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OPTIMIZED SVM FOR EXUDATE-FOCUSED DIABETIC RETINOPATHY DETECTION

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ABSTRACT
The growing prevalence of diabetes-related eye diseases is a global concern. Diabetic retinopathy, which occurs due to increased glucose levels in retinal capillaries, can lead to vision clouding and eventually blindness. Early detection through regular screening allows for timely medication interventions that can prevent further vision loss. This study introduces a smart application that leverages digital retinal image processing to aid in the swift identification of diabetic retinopathy. The application simplifies the analysis of retinal images to automatically classify the severity of the disease. By processing these images, specific features such as blood vessels, microaneurysms, and hard exudates are detected and extracted for classification using a support vector machine (SVM). An evaluation conducted 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 has significant potential to facilitate timely interventions in the treatment of diabetic retinopathy by healthcare professionals. Furthermore, the AI-driven approach proposed in this study empowers patients to access support services easily while providing physicians and researchers with advanced tools for analyzing and predicting diabetic retinopathy data. The resulting reports are crucial for assessing the severity of the disease in affected individuals.

Keywords: Diabetic retinopathy, digital image processing, machine learning, support vector machines.

I. INTRODUCTION

Retinopathy poses a substantial threat to individuals with diabetes, accounting for 5% of global blindness cases. It develops as a complication of diabetes mellitus, with approximately 2% of affected patients experiencing blindness and 10% undergoing vision degradation over a 15-year period due to complications from Diabetic Retinopathy (DR). The projected increase in diabetes prevalence, from 171 million in 2000 to an estimated 336 million in 2030, underscores the urgent need for automated analysis of retinal images to handle the increasing screening demands. Elevated sugar levels in the blood lead to damage to retinal blood vessels by disrupting the flow of blood. In the initial stages of DR, symptoms are absent, necessitating comprehensive examinations for detection. Exudates, characterized by the leakage of fats and proteins, serve as critical indicators of DR presence, with delayed diagnosis potentially resulting in complete blindness due to the accumulation of exudates in the ocular fundus. Regular screening is essential for early detection of DR. Clinicians encounter challenges in screening a large volume of images, highlighting the necessity for a smart mobile application to categorize DR stages. The primary objective of this initiative is to develop an application capable of distinguishing abnormal from normal fundus images and categorizing abnormal images by severity into mild, moderate, or severe stages. Accurate classification of DR severity and quantification of diabetic changes are crucial for evaluating therapies and risk factors associated with this common complication of diabetes. Utilizing digital images for eye disease diagnosis can facilitate early detection of DR through computerized methods. Implementing a system usable by non-experts to filter out unaffected cases would reduce the workload on specialists and improve the effectiveness of preventive measures and early therapeutic interventions, resulting in significant cost savings in public health systems. Earlier methods are segmentation of retinal vessel in fundus images were classified into three types: tracking, machine-trained and thresholding classifiers. Exudates were identified through a mixture of edge detection, region growing and seed finding techniques. Bright lesions were identified within color retinal images using a pixel classification method based on probability mapping. Automated detection of exudates employed computational intelligence techniques, including fuzzy c-

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means clustering, followed by feature vector classification using a multilayer neural network. Microaneurysms were detected in non-contrast retinal fundus images using a double-ring filter, with subsequent identification of red dots through mathematical morphological black top-hat transformation, and feature estimation carried out by an SVM classifier. A novel two-stage microaneurysm detection approach based on Radon transformation was introduced, eliminating the necessity for explicit training. Additionally, an ensemble-based framework was developed to improve microaneurysm detection efficiency through preprocessing methods and candidate extraction. This research aims to automate diabetic retinopathy detection by extracting key features from fundus images using morphological operations. Several specific features were selected and trained with a multiclass SVM classifier using a one-against-all strategy, enabling the classifier to categorize images into different classes such as normal, mild, moderate, severe, or proliferative based on these features. The work is structured into sections, with an Introduction Section I, Literature survey in Section II, Feature Extraction, Feature Selection, and Multiclass SVM Classifier in Section III, DR Application and Medical Context in Section IV, Experimental Results & Discussion in Section V, and Conclusion in Section VI.

