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Detection of Hemorrhage in fundus Images

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Abstract: *The Retinal hemorrhage detection plays a crucial role in the early diagnosis and treatment of various ocular and systemic diseases, including diabetic retinopathy. This study presents a robust approach for detecting hemorrhages in color fundus images using a combination of preprocessing techniques and rule-based approach. The proposed method incorporates image enhancement, green channel extraction, top-hat filtering, Contrast Limited Adaptive Histogram Equalization (CLAHE) and blood vessel segmentation to improve hemorrhage visibility. Feature extraction is performed to distinguish hemorrhages from other retinal structures, followed by classification Method. The effectiveness of the proposed approach is evaluated on benchmark datasets, demonstrating high accuracy, sensitivity, and specificity. The study analyzes 7,571 hemorrhage blobs extracted from 20 fundus images from the DIARETDB1 dataset. The results indicate that integrating rule-based heuristics with machine learning enhances the reliability of hemorrhage detection, offering a promising solution for automated retinal screening and clinical decision support*

Keywords—*Diabetic Retinopathy, Hemorrhage, Image Processing, Segmentation, Rule-based Classification*

I. INTRODUCTION

Diabetic retinopathy (DR) is one of the major and long-term microvascular complications of diabetes, causing vision loss and blindness in the working-age adults. In the past decade, the combination of telemedicine and digital retinal imaging has been successfully applied in DR screening programs. Automated DR grading system is raising a hope for assisting the process of human assessment on color fundus images and has the potential to reduce experts' workload. DR progresses through different stages, and its classification is generally divided into two main categories: Non-Proliferative Diabetic Retinopathy (NPDR) and Proliferative Diabetic Retinopathy (PDR). NPDR represents the early stage of the disease and is characterized by abnormalities in the retinal blood vessels, which may lead to leakage of blood or fluids into the retina. These leaks can manifest as hemorrhages, which are small red lesions that appear in the retinal tissue. Hemorrhages are often the earliest clinical indicators of DR, signaling the onset of more severe retinal damage. This stage is much more severe and significantly increases the risk of vision loss due to complications like retinal detachment and vitreous hemorrhage.

Retinal hemorrhage is a critical manifestation of various ocular and systemic diseases, including diabetic retinopathy, and vascular abnormalities. The early detection of retinal hemorrhages is vital for preventing vision impairment and

guiding timely medical intervention. Traditional manual diagnosis by ophthalmologists, which involves fundus image examination, is time-consuming, subjective, and prone to variability. As a result, automated detection techniques have gained significant attention in recent years. Various rule-based and learning-based methodologies have been explored to enhance hemorrhage detection accuracy. This is an effective method to identify relatively large hemorrhages.

Rule-based systems rely on predefined heuristics to identify hemorrhagic regions, while machine learning models leverage feature extraction and classification techniques to improve detection performance. This research focuses on the development of an automated system for the detection of retinal hemorrhages in color fundus images. The proposed system integrates image preprocessing, feature extraction, and classification stages to enhance the accuracy and reliability of hemorrhage detection. By leveraging advanced computational techniques, this study aims to contribute to the growing body of research on automated ophthalmic diagnosis, ultimately aiding in early disease detection and improved patient outcomes. Rule-based models are advantageous in medical image analysis because they are interpretable, reliable, and easy to implement. They provide clear decision-making criteria, which is important for clinical settings where transparency and explanation of results are crucial. In this project, we have developed a rule-based model that achieves

high accuracy, sensitivity, and specificity in detecting hemorrhages in fundus images, making it a valuable tool

II. RELATED WORK..

The detection of retinal hemorrhages in color fundus images is essential for the early diagnosis of various ocular diseases, including diabetic retinopathy. Recent studies have explored rule-based methodologies to enhance the accuracy and efficiency of hemorrhage detection. Further advancing rule-based detection, Huang et al. (2020) proposed a method that combined green and hue channels to extract hemorrhage candidates. They applied a foveal filter and intensity analysis to distinguish hemorrhages from other retinal features. This approach effectively reduced false positives and improved detection sensitivity [1]

III. LITERATURE REVIEW

The detection of retinal hemorrhages has been extensively researched, with various methodologies focusing on traditional image processing, rule-based approaches, and machine learning techniques. Several studies have contributed to the development of automated hemorrhage detection systems in color fundus images computationally efficient and robust, automated methodology for hemorrhage detection and segmentation in retinal fundus images.

