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# IMPLEMENTATION OF PREPROCESSING IN DIABETIC RETINOPATHY DETECTION

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## ABSTRACT
*Diabetic retinopathy, a significant complication of diabetes mellitus, stands as one of the leading causes of blindness on a global scale. The early identification and precise diagnosis of diabetic retinopathy are of utmost importance in preventing vision loss and facilitating timely treatment. The preprocessing of retinal images plays a pivotal role in the development of robust and efficient computer-aided diagnostic systems designed for the detection of diabetic retinopathy. This research is centered around the exploration of diverse preprocessing techniques applied to retinal images to enhance the quality of the input data, ultimately facilitating the identification of diabetic retinopathy features. These features include the Region of Interest (ROI), encompassing vital components such as blood vessels, the macular region, and the optic nerve, which are segmented from retinal fundus images.The research methodology commences with the collection of fundus images. These images are then uniformly resized and normalized to ensure numerical stability during the subsequent model training. We apply contrast enhancement techniques to accentuate relevant features, rendering them more distinguishable for subsequent analysis. Additionally, to eliminate image artifacts and improve feature extraction, we employ noise reduction techniques such as Gaussian blurring and median filtering. In order to focus our analysis on the critical retinal regions, we perform cropping or region of interest (ROI) selection. Moreover, to address variations in image brightness, a common issue in retinal imaging datasets, we implement illumination normalization techniques. To enhance the overall generalization of machine learning models, we apply data augmentation methods to expand the diversity of the training dataset. Furthermore, we utilize features related to Diabetic Eye Disease for classification within pre-trained models.*

*Keywords: Gray mapping,Deep Learning Neural Network,Segmentation.*

## INTRODUCTION
In today's progressive world, diabetes has arisen as a pervasive infection influencing a significant portion of the global population. Among the various medical conditions associated with diabetes, diabetic retinopathy stands out as it primarily involves damage to the retina, leading to vision loss. Modern advancements in machine learning techniques, such as neural networks and computer-aided programs, have facilitated the detection of diabetic eye conditions. hese frameworks utilize profound gaining calculations to separate elements from fundus pictures and precisely evaluate the presence of diabetic eye conditions.This mechanism enables efficient and precise detection of fundus image conditionsDiabetic retinopathy (DR) is a dynamic eye infection that transcendently influences working-age grown-ups.It can bring about irreversible states prompting visual impairment and is ordinarily analyzed through extensive eye assessments. One such demonstrative technique is Fluorescein Angiography, where a color is infused into the circulatory system to feature the veins at the rear of the eye, empowering their catch. Additionally, Optical Coherence Tomography (OCT) tests may be conducted to produce cross-sectional images of the retina, measuring its thickness. Early detection is crucial in treating the disease and preventing its progression to advanced irreversible stages. Competent medical professionals and well-equipped clinical facilities are necessary to identify the five major stages of DR. Convolutional Brain Organizations (CNNs) are a kind of brain network essentially utilized in picture order and component extraction. They comprise of a multi-facet perceptron, where every neuron in the past layer interfaces with each neuron in the ensuing layer. CNNs use pooling, a method that joins groups, to upgrade their exhibition. These organizations influence profound learning calculations to relegate importance (learnable loads and inclinations) to various perspectives or articles inside an information picture, empowering separation between them. CNNs require somewhat less pre-handling contrasted with other order calculations. While customary techniques depend on physically designed channels, ConvNets

have the ability to acquire capability with these channels and characteristics through planning. The plan of a ConvNet eagerly seems to be the organization illustration of neurons in the human frontal cortex and draws inspiration from the relationship of the Visual Cortex. Individual neurons inside a ConvNet answer helps inside a limited locale known as the Open Field. A combination of such fields covers to cover the entire visual locale. Subsequently, ConvNets are particularly strong in eliminating features for bare essential assessment of fundus pictures."

## LITERATURE REVIEW

L. Qiao, Y. Zhu and H. Zhou discussed a diabetic retinopathy (DR), one of the major cause of blindness resulting from elevated blood sugar levels damaging the retina. The timely detection and classification of DR can help stop vision loss in individuals with diabetes. The study introduced a novel and integrated approach to detect and classify DR [1]. By combining various models, the detection process was made more dependable and precise. The classification was done using a majority voting method. The approach consisted of three main steps: preprocessing, feature extraction, and classification. Preprocessing aids in identifying abnormalities and segmenting the images, thereby improving the overall effectiveness of the process. In this preprocessing technique authors aim was to enhance the given fundus image by using a series of techniques. First,application of adaptive histogram equalization and contrast stretching to improve the image quality was carried out. Then the use of a median filtering process to further refine the image was implemented. This preprocessing step was done in three color spaces: chroma blue (CB), luminance , and chroma red (CR). Next the contrast stretching and intensity normalization was implemented to improve the image's overall brightness and contrast. Finally, the image was converted back to RGB from YCbCr using an inverse transformation process.Future investigations might incorporate embedding the calculation with profound learning procedures to contrast the outcomes and this work proposed by the L. Qiao, Y. Zhu and H. Zhou.