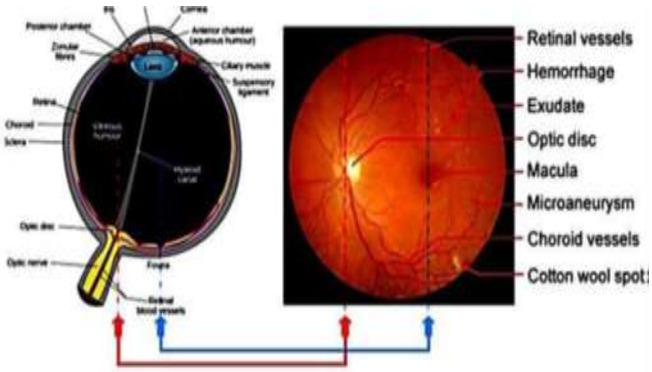

Fig.1 Eye Retina

II. LITERATURE SURVEY

The exploration of diabetic retinopathy screening and diagnosis remains a focal point for many researchers, each aiming to advance the field's methodologies. Automated detection techniques have emerged to tackle 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 warranting further medical attention, thus expediting the diagnostic pathway. Sergio Bortolin Junior [1] have introduced a automated system tailored for identifying microaneurysms and hemorrhages within color eye fundus images. Their method intricately weaves together a series of steps, including preprocessing and the detection of blood vessels, to achieve robust detection results. Sarni Suhaila Rahim [2] have likewise projected a suite of techniques for microaneurysm detection, leveraging strategies like discrete wavelet transform, adaptive histogram equalization to enhance image quality. Meanwhile, Balint Antal [4] have devised an approach to microaneurysm detection, incorporating preprocessing steps like contrast enhancement and histogram equalization to bolster detection accuracy. Sopharak A [5] have contributed a fusion methodology for pinpointing fine microaneurysms in diabetic retinopathy retinal images, mathematical morphology harnessing and machine learning algorithms. In tandem, Adal K M [6] have explored the application of semi-supervised learning and blob analysis for automated microaneurysm recognition, validated through rigorous testing against established databases. Lastly, R. A. Welikala [7] have pursued a dual-classification approach, employing two distinct vessel segmentation methods followed by SVM classification, thereby enriching the ongoing discourse on automated diabetic retinopathy screening.

III. PROPOSED WORKFLOW

The detection system for diabetic retinopathy comprises three primary phases are first pre-processing, feature extraction and classification methods. A multitude of approaches have been explored in existing works to address pre-processing techniques, extraction of features and classification aspects for diabetic retinopathy detection. Our proposal involves experimenting with various combinations of pre-processing techniques, then extraction of features and again classification techniques to enhance the recognition accuracy of diabetic retinopathy. The structure's architecture is depicted in Figure 2, utilizing images sourced from the database.

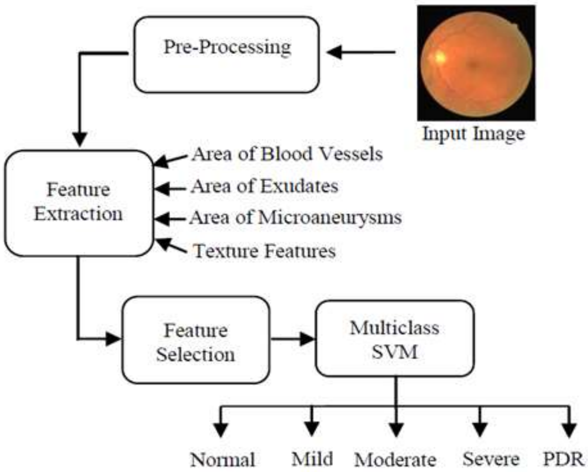

Fig. 2. Block diagram of the diagnosis system of DR

A. Pre-processing Technique

Color fundus images of retina often display variations in lighting, noise, poor contrast and necessitating preprocessing stages for improvement. Enhancements are crucial due to issues such as noise and illumination in non-uniform present in these images. Preprocessing aims to enhance contrast, commonly involving the discarding of certain information like the red and blue components to focus on enlightening the retinal images contrast. Then channel green is frequently utilized in preprocessing due to its superior display of vessel and enhanced differentiation among the retinal tissue and optic disc. Conversely, the channel red tends to be brighter, displaying vascular structures of the choroid, albeit with less contrast in retinal vessels compared to the green channel. The blue channel, characterized by noise and minimal informative content, is less commonly used in preprocessing procedures.

