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Examining Diabetic Retinopathy (DR) Through Deep Learning

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Abstract: *Diabetic retinopathy (DR) is a complex ailment affecting individuals with diabetes, leading to retinal damage and the potential onset of blindness. This condition disrupts retinal blood vessels, resulting in fluid leakage and severe distortion of vision. DR is a prevalent eye disease linked to chronic diabetes and stands as the primary cause of blindness among working-age adults globally, potentially impacting more than 93 million individuals. This study introduces an automated classification system designed to analyze fundus images under varying illumination and fields of view. Leveraging machine learning models such as Otsu, Random Forest, and Clehe algorithm, the system generates severity grades for diabetic retinopathy. The incorporation of machine learning models, particularly Random Forest, brings forth the advantage of high variance and low bias. This characteristic allows the classifier not only to diagnose diabetic retinopathy but potentially detect a broader spectrum of nondiabetic diseases. Visualizations of features learned by the Region-Based Convolutional Neural Network(RCNN) and Gray Level Matrix Co-occurrence (GLMC) demonstrate that the signals used for classification predominantly originate from clearly observable parts of the image. Notably, moderate and severe diabetic retinal images showcase macroscopic features aligned with the architecture's training and validation accuracy. This research introduces a promising avenue for automated diabetic retinopathy severity classification, offering potential advantages in early diagnosis and intervention for the eye health of diabetic patients.*

Keywords:- Diabetic Retinopathy, Classification, Image Processing, Deep Learning, Segmentation, Severity Grade.

Introduction

The realm of medical image analysis has undergone notable progress driven by the integration of machine learning techniques. Within this landscape, diabetic retinopathy (DR) emerges as a critical concern—a diabetes-related eye ailment causing damage to the retina's blood vessels, with the potential to lead to blindness if not promptly diagnosed and treated. As the leading cause of blindness among working-age adults globally, DR imposes a significant burden on global healthcare. Timely detection and classification of DR severity levels pose a key challenge in its effective management, emphasizing the need for early diagnosis and intervention.

This research focuses on the development of an automated system for classifying DR severity using deep neural networks, Random Forest, and the Clehe algorithm. The aim is to harness the power of machine learning for analyzing fund us images, accommodating variations in illumination and fields of view. The goal is to provide a precise and efficient tool that aids healthcare professionals in the swift and accurate diagnosis and management of DR.

The study delves into the capabilities of deep neural networks, Random Forest, and the Clehe algorithm in classifying DR severity levels, with an added emphasis on the interpretability of these models through visualization of learned features from fund us images. Insights gained from this research hold potential implications for advancing early DR detection and contributing to the broader field of medical image analysis.

Acknowledging that the impact of diabetic retinopathy extends beyond medical diagnosis to societal and economic realms, this research aspires to address these broader issues by proposing an automated system capable of revolutionizing DR management.

The primary objectives of the study are outlined as follows:

Automated DR Severity Classification: Develop a robust system for automated classification of diabetic retinopathy severity in fundus images, facilitating swift and accurate assessments by healthcare providers.

Machine Learning Models: Explore the capabilities of deep neural networks, Random Forest, and the Clehe algorithm as potential tools for DR severity classification, aiming to determine the most effective approach through comparative analysis.

Interpretability and Visualization: Investigate the interpretability of the models, employing visualization techniques to discern crucial features for classification. This provides insights into the decision-making process of the models.

As a complication arising from diabetes, DR entails damage to the blood vessels of the light-sensitive tissue at the back of the eye. This study addresses the imperative tasks of detecting exudates, scars, and abnormal blood vessels, contributing to automated DR analysis for timely intervention and resource optimization in diagnosis.

Interpretability and Visualization: In addition to achieving high classification accuracy, we investigate the interpretability of these models. Visualization techniques will help us understand which features are crucial for classification, providing insights into how the models arrive at their decisions.

