Using a modified U-net model to improve Retinal Vessel Segmentation

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1 Abstract

AI applications in healthcare have broad and exciting prospects, especially in medical image segmentation where AI has proved it can do a better job than human beings in specific tasks. In this project, we apply a U-net model to complete the retinal vessel segmentation task and compare the results with the morphology method which is a classical automatic segmentation technique. Besides, we also make an attempt at data enhancement in morphology methods to explore the importance of data preprocessing in digital image processing. The result shows that the U-net model produces better outcomes than the morphology method according to most of the evaluation criteria. However, data enhancement in morphology does not show significant differences from the original.

Keywords:medical image,u-net,retinal segmentation.

2 Project Results

2.1 Introduction

Diabetic retinopathy (DR) is one of the main causes of vision loss. Approximately 35% of patients with diabetes mellitus suffer from DR [Yau et al., 2012]. For DR patients, high blood sugar prevents blood flow to the small arteries, which form new arteries in the retina. These new arteries cannot grow normally and readily leak resulting in loss of vision [Khandouzi et al., 2022]. Retinal vessel segmentation (RVS) is a method for the identification of ophthalmic vessels from eye fundus images whereby abnormal arteries can be easily detected. However, it is time-consuming for experts to pick out the new vessels manually. Classic and deep learning (DL) methods are the two mainstream ways of freeing the hands of experts, and some aspects of these can achieve high accuracy. For classic methods, there are some methodologies and filters such as mathematical morphology, holomorphic, and Gaussian filters that can be utilized to segment blood vessels in eye fundus image[Ramos-Soto et al., 2021]. For DL methods, the U-net model has become the most popular model in recent years thanks to its high accuracy and processing speed [Khandouzi et al., 2022].

In this project, we selected a classic method based on mathematical morphology and a deep learning method based on the U-net model to finish the task of RVS. Due to time limits, we only selected one dataset, DRIVE, to train and test our method and model on.

2.2 Methods

2.2.1 Classic method based on morphology

The classic method we use is based on [Ramos-Soto et al., 2021]. The method is divided into three parts, image preprocessing, vessel segmentation, and postprocessing. In addition, we applied the limited contrast adaptive histogram equalization (CLAHE) method [Reza, 2004] in the preprocessing stage to enhance image contrast.

In the preprocessing stage, the green image channel is extracted as a grey-scale image. A Gaussian filter is utilized to make the image more smooth and remove noise in the image. Innovatively, we applied CLAHE to process the original green channel image to enhance the image contrast.

The process of vessel segmentation was separated into two parts, the segmentation of a thick vessel and the segmentation of a thin vessel. There are several algorithms and filters that were utilized in this process. The optimized top-hat algorithm was used to obtain a bright blood vessel from a grey-scale image with dark background [Mendonca and Campilho, 2006]. The application of a homomorphic filter diminished the low-frequency signal and strengthens the high-frequency intensities of the image signal [Roberts and Mullis, 1987]. A median filter was used to remove the salt and pepper noise generated in the previous stages. A matched filter was utilized to find linear segments of blood vessels in the eye fundus image [Chaudhuri et al., 1989]. Minimum Cross-Entropy Thresholding - Harris Hawks Optimization (MCET-HHO) was utilized to make the intensity level of pixels in the image simplified [Rodríguez-Esparza et al., 2020]. Among these algorithms and filters, the optimized top-hat and homomorphic filters were applied to both thick and thin vessel segmentation. A median filter was only utilized in thick vessel segmentation. A matched filter and MCET-HHO were utilized in thin vessel segmentation. The difference in the methods used for the two segmentations is due to the different pixel occupations of the two kinds of vessels.

At the stage of postprocessing, some morphological methods such as the dilate, erode, and connectivity tests were utilized to remove small unnecessary elements and noise generated by previous stages. Otsu [Otsu, 1979] is a method that selects a threshold to transform a probability map into a binary image, which makes the boundary of the blood vessel become more obvious.