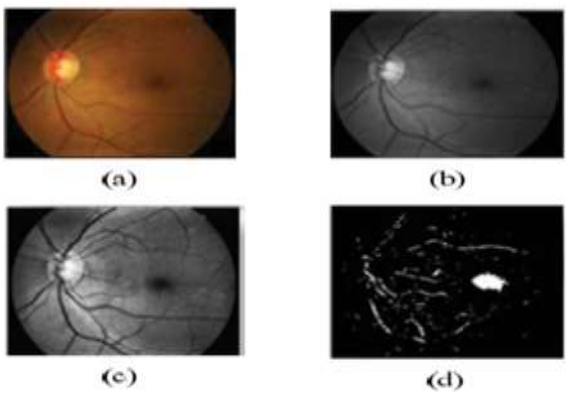

Fig. 3 (a) Color eye fundus image (b) Channel Green image (c) Enhanced image (d) Pre-processed image

To enhance the contrast level Adaptive histogram equalization (ADHE) is implemented. ADHE analyzes multiple image histograms and redistributes intensity values accordingly, making it

particularly effective for improving regional contrast and enhancing edges within every image region [8]. The image processing pipeline employs mathematical morphology operations, including a closing operation, to effectively reduce noise within the object region. This step is essential for enhancing the quality of the pre-processed images, which can be observed in Figure 3 of the study.
Upon finishing the pre-processing phase, the extraction of exudates from color fundus images commences as part of the subsequent stage in the process. The identification of exudates is crucial for microaneurysm detection, as their color closely resembles that of microaneurysms. Following the pre-processing phase, the extraction of exudates from the color fundus images proceeds with the enhancement of the green channel image using Adaptive Histogram Equalization (ADHE) to optimize contrast. A 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 within the image. The resulting image, illustrating the extraction of exudates, is depicted in Figure 4.

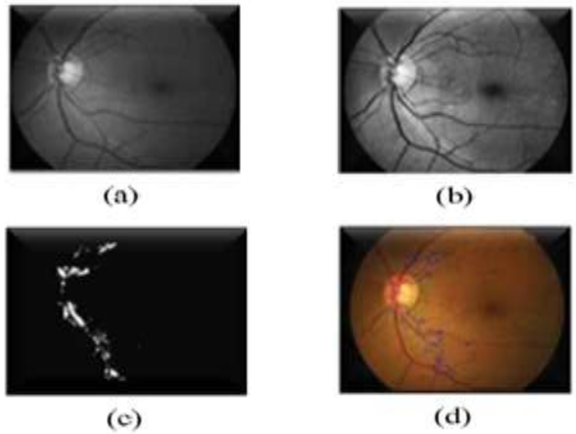

Fig. 4 (a) Image of Green channel (b) ADHE image (c) Exudates Extracted (d) Exudates in color image

After the exudates are extracted, the process of removing blood vessels begins. Initially, the RGB image undergoes conversion into a grayscale channel to enhance its contrast. The conversion to grayscale is performed using principal component analysis (PCA), a statistical method that applies orthogonal transformations to convert correlated variable observations into principal components. This approach is commonly used in data analysis and has been referenced in literature [9] and [10]. PCA serves as a powerful tool for dimensional reduction, allowing the 3-dimensional matrix (RGB) conversion into a 2-dimensional matrix (grayscale). Furthermore, contrast limited adaptive histogram equalization (CLAHE) is employed to enhance contrast, offering specific improvements in enhancing details within low-contrast retinal images.

In CLAHE, a transformation function is derived from a limited contrast procedure applied to near each pixel, primarily established to avoid noise over-amplification caused by ADHE [8]. To eliminate the background, the enhanced image is averaged and subtracted from the original enhanced image. After this background removal step, the image is converted to a binary format, facilitating the extraction of retinal blood vessels from the processed image. The resultant image, demonstrating the extraction of blood vessels, is depicted.Segmentation of optic disc involves two key steps: localization and detection. Initially, a template is generated by applying image blur with a window (6x6) and extracting an optic disc pixel (80x80). Additionally, color components like green, red, and blue are extracted, and stored the respective histograms. This method is implemented on all images within the database, and the resulting average is computed. The localized optic disc is depicted in Figure 6.