DR is a complication caused by diabetes due to damage of the blood vessels of the light-sensitive tissue at the back of the eye [6]. Toomuc sugar in the blood leads to blockage of the tiny blood vessels, cutting off its blood supply and the eye attempts to grow new blood vessels. Early DR is called non-proliferative diabetic retinopathy where new blood vessels are not growing yet, but the walls in the blood vessels weakens resulting in tiny bulges protruding from vessel walls and sometimes exudates due to leakages of fluid and blood into the retina. Larger vessels begin to dilate and results in irregular diameter. As the condition progresses, the blood vessel gets blocked and retina swells. This results in growth of abnormal new blood vessels in the retina. These new vessels can result in leakage and scar tissue formation in the eye, which can finally lead to retinal detachment and glaucoma. Figure 1 shows an image with various types of diabetic retinopathy conditions. Hence, detection of such exudates, scars and abnormal blood vessels are important diagnostic tasks in DR.

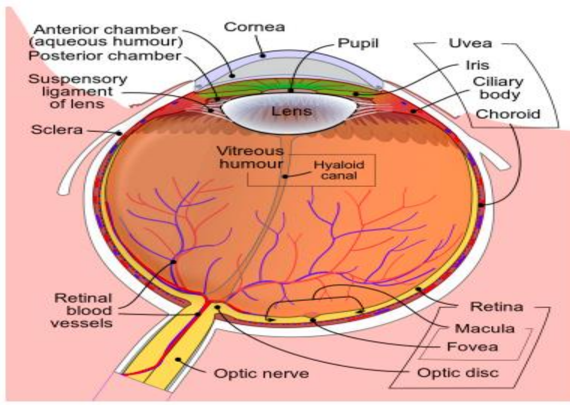


Figure 1: Diabetic retinopathy conditions.

II. Proposed Methodology

The application of Convolutional Neural Networks (CNNs) in medical image analysis has proven to be effective, and R-CNN, a region-based variant, brings specific advantages to tasks like diabetic retinopathy detection. R-CNN is particularly adept at handling object localization within images, making it well-suited for identifying and classifying anomalies in retinal images associated with diabetic retinopathy (DR).

1. Region-based Approach:

R-CNN operates in a region-based manner, enabling the network to focus on specific regions of interest within the retinal images. This is crucial in DR detection as abnormalities are often localized in specific areas of the retina.

2. Object Localization:

R-CNN excels in localizing objects within images by proposing candidate regions and then classifying those regions. In the context of diabetic retinopathy, this capability is vital for pinpointing specific signs such as micro aneurysms, hemorrhages, or exudates.

3. Multi-Stage Architecture:

R-CNN follows a multi-stage architecture comprising region proposal, feature extraction, and classification. This structure is advantageous for DR detection as it allows the model to hierarchically process information, capturing both global and local features relevant to diabetic retinopathy.

4. Handling Varied Lesion Sizes:

Diabetic retinopathy exhibits a range of lesion sizes, from micro aneurysms to larger hemorrhages. R-CNN's region-based strategy is effective in handling these variations, ensuring that lesions of different sizes can be accurately detected and classified.

5. Integration with Pre-trained Models:

Leveraging pre-trained CNN models as the backbone for R-CNN facilitates feature extraction. This is particularly beneficial for medical image analysis tasks where datasets might be limited, as pre-trained models bring generalization capabilities.

6. Mitigating Data Imbalance:

Diabetic retinopathy datasets often suffer from class imbalance, with normal images vastly outnumbering images with pathology. R-CNN's region-based approach helps in mitigating this imbalance by focusing on regions likely to contain abnormalities, improving sensitivity.

7. Interpretability through Region Proposals:

R-CNN provides interpretability by generating region proposals, indicating where the network identifies potential abnormalities. This assists clinicians in understanding the model's decision-making process.

8. Potential for Fine-tuning:

R-CNN allows for fine-tuning on specific datasets, enabling adaptation to the characteristics of diabetic retinopathy images and improving model performance.

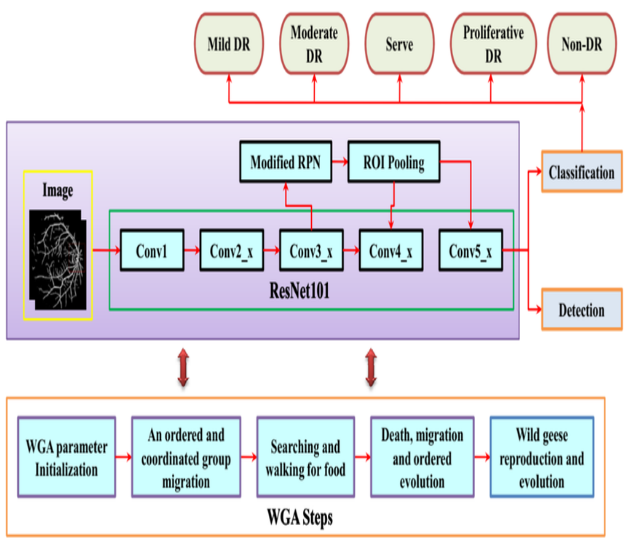


Figure 2: Proposed Model.