Diabetic retinopathy (DR) is an illness that creates as an inconvenience of diabetes and can be exceptionally perilous on the grounds that it frequently slips through the cracks, prompting visual impairment in the event that not got early. In any case, there is definitely not an exact framework for early DR discovery yet. M. Ghazal, S. S. Ali recommended a PC supported demonstrative (computer aided design) framework which utilized profound learning with convolutional brain organizations (CNNs) for the early recognition of non-proliferative DR (NPDR) [2] . The proposed framework was intended for the optical cognizance tomography (OCT) imaging technique. The M. Ghazal, S. S. Ali covered everything from preprocessing the pictures to extricating input retina patches for preparing the CNN without resizing the picture to actually utilizing move figuring out how to enhance execution by joining highlights. The preprocessing steps help to adapt to the distinction in size between the first OCT examines (input picture information) and the information layer of pre-prepared CNNs, which are utilized for highlight extraction.

With diabetes turning out to be more normal and its related confusions on the ascent, there is a developing requirement for early discovery of side effects in everybody. One of the earliest indications of diabetic retinopathy is the existence of microaneurysms (MAs) in fundus pictures. I. Usman and K. A. Almejalli presented another programmed strategy for recognizing MAs in variety fundus pictures. To develop a numerical articulation, the proposed strategy utilized Hereditary Programming (GP) [3] and an assortment of 28 chose highlights from preprocessed fundus pictures. The cycle included further developing the articulation age by age through the binarization of wellness scores.

Diabetic retinopathy (DR) is a main source of visual impairment that happens when the retina is harmed because of high sugar levels in the blood. Early location, order, and analysis of DR are pivotal to forestall vision misfortune in diabetic patients. DR. A. Bilal, G. Sun, Y. Li, S. Mazhar presented a new and joined approach for distinguishing and grouping. Various models to make the recognition cycle more dependable and less inclined to mistakes. For order a larger part casting a ballot technique was utilized. The methodology included three principal steps: preprocessing to improve irregularities and division, highlight extraction to get important elements, and arrangement utilizing classifiers like help vector machine (SVM), K-closest neighbor (KNN), and twofold trees (BT).

**IMPLEMENTATION OF PREPROCESSING**

One of the more sophisticated types of analysis used to find unknown matrices and image segments for illness identification is image preprocessing. The adequacy of element extraction and the results of picture investigation may both be emphatically improved by picture pre-handling. The numerical normalizing of an information assortment, a commonplace move toward many element descriptor draws near, is likened to picture pre-handling. Picture pre-taking care of can in like manner compare a sound structure with various controls, for instance, rough sound with no volume controls, volume control with just a tone handle, volume control notwithstanding high pitch, bass, and mid, or volume control notwithstanding a full delineations balancer, influences dealing with, and unprecedented speakers in a room with unmatched acoustics. By representing a mix of reviews and redesigns that are a basic piece of a PC vision pipeline, this part stimulates picture pre-dealing with in that way. This examination essentially centers around the fundus picture preprocessing that is finished in this diabetic retinopathy identification. Fundus picture handling is the absolute initial phase in the discovery cycle, subsequently it should be exact and clear to come by the ideal outcomes. Preprocessed fundus pictures are obtained using the Messidor-dataset. After being fed with the dataset, preprocessing was done. It involves two main steps: choosing the right data and enhancing the image. The two main components of preprocessing are the CLAHE method and morphological transformation of the images.

**Data Selection:**

Prior to feature measurement and analysis, there may be artifacts in the images from image pre-processing that need to be fixed. Here are several correctional candidates.

- Corrections for the sensor: these include vignetting, geometric lens distortion, and dead pixel correction.
- Revisions to the lighting. Deep shadows cast by lighting can hide local texture and structure, and outcomes may be affected by scenes with uneven illumination. The histogram equalisation, LUT remap, and rank filtering are examples of potential corrective techniques.
- Noise. This can take many different shapes and may require unique image pre-processing. Numerous options are available, some of which are analyzed in this discussion.
- Mathematical changes. It could be useful to change the math prior to portraying highlights assuming that the whole scene is turned or shot from the erroneous point. Various elements are pretty much impervious to mathematical change.
- Variety changes. Rearranging variety immersion or adapting to light ancient rarities in the force channel can be helpful. Variety tint is commonly one of the additional moving qualities to change, and it probably won't have the option to utilize direct gamma bends and the sRGB variety space. Later in this paper, conversations on approaches for colorimetry that are more exact.

Following is the Messodor-dataset with 1748 Images fundus images.


**Figure 1:** Messidor-dataset containing patient Fundus images

Instead of solving issues, enhancements are employed to optimize for particular feature measurement techniques. Sharpening and color balance are common enhancements produced by image processing. These image enhancements and their possible advantages for feature description are listed below.

