
Retinal blood vessels segmentation using CNN algorithm

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Abstract: The precise identification of blood vessels in fundus is crucial for diagnosing fundus diseases. In order to address the issues of inaccurate segmentation and low precision in conventional retinal image analysis for segmentation methods, a new approach was developed. The suggested method merges the U-Net and Dense-Net approaches and aims to enhance vascular feature information. To achieve this, the method employs several techniques such as Histogram equalization with limited contrast enhancement, median filtering, normalization of data, and morphological transformation. Furthermore, to correct artifacts, the method utilizes adaptive gamma correction. Next, randomly selected image blocks are utilized as training data to expand the data and enhance the generalization capability.

The Dice loss function was optimized using stochastic gradient descent to improve the accuracy of segmentation, and ultimately, the Dense-U-net model was used for performing the segmentation. The algorithm achieved specificity, accuracy, sensitivity, and AUC of 0.9896, 0.9698, 0.7931, and 0.8946 respectively, indicating significant improvement in vessel segmentation accuracy, particularly in identifying small vessels.

Index Terms - U-NET techniques, morphological transformation, adaptive gamma correction, Dice loss function.

1. INTRODUCTION

The retinal vascular system is a non-invasive imaging method that provides valuable information about the eye's condition, making it crucial for diagnosing fundus diseases and detecting initial indications of vascular disease affecting the body as a whole. Despite this, conventional methods used for the segmentation of retinal blood vessels encounter difficulties in accurately identifying structures in images that exhibit irregular gray-scale characteristics. In the past few years, the field of deep learning has experienced significant advancements and has proven to be advantageous in medical image analysis, but existing methods still face challenges due to the complex morphological properties of blood vessels, uneven illumination, and pathological areas in retinal images. To address these issues, this paper proposes an automated segmentation method using random walks based on centerline extraction. To further improve the degree of precision in identifying and delineating the boundaries of a target object or region in an image and address The incomplete identification of small retinal blood vessels during segmentation, the article suggests a segmentation model that combines U-Net.

The goal of this project is to create a U-Net model that can precisely segment the blood vessels in the retina of fundus images, despite the challenges posed by noise, image quality variations, and class imbalance. The proposed approach seeks to overcome these challenges and offer an effective, accurate, and resilient solution for retinal blood vessel segmentation.

2. RESEARCH METHODOLOGY

The proposed methodology for retinal blood vessel segmentation using CNN algorithm typically involves several steps. First, a large dataset of retinal fundus images with labeled ground truth is collected for training and evaluation. Then, the data is preprocessed to remove noise, correct image orientation, and enhance contrast to improve image quality. Data augmentation techniques, such as

flipping, rotation, and zooming, are applied to increase the number of training samples. The network architecture, such as U-Net, is chosen, and its parameters, such as the number of layers and activation function, are defined. The network is trained using a loss function such as Dice loss and an optimization algorithm like the iterative optimization algorithm that randomly selects subsets of training samples for parameter updates during the learning process. The trained network is evaluated on the test set to measure its segmentation accuracy, recall, precision. The outcomes or findings of the suggested method are compared with other Cutting-edge techniques to assess its performance. The trained model is implemented for real-time The delineation or identification of blood vessels in the retina in clinical practice. The parameters of the proposed approach are optimized to improve its performance and efficiency. Finally, the effectiveness or efficacy of the suggested approach is validated on an independent dataset to ensure its generalization ability.