2.2.2 Modified U- net model

U-net, which was originally developed for medical image segmentation, has become a popular deep-learning network in recent years in receiving high accuracy with little demand for samples. The U-net architecture includes a "U" shape encoding and decoding path which aims to capture context and precisely locate objects, respectively [Ronneberger et al., 2015]. According to [Asiri et al., 2019], many RVSs based on U-net/modified U-net architecture produce satisfying results. In this project, we made slight changes (marked in red bounded boxes) to the original traditional U-net (Fig 1, changing the transposed convolution of the original upsampling layer to bilinear interpolation, and using the dice loss function [Soomro et al., 2018], which is popular in the field of semantic segmentation [Assad and Kiczales, 2020, Yeung et al., 2022], to calculate the loss of the network.

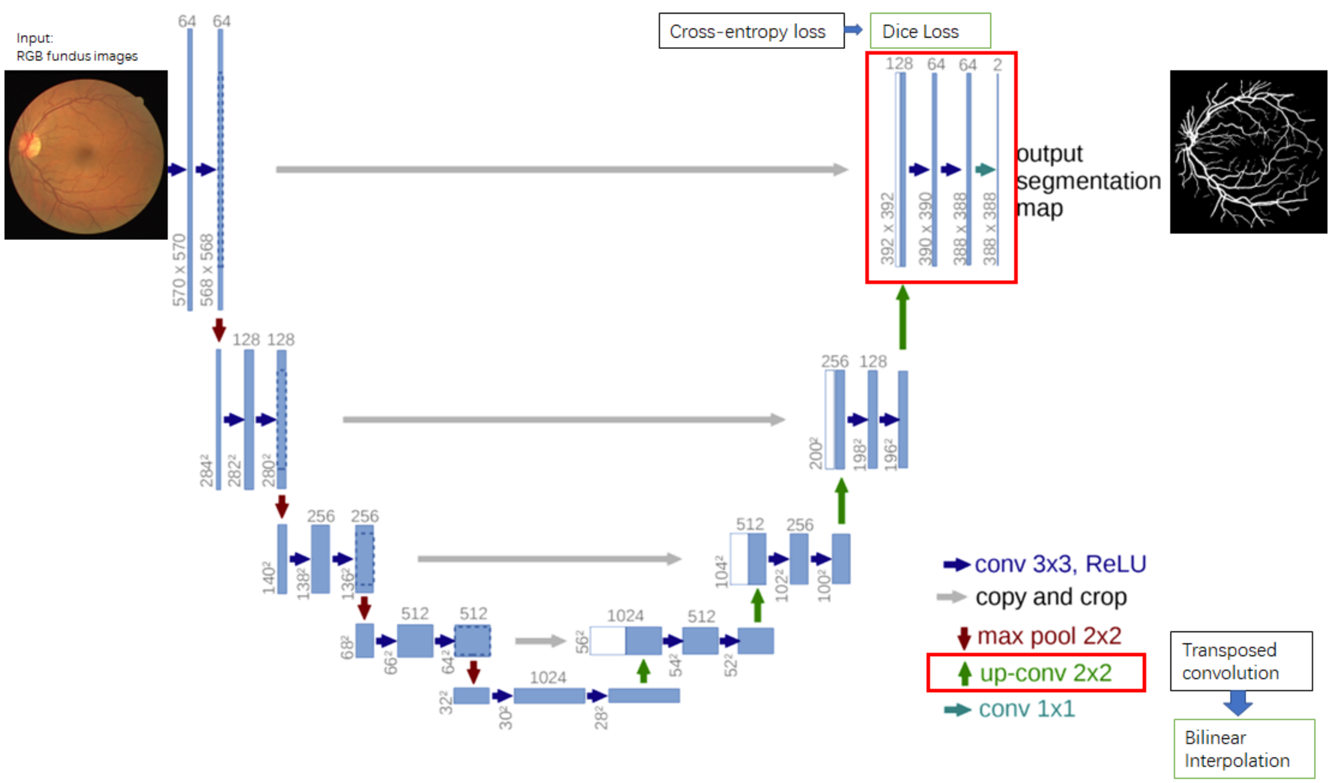
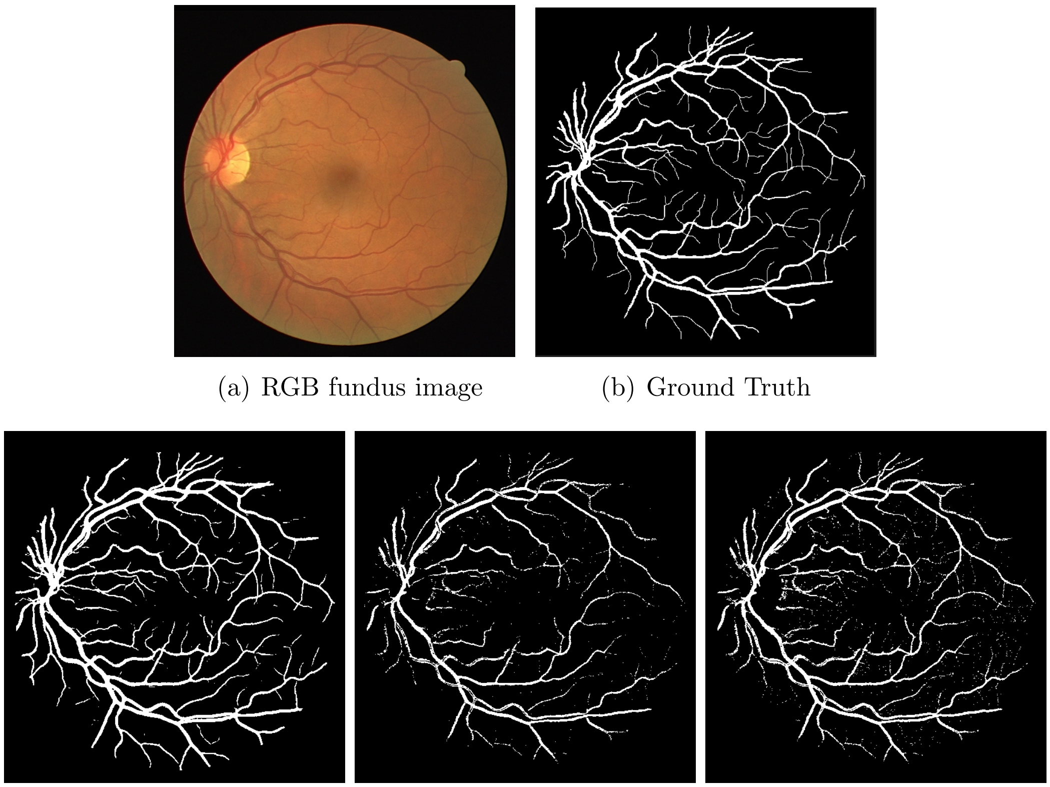