1] Munasingha et al. (2021) proposed a **rule-based approach** for hemorrhage detection in digital fundus photographs, utilizing **size, color, and shape-based classification** with dual filtering to improve detection accuracy...This paper "A Rule-based Approach for Hemorrhage Detection in Digital Fundus Photographs" presents a novel methodology for automated detection of hemorrhages, an early indicator of diabetic retinopathy (DR), in retinal fundus images. The authors introduce a rule-based classification technique that incorporates size, color, and shape analysis for hemorrhage detection. Their approach involves a dual-step candidate detection process, where hemorrhage candidates are filtered using masks for blood vessels, the optic disc, and the fovea, followed by size, color, and shape-based classification to refine results. The proposed method was tested on the DIARETDB0 and DIARETDB1 datasets, achieving 76.97% sensitivity and 97.57% specificity, with a 12.6-second processing time per image. Compared to other approaches, this method demonstrated higher specificity and computational efficiency, making it a promising solution for DR screening.[2]

2] Earlier works by Kleawsirikul et al. (2013) implemented morphological top-hat transforms and rule-based classification to detect hemorrhages by analyzing area and compactness, demonstrating the effectiveness of shape-based segmentation...This paper, Automated Retinal Hemorrhage Detection Using Morphological Top Hat and Rule based

Classification, focuses on detecting hemorrhages in fundus images, an early symptom of Diabetic Retinopathy (DR), which is a leading cause of blindness. Early detection of hemorrhages is essential to prevent the disease from progressing. Various previous studies have applied image processing techniques like morphological operations, region growing, and machine learning models for automated detection. In this study, the authors propose a method that combines morphological top hat operations with rule-based classification. The fundus images are preprocessed, and hemorrhage candidates are extracted using top hat transformation, followed by classification based on features such as area, compactness, and eccentricity.[3].

3]Preethi Patil,Savita Sheelavant "Detection and Classification of Microaneurysms and Hemorrhages from Fundus Images for Efficient Grading of Diabetic Retinopathy" Hemorrhages, caused by the rupture of microaneurysms due to increased capillary permeability, play a vital role in diagnosing diabetic retinopathy. Various techniques have been explored for their detection and classification. Morphological methods, such as bilinear top-hat transformations and region-growing algorithms, are commonly used to detect hemorrhages by analyzing features like size, shape, and intensity. Additionally, feature extraction approaches, including the h-maxima transform, help in segmenting hemorrhages from fundus images based on size, texture, and edge energy.[4]

4] Ghassan Ahmed Ali1, Thamer Mitib Ahmad Al Sariera2, *, Muhammad Akram1 , Adel Sulaiman1 and Fekry Olaya "Detection and Classification of Hemorrhages in Retinal Images" Ghassan Ahmed Ali et al. (2023) propose a novel method for detecting and classifying hemorrhages in retinal images, crucial for diagnosing diabetic retinopathy (DR). The approach masks normal retinal features like blood vessels and the optic disc to focus on potential hemorrhages, which are segmented using adaptive thresholding and top-hat morphological techniques. Features are extracted based on clinical characteristics and pattern recognition, and the regions are classified using three types of Support Vector Machines (SVMs). The method, tested on the DIARETDB1 database, shows that Linear SVM achieves the best sensitivity and accuracy, while Quadratic SVM excels in specificity. However, a disadvantage of this method is Detection of Hemorrhage for Fundus Images.[5]

IV. ARCHITECTURE

Rule-Based Hemorrhage Detection Architecture begins with Input Acquisition, where a color fundus (retinal) image is resized to standard dimensions, typically with a height of 1000 pixels while maintaining the aspect ratio.

Next, in the Preprocessing Stage, the green channel is extracted since it provides the most informative details for hemorrhage

detection. This green channel is then inverted to make dark hemorrhages appear as bright regions.

