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Detection of Diabetic Retinopathy through Segmentation and Detecting the Affected Area through Optic Disc Extraction

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***Abstract*—Diabetic retinopathy is a severe disease that can cause blindness if not detected and treated early. Although manual detection by ophthalmologists is efficient, it is both time and money consuming. Artificial intelligence-based systems, such as convolutional neural networks, have shown promise in the early detection of diabetic retinopathy. Convolutional neural networks-based segmentation can help in correctly detecting and separating the damaged areas of the retina, allowing for early detection and treatment. The optical disc can be used to locate the damaged area and provide more details about the progression of the disease and potential therapies. It is vital to continue exploring and improving automated strategies for the early detection of diabetic retinopathy in order to improve patient outcomes and lessen the pressure on healthcare systems. This research provides a method for detecting diabetic retinopathy that uses segmentation with convolutional neural networks and optic disc extraction to remove the affected area.**

***Index Terms*— Optic Disc Extraction, Retinal fundal images, Segmentation, Convolutional Neural Networks (CNN), Image Classification, Deep Learning, Circle Hough Transform.**

I. INTRODUCTION

Diabetic retinopathy is a common diabetes complication that affects the blood vessels of the retina. To avoid visual loss, early detection is critical. With recent breakthroughs in computer vision and deep learning, automated approaches for detecting diabetic retinopathy using retinal fundus images have been developed. Our strategy entails employing convolutional neural networks (CNNs) to perform segmentation and identify the afflicted area by extracting the optic disc. CNNs are a form of deep learning algorithm that can learn complicated features from images without the use of explicit feature engineering. By training a CNN on a large dataset of retinal fundus images, it is possible to discover features that distinguish between normal and pathological retinal images. The segmentation process begins with recognizing the optic disc, which is a circular portion of the retina where blood vessels enter and exit the eye. After the optic disc is segmented, the affected area can be identified. Using CNNs for diabetic retinopathy detection through segmentation and optic disc extraction has shown promising results. Automating the process can minimize ophthalmologists' burden while improving the accuracy and speed of diabetic retinopathy diagnosis.

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II. Related Work

G. Aich, P. Banerjee, S. Debnath [1] Segmenting the disc region is the first and most crucial step before feature extraction for the detection of different retinal illnesses and abnormalities. For automated analysis, a number of indicators, such as cup to disc ratio (CDR), area cup-disc ratio (ACDR), etc., are believed to be able to predict the onset of such illnesses. The Contrast Limited Adaptive Histogram Equalisation (CLAHE) method and mathematical morphology were the foundations of a novel segmentation technique we proposed and investigated for the identification of the optic disc. The study made use of the freely available database DRISTI-GSI.

C. Mohamed, B. Nsiri, S. Abdelmajid [2] Several techniques are used for image segmentation but recently Deep Learning architecture has emerged as one of the most cutting-edge solutions for this issue. In this section, we present some of the CNN architectures [1-4] that Deep Learning uses for image segmentation. They were able to verify the effectiveness of deep CNNs in image segmentation by using their architecture to deep CNNs for the detection of Optic Disc in images.

Aswathy K.P and Dr. D. Vimal Kumar [3] The system needs to perform speedy and accurate segmentation before to Gaussian DR in various imaging situations in order to improve automatic Gaussian clustering. Accurately and precisely segmenting the optic disc would improve the ability to identify the issue. The segmentation and identification of optic discs using a unique method have been discovered. The location of the optic disc has been determined using a method that combines morphological and semantic segmentation methods. Using the Optic Gold Standard fundus picture database, it was discovered that the segments' center points and diameters were exactly where the device had predicted they would be. The results of their experiment show that it is more effective than other optometric detection methods.