Figure 1: Modified U-net

2.3 Results

We trained and tested the U-net model and morphology method with a DRIVE dataset which included 40 labeled images of healthy and DR retinas. The segmented images we received from the U-net model and morphology methods are shown in Fig 2.



(a) RGB fundus image (b) Ground Truth

(c) U-net (d) Morph original (e) Morph Enhanced

Figure 2: Segmentation results of different methods

Compared with the ground truth, U-net has a better performance than the morphology method, especially in segmenting thin vessels. In addition, comparing the original data preprocessing with the enhanced one in the morphology method, the enhanced one somehow does better than the original one in segmenting thin vessels, although it brings in more noise.

We introduce several factors and assessing criteria [Khandouzi et al., 2022] to make better comparisons.

First, we present 4 factors: True Positive (TP), False Positive (FP), True Negative (TN), and False Negative (FN). TP is the number of pixels that belongs to vessels and is classified as vessels. FP is the number of pixels that are predicted as vessels but actually belong to the background. Similarly, TN is the number of pixels that are truly classified as the background. FN is the number of pixels that belong to the background while wrongfully predicted as vessels.

Then we introduce several criteria which are operated by those factors.
(a). Accuracy: The rate whereby pixels are truly classified.

$$Accuracy = \frac{(TP + TN)}{P + N}$$

(b). Sensitivity: The rate of well-classified vessel pixels conditioned on all vessel pixels.

$$Sensitivity = \frac{TP}{(TP + TN)}$$

(c). Specificity: The rate of well-classified background pixels conditioned on all background pixels.

$$Specificity = \frac{TN}{(TN + FP)}$$

(d). Dice-Coefficient: The similarity between the ground truth and the predicted segmentation.

$$Dice - Coefficient = \frac{2TP}{(2TP + FP + FN)}$$

(e). IoU: The overlapping degree between the ground truth and the predicted segmentation.

$$IoU = \frac{TP}{(TP + FP + FN)}$$

	Accuracy	Sensitivity	Specificity	Dice-Coefficient	IoU
U-net	0.9524	0.8178	0.9728	0.8139	0.6867
Morph original	0.9211	0.5431	0.9880	0.6653	0.4999
Morph Enhanced	0.9248	0.6025	0.9722	0.6685	0.5141

Table 1: Evaluation of segmentations for different methods

The evaluation of the segmentations is shown in Table 1. It is obvious that the accuracy of the U-net model is 3% better than the accuracy of the morphology method. Although the two methods have similar specificity, the U-net model achieves an outstanding sensitivity rate of about 81%, indicating that the U-net model is good at classifying vessel pixels. The Dice-coefficient and IoU rate are also significantly improved by 15% to 20%, which means that the segmentation result of the U-net model is much closer to the ground truth than the morphology method.

In conclusion, the U-net model performs better than the morphology method in the retinal vessel segmentation task, especially in predicting thin vessels.

2.4 Project Limitation

Homogeneity of the data set

In this project, due to time constraints, we did not cross-train and mix-test our network on multiple datasets. Although, after discussion, we understood the characteristics of each dataset and chose the DRIVE dataset (specifically collected for the study of DR), the amount of data in it was not sufficient. Therefore objectively the results obtained (such as accuracy and IoU) are not sufficiently rigorous and generalisable.

Limitations of the network itself

Although the U-net method has good semantic segmentation properties and is widely used for medical lesion segmentation, and we have made some minor modifications to the original U-net structure (such as changing the transposed convolution of the up-sampling layer to bilinear interpolation) to make it more compatible with the popular segmentation algorithms currently available, the final vascular segmentation results still have shortcomings. For example, a portion of the retina vessels with more branching cannot be clearly segmented and appears as discontinuous smooth dotted lines.

Failure to better address research gaps in the field of retinal vessel segmentation

Retinal vascular segmentation is a relatively well-established research topic in the medical field, but there are still many problems that have not been well resolved. For example, the probability map is slightly influenced by the presence of the lesions. In this project, we were not able to consider how best to remove the effects of other lesions in the eye (such as microvascular nodules) on the segmentation of the retinal vessels.

2.5 Discussion: Expansion to AI application

The application of AI in the medical field has become a research hotspot in recent years. We can see AI taking its part and performing satisfactory jobs in surgery, medical image processing, voice recognition, and risk assessment of disease [Park et al., 2020]. However, as a newly emerging technology, the development of AI still faces some challenges. For example, some people worry about explainability. AI generates different solutions in a black-box way that lack sufficient interpretability and transparency. Therefore, whether the results are reliable is unpredictable [Han and Liu, 2021]. In our opinion, another serious concern about AI is data privacy and security. The legality, facticity, and accuracy of training data pose huge challenges to the effective use of AI. We also think there is risk in the division of accountability. Although AI can perform better than humans in some specific tasks, we still need to reserve the final decision to human doctors rather than transfer all responsibility to AI. Who is responsible for a wrongful result given by AI is a question that is far from conclusive and needs to be discussed in the AI era.

In our submission, to improve AI applications in the biomedical field, the accuracy of task completion, data security, and the ethical problem should all be considered.