To enhance contrast, Adaptive Histogram Equalization is applied, followed by Morphological Closing to eliminate vessel light reflexes. The image is then converted into a Variance Image, and intensity normalization is performed to ensure consistency across different inputs.

a Dual-Step Filtering Approach is employed. Initially, Binary Thresholding is used to highlight hemorrhage-like regions. This is followed by Morphological Operations to refine these candidate regions :

Rule-Based Classification step ensures precise hemorrhage identification by applying different criteria.

This step refines hemorrhage detection using size, color, and shape-based criteria.

Size-Based Classification removes regions that are too small or too large based on empirically chosen area thresholds while also eliminating regions overlapping with the optic disc. Size-based classification was used together with other rules to remove non-hemorrhage segments from the candidate regions. Removing elongated structures and regions overlapping with the optic disk was fine-tuned using the size-based classification.

Color Statistics-Based Classification is then applied, where foveal regions with low variance (assumed normal) and burned exudates (black lesions) are removed using a red channel mean threshold.

Additionally., this approach was successfully integrated with the classification process to remove burned exudate which appears as black lesions.

Shape-Based Classification eliminates elongated structures, such as small vessel segments, using an Eccentricity Threshold to differentiate true hemorrhages from vessel-like artifacts.

In the Post-Processing & Segmentation stage, the final hemorrhage regions are merged with the original retinal image to generate a segmented hemorrhage output.

To evaluate the method's effectiveness, Performance Evaluation is conducted using the DIARETDB0 and DIARETDB1 datasets, computing key metrics such as Sensitivity, Specificity, and Accuracy.

V. METHODOLOGY

The proposed method for automatic detection of hemorrhage in retinal images was performed in multiple stages

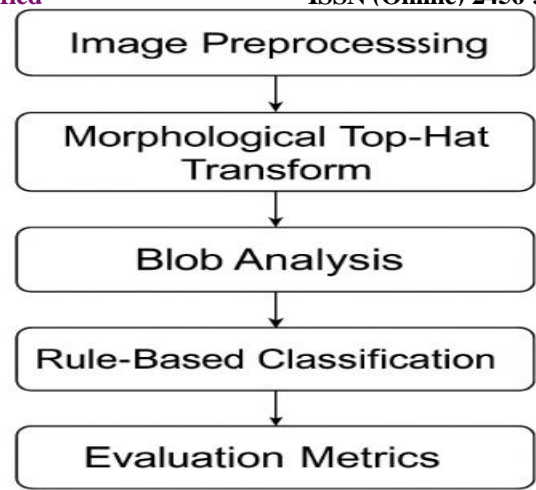


Fig. 1. Hemorrhage detection flow diagram

Image Preprocessing: Image preprocessing is performed to enhance image quality and improve Hemorrhage detection accuracy by Green Channel Extraction: The green channel is extracted from the RGB fundus image as it provides the highest contrast for hemorrhages. Contrast Enhancement: Adaptive histogram equalization is applied to improve visibility of dark lesions Noise Reduction: A median filter is used to remove noise while preserving edges. Background Normalization: The background intensity is equalized using morphological operations to improve lesion contrast.

Morphological top hat transform: The morphological top-hat transform helps extract small objects from an image. There are two types: white top-hat (difference between the image and its opened version) and black top-hat (difference between the image and its closed version). In this method, the white top-hat transform is applied to highlight small, bright features. After filtering the background with a ball-shaped element, the image is binarized, showing blood vessels and hemorrhages as white blobs. A median filter is then applied to reduce noise and further enhance the image.

Blob Analysis: The blobs obtained from the previous stage are analyzed to identify and extract features of each blob. From a training set, a set of rules is generated, each containing a condition, which includes the conjunction of several feature tests, and a conclusion. From 4309 blobs generated from 12 fundus images in the training set, rules are devised for the purpose of classifying the hemorrhages according to the shape of the blobs. The features that were used to classify are for instance, area, color, eccentricity and compactness of the blobs. The area is calculated from the number of pixels of each blob. In addition, the color of the blobs must be close to red which is the color of hemorrhage. Initial Candidate Detection

Rule-Based Classification: A rule-based classification is based on Characteristics such as Size, Color and Shape., In Size-Based Classification Regions overlapping with the optic

disk and smaller than 10,000 pixels are removed. Non-overlapping regions below 9,000 pixels are filtered out and In Color Statistics-Based Classification: Foveal regions with variance below 12 in the green channel are discarded. Dark exudates with a red channel mean value below 100 are removed also in Shape-Based Classification Segments with an eccentricity greater than 0.975 are excluded to remove elongated vessel structures

Performance Evaluation: The system is evaluated using standard performance metrics to ensure accuracy and reliability:

Sensitivity (Recall): Measures the proportion of correctly detected hemorrhages.