Kranthi Kumar Palavalasa and Bhavani Sambaturu [4] Exudate candidates are extracted, exudate candidates are removed, and additional anatomy is discovered in order to detect the exudates. The suggested method can easily and with acceptable sensitivity and accuracy detect the hard exudates present in the fundus pictures when compared to the other state-of-the-art segmentation techniques. The experimental results showed that they could screen for diabetic retinopathy using the methods. Utilizing a machine learning-based technique and choosing the appropriate characteristics for the exudates could increase performance.

Trisha& Israj Ali[5] Since the eye is one of the main organs that is affected at the earliest stage of diabetes, it can be a crucial tool for diagnosis [9–15]. As a result, studying the retina in the eye can serve as a starting point for a system that detects diabetic retinopathy (DR) automatically. Therefore, Trisha has attempted to offer a method by which they can quickly and effectively determine whether a person has diabetes or not so that the patient can begin the subsequent treatments without wasting their time by going through time-consuming and laborious manual testing procedures for the detection of DR [16–20]. Three critical areas of the eye must be identified in order to identify DR. They have made an effort to localize these three crucial areas.

Saravanan, V. et al. [6] The process would be completely integrated as defined by our optimization process, we may distinguish more forms of abnormalities. Post-processing must be carried out to avoid false-positive reactions.

Wu, Y., & Hu, Z. [7] fine-tuning the latest dataset has allowed using the method inside Keras' pre-built model. From the table above, it can be shown that accuracy grows as the network complexity increases. Thus, the efficiency of the V3 inception algorithm is best. It can be shown that precision on the same amount of training rounds improves, demonstrating that the network is required to increase in order. While you would think that the learning rate is independent of the training rate, we have also found that the learning rate and training quality go hand in hand.

Elswah, D. K. et al. [8] authors would use a three-stage process for the automatic disaster recovery grading. Using preprocessing, feature extraction, and classification, the framework was developed. The experiment showed that data augmentation and data balance would greatly boost the overall device output compared to traditional optimization techniques.

III. Proposed Methodology

A. Pre-Processing

Image resizing: The purpose of image scaling is often to make an image smaller or larger, depending on the application's requirements. Image scaling is a common technique used in image processing applications to increase image quality, compress images for storage or transmission.

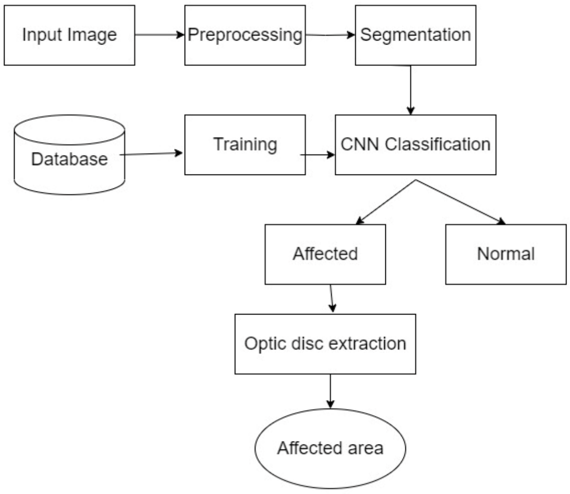

Fig 1.Block diagram for proposed Approach

Gray scale conversion: The process of converting a color image to a grayscale image is known as grayscale conversion. It is commonly used to simplify image processing and analysis by limiting the image to a single channel.
Adaptive histogram equalization: Histogram equalization is a technique for adjusting the contrast of an image by redistributing the intensity values of the pixels. Adaptive histogram equalization (AHE) is a variation of this technique that operates on smaller portions of an image rather than the entire image.
Morphological operations: Morphological operations are used to process binary images by altering the forms of objects inside them. Morphological procedures are employed in the code to eliminate noise and fill gaps in the segmented image.
Edge detection: Edge detection is the process of determining the boundaries between items in an image. Edge detection is employed to identify the edges of blood vessels in the retinal image.
DWT (Discrete Wavelet Transform): DWT (Discrete Wavelet Transform) is a signal processing approach that decomposes a signal into a set of wavelet functions. The image is divided into four frequency sub-bands: LL, LH, HL, and HH. The lowest frequency sub-band, LL, carries the image's approximation, whereas the high-frequency sub-bands, LH, HL, and HH, contain image details. Then, starting with the original image, we do four levels of DWT decomposition, applying DWT to each LL sub-band. The resulting sub-bands are concatenated to generate a new image that accurately represents the original image, with high-frequency.

