Towards Accurate Detection of Diabetic Retinopathy Using Image Processing and Deep Learning

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Abstract*—Diabetic retinopathy (DR) is a critical complication of diabetes, characterized by pathological changes in retinal blood vessels. This paper presents an innovative software application designed for DR detection and staging using fundus images. The system generates comprehensive reports, facilitating treatment planning and improving patient outcomes. Our study aims to develop an affordable computer assisted analysis system for accurate DR assessment, leveraging publicly available fundus image datasets. Key objectives include identifying relevant features for DR staging, developing robust image processing algorithms for lesion detection, and implementing machine learning models for accurate diagnosis. The research employs various pre-processing techniques to enhance image quality and optimize feature extraction. Convolutional Neural Networks (CNNs) are utilized for stage classification, achieving an impressive accuracy of 93.45%. Lesion detection algorithms, including optic disk localization, blood vessel segmentation, and exudate identification, demonstrate promising results in accurately identifying DR-related abnormalities. The developed software product integrates these advancements, providing a user-friendly interface for efficient DR diagnosis and management. Evaluation results validate the effectiveness of the CNN model in stage classification and lesion detection, with high sensitivity and specificity. The study discusses the significance of image augmentation and hyperparameter tuning in improving model performance. Future research directions include enhancing the detection of microaneurysms and hemorrhages, incorporating higher resolution images, and standardizing evaluation methods for lesion detection algorithms. In conclusion, this research underscores the potential of technology in revolutionizing DR diagnosis and management. The developed software product offers a cost-effective solution for early DR detection, emphasizing the importance of accessible healthcare solutions. The findings contribute to advancing the field of DR analysis and inspire further innovation for improved patient care.

***Keywords*—Diabetic retinopathy; fundus images; computer-assisted analysis; deep learning; image processing; convolutional neural networks component**

I. Introduction

The rapid advancement of diabetes poses a significant challenge to modern healthcare. Medical literature suggests that diabetes is associated with the emergence of serious long-term complications resulting in a variety of conditions, including cardiovascular disease, retinal complications, and retinopathy. According to a survey conducted by the International Diabetes Federation in 2015, around 410 million people worldwide suffer from diabetes. The disease also caused over 5 million deaths in the same year [1]. The disease is progressive, and its classification is based on the presence of different clinical abnormalities. Our research's main aim is to develop an affordable computer-assisted analysis system that accurately assesses the status of diabetic retinopathy (DR). By offering a cost-effective solution for DR analysis, we aim to prevent the progression of DR to its final stage and improve patient outcomes. This project highlights the potential benefits of technological innovation in healthcare and the importance of accessible solutions for DR analysis.

To achieve our aim, we have defined specific objectives. Firstly, we identified relevant features that can effectively determine each stage of DR, which were used to create a reliable diagnostic model. Secondly, we developed an image processing component capable of extracting these features from fundus images, enabling accurate detection of DR lesions. Thirdly, we build a robust and accurate machine learning model to diagnose the patient's stage of DR based on the identified features. Finally, we developed a software product that can identify the stage of DR and detect the presence of lesions in each fundus image. These goals collectively helped develop a comprehensive computer-assisted analysis system for DR diagnosis and management.

This research project is delimited to the consideration of Diabetic Retinopathy (DR) exclusively in the human population, and other retinal diseases are excluded from the scope of the study. By excluding other retinal diseases, the study is designed to have a focused and specific approach in the development of a diagnostic tool for Diabetic Retinopathy (DR).

The research utilized publicly available datasets of fundus images, annotated with DR grades, for training and testing machine learning models. The datasets utilized in this study include Kaggle dataset for DR detection [2], Messidor-1 dataset [3], Messidor-2 dataset [3], and the Indian Diabetic Retinopathy Image Dataset (IDRiD) [4]. The research project will deliver a web application for DR diagnosis, accompanied by a user manual. A research paper documenting the process, methodology, and results will also be produced. These deliverables aim to provide a cost-effective and reliable tool for the diagnosis and management of DR, improving treatment programs for diabetic patients.

