EFFICIENT RETINAL IMAGE SEGMENTATION BY U-NET FOR AGE-RELATED MACULAR DEGENERATION DIAGNOSIS

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Abstract: Age-related Macular Degeneration (AMD) is a prominent factor contributing to visual impairment in older people, characterized by deterioration of the macula, the center part of the retina. An accurate segmentation of blood vessels is essential for successful intervention and control of MAD. This study proposes an approach for effectively segmenting blood vessels using U-Net architecture. It is a specialized convolutional neural network that has shown significant potential in accurately segmenting intricate structures captured in medical images. It uses U-Net to precisely define the blood vessels from retinal images, facilitating accurate identification of macula regions for early AMD detection. The efficacy of the proposed method in achieving high accuracy and the computational economy is shown by its evaluation of a large dataset, Structured Analysis of the Retina (STARE). The findings demonstrate that the U-Net-based approach outperforms existing segmentation methods in accuracy and efficiency, making it a promising tool for identifying and monitoring AMD.

Keywords: Biomedical imaging, age-related macular degeneration, deep learning, image analysis, macular deterioration.

I. INTRODUCTION

The need for early diagnosis via regular eye exams has been highlighted by the rising incidence of eye diseases in the elderly [1]. One of the most prevalent causes of visual loss in people over the age of 45 is AMD. Emergency eye care may be needed depending on severity, and treatment varies. Deep convolutional neural networks are used to classify dry and moist AMD quickly and automatically. For prompt treatment, dry and moist kinds must be precisely

recognized. The deep neural networks' performance shows that dry vision impairment is more reliably recognized than wet.

In 2019, 19.8 million people in the United States were impacted by AMD, the primary cause of visual loss in persons aged 60 and older [7]. MAC-You-Vision is an innovative training program that helps people prepare for future vision loss while improving their quality of life. An all-inclusive platform for AMD sufferers, the app provides unique features that evolve with the condition. Early detection is crucial for AMD since it is a leading cause of blindness worldwide. More research is needed to address the difficulty of accurate early identification of AMD [8]. Improving the accuracy of AMD diagnoses suggests a new design for Convolutional Neural Networks (CNNs), a dual-path CNN. AMD One of the most common causes of blindness in the elderly is AMD, which often manifests as a central scotoma. However, eye gaze monitoring may identify AMD with just a few basic test patterns, replacing the current manual procedures [9]. According to experimental data, this may pave the way for future system devices for AMD screening. Figure 1 shows that the prevalence of AMD increases from 50 to 80+.

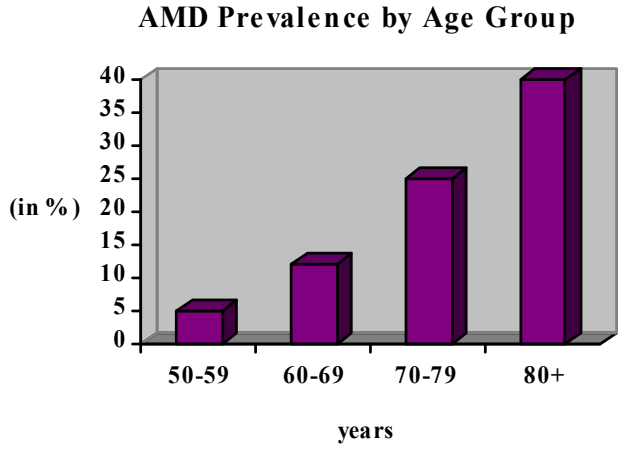

Fig. 1 Age-Related Macular Degeneration Prevalence

II. RELATED WORKS

An innovative strategy for automated macular fibrosis categorization in neovascular AMD is the Cross-modal Fusion Method (CrossFM) [2]. The cross-modal attention method, a CoTransNet network, and a dual-branch CoTransNet network enhance the ability to describe lesions. By surpassing state-of-the-art multimodal approaches on both public and manufactured datasets, experimental findings demonstrate the efficacy of CrossFM. To diagnose AMD, provide an AI method that is both automatic and explainable [3]. By simulating human visual processing, the proposed xAI system can distinguish between healthy retinas, various stages of AMD, non-AMD diseases, and GA using features derived from optical coherence tomography (OCT) B-scan images.

It presents a novel approach to diagnosing ocular diseases using a support vector machine classifier [4]. This work aims to use optical field sensitivity test findings to diagnose blinding illnesses correctly. Using pre-processed retinal images, the method creates a data vector for support vector machine classification by extracting statistical and vascular properties to identify

AMD. A novel approach is investigated in this study to identify Parkinson's disease by analyzing AMD fundus images in individuals with Parkinson's disease [5]. The focus is on identifying genetic predispositions and environmental risk factors that may hinder early identification, particularly in patients with PD. Older adults might suffer from diabetic retinopathy (DR) and AMD [6].