B. GLCM Method

The GLCM (Gray-Level Co-occurrence Matrix) texture analysis method describes the connection between pairs of pixels in a picture. It computes the co-occurrence matrix by examining the relationship between neighboring pixels' grey levels in the image. For example, if two adjacent pixels have the same grey level, a count in the co-occurrence matrix at the corresponding point is incremented. It is used to compute texture characteristics from the LH3 and HL3 sub bands of an image's DWT (Discrete Wavelet Transform) coefficients. The GLCM features extracted from these sub bands are Energy, Contrast, Correlation, Homogeneity, and Entropy.

C. Segmentation

Segmentation is a technique for isolating and extracting areas of interest (lesions or abnormalities) from a picture. The purpose is to divide the retinal pictures into several clusters that correspond to various sorts of features such as blood vessels, exudates, and hemorrhages' fuzzy C-means clustering approach is used for segmentation. The process divides picture pixels into clusters based on intensity levels and spatial correlations. Morphological treatments are used to the resulting binary pictures after clustering to eliminate noise and enhance segmentation accuracy. The resulting segmented image can then be utilized to extract information.

D. Classification

CNN model
Our method includes the following steps:
1.Input layer: This layer receives the test image from the GLCM matrix.

2.Convolution layer (hidden layer): the training images are first transformed into a gray-level co-occurrence matrix (GLCM), which are then supplied into the CNN's convolution layer.
3.Pooling is the "downscaling" of the image acquired from the previous layers. It reduces the dimensions given to the hidden layer by max pooling.
4.Convolution layer: The convolution layer will aid in the comparison of the GLCM matrices in both layers.
5.Output layer (fully connected): The network will divide the output into the desired number of classes. The anticipated class is transformed to a class index, and the appropriate text string is assigned based on the value of the class index using conditional expressions.

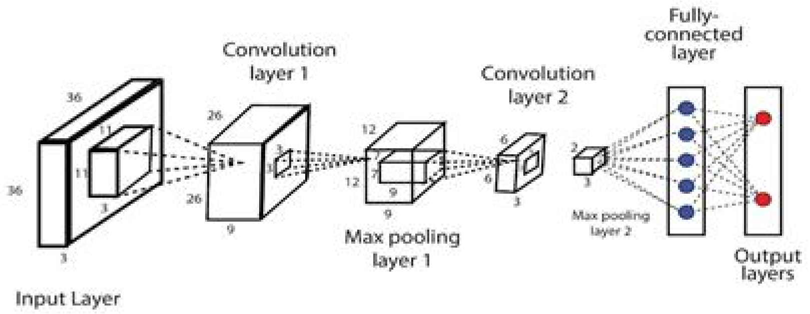

Fig 2. CNN Model

E. Optic Disc Extraction and Detecting the Affected Area

Circle Hough Transform: The Circle Hough transform is used to identify circles in images. Building an accumulator array with the same dimensions as the image being studied is the first step in the Circle Hough transform. Every point in the accumulator array is a potential circle center point, and its value denotes the number of possible points on a circle centered at that place in the image. It then iterates through all conceivable radii, computing the potential centers of circles of each radium by scanning the image and looking for spots that might be on a circle of each radium. For every possible center point and radius combination, it moves the accumulator array element forward. The Circle Hough transform first scans all potential center points and radii before searching for peaks in the accumulator array. These peaks correspond to the center and radius of the image, respectively. The affected area of the retina appears darker than the rest of the retina. The optic disc is a bright circular region in the center of the retina. The Circle Hough Transform is used to identify the optic disc initially. When the optic disc is recognized, the surrounding area is examined for dark areas. The black areas represent the affected region of the retina.