- **Scale-Space Pyramids:** Sub-examining curios and spiked pixel changes are presented at the point when a pyramid is built utilizing an octave scale and pixel destruction to sub-test pictures. The unpleasant relics are shed by applying a Gaussian cloudiness channel to the sub-examined pictures as a component of the scale-space pyramid building process.
- **Lighting:** As a rule, lighting can constantly be gotten to the next level. Straightforward pixel point , LUT remapping activities, histograming balances, and pixewisel re-mapping can be in every way used to work on worldwide light. Angle channels, neighborhood histogram evening out, and rank channels can all work on nearby brightening.
- **Upgrades for Obscure and Center:** During the pre-handling step, an assortment of notable sifting strategies for honing and obscuring might be utilized. For example, hone channels can be utilized to further develop the edge highlights before slope calculations to address for pixel associating blunders created by turn that might appear as obscured pixels that conceal fine detail. On the other hand, the rotational relics can be excessively conspicuous and could disposed of by obscure.

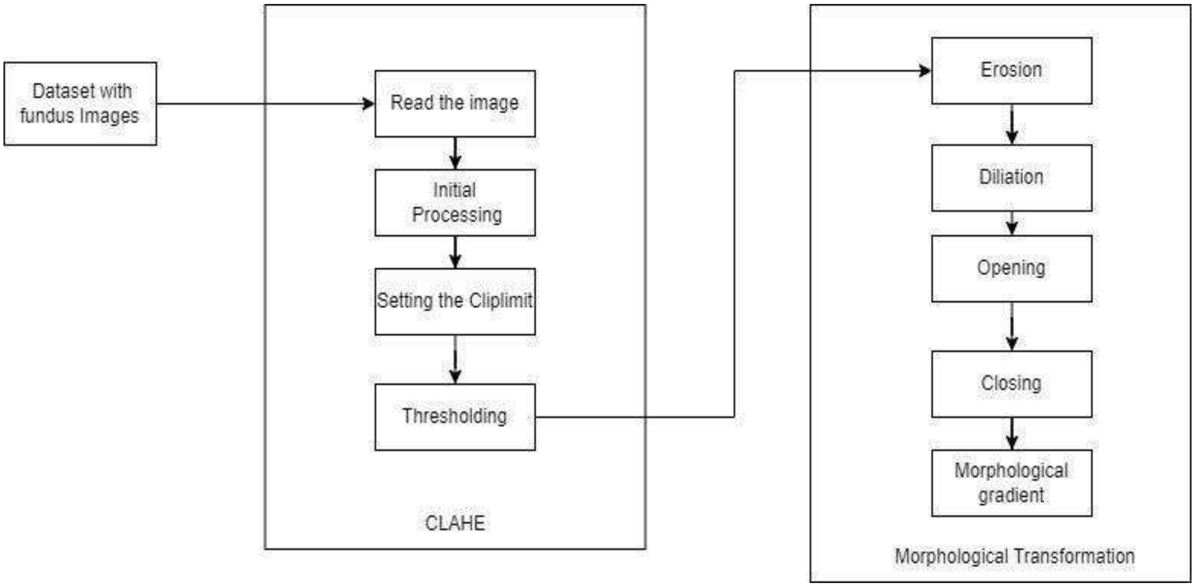


**Figure 2:** Preprocessing

## CLAHE

CLAHE, which represents Differentiation Restricted Versatile Histogram Evening out, is a strategy that depends on the idea of Versatile Histogram Leveling (AHE). AHE is a picture handling technique used to improve the differentiation of pictures by rearranging the pixel power values in a versatile way founded on neighborhood picture measurements. CLAHE builds upon AHE by adding a contrast limiting mechanism. In AHE, the contrast enhancement can be significant, and this may lead to noise amplification and other artifacts in the image. To address this issue, CLAHE introduces a constraint that limits the contrast enhancement locally. By doing so, CLAHE ensures that the contrast improvement is more controlled and prevents over-amplification of noise, which can occur in AHE.The CLAHE algorithm involves dividing the image into small, overlapping blocks or tiles. For each tile, a neighborhood histogram is figured, addressing the dissemination of pixel powers inside that tile. The histogram is then leveled to upgrade the differentiation inside that area. In any case, to stay away from extreme difference improvement, a differentiation limit is set, guaranteeing that the pixel power values are not spread too broadly.The resulting contrast-enhanced tiles are then stitched back together to create the final image, and interpolation is used to smooth the transitions between the tiles. CLAHE is widely used in image processing applications where improving contrast while maintaining visual quality is essential.Overall, CLAHE is an effective adaptation of AHE, providing better control over contrast enhancement and mitigating potential issues with noise amplification, making it a valuable tool in various image processing tasks.

### Parameters

Here's a simplified explanation of the formulas used in CLAHE:

### Image Division into Tiles:

The picture is partitioned into little, covering tiles or blocks.

### Histogram Calculation:

For each tile, a histogram of pixel powers is figured. The histogram addresses the appropriation of pixel values inside that tile.

### Contrast Enhancement:

The cumulative distribution function (CDF) of the histogram is computed, and contrast enhancement is applied to redistribute pixel intensities to make the histogram more uniform.

**Contrast Limiting:**
In CLAHE, a contrast limit is set to prevent excessive amplification of pixel values. If the number of pixel values exceeds this limit in the CDF, they are redistributed to ensure that the contrast remains limited.