The AMD is a major contributor to people losing their eyesight. Using deep learning methods, this research suggests an automated method for analyzing fundus images and rating AMD [10]. To ensure that the data is distributed evenly, augmentation and data sampling on points extracted from three separate datasets are used. Build a three-class classification model that labels fundus images as either having no AMD, moderate AMD, or severe AMD using EfficientNet-B3, an application of deep learning. An eye condition often seen in the elderly, AMD is detected by presenting the synthesis result of an extreme learning machine (ELM), a machine learning approach. Feeding the model OCT scans during training may achieve the desired clock period, area, and power [11]. This is the first synthesis outcome of using ELM to detect AMD in OCT images.

In the elderly, AMD is a retinal degenerative disease. Traditional fundus images may be manually inspected for AMD. Physicians cannot comprehend all fundus imaging data; hence, their diagnoses are subjective [12]. A lightweight convolution neural network handles images for AMD diagnostic speed and standardization. Lightweight CNN starts with a feature extraction method that automatically extracts retinal characteristics from a fundus image. The proposed technique identifies AMD in the second phase based on first-step attributes. A retinal disorder known as AMD accounts for 8.7 percent of all cases of blindness globally. It has two parts: the wet and the dry [13]. It presents a technique for automatically detecting dry and wet AMD in eye images by analyzing the proportion of white pixels. The system is evaluated into 30 categories, including healthy, wet, and dry eyes.

Diagnosing and treating disorders like AMD, glaucoma, and retinopathy of prematurity relies heavily on artificial intelligence and deep learning in the field of ophthalmology. However, interpretability is severely restricted when additional inputs are used [14]. Considering demographic details, risk factors, and genetic variations derived from DNA genotyping suggests a technique that utilizes Artificial Hydrocarbon Networks (AHN) to diagnose AMD. It investigates the feasibility of using transfer learning to screen individuals for AMD using deep convolution neural networks. Use the AREDS dataset, which contains more than 150,000 images and includes qualitative grading information supplied by ophthalmologists and professional graders [15]. Apply batch normalization to the last fully connected layers of a tweaked VGG16 neural network.

A major contributor to global blindness, AMD distorts and blurs central vision. Avoiding a worsening of symptoms in the absence of therapy requires prompt diagnosis and regular monitoring [16]. Machine learning techniques such as CNN and Support Vector Machines (SVM) have been considered for diagnosing AMD. Based on fundus images, this research found that CNN-SVM with RBF kernel had the best recall and accuracy but the worst precision compared to other CNN and SVM combinations used to identify AMD. Detection and treatment of AMD at an early stage may avert catastrophic vision loss; the disease is a major contributor to blindness [17]. It provides a new approach to drusen segmentation that uses Growcut; this technique finds local maximum and minimum points, determines whether drusen or not, and then uses Growcut to get the borders of the drusen. A dataset consisting of 96 images that have been manually labeled is used to evaluate the method's performance.

This research explores a disorder that causes AMD and blindness in old age and uses a tabular technique to categorize retinal images according to the presence or absence of AMD [18]. Instead of relying on feature segmentation, the

suggested method uses full image encodings, a new twist. Features are statistical parameters directly or indirectly retrieved from the images. Automatic AMD identification using OCT images generally excludes the choroid and uses retinal layers. The choroid produces AMD symptoms only in later stages, and clinical literature is mixed on its function in early AMD detection [19]. A more recent clinical study reveals that the choroid is damaged early. The proposed experiment verifies the impact of incorporating the choroid in intermediate-stage AMD OCT image detection. Offer a deep learning AMD detection system and evaluate its accuracy with and without the choroid. AMD is the leading cause of blindness in those over 50 if left untreated. Since over 100 million Americans are over 50, it is crucial to find strategies to identify those at risk of acquiring the advanced stage that might cause significant vision loss [20]. It evaluates the transfer of pre-trained deep neural network visual characteristics to AMD detection.

III. PROPOSED SYSTEM

AMD, a chronic eye condition, results in gradual deterioration of vision. Timely therapies may prevent future visual damage; thus, it is crucial to detect this issue early. Figure 2 shows the normal fundus and fundus with AMD (Downloaded from https://www.hopkinsmedicine.org/health/conditions-and-diseases/agerelated-macular-degeneration-amd).