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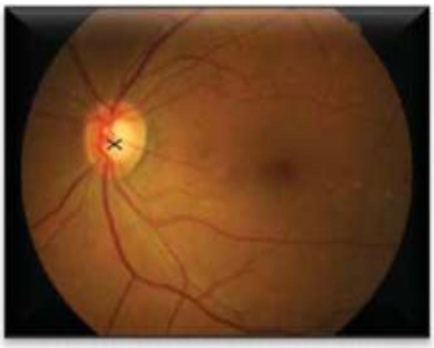

Fig. 5 Optic disc Located in color image

Localization of the fovea relies on a pre-processed image. Basic morphological operations are utilized to eliminate areas smaller than 25 pixels, as the fovea typically occupies a larger area compared to other structures. Accurate fovea localization is crucial to minimize false microaneurysm detections, with its area varying between images. Figure 7 (b) showcases the fovea.

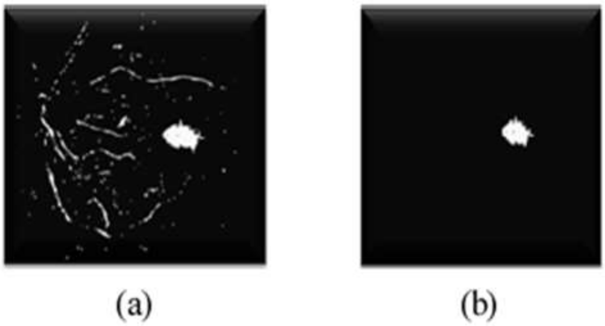

Fig. 6 (a) Image pre-processed (b) Fovea

Microaneurysm detection involves subtracting blood vessels, fovea, optic disc and exudates from the pre-processed image. The extracted microaneurysms are displayed.

B. Feature Extractions

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 up the number of pixels in white within the extracted microaneurysm image, as demonstrated in Fig. 8. The quantification of microaneurysms involves counting the transitions from white to black pixels within the image.

C. Classification

Utilizing an SVM classifier is integral to the detection of diabetic retinopathy (DR). It categorizes images into two classes: those indicative of DR and those representing healthy eyes. The SVM classifier's parameters are established based on the features extracted from microaneurysms, facilitating accurate classification.

SUPPORT VECTOR MACHINE (SVM)

SVM, formulated by Bladimir Vapnik within learning theory, is founded on a convex objective function, guaranteeing avoidance of local maxima. The optimal hyperplane, central to SVM, assumes the role of a separating hyperplane, with the optimization problem's objective function being independent of the dimensionality of input vector's but reliant solely on the two vectors inner products. This distinct characteristic enables the construction of separating hyperplanes even in high-dimensional spaces, including dimensions of infinite.

SVM are fine-tuned through training, leveraging two input features are the area and number of microaneurysms (MAs). Classification of DR hinges on thresholds established by the average number and area of microaneurysms. For training SVM parameters, a linear kernel with fivefold validation is employed. Subsequently, once SVM is trained, fresh testing data is fed into the classifier, leading to improved results.

IV. DIABETIC RETINOPATHY APPLICATION

Numerous telemedicine platforms have emerged worldwide to detect various retinal diseases, and research underscores diabetes as a leading cause of retinal blindness. By 2022, it is estimated that over 82 million individuals aged 64 and above in emerging countries lacking sufficient healthcare infrastructure will have diabetes, with nearly 40 million residing in regions of established nations affected by diabetic retinopathy and cataracts. The images in Figure.9 illustrate different stages of diabetic retinopathy.

Fig. 7. Effect of diabetic retinopathy: (a) Normal vision, (b) Vision with DR. (National Institute of Health).

Figure.9 vividly illustrates how diabetic retinopathy can get worse if it is not promptly detected and treated properly, a problem this study aims to address. As the condition advances through stages B, C, D, and ultimately E, untreated cases progress to severe vision impairment, with stage E potentially leading to complete blindness.

Recognizing the urgency to mitigate the escalating risks associated with diabetic retinopathy, we have developed a smart teleophthalmology application for its diagnosis. This application aims to bridge existing gaps in DR diagnosis and patient-provider communication, thereby enhancing the efficiency of healthcare systems, particularly in managing the diabetic retinopathy. Surgeons will have enhanced capabilities to recognize, manage, and treat cases promptly. Furthermore, the application not only provide essential data but also facilitate comprehensive studies and predictive analytics on future DR trends. Digital healthcare systems, such as the one proposed herein, have the potential to leverage IoT and big data, enabling seamless connectivity between patients and providers across diverse healthcare systems.