**Interpolation:**
To blend the enhanced tiles together, interpolation is performed to avoid visible tile boundaries and create a smooth transition in the final image.

The main limitation of traditional Histogram Equalization is that it can amplify noise and result in unnatural-looking images, particularly in regions with limited data. To address this issue, CLAHE was introduced. Here's how CLAHE works:

Divide the image into smaller, non-overlapping blocks or tiles.

Apply traditional Histogram Equalization to each of these blocks independently. This enhances the contrast within each block, but may still lead to amplified noise.

To forestall commotion enhancement, a difference restricting instrument is utilized. It cuts the histogram of each block, restricting the quantity of pixels with a similar force esteem. This guarantees that the improvement is controlled and doesn't unreasonably intensify clamor.

After histogram equalization and contrast limiting for each block, the results are combined to create the final enhanced image.

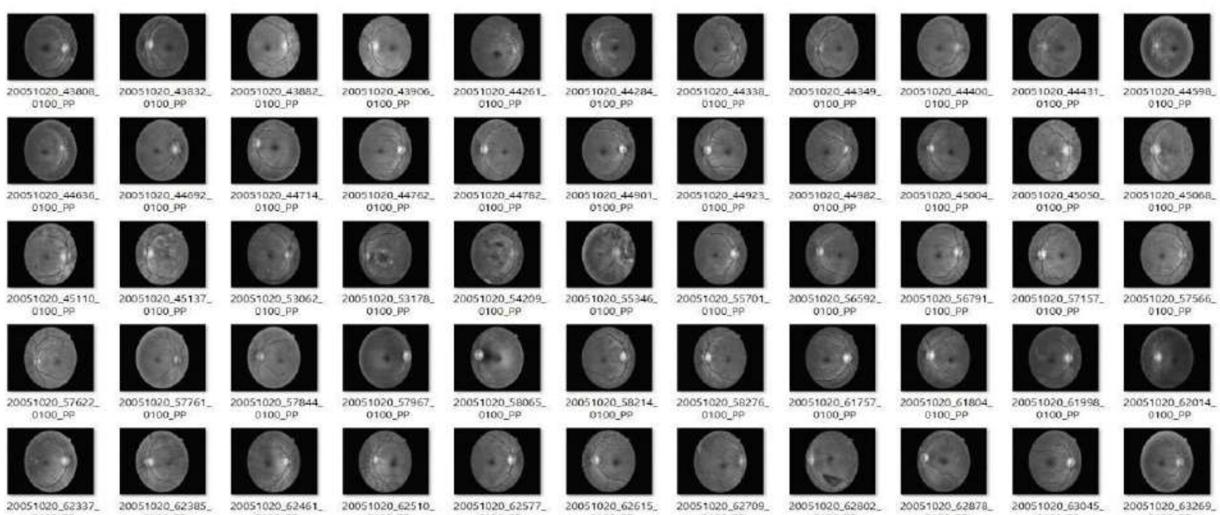

**Figure 3:** CLAHE implementation on the original dataset.

**Morphological Transformations:**
Morphological transformations are valuable preprocessing techniques used in diabetic retinopathy detection. Diabetic retinopathy is a serious eye condition caused by diabetes, and early detection is crucial for effective treatment. Morphological transformations involve operations on image shapes and structures. Dilation and erosion are two common morphological procedures. Dilation expands the boundaries of the detected structures, while erosion shrinks them.In diabetic retinopathy detection, morphological transformations can be applied to enhance and refine blood vessel structures in retinal images. By using dilation, blood vessels can be made more prominent and connected, aiding in the accurate extraction of vascular features. On the other hand, erosion can help remove small unwanted structures or noise, leading to a cleaner image representation.Additionally, other morphological operations like opening and closing can be used to further improve the quality of the retinal image. Opening is a combination of erosion followed by dilation and can help remove noise while preserving the larger structures.

Closing, which is dilation followed by erosion, can fill small gaps in blood vessels and make the structures more complete.By effectively using morphological transformations as a preprocessing step in diabetic retinopathy detection, the subsequent analysis and classification algorithms can be more accurate and reliable, leading to better diagnosis and treatment planning for patients with diabetic retinopathy.Morphology is used to identify polygon-shaped features in images, which are then segmented for autonomous processing and analysis. Different metrics, such as global, regional, and local interest points, can be combined as object signatures. However, segmentation and morphology are challenging tasks due to the uniqueness of each image and the availability of many methods. Versatile techniques utilize variable portions and limits in view of nearby pixel force measurements, permitting morphology to change in accordance with the encompassing region and yield improved brings about certain cases. Dark scale morphology can orchestrate and consolidate pixels into uniform force groups, while variety morphology can influence different variety parts. The fundamental methods for dark scale or variety morphology are MIN, MAX, and MINMAX, which bunch pixel values into equivalent qualities to make a homogeneous zone.A form that interacts with an existing image is referred to as a structuring element. Based on how it fits or misses the image, it helps us make inferences. It is used in morphological processes like gradient, opening, closing, and erosion.

getStructuringElement (shape, ksize, anchor)

The following conditions must be met for the syntax mentioned above:

- **Shape:** The structural element's shape can be either MORPH RECT, MORPH ELLIPSE, or MORPH CROSS.
- **Ksize:** The anchor's size as a structural element
- **Anchor:** position of the anchor within the structuring element. The default value, [-1, -1], designates the position of the structuring element's centre.

