A Segmentation Scheme For Robust Iris Based On Improved U-Net

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Abstract: The reliance of the iris recognition system on high-quality iris segmentation creates a strong foundation for future iris recognition research and greatly improves the efficiency of iris identification. By using the same datasets for training and testing, we were able to obtain the top network model, FD-UNet. This network architecture combines elements from U-Net and four others that have proven effective. By switching from original convolution to dilated convolution, the FD-UNet improves picture processing by extracting more global features. Datasets such as UBIRIS.v2 for visible light illumination, CASIA-iris-interval-v4.0 and ND-IRIS-0405 for near-infrared illumination, and others were utilised to evaluate the proposed method. Our model hit f1 scores of 97.36%, 96.74%, and 94.81% on the CASIA-iris-interval-v4.0, ND-IRIS-0405, and UBIRIS.v2 datasets, respectively. Our network model outperforms the competition with a reduced error rate, according to the trial data. It is quite reliable and performs admirably with iris datasets that use both visible light and near-infrared lighting.

Keywords: FD-UNet, Iris segmentation, UBIRIS.v2, CASIA-iris-interval-v4.0, ND-IRIS-0405

1 Introduction

As information technology advances, so does the significance and challenge of identity recognition. Traditional identifying methods like identity cards and passwords are no longer appropriate for usage in today's culture due to their flaws, which include being simple to lose, counterfeit, crack, etc. Biometric identification has become more and more common in recent years because to its numerous positive attributes, such as stability, ease of use, and difficulty in forging. It also makes it easier to integrate computer systems with management, security, and monitoring systems, which makes autonomous management possible. Traditional biometrics include fingerprints, voiceprints, facial traits, and handwriting. However, these outdated biometric systems include vulnerabilities that could result in hidden losses or even irreversible damage for the protected. The security, ease, and efficiency of people's life could all be enhanced by biometric technology based on iris texture.

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2 Literature Review

The five main steps of most iris recognition systems include preprocessing, collecting the iris image, dividing it, extracting features, and finally confirming or detecting a match. An essential part of iris recognition is accurate iris segmentation. One easy method to make the iris recognition system more accurate is to use the correct part of the iris to extract data. An autonomous iris segmentation method based on U-Net is presented in this work. Ground truth images and standard datasets are used to train and test the approach. Through testing on four datasets, we found that our network model delivers exceptional accuracy in iris segmentation. The following are our primary contributions and innovations:

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1. To segment iris photos, a new network model is proposed that combines U-Net with dilated convolution. An improvement in segmentation can be achieved by integrating dilated convolution with image feature extraction.
2. Using the identical training and testing datasets, we prove that FD-UNet is the best network model and present four new, practical network strategies.
3. FD-UNet achieves superior performance compared to the other networks on the iris datasets for both visible light illumination and near-infrared illumination.

The remainder of the paper is organised as follows: Section 2 examines the literature on iris segmentation, which includes both classic and modern deep learning techniques. In Section 3, four different network representations are shown. The methodology, datasets, and outcomes of our experiment are described in Section 4. In order to find out how effective our strategy is, Section 5 compares and contrasts it with others.

3 Methodology

This study uses convolution and pooling layers in place of UNET to improve the author's previous work. While the author's earlier work mostly relied on convolution and pooling layers, which reduced the quality of the picture features, this will produce segmented images that are more accurate. The matching up-sampling process in the U-Net contraction approach re-enlarges the image after the pool operation reduces its size, albeit with some information lost. A Part Dilated Convolution that combines U-Net (PD-UNET) with four distinct modifications is one potential solution to this problem.
The creator of Fully Dilated Network adds a dilated rate to all but one of the UNET layers to make up for the feature loss. As a result, the model can operate as intended.

ALGORITHMS

UNET algorithm

We require an improved method to acquire segmented images because the present UNET strategy is dependent entirely on convolution and pooling layers, which degrade the picture feature quality. The up-sampling technique brings the image back to its former size, albeit with some lost detail, after the pool operation of the U-Net contraction path reduces its size.