II. Related work

Diabetic Retinopathy is a complication of diabetes that is caused by pathological changes of the blood vessels which nourish the retina and lead the blood vessels of the retina to swell and to leak fluids and blood. In an advanced stage of diabetic retinopathy, it can lead to a loss of vision. Diabetic retinopathy is the most common cause of blindness in people aged 30–69 years [5]. According to Diabetes Control and Complication Trail (DCCT), DR is considered one of the four leading causes of blindness. A macular is a condition that affects vision and occurs when fluid leaks from blood vessels in the retina, leading to the formation of lesions. It is the leading cause of blindness among people with diabetes [6]. Retina regular screening is crucial for people with diabetes to detect and treat DR in its initial stages, as this can help prevent the risk of blindness [7]. The detection of DR involves identifying distinct types of lesions in a retina image. Microaneurysms (MA), Hemorrhages (HM), soft and hard Exudates (EX) [8-10].

K. Xu et al. [11] automatically classified the images of the Kaggle [12] dataset into normal images or DR images using CNN. The researchers selected 1000 images from the Kaggle dataset, and applied data augmentation and resizing to 224 x 224 x 3 before feeding the images to their CNN model. Their CNN architecture consisted of eight convolution layers, four max-pooling layers, and two fully connected layers. The SoftMax function was utilized in the final layer of the CNN for classification. This method achieved an accuracy of 94.5%. M. T. Esfahan et al. [13] used a known CNN, which is ResNet34 [14] in their study to classify DR images of the Kaggle dataset into normal or DR image. To enhance the quality of the images, they applied a set of image preprocessing techniques, such as Gaussian filtering, weighted addition, and normalization. The reported accuracy of their method was 85%, and the sensitivity was 86%.

The work by V. Gulshan et al. [15] introduced a method to detect DR and diabetic macular edema (DME) using the CNN model. They used Messidor-2 [3] and eyepacs1 datasets which contain 1748 images and 9963 images, respectively to test the model. They trained 10 CNNs with the pre-trained Inceptionv3 [16] architecture with a various number of images and the result was computed by a linear average function. However, the study did not focus on explicitly detecting non-DR or the five stages of DR. H. Pratt et al. [17] proposed a method based on a CNN to classify images from the Kaggle dataset into five DR stages. The researchers used a custom CNN architecture to classify 80,000 test images after performing color normalization and resizing them to 512x512 pixels. However, it is important to note that their CNN was unable to detect the lesions in the images, and they only evaluated their CNN on a single dataset. S. Dutta et al. [18] detected and classified DR images from the Kaggle dataset into five DR stages. The researchers evaluated the performance of three distinct types of neural networks - back propagation neural network (BNN), deep neural network (DNN), and convolutional neural network (CNN) - using a dataset of 2000 images.

Ege et al. [19] located exudates and cotton wool spots in 38 color images. The authors used a combination of template matching, region growing, and thresholding techniques to detect abnormalities. Wang et al. [20] addressed the same problem by using a minimum-distance discriminant classifier to identify the retinal bright lesions such as exudates and cotton wool spots. They represented color features in a spherical color space.

Our study identifies a gap in the existing tools available for generating comprehensive reports on the status of patients with diabetic retinopathy. To address this gap, we propose the development of a software product capable of storing patient medical history, detecting DR, and improving treatment programs. This software product would generate detailed reports summarizing the patient's treatment program and store relevant information in a database. By providing doctors with a more complete understanding of the patient's medical history and DR stage, the proposed software product would enable more effective treatment planning and ensure appropriate care. This research emphasizes the significance of technological innovation in healthcare and highlights the potential benefits of software products in enhancing patient outcomes.

