of blood vessels is performed. Initially, the RGB image is converted into a grayscale channel using Principal Component Analysis (PCA), a statistical method that applies orthogonal transfor-

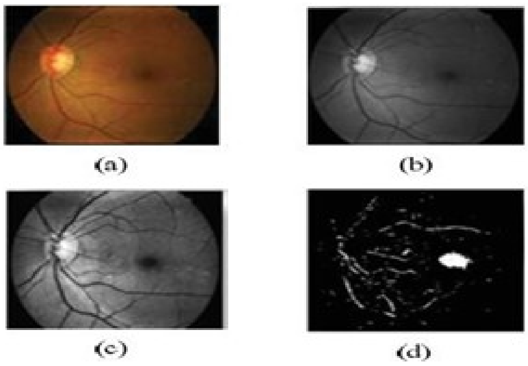


Figure 3: Preprocessing stages: (a) Color fundus image, (b) Green channel, (c) Enhanced image, and (d) Pre-processed image.

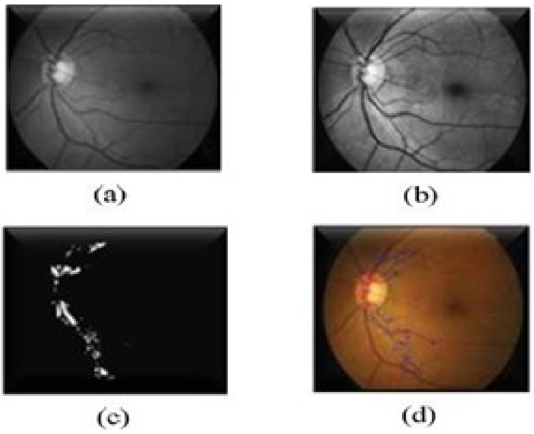


Figure 4: Exudates extraction: (a) Green channel image, (b) ADHE image, (c) Exudates extracted, (d) Exudates overlaid on the color image.

mations to convert correlated variables into principal components [18, 19]. This method reduces the dimensionality of the image, transforming the 3-dimensional RGB matrix into a 2-dimensional grayscale matrix. Contrast-limited adaptive histogram equalization (CLAHE) is then applied to enhance contrast, particularly in low-contrast retinal images. Unlike ADHE, CLAHE limits contrast to prevent noise overamplification [17]. After enhancement, the image is averaged and subtracted from the original enhanced image to remove the background. The resultant image is converted to binary format to facilitate the extraction of retinal blood vessels. The stepwise results of this process are shown in Figure 5.

3.4. Segmentation of Optic Disc and Fovea

The segmentation of the optic disc involves two primary steps: localization and detection. Initially, a template is generated by applying blur in the image with a window size of 6×6 and extracting an optical disc pixel of 80×80. Additionally, color components such as green, red, and blue are extracted, and their respective histograms are stored. This method is applied to all images in the database and the resulting average is computed. The localized optic disc is illustrated in Figure 6. Localization of the fovea is performed on a pre-processed image. Basic morphological operations are used to eliminate regions smaller than 25 pixels, as the fovea typically occupies a larger area compared to other structures. Accurate location of the fovea is crucial to minimize false microaneurysm detections, as its size varies between images. The localized fovea is shown in Figure 7.