2.6 Conclusion

In this project, we started with a plan to use the joint loss function [Yan et al., 2018] for the U-net method but later changed to a simpler algorithm [Soomro et al., 2018] to make minor changes to the network to segment the retinal vessels in the DRIVE dataset, achieving good segmentation results. The fact that we had to change the algorithm in the middle of the project due to some technical problems that were difficult to solve in a short period of time shows that we are not yet fully aware of the risks involved, but also improves our ability to tackle unexpected situations. Based on the U-net segmentation, we decided to add a set of results from the mathematical morphology method of segmenting retinal vessels. The comparison of the two segmentation methods gave us a clearer understanding of the strengths and potential of DL in conducting retinal vessel segmentation, as well as the advantages of the traditional mathematical morphology method being faster and less code-intensive, broadening our understanding of the field. In future in-depth investigations, we hope to improve our programming skills and conduct further investigations using the method chosen at the outset, while focusing on proposing certain solutions to the limitations mentioned earlier.

3 Project skills

3.1 Detail contributions of individuals to the project

The actual project progressed with a detailed division of work, which is detailed in the table below. (Table 2) The green cells indicate the parts that were done together, and the other coloured cells represent the different tasks that different members focused on.

	Literature reading	**Proposal & Report**	**Mathematical Morphology**	**Network training & testing**	**Result assessment**	**AI discussion**
Minnie						
Severin						
Sarah						
Priya						
Gloria						

Table 2: Detail Contribution

Although most of the time we conducted the specific tasks allocated to each person, we would send our work onto the group Trello board so that all of the group members could learn and understand every part of the project from coding to AI discussion.

3.2 Challenges

During the project time, we encountered some problems that blocked our progress. None of our group members had experience in Python programming. Therefore, it was difficult for us to understand the meaning of the code and how the code is run.

Initially, we adopted the U-net model with a joint loss function [Yan et al., 2018]. The code was been downloaded from GitHub, and a great deal of research has been done on joint loss function. However, the required programming environment is Caffe which was difficult to configure since it needs to be installed on a virtual machine. We were unable to build a complete environment for this code after a few days of hard work. Realizing the original plan was not feasible, we turned to another plan that achieved the goal of retinal vessel segmentation with Pytorch [Soomro et al., 2018] after a long discussion. Additionally, a classical method based on mathematical morphology [Ramos-Soto et al., 2021] run in MATLAB was added to our project as a comparison with the deep learning method to enrich our results.

3.3 Project Management

In response to the challenges we have mentioned above, we proposed the following project management solution, which was adapted to the current situation as the project continued to progress.

In the early stages of the project, to make up for our lack of knowledge of machine learning and deep learning algorithms, we not only arranged for each member of the group to read the project literature but also required each of us to do additional learning on the methods we were using (including algorithms and programming techniques). As we continued to learn more about the algorithms and the characteristics of the datasets, we realised the time constraints and adjusted our plans appropriately, such as simplifying the evaluation of the results and selecting datasets that were more relevant to the research topic.

In the middle stages of the project, we encountered mainly technical problems with the configuration of the programming environment and debugging of the code. After several days of trying to solve some tricky code, and given the time constraints, we decided to temporarily adjust the basic framework of the network with a simpler and more feasible algorithm without changing it. To increase our understanding of the topic, we decided to add a contrasting result: retinal vessel segmentation using the traditional mathematical morphology method. The timely project management adjustment not only allowed us to obtain the expected vascular segmentation results on time but also somewhat deepened our understanding of the classical and deep learning methods.

In the latter stages of the project, we focused on a numerical evaluation of the results obtained, while communication with the group was intensified to ensure that all could fully understand the important adjustments made in the middle of the project and the changes in the overall project structure.
To visualise the role of project management in the 3 main stages, we have drawn up the flow chart below. (Figure 3)