Pre-processing:

Patient movement, poor focus, bad positioning, reflections, inadequate illumination can cause a significant proportion of images to be of such poor quality as to interfere with analysis. In approximately 10% of the retinal images, artifacts are significant enough to impede human grading. Preprocessing of such images can ensure adequate level of success in the automated abnormality detection. In the retinal images there can be variations caused by the factors including differences in cameras, illumination, acquisition angle and retinal pigmentation. First step in the preprocessing is to attenuate such image variations by normalizing the color of the original retinal image against a reference image. Few of the retinal images acquired using standard clinical protocols often exhibit low contrast. Also, retinal images typically have a higher contrast in the center of the image with reduced contrast moving outward from the center. For such images, a local contrast enhancement method is applied as a second preprocessing step.

Segmentation:

Involves the partitioning of an image or volume into Involves the partitioning of an image or volume into distinct (usually) non-overlapping regions in a meaningful way.

Segmentation-

- Identifies separate objects within an image Identifies separate objects within an image.
- Finds regions of connected pixels with similar properties.
- Finds boundaries between regions.
- Removes unwanted regions.

Feature Extraction:

Feature extraction a type of dimensionality reduction that efficiently represents interesting parts of an image as a compact feature vector. This approach is useful when

image sizes are large and a reduced feature representation is required to quickly complete tasks such as image matching, classification and retrieval.

Classification:

Image classification analyzes the numerical properties of various image features and organizes data into categories. Classification algorithms typically employ two phases of processing: *training* and *testing*. In the initial training phase, characteristic properties of typical image features are isolated and, based on these, a unique description of each classification category, *i.e. training class*, is created. In the subsequent testing phase, these feature-space partitions are used to classify image features.

RGB to Green Channel:

The color image is converted to a gray scale image and then the green channel is extracted from it. Green channel is better than the red or blue channels because the red channel image is too bright and the blue channel image is too dark. All the anomalies are visible properly in the green channel image. A comparison of the images of the three channels is shown in Figure 5

Figure 3: Red, Blue and Green channel images.

Mask Generation:

The mask serves as a binary image with the same resolution as the fundus image, where positive pixels correspond to the foreground area. Its primary purpose is to effectively separate the fundus from its background, ensuring that subsequent processing focuses exclusively on the fundus without interference from background pixels. In the funds mask, pixels belonging to the fundus are designated with ones, while those corresponding to the background are marked with zeros.

To achieve this separation, the original fund us image undergoes a conversion from the RGB to HSI color system. Within the HSI color space, a specific channel is dedicated to representing the intensity values of the image. Subsequently, the intensity channel image is subjected to thresholding using a low threshold value, given that background pixels tend to be significantly darker than fund us pixels. This thresholding operation facilitates the initial creation of the fund us mask.

To refine the mask and enhance its robustness, a median filter is applied to eliminate any noise present in the created fund us mask. Additionally, morphological erosion is employed to remove edge pixels, further refining the mask. The resultant mask effectively delineates the fundus from its background, providing a clear and accurate representation for subsequent image processing steps.

The final mask, illustrating the successful separation of the fundus from the background, is presented in Figure 7. This process ensures the integrity of subsequent analyses by focusing exclusively on the fundus region, contributing to the overall effectiveness of the image processing pipeline.

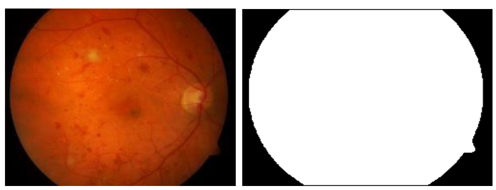


Figure 4: Input image and the generated mask Vessel Detection and removal.