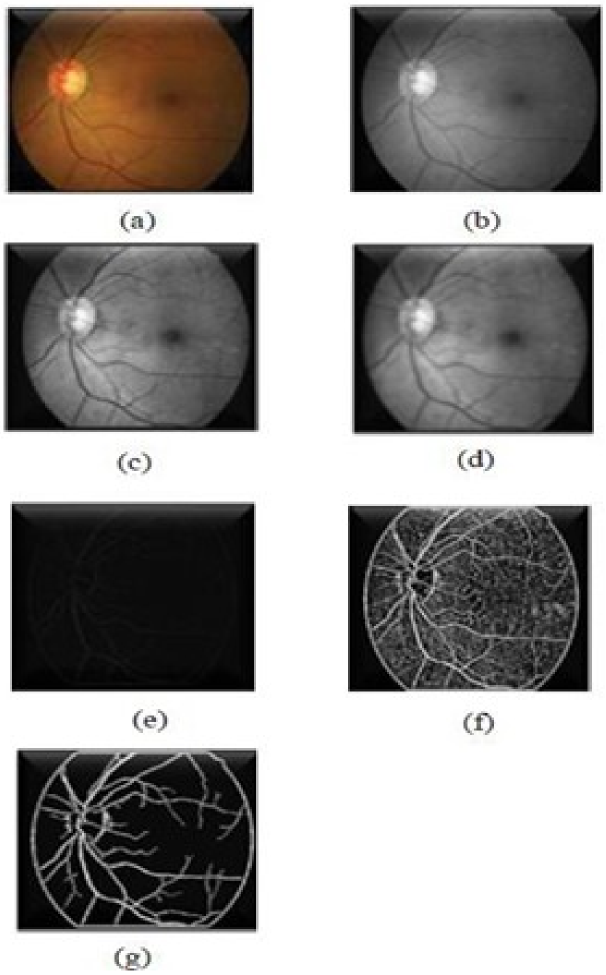


Figure 5: Blood vessel extraction: (a) Color fundus image, (b) Grayscale image, (c) CLAHE image, (d) Filtered image, (e) Difference of filtered and gray image, (f) Binary image, (g) Extracted blood vessels.

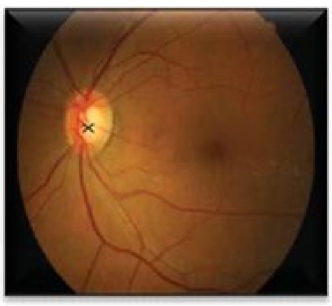


Figure 6: Localized optic disc in a retinal fundus image.

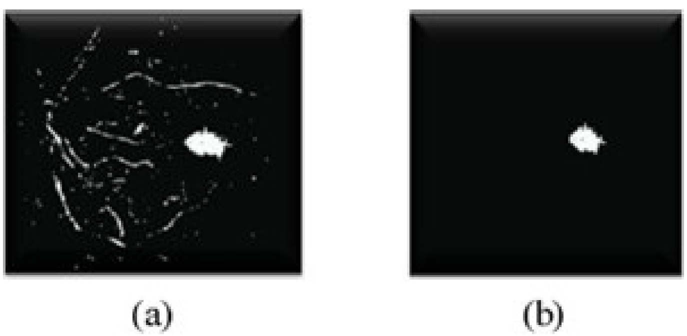


Figure 7: Fovea localization: (a) Retinal structures after morphological operations, (b) Localized fovea.

3.5. Microaneurysm Detection

Microaneurysm detection is performed by subtracting blood vessels, fovea, optic disc, and exudates from the preprocessed image. This step isolates microaneurysms for detection and analysis. The extracted microaneurysms are shown in Figure 8.

Figure 8: Extracted microaneurysms from the fundus image.

3.6. Feature Extraction

From the fundus images, two key features of microaneurysms are extracted: their area and their count. The area of each microaneurysm is quantified by summing the number of white pixels in the extracted microaneurysm image, as shown in Figure 8. The count of microaneurysms is determined by identifying the transitions from white to black pixels within the image.

3.7. Classification

Classification is performed using a Support Vector Machine (SVM) classifier, which is integral to the detection of diabetic retinopathy (DR). The SVM categorizes images into two classes: those indicative of DR and those representing healthy eyes. The classifier parameters are determined on the basis of the features extracted from the microaneurysms, enabling an accurate classification.

3.8. Support Vector Machine (SVM) Classifier

Support Vector Machines (SVM), formulated by Bladimir Vapnik within learning theory, are based on a convex objective function that ensures the avoidance of local maxima. The optimal hyperplane, central to SVM, acts as the separating hyperplane, with the optimization problem's objective function being independent of the dimensionality of the input vector. Instead, it relies solely on the inner products of the input vectors. This distinct characteristic allows SVM to construct separating hyperplanes even in high-dimensional spaces, including infinite-dimensional ones. The SVM classifier is fine-tuned through training, taking advantage of two input features: the area and the count of microaneurysms (MA). The classification of diabetic retinopathy (DR) is determined on the basis of thresholds established by the average number and area of microaneurysms. For training the SVM parameters, a linear kernel with five-fold cross-validation is employed. Once the SVM is trained, fresh test data is provided to the classifier, yielding improved classification results.