**Erosion:**

The morphological interaction used to diminish the size of the closer view object called disintegration. Like soil disintegration, it eliminates the closer view article's limits. While doing this method, the bit slides through the picture and possibly perceives a pixel as having esteem 1 when each of the pixels in the organizing component do. If not, it will disintegrate. As such, the pixels near the limit will be disposed of, yielding a closer view object that is more modest inside the picture.

erode1 (src1, ds1t, kernel1, anchor, iterations1, borderTyp1e, borderValue1)

**Parameters:**

- src1: Input picture
- dst1: Yield picture
- kernel1: The organizing component utilized for disintegration.
- anchor1: Anchor position inside the organizing component. The default esteem is [-1, - 1} implying position as the focal point of the organizing component.
- iterations1: Number of times disintegration is applied.
- borderType1: Sort of line (BORDER_CONSTANT, BORDER_REPLICATE, and so forth.)
- borderValue1: Line esteem

  Erosion shrinks the boundaries of the foreground (white) regions in a binary image. It is performed by scanning a structuring element (kernel) over the image and setting each pixel's value to 0 if any of the corresponding neighborhood pixels (under the kernel) is 0.

Mathematically, the erosion of an input binary image A by a structuring element B is given by:

$A \ominus B = \{z \mid \forall b \in B, z = a + b, a \in A\}$

**Dilation:**

Expansion is something contrary to disintegration in that it extends the closer view object as opposed to making it more modest. The underlying part (bit) is slid through the picture during this activity. However, for this situation, a pixel has a worth of 1 on the off chance that something like one of its neighbors does. Subsequently, an extended picture is created as the item develops around the limit.

Dimation1 (src1, dst1, portio1n, anchor, cycles1, borderType1, borderValue1)

**Parameters:**

- src: Input picture
- dst: Yield picture
- Bit: Organizing component utilized for expansion.
- Anchor: Anchor position inside the organizing component. The default esteem is [-1, - 1} implying position as the focal point of the organizing component.
- Iterations: Number of times expansion is applied.
- borderType: Sort of line (BORDER_CONSTANT, BORDER_REPLICATE, and so forth.)
- borderValue: Line esteem

Dilation expands the boundaries of the foreground (white) regions in a binary image. It is performed by scanning a structuring element (kernel) over the image and setting each pixel's value to 1 if there is at least one 1 in the corresponding neighborhood of the kernel.

Numerically, the widening of an information paired picture A by an organizing component B is given by:

$A \oplus B = \{z \mid \exists b \in B, z = a + b, a \in A\}$

**Opening:**

Erosive dilatation is simply another name for opening. It helps to reduce noise.

**Closing:**

Opening is trailed by Widening, then, at that point, Disintegration in the end cycle. Covering over little breaks or small dark spots on things in the foreground can be utilized.

**Morphological Gradient**

The morphological gradient distinguishes between an image's degradation and dilatation.

**Segmentation**

Segmentation of exudate regions in retinal images involves the use of image processing techniques and/or machine learning algorithms to automatically identify and delineate the areas that contain exudates. Here's a more detailed explanation of the steps involved in this process:

**Data Preprocessing:**

The first step is to acquire retinal images, which are usually obtained using fundus cameras. Since retinal images can have variations in lighting, contrast, and artifacts, preprocessing steps like cropping, resizing, denoising, and contrast enhancement may be applied to improve the quality and consistency of the images.

**Candidate Region Detection:**
In this step, initial candidate regions that potentially contain exudates are identified.Common techniques include thresholding, edge detection, and morphological operations.Thresholding: A simple and widely used technique where pixels with intensity values above a certain threshold are considered as potential exudate candidates.Edge Detection: Methods like the Canny edge detector can help identify sharp intensity changes in the image, which could correspond to exudate boundaries.Morphological Operations: Techniques like dilation and erosion can be used to enhance candidate regions and fill gaps in the detected regions.

**False Positive Reduction:**
The candidate regions obtained in the previous step may include false positives, i.e., regions that are not exudates but were incorrectly detected as such. To reduce false positives, more sophisticated filtering techniques are employed.Feature Extraction consists of features, such as intensity statistics, texture descriptors, and shape attributes, can be computed for each candidate region. Machine Learning Classification Is a trained classifier (e.g., SVM, Random Forest, CNN) can be used to distinguish true exudates from false positives based on the extracted features.

**Post-processing:**
After classification, further refinement of the segmentation results is carried out to improve accuracy. Techniques like connected component analysis, region-growing may be applied to clean up the segmented regions and remove small artifacts.

Visualization and Analysis:

The final segmented exudate regions are visualized by overlaying them on the original retinal image.Quantitative metrics such as the area, number, and distribution of exudates can be computed for further analysis and disease assessment.