Blood vessel segmentation plays a crucial role in the detection of red lesions, particularly micro aneurysms and hemorrhages, within funds images. Given that both blood vessels and red lesions share a similar color tone, extracting the blood vessels is a necessary preprocessing step to effectively identify micro aneurysms and hemorrhages.

To achieve this, a Contrast Limited Adaptive Histogram Equalization (CLAHE) is performed on the negative of the green channel image. This enhances the contrast of the image, making it conducive for subsequent processing. The next step involves the application of a Top-hat filter operation, utilizing a flat disc-shaped structuring element. Top-hat filtering is akin to subtracting the result of a morphological opening operation from the input image, effectively isolating the blood vessels.

A suitable threshold is then applied to segment out the blood vessels. The determination of this threshold is based on a priori knowledge of the image quality. The resultant image includes not only blood vessels but also hemorrhages, micro aneurysms, and other stray structures. To refine the segmentation and eliminate undesired structures, any components with an area less than a predetermined threshold are removed. This process yields a final image containing only the segmented blood vessels.

Boundary detection and removal:

The boundary of the funds image gets separated in the process of segmentation and has to be removed as it causes false detections. By using the generated mask the boundary is removed.

Proposed algorithm

Input: Fund us image

Output: Grade of severity (0, 1, 2, 3)

Step 1: Input fundus image is retrieved from the test set Step 2: Green channel of the image is extracted

Step 3: The image is then passed through median filter Step 4: CLAHE is applied to the output of previous step

Step 5: The image is then resized to a standard size of 576*720

Step 6: Morphological operations are applied to extract micro aneurysms and Haemorrhages

Step 7: Area and count of these anomalies are extracted as features. Statistical and GLCM features are also extracted

Step 8: The feature set extracted is then provided to the Random forest classifier for classification of severity levels.

Otsu thresholding algorithm

Otsu thresholding divides image into Foreground and Background Pixels, thus assigning Pixels nearer to the black level as 0 and white level as 1, converting image to binary. The thresholding identifies minimum variance between these pixels to aptly identify them.

Otsu's thresholding method involves iterating through all the possible threshold values and calculating a measure of spread for the pixel levels each side of the threshold,

i.e. the pixels that either fall in foreground or background. The aim is to find the threshold value where the sum of foreground and background spreads is at its minimum.

Otsu thresholding algorithm has the following steps:

Input: Pre-processed image

Output: Binary image

Step 1: Read a gray scale image. Step 2: Calculate image histogram.

Step 3: Select a threshold and referred as t,

3.1 Calculate foreground variance.

3.2 Calculate background variance. Step 4: Calculate Within-Class variance.

Step 5: Repeat steps 3 and 4 for all possible threshold value.

Step 6: Final global threshold, T = threshold in MIN (Within-class variance) Step 7: Binarize Image = gray scale image > T

III. Result

A structuring element (SE) is a fundamental concept in binary morphology, which is used to analyze and manipulate images. It is essentially a binary matrix characterized by the presence of 0's and 1's, and it can take on various shapes and sizes. The pixels within the structuring element with a value of 1 define the neighborhood that is considered during image processing operations.

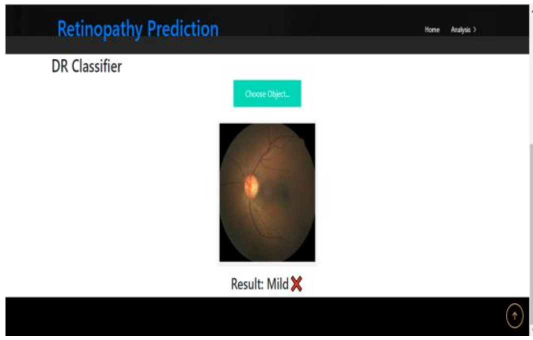


Figure 5: Mild Diabetic Detection.

Figure 5 is show mild diabetic detection. The term "Mild Diabetic Detection" likely refers to the identification or diagnosis of mild cases of diabetes mellitus. Detecting mild diabetes involves recognizing early signs or indicators of the condition, which can be crucial for timely intervention and management.

