2023 IEEE International Conference on Artificial Intelligence in Engineering and Technology (IICAIET) | 979-8-3503-0415-2/23/$31.00 ©2023 IEEE | DOI: 10.1109/IICAIET59451.2023.10291722

U-Net Segmentation of Ultra-widefield Retinal Fundus Images for Retinal Vein Occlusion Associated Lesion Recognition

Ivy Siaw Yin Ong[1], Lik Thai Lim[2*], Muhammad Hamdi Mahmood[3], Nung Kion Lee[4*]

[1, 4] Faculty of Cognitive Sciences and Human Development
Universiti Malaysia Sarawak
Kota Samarahan, Sarawak

[2, 3] Faculty of Medicine and Health Sciences
Universiti Malaysia Sarawak
Kota Samarahan, Sarawak

Email: ivyyyin@gmail.com[1], ltlim@unimas.my[2], mmhamdi@unimas.my[3] nklee@unimas.my[4]

***Abstract*—Inspection of fundus images can identify haemorrhages and cotton wool spots associated with Retinal Vein Occlusion (RVO) disease. Detection of the lesion in fundus images using a computer can aid in early interventions. Previous studies have employed image-processing techniques and feature engineering approaches to identify features from regular images and construct machine learning models. There are limited studies on using Ultra-widefield (UWF) fundus images for machine learning owing to the lack of gold-standard datasets. In addition, it investigates the efficacy of prediction models trained with regular images in predicting RVO symptoms in UWF images. This study employed a deep learning approach to detect RVO lesions and subsequently used them to construct a classifier. We leveraged regular fundus images for lesion segmentation due to the limited availability of public UWF datasets and compared their effectiveness with a segmentation model trained solely on UWF images. Our results found that the segmentation model trained on regular fundus images is less effective in detecting haemorrhages and cotton wool spots in UWF images. Finally, we found that the lesion regions work perfectly in building a classifier that can discriminate between RVO and non-RVO fundus images.**

***Keywords*—U-Net image segmentation, retinal vein occlusion, retinal fundus screening, deep learning**

I. Introduction

Retinal vein occlusion (RVO) is a retinal disease that can result in visual impairments and blindness if left untreated. RVO occurs when there is a disruption in the blood flow in the retinal veins due to retinal vein hardening and blood clotting [1]. Retinal imaging is a standard method for screening, monitoring, and diagnosing RVO. A specialised retinal fundus camera can capture detailed retina images that can reveal signs of RVO, such as haemorrhages and cotton wool spots [2]. Fundus images can be categorised into two categories according to the image view angle of a retina. A regular fundus image has a view angle of up to 75º, while an ultra-widefield (UWF) image has up to 200º view of the retina. Figure 1 illustrates an example of a regular and a UWF retinal fundus image.

[2,4]Corresponding authors

Computer approaches can rapidly detect signs associated with different diseases in fundus images. Feature engineering techniques have been utilised to construct discriminative features from the fundus images for classifier learning [3]. In recent years, deep-learning neural networks have become popular for learning fundus images due to their effective learning ability. For example, convolutional neural networks (CNN) have been used to classify retinal diseases such as diabetic retinopathy and branch retinal vein occlusion (BRVO). [4] achieved an accuracy of 97.08% in classifying regular fundus images into five grades of diabetic retinopathy (DR) using a CNN model and the EyePACS public dataset. [5] employed pre-trained Inception-V3 identified healthy and DR cases on regular fundus images achieving an accuracy of 90.90%. [6] performed classification of UWF fundus images into BRVO using VGG-16 architecture with pre-trained weights and achieved a sensitivity of 94.0%. [7] constructed a classifier utilising a pre-trained DenseNet121 and the UWF dataset to predict DR, RVO, sickle cell retinopathy, and healthy cases with an overall accuracy of 88.40%.

A fundus image has a large area of background pixels, therefore, effective image denoising is critical to a classifier's successful learning of disease signs. Image processing techniques have been employed to remove background pixels before further processing. For example, the Gaussian and median filters are known for identifying noise with neighbouring information [8].

Image segmentation is another common technique to identify the pixels of objects of interest within an image from the background pixels. The U-Net architecture [9] is developed specifically for biomedical image segmentation tasks. The architecture of U-Net has an encoder, a decoder, and a bottleneck. The encoder, the contracting path, is responsible for the feature extraction process. The contracting path