Following are fundus images obtained after morphological transformation and segmentation

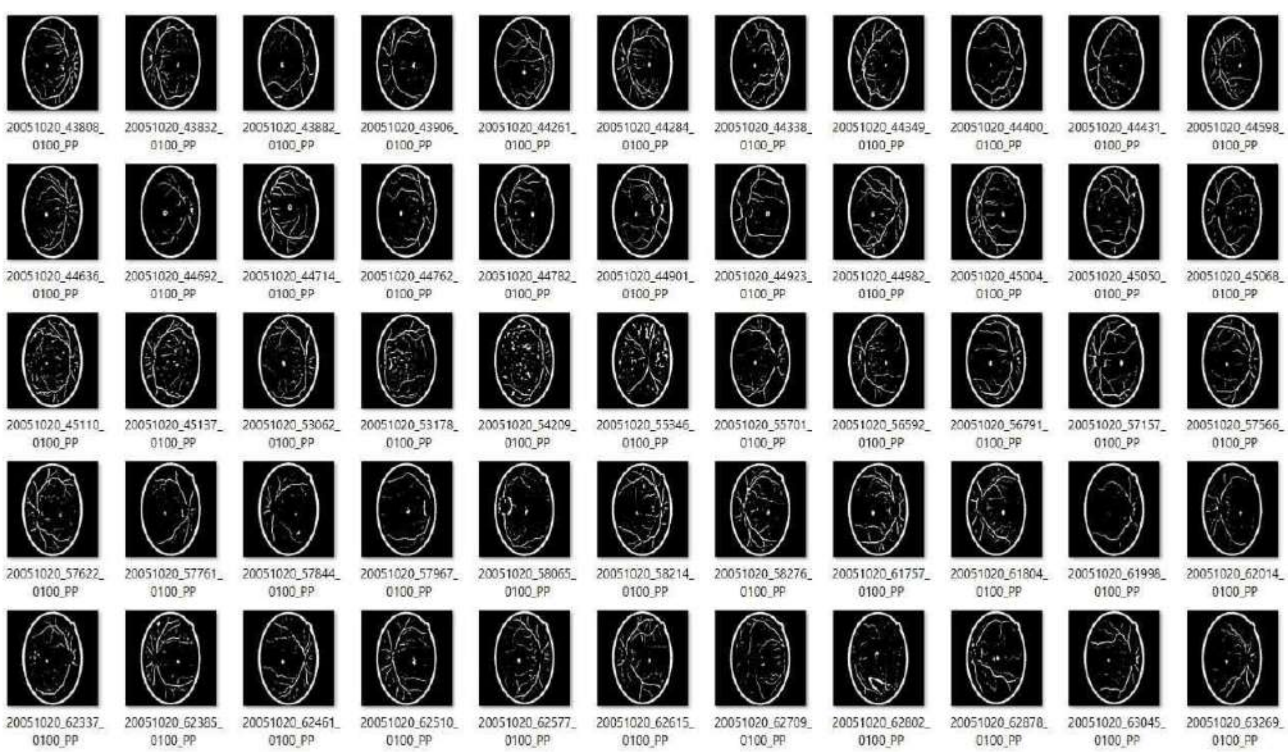


**Figure 4:** Images obtained after morphological transformation stage

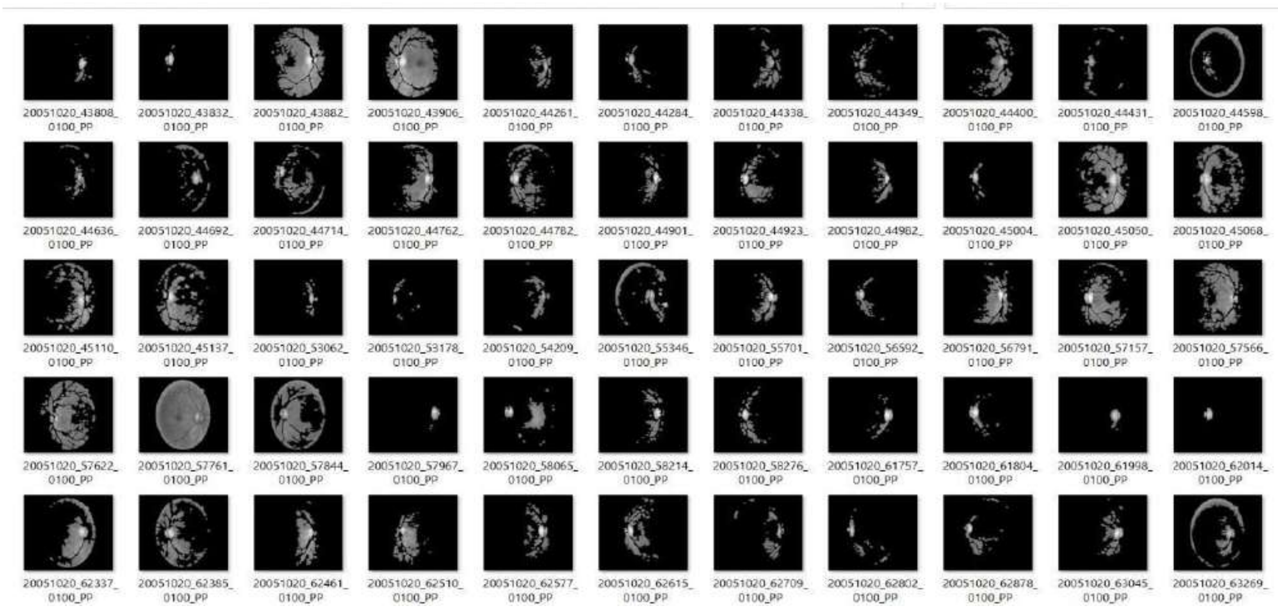


**Figure 4:** Images obtained after segmentation

## CONCLUSION

Preprocessing is an essential step that improves images and creates a solid foundation for obtaining accurate results. We completed the implementation of preprocessing, resulting in crisp and clear images with enhanced contrast, highlighting the important areas of the fundus images. This helps neural networks work efficiently and extract precise data for predictions. We also successfully applied morphological transformations, which are simple operations based on the image attributes of fundus images. These operations, like Erosion and Dilation, help process the images effectively. Additionally, we used the Clahe method for image enhancement, resulting in a clearer representation of the images.In conclusion, diabetic retinopathy is a significant global health concern and a leading cause of blindness, emphasizing the need for early detection and precise diagnosis. This research has focused on the crucial role of image preprocessing techniques in improving the quality of retinal images for the development of robust computer-aided diagnostic systems. These techniques include contrast enhancement, noise reduction, region of interest (ROI) selection, and illumination normalization. Additionally, data augmentation and the use of pre-trained models have been employed to enhance the generalization of machine learning models for diabetic retinopathy classification. The literature review highlights various studies and approaches to diabetic retinopathy detection, showcasing the importance of accurate preprocessing techniques. These studies explore the integration of deep learning, feature extraction, and classification methods to improve the reliability and precision of detection systems. The implementation of preprocessing techniques, specifically Contrast Limited Adaptive Histogram Equalization (CLAHE) and morphological transformations, has been discussed in detail. CLAHE offers better control over contrast enhancement while mitigating noise amplification, making it a valuable tool in image enhancement. Morphological transformations, including dilation and erosion, are essential for enhancing and refining blood vessel structures in retinal images, which is crucial for accurate feature extraction and classification. Segmentation of exudate regions in retinal images is a vital step in diabetic retinopathy detection. This process involves multiple stages, including data preprocessing, candidate region detection, false positive reduction, feature extraction, machine learning classification, and post-processing. These steps collectively contribute to the accurate identification and delineation of exudates in retinal images. In summary, the research presented in this content underscores the critical role of image preprocessing in diabetic retinopathy detection and provides insights into various approaches and techniques that can aid in the early diagnosis and prevention of vision loss associated with this condition.CLAHE calculation is effectively carried out for improving the quality of the microstructure pictures utilized for the review reason. It is obviously seen that the acquired upsides of the quantitative measurement highlights for example Entropy esteem and RMS Difference esteem were high in contrast with the other microstructures utilized in different variety space. In this way, it can be inferred that high entropy and RMS contrast worth of the improved CLAHE microstructures are of great in contrast with their parent microstructures.