SEGNET with Attention algorithm

This algorithm is superior to UNET and it's giving better segmentation training F-SCORE compare to all algorithms

Architecture

Hybrid Dilated U-Net

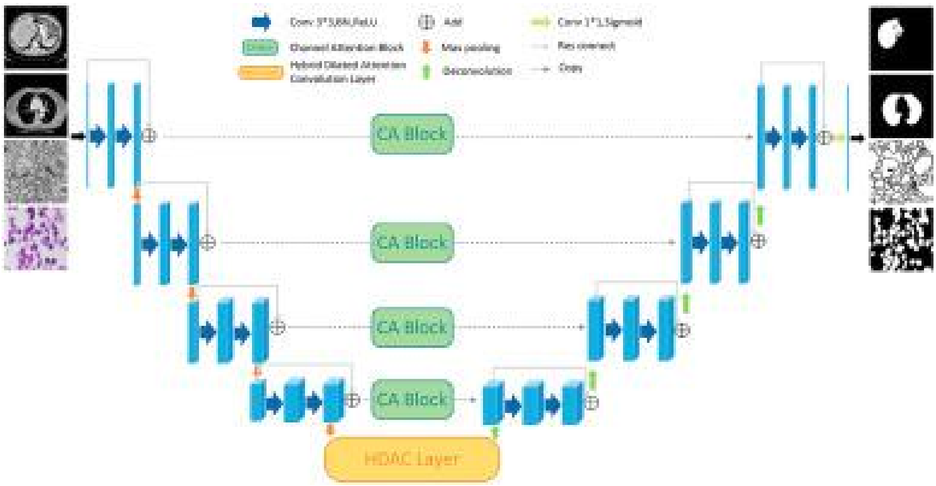
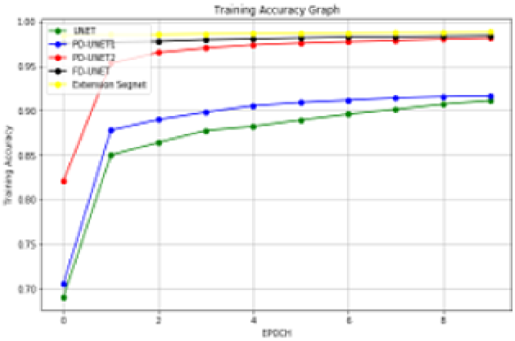


Fig. 1. Hybrid Dilated U-Net(https://ars.els-cdn.com/content/image/1-s2.0-S0010482521002432-ga1.jpg)

4 Results and Discussions

The graph illustrates the training accuracy trajectories for several neural network architectures specifically designed for image segmentation tasks. The models evaluated include the standard UNET, two variations of PD-UNET (denoted as PD-UNET1 and PD-UNET2), FD-UNET, and an Extension Segnet. The PD-UNET2 and FD-UNET models exhibit superior performance, achieving near-perfect training accuracy (close to 100%) within the initial epochs. This rapid convergence suggests that both PD-UNET2 and FD-UNET are highly effective at learning the training data, potentially due to enhancements in their network architecture that facilitate better feature extraction and representation. The Extension Segnet also demonstrates high training accuracy, paralleling the performance of PD-UNET2 and FD-UNET. However, it starts with a slightly lower initial accuracy, indicating a slower start but quickly catching up in subsequent epochs. The PD-UNET1 model shows a steady improvement in training accuracy, reaching approximately 95% by the end of the training period. While it doesn't match the top-performing models, PD-UNET1 still outperforms the base UNET model significantly. The standard UNET model shows the slowest improvement in training accuracy. By the end of the training epochs, it stabilizes around 90%, indicating that while it is effective, it is less capable of achieving the same high levels of accuracy as the other models within the same number of epochs. The observed differences in training accuracy suggest that the modifications and enhancements in PD-UNET2, FD-UNET, and Extension Segnet architectures provide substantial benefits over the standard UNET and its first variation, PD-UNET1. These enhancements likely include more sophisticated layers or mechanisms for capturing complex patterns in the data, thus leading to better performance in image segmentation tasks.This comparison underscores the importance of architectural innovations in neural networks for image segmentation. The results indicate that while the base UNET model provides a solid foundation, significant improvements can be achieved through targeted modifications, as evidenced by the performance of PD-UNET2, FD-UNET, and Extension Segnet. These findings highlight the potential for these advanced models to be more effective in practical applications where high accuracy is crucial.



Graph 2. Training Accuracy Graph of Different Algorithms

5 Conclusion

An essential part of iris identification systems is iris segmentation. To make iris segmentation more accurate, we provide a more exact method that can achieve end-to-end iris segmentation. Using the dilated convolution, U-Net can provide better results and precision in iris segmentation. This strategy allows for the simultaneous collection of more details and the extraction of more information from the photos.Three separate iris datasets with varied amounts of visible and near-infrared light are used to train and test our network model. The network's performance is evaluated using three industry-standard segmentation ratings.

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