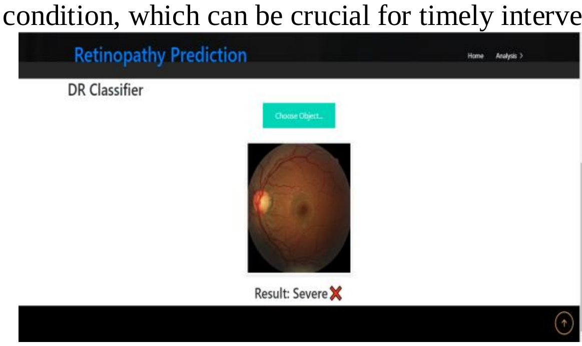


Figure 6: Severe Diabetic Detection.

Figure 6 is show Detecting severe diabetes involves identifying cases where the condition has progressed to an advanced stage, posing significant health risks. Severe diabetes, often characterized by poorly controlled blood sugar levels, requires prompt diagnosis and intervention.

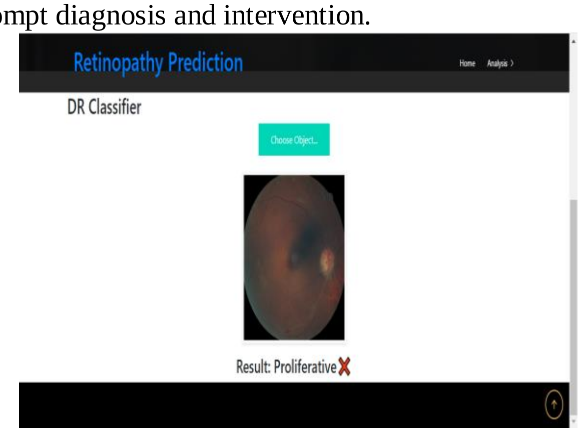


Figure 7: Proliferative Diabetic Detection.

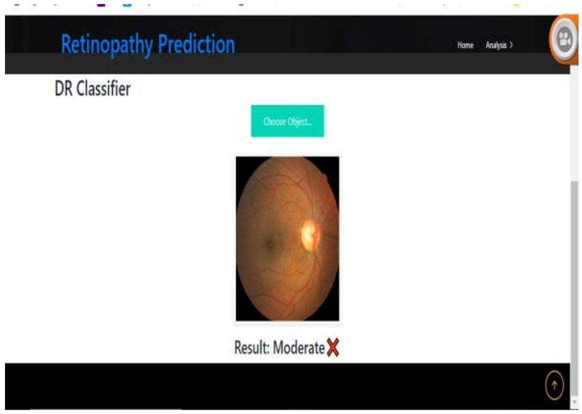
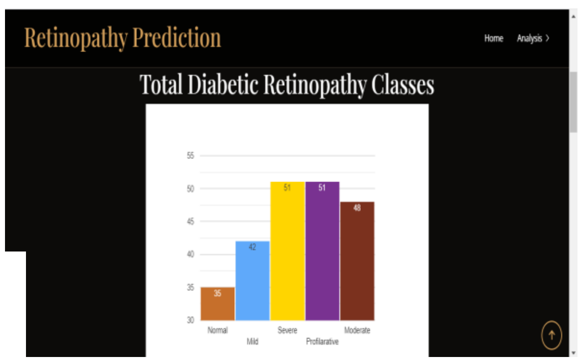


Figure 8: Moderate Diabetic Detection.

Result analysis chart



Detection

Figure 9: Different diabetic condition.

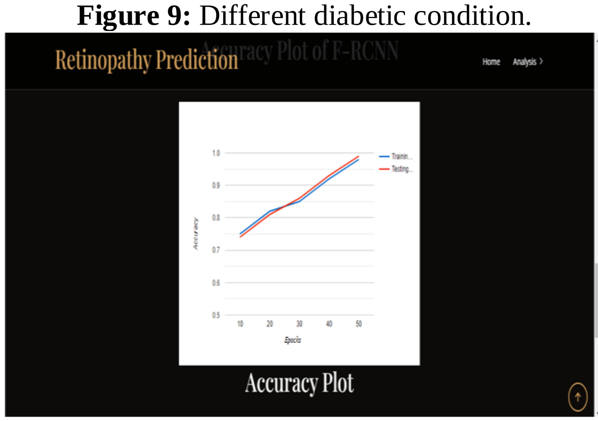
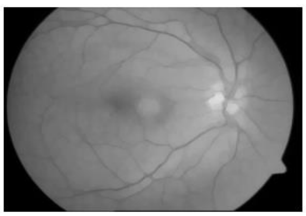


Figure 10: Accuracy.