V. RESULTS AND DISCUSSION

This paper delineates the creation of an AI-driven Smart application devised specifically for diagnosing diabetic retinopathy, tailored for use on Android platforms. Its core function is to streamline the process of early detection and screening of diabetic retinopathy, thereby facilitating more efficient health interventions and management strategies. Both healthcare providers and patients stand to benefit from the diverse array of features embedded within this application, fostering improved interaction and enabling seamless exchange of intelligent medical data. Utilizing TensorFlow deep learning algorithms, the app conducts diagnose and promptly communicates results to patients via email, a service facilitated by healthcare facilities or physicians. The data produced by the application shows considerable potential in addressing the increase in cases of eye-related diseases.

The proven efficacy of AI applications, as showcased in this system, offers potential for initial detection, treatment, and prediction of emerging pandemics, providing valuable insights into possible treatment strategies. Additionally, this application serves as a catalyst for bolstering data collection

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and analysis regarding diabetic retinopathy, thereby raising awareness about the disease and advocating for preventative measures by authorities.

By furnishing experts with enhanced insights into the evolving patterns of diabetic retinopathy, the application presented in this paper aims to equip them with the necessary tools to offer improved, real-time assistance to both physicians and patients, thereby enhancing the overall standard of care.

A. Application Execution

To utilize the developed application effectively, users must adhere to the following steps:

Step 1: Commence by installing the application and granting all requisite permissions.
Step 2: Upon installation and launch of the app, users will encounter a Splash screen, followed by an authentication prompt necessitating a user details. The login page screenshot can be viewed in Figure 10.
Step 3: Upon successful authentication, the Menu screen will swiftly appear in Figures 11.
Step 4: Within the Menu screen, users should proceed by selecting the first item.
Step 5: When users select the menu option, they will be prompted to fill out the list, and all entered data will be securely stored in an internal SQLite database. This database operates independently, ensuring data storage and retrieval without reliance on servers or internet connectivity.
Step 6: Database will automatically populate, facilitating easy access to contacts for both patients and treating ophthalmologists.
Step 7: A crucial step involves conducting image background test for a designated patient, denoted as "Patient X."
Step 8: Subsequently, users can dispatch the test results to their preferred ophthalmologist via various email servers such as Yahoo, Hotmail, or Gmail.
Step 9: Multiple tests can be conducted for patients, including those with darker eye colors, to ensure comprehensive examination. The image background tests for Patient X are meticulously detailed in Figures 12,13, and 14, typically reviewed by medical professionals’ post-examination.

Fig. 8. Login Page

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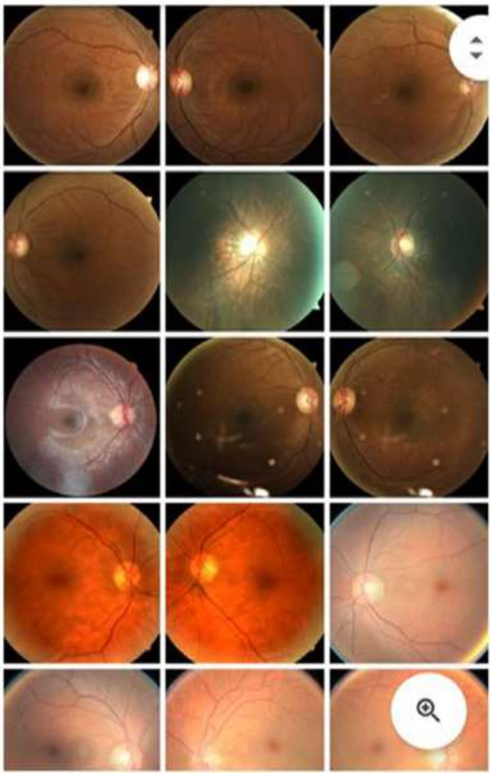
Fig. 9. DR database.