III. Methodology

The rapid advancement of diabetes poses a significant challenge to modern healthcare. Medical literature suggests that diabetes is associated with the emergence of serious long-term complications resulting in a variety of conditions, including cardiovascular disease, retinal complications, and retinopathy. According to a survey conducted by the International.

A. *Pre-processing*

In this research study, a series of pre-processing steps were conducted to improve the quality and uniformity of retinal fundus images. These steps included capturing the retina by removing the background using adaptive thresholding and contour detection, minimizing lens flares by cutting off the outermost area of the image, and resizing the images for quicker processing. Additionally, normalization was applied to the images with respect to a reference image to match their histogram distribution. Image enhancement techniques were employed using contrast-limited adaptive histogram equalization (CLAHE) on both RGB and HSI channels. For RGB channels, the images were divided into their components, enhanced using CLAHE, and filtered to reduce noise. For HSI channels, the images were transformed, enhanced, converted back to RGB, and filtered. The HSI approach was favored over RGB due to minimal color shift. These pre-processing steps aimed to enhance lesion detection and were crucial in the subsequent stage classification experiments.

B. *Stage Classification*

In our research, the focus was on the classification of various stages of Diabetic Retinopathy (DR). Convolutional Neural Networks (CNNs) were chosen as the primary method due to their effectiveness in previous studies. Transfer learning was employed, utilizing pre-trained models available in the Keras deep learning framework to improve classification performance.

We experimented with various CNN models, including ResNet50, InceptionV3, VGG, and custom models, exploring different parameters and learning rate adjustment approaches. Initially, a fixed learning rate was used, but we later implemented a dynamic approach using the “ReduceLROnPlateau” method based on validation loss. To prevent overfitting, we employed early stopping using the “EarlyStopping” function. Evaluating the performance of different pre-trained models, such as ResNet50, InceptionV3, and VGG, showed no significant differences. Hence, hyperparameter tuning was performed on selected models, considering their previous performance and relevant literature. Additionally, the possibility of implementing an ensemble method was explored if multiple models demonstrated satisfactory performance.

C. Stage Classification

1) Localization of optic disk: Two approaches were experimented with for the localization of the optic disk: the Kmeans clustering-based approach (see Fig. 2) and the intensity variation-based approach (see Fig. 1). In the K-means clustering-based approach, the algorithm is used to group pixels in the image based on their color intensities. The highest intensity cluster, representing the brightest pixels, is identified as the optic disk. The accuracy of this approach was evaluated on the Messidor and Kaggle datasets, achieving approximately 80.5% and 63.2% accuracy, respectively. However, issues such as lens flares and determining the optimal value of k for clustering can affect the accuracy of optic disk localization using this method.

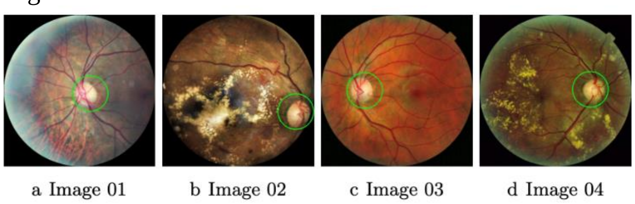

Fig. 1. Results from localization of optic disk by intensity variation-based approach.

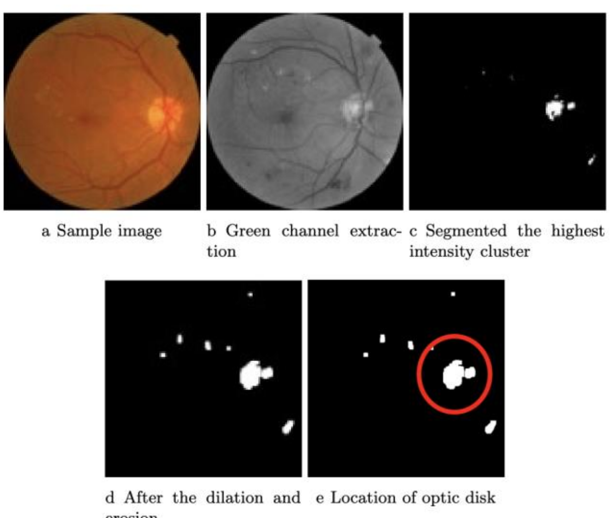

Fig. 2. Optic disk localization using K-means.