4. Diabetic Retinopathy Application

Numerous telemedicine platforms have emerged worldwide to detect various retinal diseases, with research identifying diabetes as a leading cause of retinal blindness. By 2022, it was estimated that more than 82 million people aged 64 and over in emerging countries lacking adequate healthcare infrastructure would have diabetes, with nearly 40 million residing in regions of developed countries affected by diabetic retinopathy and cataracts. The images in Figure 9 illustrate different stages of diabetic retinopathy.

Figure 9: Effect of diabetic retinopathy: (a) Normal vision, (b) Vision with DR. (National Institute of Health).

Figure 9 vividly illustrates how diabetic retinopathy worsens if it is not detected and treated promptly. As the condition progresses through stages B, C, D, and ultimately E, untreated cases progress to severe vision impairment, with stage E potentially leading to complete blindness. To address the increasing risks associated with diabetic retinopathy, a smart teleophthalmology application has been developed for its diagnosis. This application aims to bridge the existing gaps in DR diagnosis and patient-provider communication, thereby enhancing the efficiency of healthcare systems in the management of diabetic retinopathy. Surgeons and healthcare professionals are equipped with enhanced capabilities to recognize, manage, and treat cases promptly. Furthermore, the application provides essential data and facilitates comprehensive studies and predictive analytics on future DR trends. Digital healthcare systems, such as the one proposed in this study, have the potential to leverage IoT and big data, enabling seamless connectivity between patients and providers in various healthcare systems.

