Application of Deep Learning in Latent Fingerprint Enhancement

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INTRODUCTION

Red envelopes are commonly collected as evidence in fraud and theft cases in Taiwan. The coated paper surface of these red envelopes has various patterns, making it difficult to photograph or enhance fingerprints even if they are developed. Poorly photographed or distorted images can significantly impact the Automated Fingerprint Identification System (AFIS).

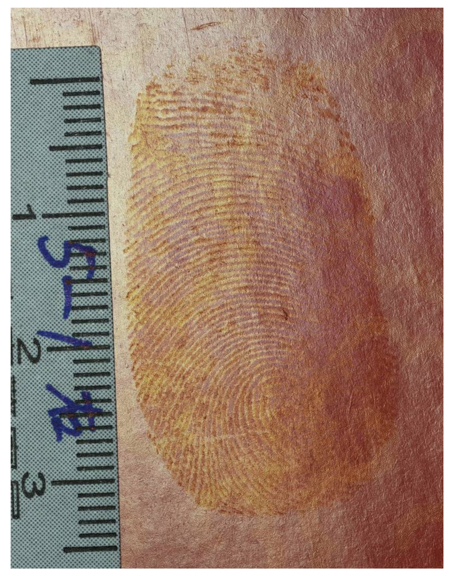

Fig. 1 Fingerprint image on red envelope surface developed by ethyl cyanoacrylate fuming

Traditional manual methods for improving these images are time-consuming and error-prone. Recently, we have applied AI tools, which have garnered interest across various research fields, to enhance and analyze fingerprints, aiming to overcome these existing drawbacks. Fully Convolutional Networks (FCN) and U-Net models were evaluated to enhance fingerprint images. By simulating common fingerprint defects encountered at crime scenes, the study aims to improve the accuracy and efficiency of fingerprint identification.

MATERIALS & METHODS

Data Collection and Preparation of Datasets

Fingerprint images were collected from the internet for the training process. The dataset includes 1,000 incomplete fingerprint images with synthesized backgrounds to simulate the red envelope case scenario. Additionally, fingerprint images developed using ethyl cyanoacrylate fuming on red envelope surfaces are included. Of the collected images, 800 are used for training and 200 are used for testing two deep learning models, FCN and U-Net.

Image Processing

The FCN and U-Net architectures were used for image processing, which consists of Segmentation and Reconstruction stages.

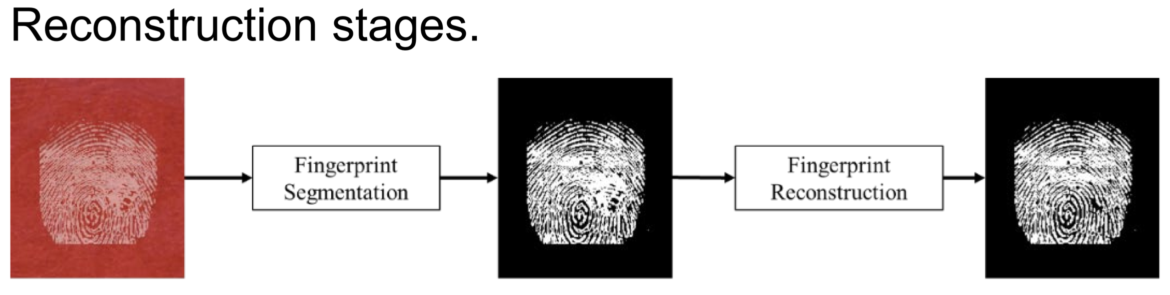

Fig. 2 Image processing stages in deep learning methods

During segmentation, the ground truth image was extracted from the raw image containing background noise and patterns. Reconstruction restores and enhances segmented regions for better quality and completeness.

RESULTS & DISCUSSION

To analyze the results obtained from the U-Net and FCN models, five evaluation indicators were utilized for the segmentation stage, and two indicators were employed to evaluate the reconstruction stage (Table 1).

Table 1

Indicators used to evaluate the image enhancement results

Stage	Evaluation Indicators	Equation
Segmentation	Accuracy	$\frac{TP+TN}{TP+FP+TN+FN} \cdots (1)$
	Specificity	$\frac{TN}{FP+TN} \cdots (2)$
	Sensitivity	$\frac{TP}{TP+FN} \cdots (3)$
	Jaccard Index (JI)	$\frac{TP}{TP+FP+FN} \cdots (4)$
	Dice Similarity Coefficient (DCS)	$\frac{2\times TP}{FP+2\times TP+FN} \cdots (5)$
Reconstruction	Mean Square Error (MSE)	$\frac{1}{n}\sum_{i=1}^{n}(y_i - y_i{}^p)^2 \cdots (6)$
	Mean Absolute Error (MAE)	$\frac{1}{n}\sum_{i=1}^{n}\lvert y_i - y_i{}^p\rvert \cdots (7)$