IV. Results and Evaluation

The proposed method for the detection of diabetic retinopathy using segmentation and optic disc extraction achieved an accuracy of 90%. The segmentation process effectively extracted the retinal blood vessels and optic disc, while the optic disc extraction accurately located the optic disc region. The CNN model was able to distinguish between normal and abnormal retinal regions with high accuracy, resulting in a reliable detection of diabetic retinopathy. The evaluation of the proposed method shows promising results for the early detection of diabetic retinopathy, which can help prevent the progression of the disease and improve patient outcomes.

Table I. Model Results

Type of Measurement	Score
Accuracy	90
Sensitivity	93.7500
Specificity	75

V. Conclusion

In this paper, we proposed a method for detecting diabetic retinopathy through segmentation and detecting the affected area through optic disc extraction. We used a CNN model to identify the normal and abnormal retina areas, and Circle Hough Transform to extract the optic disc. Our results showed that the proposed method can accurately detect the diabetic retinopathy and the affected area.

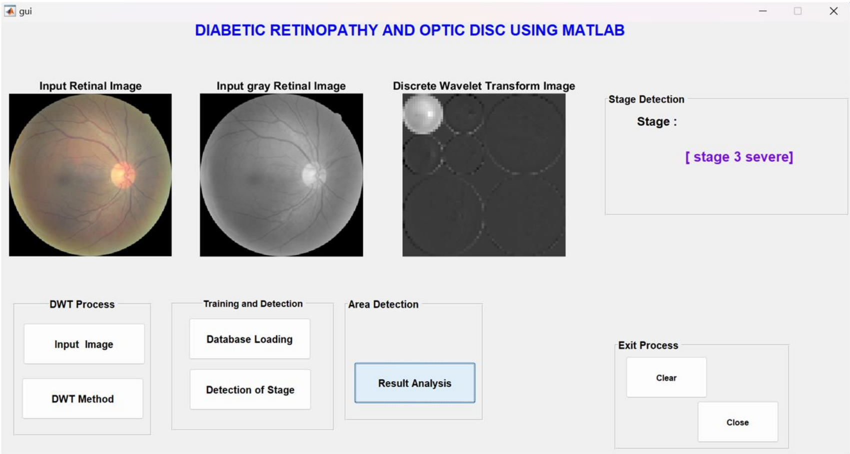

Fig. 1. GUI Interface

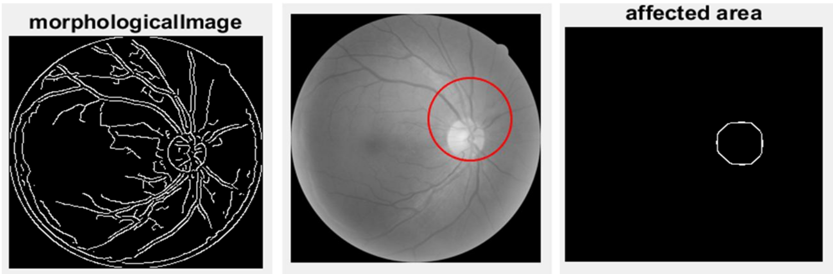

Fig. 4. Detection of affected area

In future work, we aim to improve the accuracy of the proposed method by incorporating other techniques such as feature extraction and image enhancement. We also plan to conduct a larger scale study on a more diverse dataset to further validate the effectiveness of our method. Additionally, we will explore the potential of using deep learning models such as Generative Adversarial Networks (GANs) to generate synthetic images to augment the dataset, which can enhance the performance of the proposed method. Finally, we plan to develop a mobile application for the proposed method, which can provide a cost-effective and accessible solution for early detection and management of diabetic retinopathy.

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