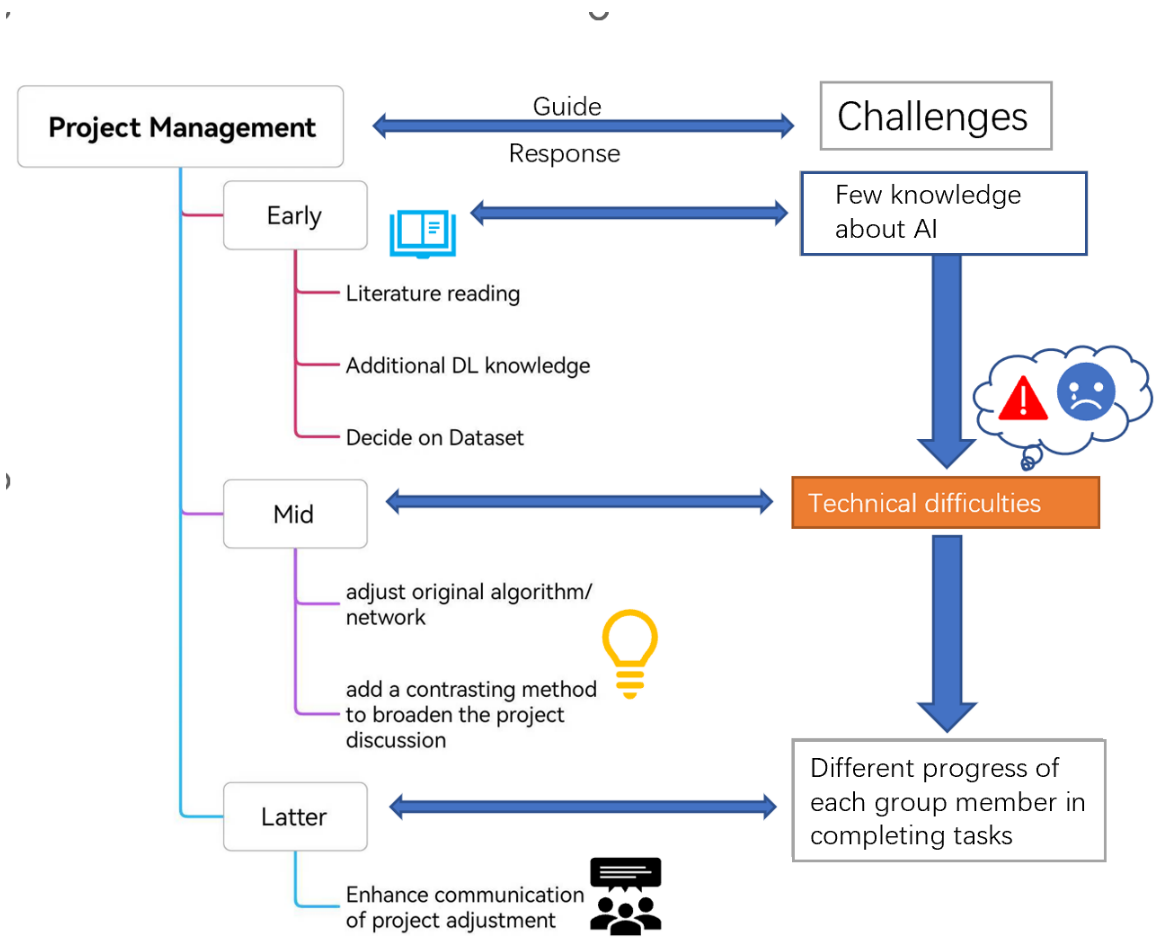


Figure 3: Project Management & Challenges

Our group adopted a project management approach in which challenges guide responses. Throughout the project, we insisted on adjusting the plan for each phase of the project according to the actual situation, conducting group meetings for different challenges in the 3 phases and adjusting the plan in time, successfully avoiding a series of problems, such as not being able to produce the experiment results on time with poor communication.

Author contribution
Conceptualization: Z.W, J.H, H.Z, Z.G and X.G.
Methodology implementation, validation: Z.W and J.H.
Experimental data collation and analysis: H.Z.
Writing–original draft preparation, visualization: Z.W, J.H, H.Z, Z.G, and X.G.
Writing—-review and editing, visualization, supervision: Z.W, J.H, and H.Z.
Project administration: Z.W, J.H, and H.Z.

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Ethical principles were followed according to the guidelines of Cambridge University.

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.
Data Availability: Please contact the corresponding author for all reasonable requests for access to the data.
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Conflicts of Interest: The authors declare no conflict of interest.
Intellectual Property: The authors attest that copyright belongs to them, the article has not been published elsewhere, and there is no infringement of any intellectual property rights as far as they are aware.

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