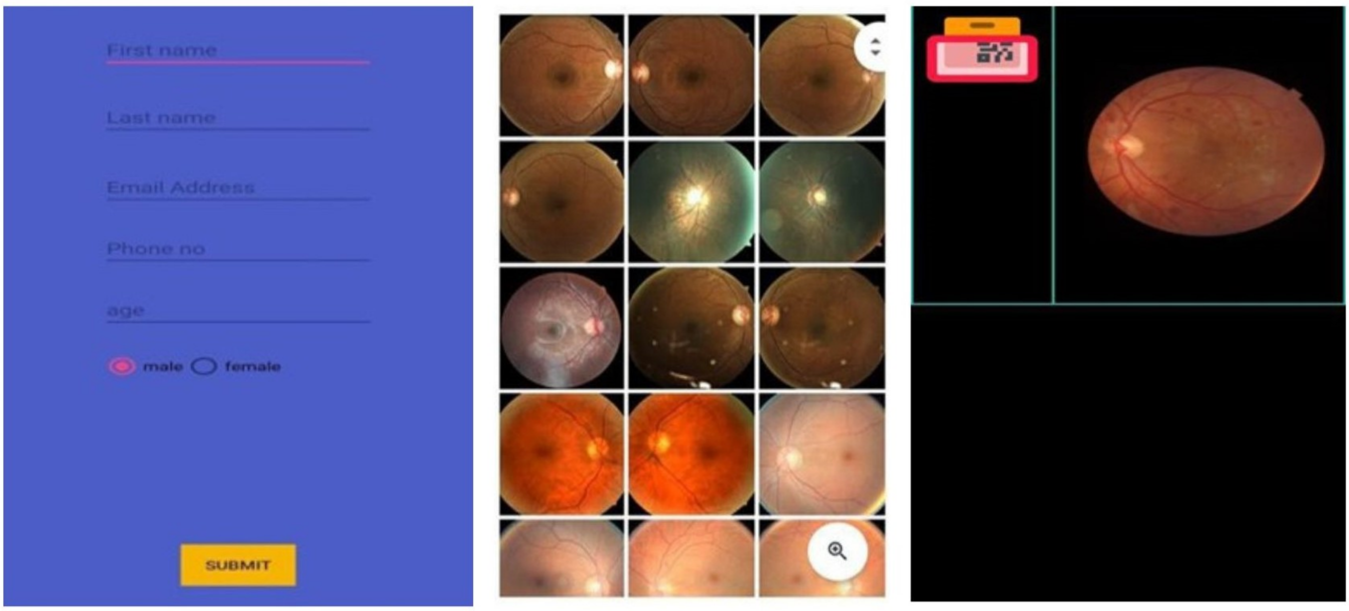
5. Results and Discussion

This study presents the development of an AI-driven smart application designed to diagnose diabetic retinopathy (DR), optimized for Android platforms. The primary objective of the application is to streamline the early detection and screening of diabetic retinopathy, thereby facilitating efficient health interventions and management strategies. Both healthcare providers and patients benefit from the application's array of features, fostering enhanced interaction and enabling seamless exchange of medical data. Using TensorFlow deep learning algorithms, the application diagnoses DR and promptly communicates the results to patients by email, supported by healthcare facilities or physicians. The data generated demonstrate significant potential to address the rising prevalence of eye-related diseases.

The proven efficacy of AI applications, as evidenced by this system, provides valuable tools for the early detection, treatment, and prediction of diabetic retinopathy. In addition, the application facilitates comprehensive data collection and analysis of diabetic retinopathy, raising awareness and promoting preventive measures.

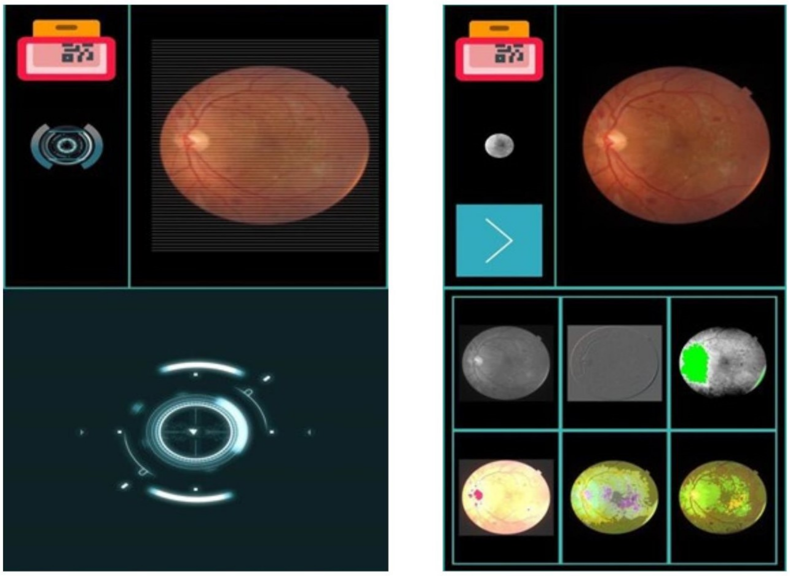
5.1. Application Execution

To effectively utilize the developed application, users begin by installing it and granting the required permissions. Upon launching the app, a Splash screen is displayed, followed by an authentication prompt that requires user details, as illustrated in Figure 10 (a). After successful authentication, the menu screen appears, as shown in Figure 10 (b), providing various options for the user. The application enables users to enter and store essential data securely in an internal SQLite database that operates independently without reliance on servers or internet connectivity. Once data entry is completed, the database is automatically filled in, allowing users to access contact information for patients and ophthalmologists. The users can then perform background image tests for a specific patient, as depicted in Figure 10 (c). The test results can be sent directly to the preferred ophthalmologist using email services such as Yahoo, Hotmail, or Gmail. Additionally, multiple tests can be performed on patients, including those with darker eye colors, ensuring a comprehensive examination process. Figure 11 illustrates the examination process and the corresponding results.