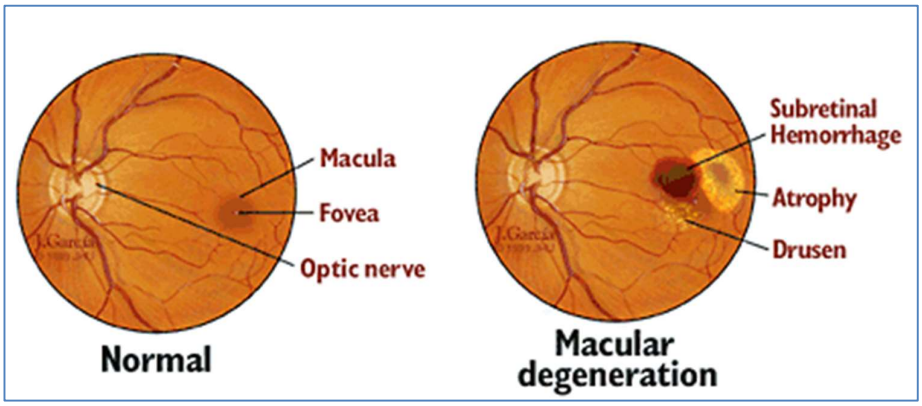

Fig. 2 Normal and macular degeneration details in fundus images

Fast and reliable segmentation of blood vessels within retinal images is very important for effectively segmenting the macula region. The proposed system uses the U-Net architecture to segment retinal images to diagnose AMD effectively.

A. U-Net Architecture for Retinal Image Segmentation

The core of this system is the U-Net architecture, which was developed mainly to segment biological images. It is characterized by its U-shaped architecture and two paths, one for downsampling and one for upsampling, that work together to form the network. The expanding route recovers the image's spatial resolution by concatenating appropriate features from the contracting path, while the contracting path collects the retinal image's contextual information via successive convolutional layers. Several convolutional processes rectified linear

unit activations and max pooling, all steps in the contracting route that take an input image.

This technique gradually decreases the spatial dimensions while increasing the depth of the feature maps to extract high-level representations of retinal structures, including the macula. The feature maps are upsampled in the expanded path using transposed convolutions to restore the original image size while keeping the learned features. The conservation of fine-grained information is essential for precise border recognition in the retinal image, and skipping connections between the contracting and expanding routes makes this possible. To enhance segmentation performance, these skip connections merge the expanding path's upsampled outputs with the contracting path's high-resolution features. Figure 3 shows the U-Net architecture.

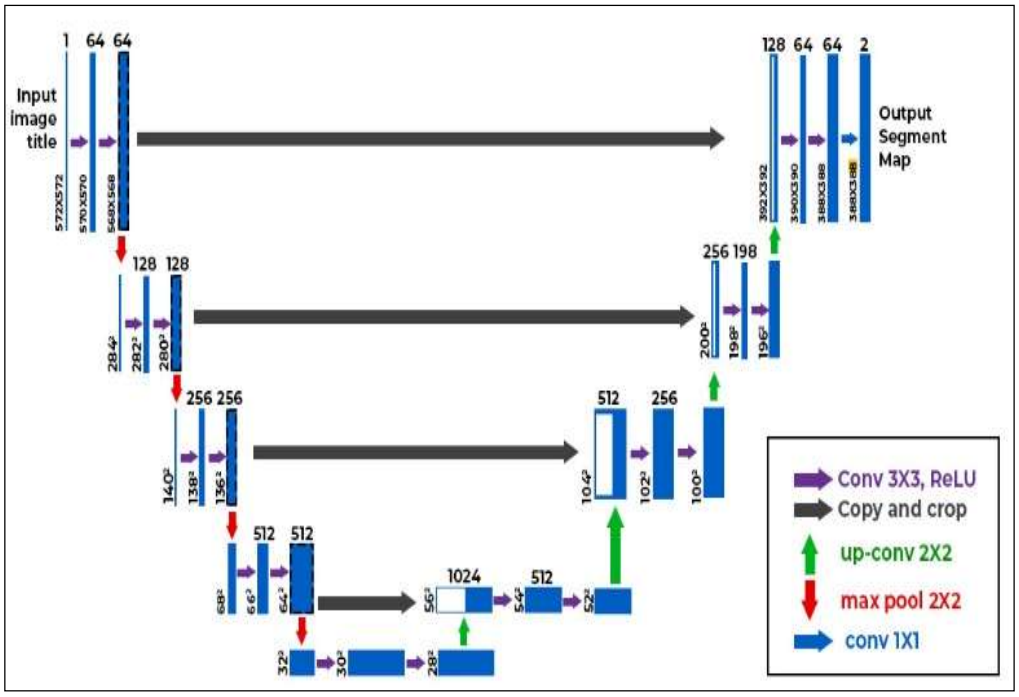

Fig. 3 U-Net architecture

B. Post-processing and Real-Time Feedback

The system produces segmented blood vessels after the U-Net model processes the retinal images. These results allow for accurately identifying the macular area by removing the blood vessels and applying a simple Otsu thresholding. The segmentation mask facilitates doctors' early detection of AMD. The STARE dataset of retinal images with manually annotated segmentation masks trains the model to identify blood vessels. During training, the system improves its capability to distinguish the blood vessels and macular area from the background by penalizing wrong classifications at the pixel level using a pixel-wise cross-entropy loss.