The intensity variation-based approach identifies the optic disk by detecting rapid intensity variations caused by dark blood vessels and bright nerve fibers. The average intensity variance within a window is calculated, and the highest intensity point is marked as the optic disk center. This approach demonstrated high accuracy, correctly identifying the optic disk in approximately 98.13% of the images from the Messidor dataset and 93.6% of the images from the Kaggle dataset, including those with lens flares which is summarized in Table 1.

TABLE I. SUMMARY ON OPTIC DISK LOCALIZATION APPROACHES

Approach	**Messidor-2 Dataset (375 images)**	**Kaggle Dataset (250 images)**
K-means clustering based approach	80.5 %	63.2 %
Intensity variation-based approach	98.13 %	93.6 %

Both approaches have their advantages and limitations, and the intensity variation-based approach shows promise in improving the accuracy of optic disk detection.

2) Localization of blood vessels: To detect blood vessels in the retinal fundus images, a series of steps were followed. First, the green channel was extracted to enhance the contrast. Then, Contrast Limited Adaptive Histogram Equalization (CLAHE) was applied to further enhance the image. Morphological operations involving opening and closing were performed using ellipsoidal structuring elements of varied sizes to remove small objects and smooth larger ones. The result of the CLAHE step was subtracted from the input image to isolate the blood vessels. A threshold was applied to binarize the blood vessel image. Finally, small contours were removed from the binarized image using an area-based criterion.

3) Detection of exudates: The detection of exudates from fundus images can be accomplished through various approaches. In the k-means clustering-based approach, the intensity values of the optic disk on the green channel image are set to zero, followed by dilation to remove lens flare. The highest intensity clusters are then identified using kmeans, with the brightest pixels representing the exudates. Experimentation with different k-values and normalization with a reference image are performed to enhance accuracy. However, false positive detections can occur if high-intensity pixel clusters are falsely identified as exudates. Alternatively, the edge detection approach involves extracting the green channel and applying the Canny edge detection algorithm to identify all edges. To isolate exudate edges, localization of blood vessels is first performed. The edges corresponding to blood vessels and the optic disk are then subtracted from the result. Contour analysis is employed to address the inclusion of tiny blood vessels during the extraction process. Although the edge detection approach is more reliable than the k-means approach, it may detect additional features like blood vessels, microaneurysms, and hemorrhages, making exudate identification more challenging. Consequently, another approach, namely Recursive Region Growing, is experimented with, which focuses on identifying regions with similar color or intensity likely to be exudates. The steps involved in this approach include extracting the green channel, applying the region growing and merging segmentation algorithm, producing a binary image using thresholding, localizing the optic disk, and subtracting it from the result.

4) Detection of detection of microaneurysms and hemorrhages: The process of detecting microaneurysms and hemorrhages using a k-means clustering approach in fundus images involves the following steps. First, the green channel is extracted as it provides better contrast for identifying red lesions. The images are then normalized with a reference image to ensure homogeneity and align with the selected value of k in the k-means algorithm. Next, k-means clustering is applied to identify clusters of similar pixel intensity values. The lowest intensity cluster is selected as it is expected to contain the microaneurysms and hemorrhages. The pixels in this cluster are thresholder and binarized to separate them from the rest of the image. Finally, the blood vessels are localized and removed from the segmented cluster.

IV. Implementation

The rapid advancement of diabetes poses a significant challenge to modern healthcare. Medical literature suggests that diabetes is associated with the emergence of serious long-term complications resulting in a variety of conditions, including cardiovascular disease, retinal complications, and retinopathy. According to a survey conducted by the International.