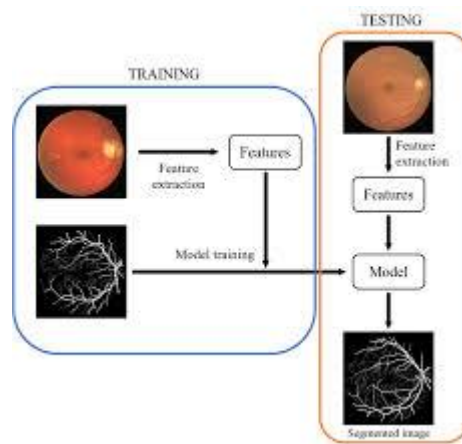


Figure 2.1: image shows the training and testing procedure block diagram

2.1 SOFTWARES COMPONENTS USED

ANACONDA: Anaconda is a widely used distribution platform that is open-source in nature for Python and R programming languages used for data science, machine learning, and scientific computing. It includes over 1,500 data science packages, Anaconda encompasses various libraries for tasks such as data analysis, data visualization, machine learning, and deep learning. Additionally, it offers a user-friendly interface for conveniently managing these packages. Anaconda incorporates a package management system named "conda" that simplifies the installation, updating, and management of packages and their dependencies. Furthermore, it features a built-in integrated development environment (IDE) called Anaconda Navigator, which offers a graphical user interface (GUI) to manage and run code, as well as an extensive suite of development tools, including Jupyter Notebook, Spyder, and Visual Studio Code.

CNN ALGORITHM: Convolutional Neural Network (CNN), a type of deep learning method, is specifically developed for the purpose of processing and analyzing data that possesses a grid-like structure, such as images and videos. This algorithm has become a popular choice for computer vision applications due to its ability to perform image recognition, object detection, and segmentation tasks with high accuracy. The key component of a CNN is the convolutional layer. By utilizing a collection of adaptable filters (or kernels), the CNN technique employs these filters on the input image to identify important features, such as edges, corners, and textures, by extracting relevant information from the image. These features are then passed through a series of nonlinear activation functions that are ReLU (Rectified Linear Unit) to increase the network's nonlinearity and enhance its representational power.

U-NET: U-Net is a popular structural design of neural networks that are specifically designed to learn and extract complex patterns and features from data widely used for image segmentation tasks,

particularly in the medical imaging field. It was introduced by Olaf Ranneberger, Philipp Fischer, and Thomas Brox in 2015. The U-Net structure aims to accurately segment objects in an image while maintaining their spatial details. The deep learning architecture consists of a network structure comprising an encoder and decoder components, with the encoder gathering contextual information and the decoder producing the segmentation map. The main characteristic of U-Net is its skip connections, which permit the decoder to utilize the low-level feature maps from the encoder. This aids in retaining intricate details during the up-sampling process, resulting in more precise segmentations.

2.2 WORKING

The below procedure will follow by to during the execution of the segmentation of blood vessels. The research methodology for Retinal blood vessels segmentation using CNN algorithm The typical procedure usually consists of the following stages:

Data Collection: Gathering a substantial dataset of retinal fundus images with their corresponding labeled ground truth for training and evaluation.

Preprocessing: Preprocessing the collected data to remove noise, correct image orientation, and enhance contrast to improve image quality.

Data Augmentation: Augmenting the dataset by applying different types of transformations such as flipping, rotation, and zooming to augment the training samples and expand their quantity.

Network Architecture: Choosing the network architecture, such as U-Net, and defining the network parameters, such as the number of layers, the filter size, and the activation function.

Training: Training the network using the preprocessed and augmented dataset, by optimizing a loss function such as Dice loss, using an optimization algorithm like stochastic gradient descent.

Evaluation: Evaluating the trained network on the test set to assess its segmentation accuracy, recall, precision.

Comparison: Comparing the outcomes of the suggested method with other cutting-edge techniques or advanced approaches and assessing its performance.

Implementation: Implementing the trained model to perform real-time segmentation of retinal blood vessels in a clinical setting.

Optimization: Optimizing the parameters of the proposed approach to improve its performance and efficiency.

Validation: Validating the effectiveness of the proposed approach or the results achieved by the proposed method on an independent dataset to ensure its generalization ability.