The system is designed for low-latency execution to provide performance in real-time. A post-processing step cleans up the output by eliminating any misclassified artifacts or noise that may have been presented after the U-Net model has generated the segmentation masks. This step uses morphological

operations like erosion and dilation to clean up the segmentation mask to get more precise boundaries. The system can provide real-time feedback by optimizing the U-Net model's deployment on computationally powerful hardware, such as GPUs or edge devices in clinical settings. The device can scan retinal images in seconds and provide a physician's quick feedback.

III. RESULTS AND DISCUSSIONS

The U-Net model's segmentation accuracy and performance were evaluated on the STARE database of 400 annotated retinal images. The database can be downloaded from https://cecas.clemson.edu/ahoover/stare/. Figure 4 shows sample images from the STARE database.

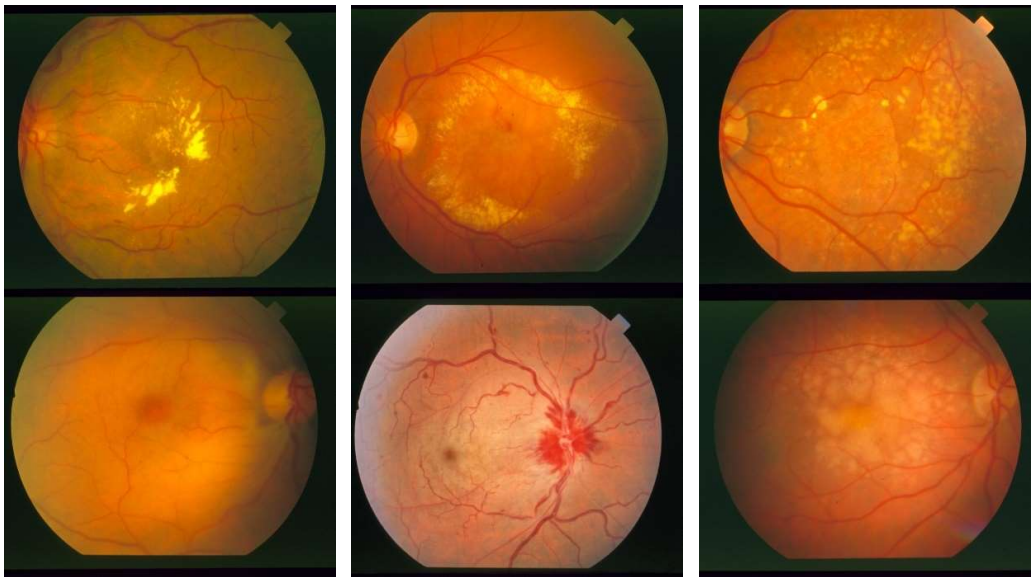

Fig. 4 Fundus images in the STARE database

With an average processing time of 2.5 seconds per image, the proposed system is well-suited for inclusion in standard ophthalmology studies. Physicians may get prompt diagnostic input by ensuring this speed, enabling quicker decision-making and action. Despite the commendable performance, several difficulties were noted. In instances with significant retinal distortions or artifacts, the precision of the model's segmentation was somewhat diminished, resulting in a decreased clarity of the blood vessels' segmentation borders. These problems indicate that more enhancements are required in the preparation phase and the augmentation of the dataset.

Enhancing the training dataset with more varied and demanding images and improving preprocessing approaches might enhance the model's resilience and accuracy in handling different retinal situations. Skip connections in the U-Net structure, which combine characteristics from the encoder route with those from the decoder path, were crucial in maintaining spatial details and improving segmentation accuracy. These connections enabled the model to sustain high-resolution output and satisfactorily capture intricate features required for

accurate AMD identification. Figure 5 shows the results of the U-Net architecture for blood vessel segmentation.