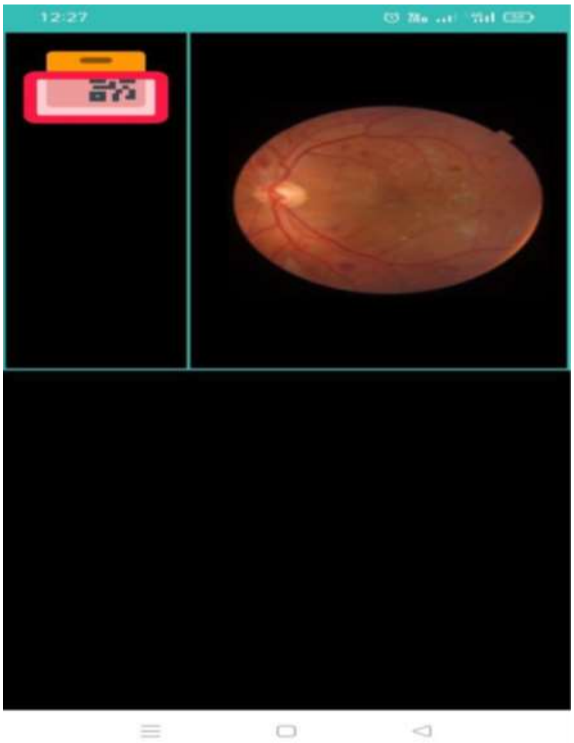
Fig. 10. Choice of picture to be examined.

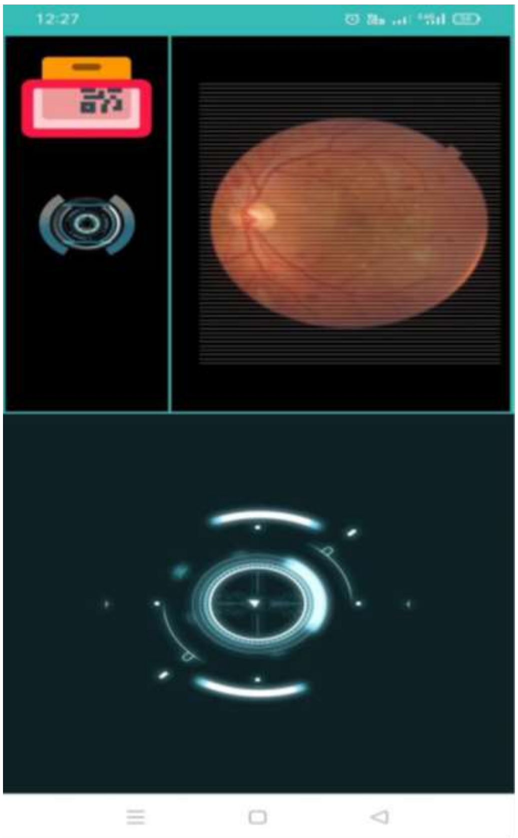
Fig. 11. Examining the selected image

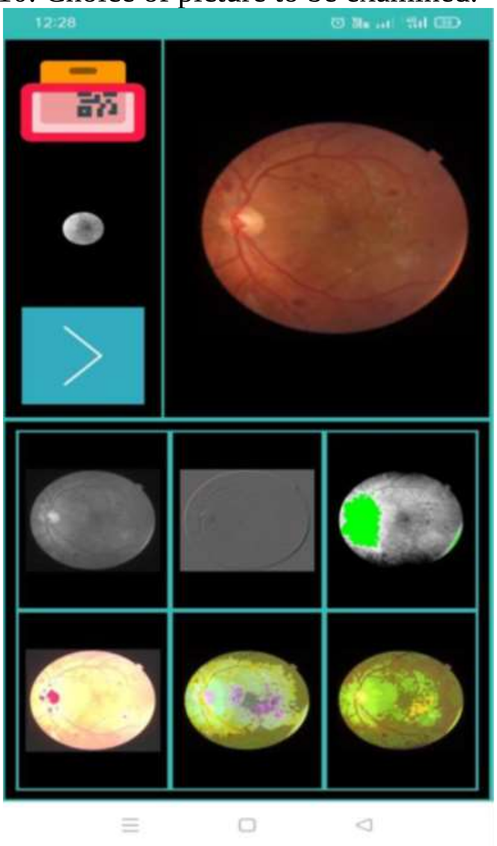
Fig. 12. Examination Results.

B. Smart Application Benefits

1. It improves the utilization of intelligent healthcare applications and accelerates the recognition of diabetic retinopathy.

2. Utilizing TensorFlow for the recognition of Diabetic Retinopathy from the Kaggle database, providing immediate reports.