In the realm of image processing, the combination of dilation and erosion operations often gives rise to more intricate procedures. Specifically, when erosion precedes dilation, this composite operation is termed an "open" operation, denoted as $A \circ B$, where A represents the input image, and B is the structuring element. The primary purpose of the "open" operation is to refine the contours of objects, sever narrow connections (isthmuses), and eliminate slender protrusions within the image. Mathematically, opening is articulated as $A \circ B = (A \ominus B) \oplus B$, signifying the sequential application of erosion followed by dilation. Alternatively, it can be represented as $A \circ B = \cup \{B : Bw \subseteq A\}$, denoting that the outcome encompasses all points Bw wholly contained within A after erosion.

Conversely, when dilation precedes erosion, it is termed a "close" operation, symbolized as $A \cdot B$. This operation serves to smooth specific contours, bridge narrow gaps or breaks, fill minute holes in contours, and eliminate interruptions within contours. The mathematical representation of closing is $A \cdot B = (A \oplus B) \ominus B$. Figure 5.3a visually illustrates the distinction between an opening operation and a closing operation when applied to fondues images.



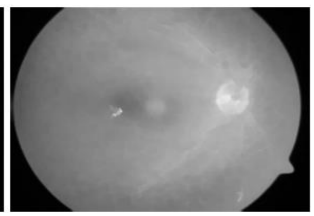


Figure 11a: Opening operation with Figure 11b: Closing operation with

Edge detection is a crucial process in image analysis that involves identifying and locating abrupt changes in image intensity, commonly associated with object boundaries. These edges play a pivotal role in various image-related tasks such as object size measurement, object-background isolation, and object recognition or classification. The Canny edge detection method has emerged as a highly effective approach for edge detection due to its robustness.

The Canny method operates by searching for local maxima in the image gradient, computed using the derivative of a Gaussian filter. Notably, this method employs two thresholds: one for detecting strong edges and another for identifying weak edges. Only weak edges connected to strong edges are included in the final output, making the Canny method resilient to noise and proficient in detecting genuine weak edges. Figure 11a and 11b visually demonstrate the efficacy of the Canny edge detection method, showcasing its ability to discern subtle features such as delicate blood vessels within the image. This highlights the suitability of the Canny method for edge detection in contexts where precision and sensitivity are paramount.

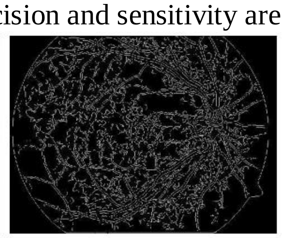


Figure 12 a: Original image. **Figure 12** b: Canny edge detected image.

Median Filtering

Median filtering is a non-linear image processing technique widely utilized to mitigate the impact of "salt and pepper" noise. Unlike convolution-based methods, median filtering demonstrates effectiveness in noise reduction while preserving edges. The core concept of median filtering lies in determining the middle value within a set of ordered values. In cases where there is an even number of values, the median is calculated as the mean of the two middle values. Figure 12a visually depicts the application of a 3 x 3 median filter to a set of sorted values, showcasing the process of determining the median value. This approach proves particularly valuable in scenarios where noise reduction is essential, ensuring a balance between noise removal and edge preservation.

IV. Conclusions

This research has delved into the critical realm of diabetic retinopathy (DR) detection, employing a sophisticated Region-based Convolutional Neural Network (R-CNN) approach. The significance of early diagnosis and intervention in diabetic retinopathy, a leading cause of blindness among working-age adults worldwide, has underscored the importance of developing advanced and efficient detection methods.

The use of R-CNN has proven instrumental in addressing the nuances of DR detection, particularly its region-based strategy that facilitates precise localization and classification of abnormalities within retinal images. The multi-stage architecture of R-CNN allows for a hierarchical understanding of global and local features, enhancing the model's ability to discern various manifestations of diabetic retinopathy.

Our findings indicate that R-CNN not only handles varied lesion sizes effectively but also mitigates issues associated with imbalanced datasets, commonly encountered in diabetic retinopathy research. By proposing region-specific candidates for classification, R-CNN optimally navigates the challenges posed by the diverse manifestations of DR, including microaneurysms, hemorrhages, and exudates.

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