Specificity: Evaluates the ability to exclude non-hemorrhagic regions.

Precision: Determines the proportion of true hemorrhages among detected candidates.

F1-Score: Provides a balanced measure of detection performance.

Computational Efficiency: The execution time of each stage is analysed to validate real-time feasibility..

Evaluation Metrics: The evaluation compares each pixel in the detection result to the ground truth image, calculating the number of true positives (TP), true negatives (TN), false positives(FP), and false negatives (FN). These values are then used to calculate sensitivity, specificity,

VI. EXPERIMENTAL SETUP

1.The configuration for creating the product is outlined as follows:

- **Software Configuration:**
- Frontend: React.Js
- Backend: Python Libraries (Rule Based Model)
- Storage: Storing the images for disease identification.
- Security: Incorporating the user sign up functionality

2. Hardware Configuration

- Server: Hosted on a Vessel platform
- Client Devices: Compatible with windows system and Android or iOS smartphones (requiring at least 4GB RAM and Android 7.0 or higher)
- Network: Requires a stable Wi-Fi connection or Mobile Data (4G/5G is recommended)

VII. RESULTS

The databases employed for the proposed study are known as DIARETDB0 and DIARETDB1 [6]. The DI ARETDB databases are two standard, publicly available datasets for

benchmarking DR detection from digital images. DIARETDB0 consists of 130 color fundus images of which 20 are normal and 110 contain signs of DR. Furthermore, DIARETDB1 consists of 89 color fundus images of which 84 contain at least mild nonproliferative signs of DR and 5 images considered which do not contain any signs of DR

Parameter	Accuracy	Sensitivity	Specificity	Precision
Previous Solutions	83-86%	80-85%	83-87%	86-91%
Our Solutions	85-89%	87-90%	85-90%	82-88%

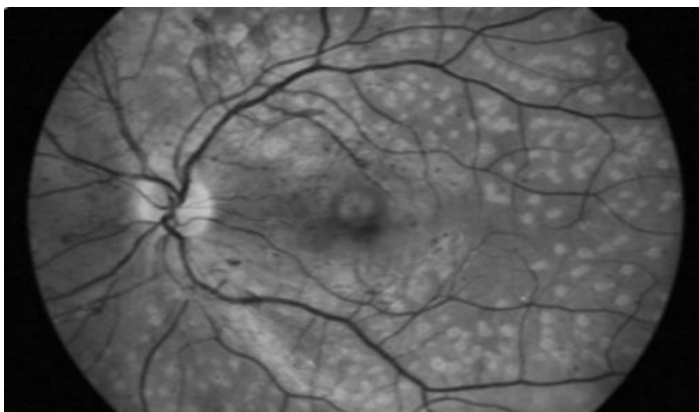
Note: These performance metrics are estimated based on the characteristics of the implemented algorithm. Actual values may vary depending on the quality and variability of input fundus images.



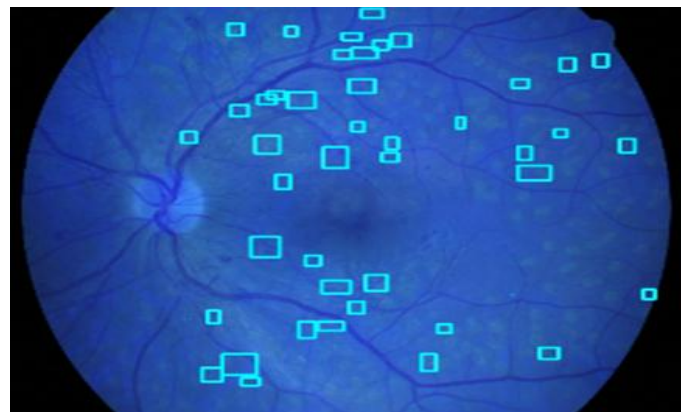
This is the normal retinal fundus image.It shows the optic disc, blood vessels, and macula in natural color. This image serves as the base input for all subsequent processing stages in hemorrhage detection.