A. CNN model for Stage Classification

After conducting hyperparameter tuning on the pre-trained ResNet50v2 model, we found that setting the learning rate to 0.00001 and using three hidden layers, each with 230 neurons, resulted in the best performance. Based on these optimized hyperparameters, we finalized our ResNet50v2 model. The architecture of the model can be seen in Fig. 3.

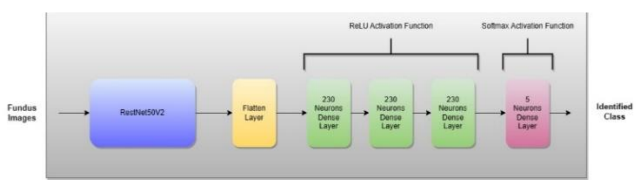

Fig. 3. CNN model for stage classification.

B. System for Lesion Detections

In our research, we focused on lesion detection in fundus images and successfully integrated the method into our application, Seer, using the OpenCV library. Seer not only accurately classifies various stages of Diabetic Retinopathy (DR) but also provides comprehensive reports on the DR class and identified lesions. By incorporating lesion detection into our analysis system, we have significantly enhanced the potential for early detection and effective management of DR, highlighting the importance of innovative solutions in healthcare. Through experimentation, we compared different approaches for localizing the optic disk and chose the intensity variation-based method for its superior accuracy. We also evaluated multiple techniques for exudate detection and determined that the recursive region-growing-based approach yielded the best performance. Additionally, we employed the k-means clustering approach to detect microaneurysms and hemorrhages and conducted experiments on localizing blood vessels. These advancements in lesion detection contribute to the overall effectiveness and reliability of Seer in diagnosing and managing DR.

C. Implementation of Software product

The implemented software product is a comprehensive and sophisticated solution designed to streamline the management of Diabetic Retinopathy (DR) in healthcare institutions. It offers a range of powerful functionalities that enhance various aspects of DR management. The software provides secure user authentication and authorization, ensuring that only authorized individuals can access the system. It utilizes advanced algorithms to predict the stage of DR based on fundus images, assisting in early detection and treatment planning. The software also offers intuitive visualization tools for DR lesions, enabling healthcare professionals to analyze and interpret the images with ease. It generates detailed reports that summarize the DR class and provide insights into the identified lesions, facilitating documentation and communication among healthcare teams. Furthermore, the software allows for efficient management of patient DR history, ensuring comprehensive records and tracking of their condition over time. User and institution management features are included to provide administrative control and customization options. Overall, this software product simplifies and streamlines DR management, empowering healthcare providers to deliver more effective care through its user-friendly interface and comprehensive range of functionalities.

1) Tools and Technologies: The proposed solution is being developed on the basis of the following tools:

- Application Framework: Python Flask
- Database: MySQL Database
- Additional tools: OpenCV

V. Evaluation

The rapid advancement of diabetes poses a significant challenge to modern healthcare. Medical literature suggests that diabetes is associated with the emergence of serious long-term complications resulting in a variety of conditions, including cardiovascular disease, retinal complications, and retinopathy. According to a survey conducted by the International.

A. Evaluation of CNN Model for Stage Classification

We evaluated our model against following dataset variations which derived from the Messidor-2 and Kaggle datasets to class balance and improve the quality.

- Dataset 03: Dataset generated by applying image augmentation to pre-processed images with minimized lens flares
- Dataset 04: Dataset generated by applying image augmentation to pre-processed images by applying CLAHE on RGB channels

- Dataset 05: Dataset generated by applying image augmentation for pre-processed images by applying CLAHE on HSI channels
- Dataset 06: Dataset generated by class balancing with approximately 600 images per class.

1) Evaluation of model with respect to Dataset 03: The results gained by testing the stage classification model on different variations of Dataset 03 and the confusion matrix and ROC curve are calculated to evaluate the performance of the model (see Fig. 4).