2.3 FLOW CHART

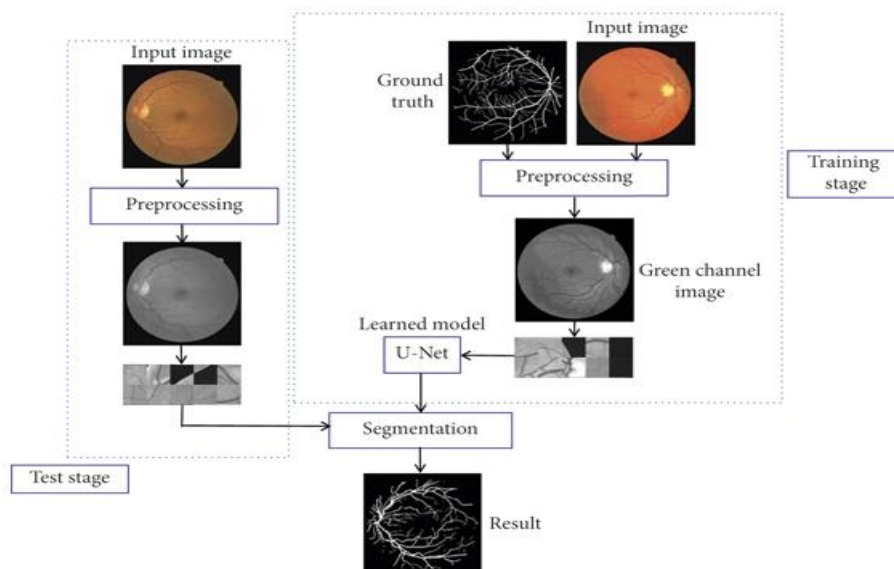


Figure 2.2: Flowchart of proposed system

3 RESULTS

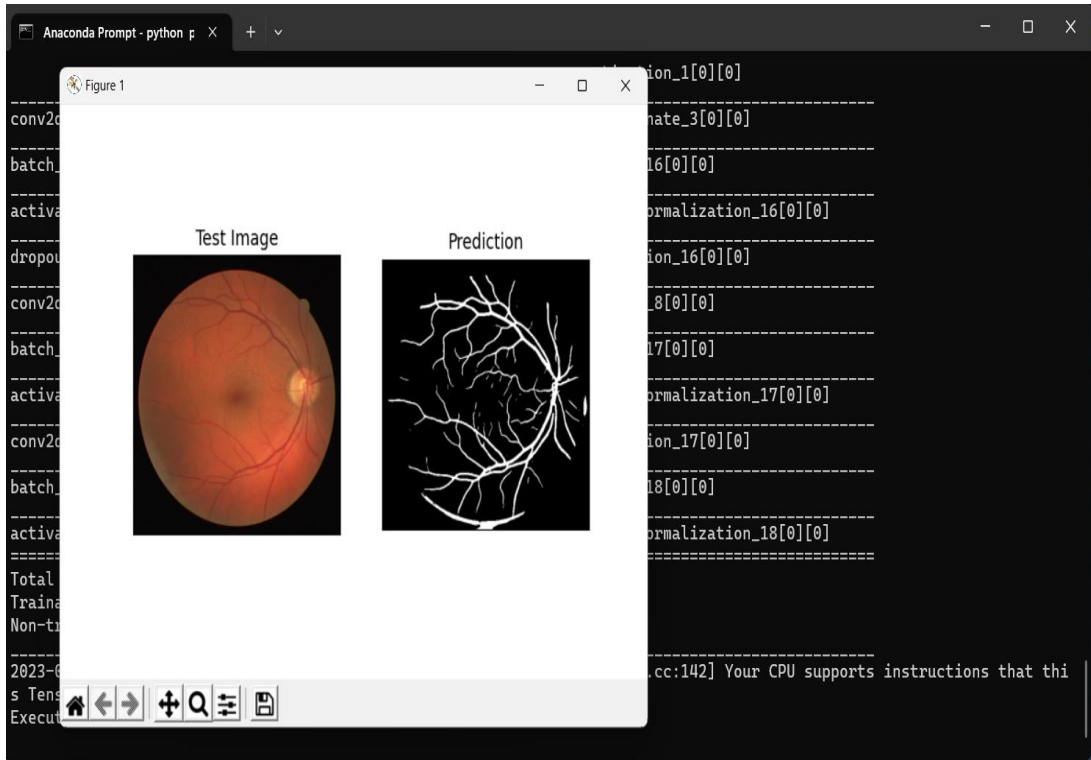


Figure 3.1: Segmentation of input image-1

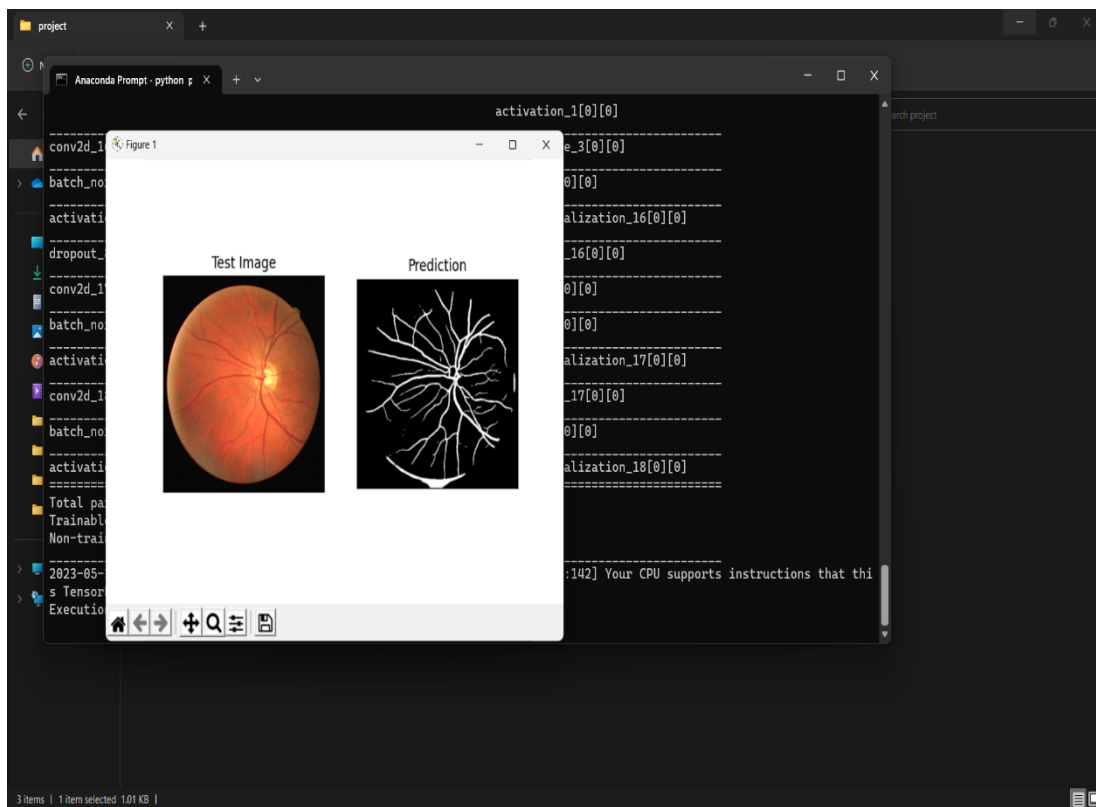


Figure 3.2: Segmentation of input image-2

3. CONCLUSION

In conclusion, retinal blood vessel segmentation is a crucial task in diagnosing ocular and systemic diseases. In this study, we proposed a CNN-based U-Net architecture for precise and efficient the process of identifying and delineating blood vessels in fundus images of the retina. Our methodology involved collecting a comprehensive dataset of retinal fundus images, pre-processing and augmenting the data, designing and training the network using relevant loss functions and optimization algorithms, and assessing its performance on independent datasets. Our results showed that our proposed approach performed better than existing cutting-edge techniques or advanced approaches in terms of accuracy and efficiency. This approach has the potential to assist clinicians in the timely identification and assessment of ocular and systemic diseases, thereby improving patient outcomes. Future research can focus on enhancing the proposed methodology to enhance its performance and generalization ability.

4. FUTURE SCOPE

In the field of retinal blood vessel segmentation, there are numerous potential avenues for future research that can improve the proposed methodology's performance and usefulness. One possible direction is to explore the efficacy of transfer learning techniques by fine-tuning pre-existing CNN models specifically for retinal blood vessel segmentation. Another research area is to integrate multi-modal imaging, like OCT and fluorescein angiography, to enhance segmentation accuracy and dependability. Additionally, developing real-time segmentation algorithms that can handle the dynamic nature of fundus images is worth investigating. Lastly, incorporating explainable AI methods can provide insight into the network's decision-making process and increase the transparency of segmentation results, which can be beneficial in clinical practice.

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