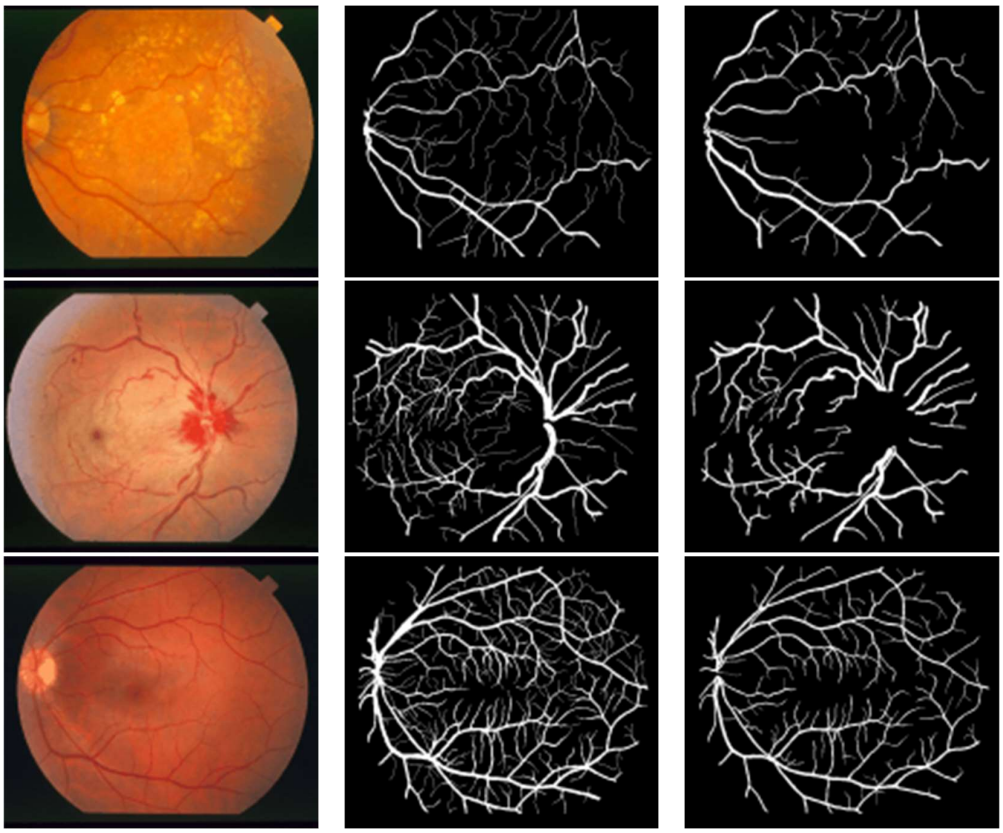

Fig. 5 (a) Input Image (b) Annotated image (c) U-Net segmented output

The model attained a 92% overall pixel segmentation accuracy, indicating its robust ability to detect blood vessels accurately. An 85% IoU score, a critical measure for segmentation tasks, was computed. The score shows a significant similarity between the predicted segmentation masks and the ground-truth annotations, demonstrating the model's ability to capture blood vessels. The precision and recall ratings provide further clarification of the model's performance. The precision score was 89%, indicating the ratio of accurate positive predictions to all valid identifications generated by the model. The excellent accuracy rate of the U-Net model indicates its accurate identification of AMD areas with few false positives. With a recall score of 81%, the model can accurately identify a substantial fraction of the real AMD-affected areas in the images. This score measures the model's ability to record pertinent information and is essential for thorough AMD identification. The U-Net model demonstrated excellent efficiency in real-time processing, which is crucial for clinical applications.

Large datasets may provide challenges for real-time processing due to the high computational resource demands. Potential improvements include combining advanced preprocessing approaches to manage noise and artifacts, introducing more resilient regularization methods, and investigating lightweight model

variations for real-time applications. Furthermore, expanding the method to multi-modal imaging should enhance the precision of diagnosis and promote more effective generalization across various phases of AMD.

IV. CONCLUSIONS

The proposed blood vessel segmentation using the U-Net architecture has shown exceptional effectiveness in diagnosing AMD. The model's resilience in reducing mistakes is shown by the substantial reductions in training and validation loss that followed the deployment of U-Net. The accuracy and precision with which architecture validates its capacity to detect AMD and can be used for other retinal diseases. While the system is successful, it does have certain limits. For example, it struggles with noisy images and has significant computing needs, which may affect its ability to analyze images in real time. Future efforts should focus on improving the model's capacity to handle image artifacts and noise and creating more computationally efficient variations to accommodate real-time applications. Improving diagnosis accuracy and making the system more adaptable for different phases of AMD might be achieved by expanding the system to include multi-modal imaging approaches. U-Net-based method provides a solid basis for sophisticated retinal image processing and may make important strides in AMD early identification and monitoring.

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