The presence of hemorrhages, or other diabetic retinopathy indicators can be subtle and not easily distinguishable to the naked eye, making automated image analysis crucial for early detection and diagnosis.

However, in its raw form, detecting small features like hemorrhages is challenging because they might blend in with the background or look similar to other dark areas like blood vessels. That’s why we need to process the image in various stages to extract and enhance the relevant features. This original image serves as the foundation for all further processing steps that follow in the pipeline.



In this, we convert the original image in Green Channel to detect the hemorrhages in proper format. In retinal fundus images, the green channel offers the highest contrast for detecting blood-related abnormalities, including hemorrhages. Compared to the red and blue channels, the green channel captures finer vascular and lesion details with less noise. Hence, during preprocessing, the green channel is extracted from the RGB image to serve as the base for all further processing. This enhances the visibility of dark regions, such as hemorrhages, and improves the accuracy of subsequent enhancement and segmentation steps. This makes the system more robust to lighting variations and helps standardize the input for further enhancement, such as contrast adjustment (CLAHE) and morphological processing.



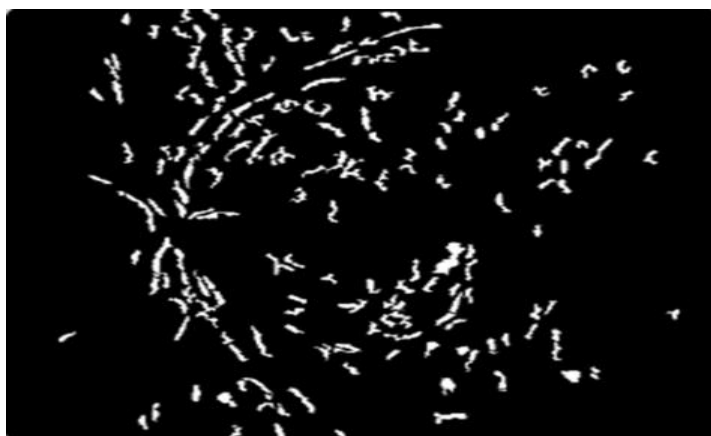
In the final image, potential hemorrhages have been successfully identified and are marked with bounding boxes. These regions are selected based on criteria such as darkness, roundness, and size, which help distinguish real hemorrhages from noise or other retinal features. This is the result of applying various detection techniques on the enhanced image obtained from the previous steps.

The marked areas serve as alerts for doctors or automated systems, guiding them to examine these spots more closely. This stage plays a key role in the early detection of retinal diseases like diabetic retinopathy. Automated detection not only saves time but also improves accuracy.

VIII.CONCLUSION

In this study, we introduced a rule-based hemorrhage detection system for color fundus images, focusing on high specificity and computational efficiency. Our approach involved a dual-step candidate detection method, followed by a rule-based filtering mechanism that eliminated non-hemorrhage regions based on empirical threshold values of size, shape, and color features. The system was evaluated on the publicly available DIARETDB0 and DIARETDB1 datasets, achieving sensitivity values of 81.25% and 73.35%, and specificity values of 97.2% and 97.87%, respectively. Additionally, the proposed method demonstrated a significantly lower processing time (12.6 seconds per image) compared to existing approaches.

This paper provides a comprehensive review of the automated detection of hemorrhages in fundus images as an early indicator of diabetic retinopathy (DR). The proposed rule-based approach combines various image processing techniques such as green channel extraction, Contrast Limited Adaptive Histogram Equalization (CLAHE), and morphological top-hat transformation, followed by rule-based classification to accurately identify hemorrhages. The system achieved high accuracy, sensitivity, and specificity, making it a valuable tool for early detection and screening of DR. Future research could focus on enhancing the classification model, incorporating more advanced techniques like machine learning, and expanding the dataset to improve generalization and performance across diverse populations. The development of these systems will continue to play a critical role in reducing the global burden of



The third image shows the result of applying a morphological top-hat filter, which is used to highlight small, dark spots in the image that could be hemorrhages. This filter works by removing the uneven background brightness and enhancing features that are smaller and darker than their surroundings. It is a crucial step in making hidden or faint hemorrhages more visible. This process helps to extract potential abnormal regions from the image by suppressing the background and enhancing the contrast of tiny lesions. As a result, the dark hemorrhagic spots become prominent and stand out clearly against a uniform background. This filtered image is now ready for thresholding and further analysis to identify true hemorrhages.