3. The system is capable of sending comprehensive emails that include the patient's name, detailed retinopathy reports, and background images.

4. Advancing accessibility to medical services, fostering improved health outcomes.

5. Promoting smart health initiatives and facilitating enhanced interaction between physicians and patients.

6. Streamlining medical data management, healthcare delivery processes, and contributing to cost reduction efforts.

7. Improving the efficiency of diagnosis and enabling timely treatment interventions.

8. Enhancing the overall medical experience for patients and facilitating improved access to healthcare resources.

C. Tests and Results

The effectiveness of the algorithm blocks within our application can be analyzed using recognized parameters from the literature. These parameters, including precision, specificity, and sensitivity, are correlated with specific types of pathologies and serve as benchmarks for evaluating the performance of our system.

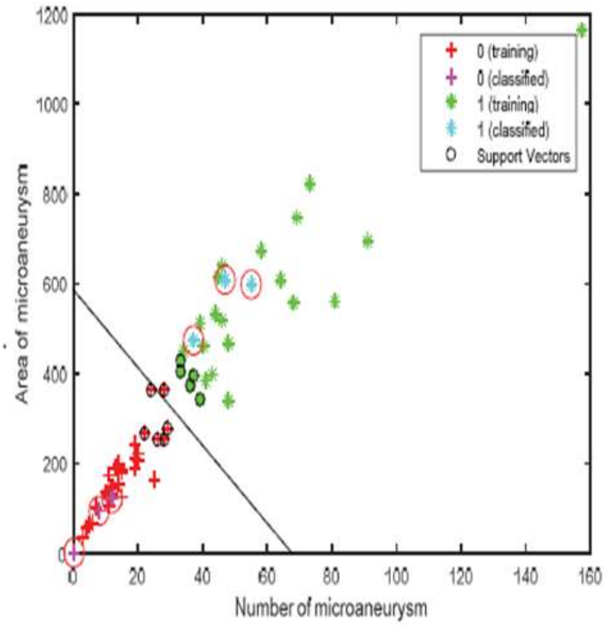

Fig. 13. Output of SVM classifier for training and testing images.

Calculated these three parameters are as follows:

Precision = Total number of eye bases detected DR / No DR Total number of eye bases (1)

Specificity = Total number of No DR eye bases detected / Total number of No DR eye bases (2)

Sensitivity = Total number of DR eye bases detected / Total number of DR eye bases (3)

We leveraged samples processed by our DIABETIC VISION application from the Kaggle database. The findings from these samples are detailed in Table 1 and Table 2, which are provided in the subsequent sections.

TABLE 1. Comparison of the results between the Kaggle database and our application diabetic vision

	NODR	**DR**
KAGGLE	6190	494
DIABETIC VISION	5655	457

TABLE 2. Results

	DIABETIC VISION
PRECISION	91.44%
SPECIFICITY	91.35%
SENSITIVITY	92.51%

VI. CONCLUSION AND FUTURE WORK

The utilization of Artificial Intelligence presents a promising avenue for revolutionizing smart healthcare, fostering greater accessibility and efficiency in medical services. Integrating AI with emerging technologies such as 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. Therefore, the ongoing quest to enhance diabetic retinopathy diagnosis underscores the importance of our work in providing diagnostic support through telemedicine tools and techniques, particularly in analyzing background images. As the prevalence of diabetes continues to rise annually, there is an urgent need to elevate the quality of patient care to meet escalating healthcare demands.

The AI-powered smart tele-ophthalmology application introduced in this study, tailored for diabetic retinopathy diagnosis, represents a significant step forward in facilitating early detection and screening. By bolstering smart healthcare initiatives, the application streamlines diagnosis and treatment processes, ultimately contributing to reducing mortality rates associated with diabetic retinopathy. Looking ahead, our future endeavors will focus on optimizing heavy machine learning models by integrating a TensorFlow Lite with fixed-point model, thus enhancing processing efficiency. We firmly believe that the convergence of Artificial Intelligence, IoT, blockchain and other evolving technologies will continue to reshape the landscape of healthcare delivery, necessitating stakeholders to acquire modern skills to drive the adoption of smart healthcare systems. Additionally, our research will explore the development of AI-driven devices for diagnosing conditions like myopia and Apea syndrome.

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