**REFERENCES**

1. van der Geer, J., Hanraads, J. A. J., & Lupton, R. A. (2000). The art of writing a scientific article. *J. Sci. Commun.*, *163*, 51–59.
2. Qiao, L., Zhu, Y., & Zhou, H. (2020). Diabetic retinopathy detection using prognosis of microaneurysm and early diagnosis system for non-proliferative diabetic retinopathy based on deep learning algorithms. In *IEEE Access*, *8*, 104292–104302. https://doi.org/10.1109/ACCESS.2020.2993937
3. Ghazal, M., Ali, S. S., Mahmoud, A. H., Shalaby, A. M., & El-Baz, A. (2020). Accurate detection of non-proliferative diabetic retinopathy in optical coherence tomography images using convolutional neural networks. In *IEEE Access*, *8*, 34387–34397. https://doi.org/10.1109/ACCESS.2020.2974158
4. Usman, I., & Almejalli, K. A. (2020). Intelligent automated detection of microaneurysms in fundus images using feature-set tuning. In *IEEE Access*, *8*, 65187–65196. https://doi.org/10.1109/ACCESS.2020.2985543
5. Bilal, A., Sun, G., Li, Y., Mazhar, S., & Khan, A. Q. (2021). Diabetic retinopathy detection and classification using mixed models for a disease grading database. In *IEEE Access*, *9*, 23544–23553. https://doi.org/10.1109/ACCESS.2021.3056186
6. Khan, Z., Khan, F. G., Khan, A., Rehman, Z. U., Shah, S., Qummar, S., Ali, F., & Pack, S. (2021). Diabetic retinopathy detection using VGG-NIN a deep learning architecture. In *IEEE Access*, *9*, 61408–61416. https://doi.org/10.1109/ACCESS.2021.3074422
7. Al-Antary, M. T., & Arafa, Y. (2021). Multi-scale attention network for diabetic retinopathy classification. In *IEEE Access*, *9*, 54190–54200. https://doi.org/10.1109/ACCESS.2021.3070685
8. Usman, I., & Almejalli, K. A. (2020). Intelligent automated detection of microaneurysms in fundus images using feature-set tuning. In *IEEE Access*, *8*, 65187–65196. https://doi.org/10.1109/ACCESS.2020.2985543
9. Wang, J., Bai, Y., & Xia, B.. (2020). Simultaneous diagnosis of severity and features of diabetic retinopathy in fundus photography using deep learning. In *IEEE Journal of Biomedical and Health Informatics*, 24(12), 3397–3407. https://doi.org/10.1109/JBHI.2020.3012547
10. Eladawi, N., Elmogy, M., Ghazal, M., Fraiwan, L., Aboelfetouh, A., Riad, A., Sandhu, H., & El-Baz, A. (2019). Diabetic retinopathy grading using 3D multi-path convolutional neural network based on fusing features from octa scans, demographic, and clinical biomarkers IEEE International Conference on Imaging Systems and Techniques (IST), Abu Dhabi, United Arab Emirates, 2019 (pp. 1–6). https://doi.org/10.1109/IST48021.2019.9010210
11. Qiao, L., Zhu, Y., & Zhou, H. (2020). Diabetic retinopathy detection using prognosis of microaneurysm and early diagnosis system for non-proliferative diabetic retinopathy based on deep learning algorithms. In *IEEE Access*, *8*, 104292–104302. https://doi.org/10.1109/ACCESS.2020.2993937
12. Momeni Pour, A., Seyedarabi, H., Abbasi Jahromi, S. H., & Javadzadeh, A. (2020). Automatic detection and monitoring of diabetic retinopathy using efficient convolutional neural networks and contrast limited adaptive histogram equalization. In *IEEE Access*, *8*, 136668–136673. https://doi.org/10.1109/ACCESS.2020.3005044