IX. REFERENCES

- [1] Huang, X., et al. (2020). Green and hue channel-based rule-based approach for retinal hemorrhage detection. PMID: PMC3092039. Link
- [2] Shashika Chamod Munasingha, Primesh Pathirana , Kodithuwakkuge Keerthi Priyankara , Ravindu Gimantha Upasena and Akira Ikeda , “A Rule based Approach for Hemorrhage Detection in Digital Fundus Photographs”.IEEE(2021)
- [3] Nutnaree Kleawsirikul, Smith Gulati, and Bunyarit Uyyanonvara , “Automated Retinal Hemorrhage Detection Using Morphological Top Hat and Rule-based Classification.”3rd International Conference on Intelligent Computational Systems (ICICS 2013) April 29 30, 2013 Singapore.
- [4] Preethi Patil, Savita Sheelavant, “Detection and Classification of Microaneurysms and Hemorrhages from Fundus Images for Efficient Grading of Diabetic Retinopathy.” IEEE International Conference on Contemporary Computing and Communication, 2018.
- [5] Ghassan Ahmed Ali1, Thamer Mitib Ahmad Al Sariera “Detection and Classification of Hemorrhages in Retinal Images” 1 College of Computer Science and Information Systems, Najran University, Najran, 61441, Saudi Arabia,2022
- [6] R. K”alvi”ainen and H. Uusitalo, “Diaretdb1 diabetic retinopathy database and evaluation protocol,” in Medical Image Understanding and Analysis, vol. 2007, p. 61, Citeseer, 2007.
- [7] A. R. Chowdhury, T. Chatterjee and S. Banerjee, “A random forest classifier-based approach in the detection of abnormalities in the retina,
- [8] "Automatic Detection of Microaneurysms and Hemorrhages in Digital Fundus Images" by Giri Babu Kande et al. (2009).
- [9] "Detection of Hemorrhages in Colored Fundus Images Using Non-Uniform Illumination Estimation" by M. Usman Akram et al. (2014).
- [10] "Automatic Detection of Microaneurysms and Hemorrhages in Color Eye Fundus Images" by Sergio Bortolin and Daniel Welfer (2013)
- [11] "Hemorrhage Detection Based on 3D CNN Deep Learning Framework and Feature Fusion for Evaluating Retinal Abnormality in Diabetic Patients" by authors in Sensor's journal (2021)
- [12] L. Tang, M. Niemeijer, J. Reinhardt, M. Garvin andM. Abramoff, “Splat feature classification with application retinal haemorrhage detection in fundus images,” IEEE Transactions on Medical Imaging, vol. 32, no. 2, pp. 364–375, 2012.
- [13] J. I. Orlando, E. Prokofyeva, M. Del Fresno and M. B. Blaschko, “An ensemble deep learning based approach for red lesion detection in fundus images,” Computer Methods and Programs in Biomedicine, vol. 153, pp. 115–127, 2018.
- [14] T. Aziz, A. E. Ilesanmi and C. Charoenlarnopparut, “Efficient and accurate hemorrhages detection in retinal fundus images using smart window features,” Applied Sciences, vol. 11, no. 14, pp. 6391, 2021.
- [15] S. Maqsood, R. Damaševičius and R. Maskeliūnas, “Hemorrhage detection based on 3D CNN deep learning framework and feature fusion for evaluating retinal abnormality in diabetic patients,” Sensors, vol. 21, no. 11, 2021
- [16] N. Asiri, M. Hussain, F. Al Adel and H. Aboalsamh, “A deep learning-based unified framework for red lesions detection on retinal fundus images,” arXiv preprint arXiv: 210\
- [17] Vasudevan Lakshminarayanan, Hoda Kheradfallah , Arya Sarkar and Janarthanam Jothi Balaji “Automated Detection and Diagnosis of Diabetic Retinopathy”, MDPI,2021.