The accuracy and sensitivity of the test have been calculated for each class individually, and the results are presented below.

- Class 0: Accuracy = 0.806, Sensitivity = 0.979
- Class 1: Accuracy = 0.958, Sensitivity = 0.868
- Class 2: Accuracy = 0.982, Sensitivity = 0.948
- Class 3: Accuracy = 0.987, Sensitivity = 1.000
- Class 4: Accuracy = 1.000, Sensitivity = 0.962

The overall performance is listed below.

- Overall Accuracy: 0.935
- Overall Precision: 0.951
- Overall Specificity: 0.9

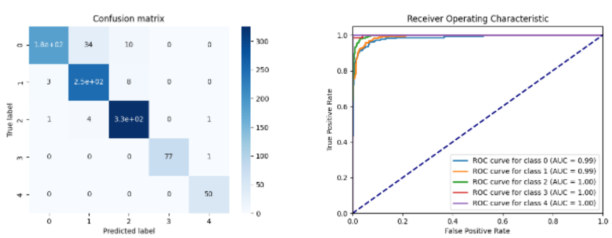

Fig. 4. Evaluation results with respect to Dataset 03.

2) Evaluation of model with respect to Dataset 04: The results gained by testing the stage classification model on different variations of Dataset 03 and the confusion matrix and ROC curve are calculated to evaluate the performance of the model (see Fig. 5).

The accuracy and sensitivity of the test have been calculated for each class individually, and the results are presented below.

- Class 0: Accuracy = 0.819, Sensitivity = 0.870
- Class 1: Accuracy = 0.916, Sensitivity = 0.839
- Class 2: Accuracy = 0.919, Sensitivity = 0.947
- Class 3: Accuracy = 0.987, Sensitivity = 0.987
- Class 4: Accuracy = 0.980, Sensitivity = 1.000

The overall performance is listed below.

- Overall Accuracy: 0.930
- Overall Precision: 0.928
- Overall Specificity: 0.953

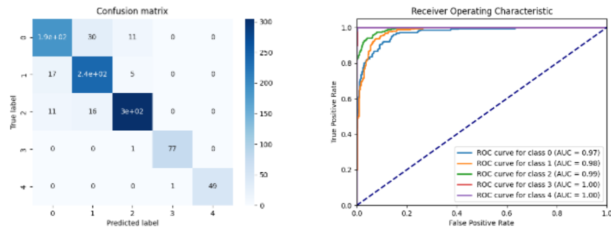

Fig. 5. Evaluation results with respect to Dataset 04.

3) Evaluation of model with respect to Dataset 05: The results gained by testing the stage classification model on different variations of Dataset 03 and the confusion matrix and ROC curve are calculated to evaluate the performance of the model (see Fig. 6).

The accuracy and sensitivity of the test have been calculated for each class individually, and the results are presented below.

- Class 0: Accuracy = 0.894, Sensitivity = 0.839
- Class 1: Accuracy = 0.912, Sensitivity = 0.881
- Class 2: Accuracy = 0.880, Sensitivity = 0.954
- Class 3: Accuracy = 0.974, Sensitivity = 0.950
- Class 4: Accuracy = 0.980, Sensitivity = 0.980

The overall performance is listed below.

- Overall Accuracy: 0.905
- Overall Precision: 0.921
- Overall Specificity: 0.950

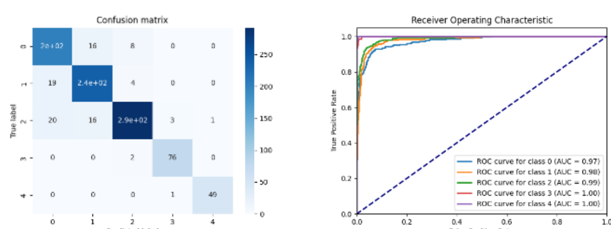

Fig. 6. Evaluation results with respect to Dataset 05.