13. Samsani, S. (2016). An RST based efficient preprocessing technique for handling inconsistent data IEEE International Conference on Computational Intelligence and Computing Research (ICCIC), *2016* (pp. 1–8). https://doi.org/10.1109/ICCIC.2016.7919591

14. Huang, W., Oh, S.-K., & Pedrycz, W. (2016). Polynomial neural network classifiers based on data preprocessing and space search optimization Joint 8th International Conference on Soft Computing and Intelligent Systems (SCIS) and 17th International Symposium on Advanced Intelligent Systems (ISIS), *2016* (pp. 769–773). https://doi.org/10.1109/SCIS-ISIS.2016.0167

15. B, A. K., & Kodabagi, M. M. (2020) International Conference on Smart Technologies in Computing, Electrical and Electronics (ICSTCEE), *2020* (pp. 338–341). https://doi.org/10.1109/ICSTCEE49637.2020.9277221

16. Eratak, Ö., & D. (2014). Yeraltı kömür Madenciliğinde güvenlik İçin risk Yönetimde analiz ve Modelleme, *Doktora tezi, ODTÜ*.

17. Akboğa, Ö., & Baradan, S. (2015). İnşaat Sektöründeki ölümlü İşKazalarının Karakteristiklerinin İncelenmesi: İzmir alan çalışması , 5. *İşçi sağlığı ve İş güvenliği Sempozyumu*,215–224 s.

18. Wang, Z., & Bovik, A. C. (March 2002). A universal image quality index. In *IEEE Signal Processing Letters*, *9*(3), 81–84. https://doi.org/10.1109/97.995823

19. Grover, S., Arora, K., & Mitra, S. K. (2009). Text extraction from document images using edge information. In Annual IEEE India Conference (INDICON), *1–4*. IEEE Publications. https://doi.org/10.1109/INDCON.2009.5409409

20. Nagabhushan, P., & Nirmala, S. (2010). Text extraction in complex color document images for enhanced readability. *Intelligent Information Management*, *02*(2), 120–133. https://doi.org/10.4236/iim.2010.22015

21. Yang, Z. R. (2006). A novel radial basis function neural network for discriminant analysis. *IEEE Transactions on Neural Networks*, *17*(3), 604–612. https://doi.org/10.1109/TNN.2006.873282

22. Huang, W., Oh, S. K., Guo, Z., & Pedrycz, W. (2013). A space search optimization algorithm with accelerated converagence strategies. *Applied Soft Computing*, *13*(12), 4659–4675. https://doi.org/10.1016/j.asoc.2013.06.005

23. Parvin, H., Mirnabibaboli, M., & Alinejad-Rokny, H. (2015). Proposing a classifier ensemble framework based on classifier selection and decision tree. *Engineering Applications of Artificial Intelligence*, *37*, 34–42. https://doi.org/10.1016/j.engappai.2014.08.005

24. Wang, Z., & Bovik, A. (2009). Mean squared error: Love it or leave it? a new look at signal fidelity measures. *IEEE Signal Processing Magazine*, *26*, 98–117

25. Wu, Z.-Q., Jia, W.-J., Zhao, L.-R., & Wu, C.-H. (February 2016). Maximum wind power tracking based on cloud RBF neural network. *Renewable Energy*, *86*, 466–472. https://doi.org/10.1016/j.renene.2015.08.039