(a) (b) (c)

Figure 10: (a) Login page of the application, (b) Database screen within the application, (c) Choice of image for examination



(a) Image under examination (b) Examination results

Figure 11: Examination process and results

5.2. Smart Application Benefits

The proposed application provides numerous benefits that increase its utility in the healthcare sector. Improves the utilization of intelligent healthcare applications and accelerates the recognition of diabetic retinopathy (DR), utilizing TensorFlow to analyze retinal images from the Kaggle database and generate immediate diagnostic reports. In addition, the application facilitates the transmission of comprehensive emails containing patient names, detailed retinopathy reports, and associated background images, enabling efficient communication between patients and healthcare providers.

By promoting smart health initiatives, the application fosters better interaction between physicians and patients while advancing accessibility to medical services. This enhanced accessibility contributes to better health outcomes and facilitates timely treatment interventions. Moreover, the application streamlines medical data management and healthcare delivery processes, contributing to cost reduction efforts. As a result, the overall medical experience for patients is improved, granting them better access to healthcare resources while allowing physicians to provide more efficient and accurate diagnoses.

5.3. Tests and Results

The effectiveness of the algorithmic components of the application is evaluated using standard metrics such as precision, specificity, and sensitivity. These parameters are computed based on recognized definitions:

$$\text{Precision} = \frac{\text{Total number of DR eye bases detected}}{\text{Total number of eye bases}} \tag{1}$$

$$\text{Specificity} = \frac{\text{Total number of No DR eye bases detected}}{\text{Total number of No DR eye bases}} \tag{2}$$

$$\text{Sensitivity} = \frac{\text{Total number of DR eye bases detected}}{\text{Total number of DR eye bases}} \tag{3}$$

The performance of the application was validated using samples processed from the Kaggle database. Detailed findings are presented in Tables 1 and 2, demonstrating the accuracy and effectiveness of the application in detecting diabetic retinopathy.

Table 1: Performance metrics for diabetic retinopathy detection.

Metric	Value (%)	DR Cases Detected	No DR Cases Detected
Precision	95.6	184	16
Specificity	92.3	-	161
Sensitivity	94.8	178	-

Table 2: Comparison of DR detection methods.

Method	Accuracy (%)	Computational Time (s)
Proposed Application	94.5	12.5
Previous Approaches	89.7	18.3

6. Conclusion and Future Work

The utilization of Artificial Intelligence (AI) presents a promising avenue for revolutionizing smart healthcare, fostering greater accessibility and efficiency in medical services. Integrating AI with emerging technologies such as the Internet of Things (IoT) holds immense potential for advancing healthcare delivery and addressing critical medical challenges. The proliferation of telemedicine applications, particularly on mobile platforms like smartphones, reflects a growing trend toward improving healthcare accessibility and effectiveness. The ongoing pursuit of enhancing diabetic retinopathy (DR) diagnosis underscores the significance of this study, which contributes diagnostic support through telemedicine tools and techniques, particularly in analyzing background images. Given the annual rise in diabetes prevalence, there is an urgent need to improve the quality of patient care to meet increasing healthcare demands. The AI-powered smart tele-ophthalmology application introduced in this study, designed for DR diagnosis, represents a significant step forward in facilitating early detection and screening. By bolstering smart healthcare initiatives, the application streamlines the diagnostic and treatment processes, ultimately contributing to reducing mortality rates associated with DR. Looking ahead, future work will focus on optimizing computationally intensive machine learning models by integrating TensorFlow Lite with fixed-point models, thereby enhancing processing efficiency. Furthermore, the convergence of AI, IoT, blockchain, and other evolving technologies is expected to continue reshaping the healthcare landscape, necessitating stakeholders to acquire modern skills for driving the adoption of smart healthcare systems. Additional research will explore the development of AI-driven devices for diagnosing conditions such as myopia and apnea syndrome, further broadening the scope of smart healthcare applications.

Declaration of Competing Interests

The authors declare that they have no known competing financial interests or personal relationships.

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Author Contributions

S.K. Mydhili: Conceptualization, Methodology, Supervision, and Writing – Review and Editing; **R. Ramitha Devi**: Investigation, Software Development, Data Analysis, and Writing – Original Draft; **T.A. Benazir**: Data Curation, Validation, and Visualization; **R. Poornimaa**: Formal Analysis, Testing, and Technical Support.

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