4) Evaluation of model with respect to Dataset 63: The results gained by testing the stage classification model on different variations of Dataset 03 and the confusion matrix and ROC curve are calculated to evaluate the performance of the model (see Fig. 7).

The accuracy and sensitivity of the test have been calculated for each class individually, and the results are presented below.

- Class 0: Accuracy = 0.717, Sensitivity = 0.860
- Class 1: Accuracy = 0.825, Sensitivity = 0.780
- Class 2: Accuracy = 0.892, Sensitivity = 0.754
- Class 3: Accuracy = 0.908, Sensitivity = 0.732

- Class 4: Accuracy = 0.647, Sensitivity = 0.951

The overall performance is listed below.

- Overall Accuracy: 0.798
- Overall Precision: 0.815
- Overall Specificity: 0.939

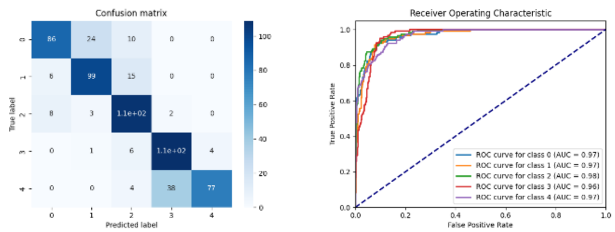

Fig. 7. Evaluation results with respect to Dataset 06.

B. Evaluation of Lesion Detection

To evaluate the effectiveness of a lesion detection method on a dataset of fundus images containing retinal lesions, an initial attempt was made to engage a medical professional to manually inspect the lesions. However, this approach proved unsuccessful due to several reasons. As an alternative, the Indian Diabetic Retinopathy Image Dataset (IDRiD) was discovered, which provided annotated ground truths of the lesions by a clinician. A 5x5 pixelation approach was adopted to facilitate the comparison between the detected lesions and the ground truth markings. The method's performance was evaluated by measuring true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN), and accuracy was calculated accordingly. Masks were generated using the IDRiD dataset, and these masks were compared to the ground truth markings to assess the performance of the lesion detection method.

1) Evaluation results by detection of exudates: This test was done on 27 images of the Indian Diabetic Retinopathy Image Dataset (IDRiD). Evaluation results by Detection of Exudates are given in Table 2.

TABLE II. EVALUATION RESULTS ON DETECTION OF EXUDATES

	Segments classified as Exudates	Segments classified as normal
Exudates	1005	790
Normal	1332	230728

TABLE III. EVALUATION RESULTS ON DETECTION OF MICROANEURYSMS AND HEMORRHAGES

	Segments classified as Microaneurysms and Hemorrhages	Segments classified as normal
Microaneurysms and Hemorrhages	546	2820
Normal	1173	344443

- Sensitivity: 0.560
- Specificity: 0.994
- Accuracy: 0.990

2) Evaluation results by detection of evaluation results by detection of microaneurysms and hemorrhages: This test was done on 27 images of the Indian Diabetic Retinopathy Image Dataset (IDRID). Evaluation results by Detection of Microaneurysms and Hemorrhages are given in Table 3.

- Sensitivity: 0.318
- Specificity: 0.992
- Accuracy: 0.989

C. Discussion

To enhance the features in fundus images, there are several effective pre-processing techniques that can be employed. A crucial step involves removing the background and centering the image, which helps to bring attention to the important regions while eliminating unnecessary distractions. Another valuable method is normalizing the fundus images using a reference image, ensuring consistent brightness and contrast for accurate comparisons. Enhancing the image on RGB channels and intensity channel in HSI format can improve overall image quality by employing CLAHE. By applying median blur, any remaining noise or artifacts can be further reduced, resulting in a cleaner image. Lastly, image augmentation, which involves techniques like random rotation, shifting the image horizontally and vertically, Shearing and Horizontal flips introduces variations to the training set, enabling the model to learn more robust features. By incorporating these pre-processing methods, the features in fundus images can be effectively enhanced, leading to more accurate and reliable analysis.

Based on the information provided, a ResNet50V2 model, which is a pre-trained CNN, was used for stage classification. This model achieved an impressive accuracy of 93.45% when evaluated on 900 augmented images from the Messidor-2 and Kaggle datasets. This suggests that a CNN-based model like ResNet50V2 can be highly effective for stage classification tasks in this context.

After conducting hyperparameter tuning on the pre-trained ResNet50V2 model for stage classification, the most suitable combination of hyperparameters was determined. The best results were obtained with a learning rate of 0.00001, 3 hidden layers, and 230 neurons in each hidden layer. This configuration maximized the model’s learning capacity and allowed it to capture the complex patterns and relationships present in the stage classification task. Hyperparameters such as learning rate and network architecture can significantly impact the performance of a CNN model. By carefully selecting and optimizing these hyperparameters, the model’s accuracy and ability to classify different stages can be enhanced.

After experimenting with three different approaches - K-means approach, Canny Edge detection approach, and Recursive Region Growing approach - it was determined that the Recursive Region Growing approach is the most suitable method for correctly identifying the locations of Exudates. Among the three approaches, Recursive Region Growing demonstrated superior performance in accurately detecting and delineating the regions of Exudates in the images. The Recursive

Region Growing method, based on a seed point and specific criteria for region expansion, effectively identifies and segments the Exudates areas with a higher level of precision.

To accurately identify the locations of Microaneurysms and Hemorrhages, the Kmeans clustering approach can be employed, along with the Elbow method to dynamically determine the optimal value of K for each fundus image. By finding the" elbow" point on the resulting plot, the optimal K value can be determined for accurate identification of the locations of Microaneurysms and Hemorrhages.

VI. Conclusion

In conclusion, we have successfully developed an affordable computer-assisted analysis system for accurate assessment of diabetic retinopathy status by utilizing Kaggle and Messidor-2 public datasets, along with an augmented dataset. We trained a ResNET50v2 model was trained using Bayesian Optimization for hyperparameter tuning. Our model achieved an accuracy of more than 0.9 for stage classification. Our application, Seer, utilizes this model to classify fundus images and provide a detailed report on DR class and lesions, which has the potential to significantly improve the detection and management of DR. Our research highlights the need for accessible solutions for DR analysis and the potential benefits of technological innovation in healthcare. We hope that our work inspires further development of cost-effective solutions for DR analysis, leading to improved patient outcomes.

VII. Future work

In future work, one of the key areas to focus on is the accurate detection and differentiation of Microaneurysms and Hemorrhages from blood vessels. This requires addressing the challenge of their similarity and developing new techniques that can effectively localize blood vessels and distinguish these lesions. Advanced image processing algorithms, feature extraction methods, and deep learning architectures could be explored to achieve this goal. Improving the accuracy of detecting hemorrhages and microaneurysms is another important aspect for future research. This can involve refining the existing algorithms to better identify red-colored and addressing limitations such as the algorithm's inability to detect hemorrhages near blood vessels. Further studies can be conducted to enhance the performance of these detection methods.

For stage classification, incorporating higher resolution images in the model training process could be a potential improvement. Although it would require more computational resources, training the model on higher resolution images can enable the capture of finer details and subtle features associated with distinct stages. This can potentially lead to improved accuracy in stage classification. To facilitate standardized evaluation of lesions, the implementation of a standardized method is crucial. This would ensure consistency in the evaluation process across different studies and research efforts. A standardized method for evaluating lesions would allow for better comparison and benchmarking of different algorithms, models, or techniques, advancing the field.

These future works highlight the ongoing efforts and areas of focus in improving the detection and classification of Microaneurysms, Hemorrhages, and other relevant abnormalities in fundus images. By addressing these challenges and advancing the state-of-the-art techniques, we can achieve more accurate diagnoses and provide improved patient care in the field of Diabetic Retinopathy management.

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