Table 2

Segmentation Performance of testing datasets for the proposed U-net and FCN

	U-net			FCN		
Depth	4	5	6	4	5	6
Accuracy	0.9952	0.9946	**0.9956**	0.9633	0.9661	0.9617
	(0.0014)	(0.0017)	**(0.0013)**	(0.0119)	(0.0109)	(0.0120)
JI	0.9929	0.9920	**0.9936**	0.9494	0.9524	0.9469
	(0.0021)	(0.0025)	**(0.0019)**	(0.0156)	(0.0149)	(0.0161)
DSC	0.9399	0.9398	**0.9399**	0.9387	0.9386	0.9386
	(0.0119)	(0.0119)	**(0.0119)**	(0.0122)	(0.0122)	(0.0122)
Sensitivity	0.9958	0.9948	**0.9968**	0.9762	0.9747	0.9736
	(0.0015)	(0.0019)	**(0.0013)**	(0.0071)	(0.0082)	(0.0081)
Specificity	0.9904	**0.9927**	0.9861	0.8562	0.8940	0.8629
	(0.0045)	**(0.0032)**	(0.0055)	(0.0602)	(0.0421)	(0.0516)

m(s)*, m is the mean and s is the standard deviation.

Table 3

Reconstruction Performance of testing datasets for the proposed U-net and FCN

	U-net			FCN		
Depth	4	5	6	4	5	6
MSE	0.0077	**0.0060**	0.0061	0.016	0.0272	0.0252
	(0.0030)	**(0.0028)**	(0.0034)	(0.0051)	(0.0085)	(0.0072)
MAE	0.0201	0.0172	**0.0168**	0.0327	0.0456	0.0487
	(0.0064)	(0.0060)	**(0.0059)**	(0.0096)	(0.0133)	(0.0127)

m(s)*, m is the mean and s is the standard deviation.

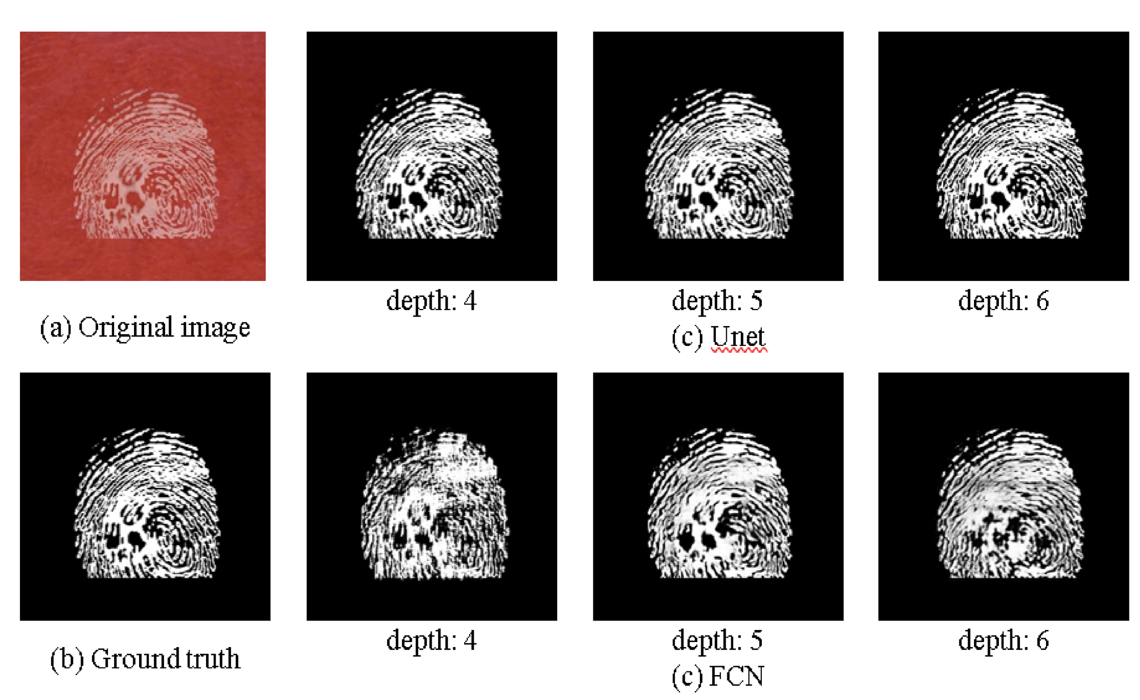

Fig 4. Segmentation results of the single fingerprint on various models

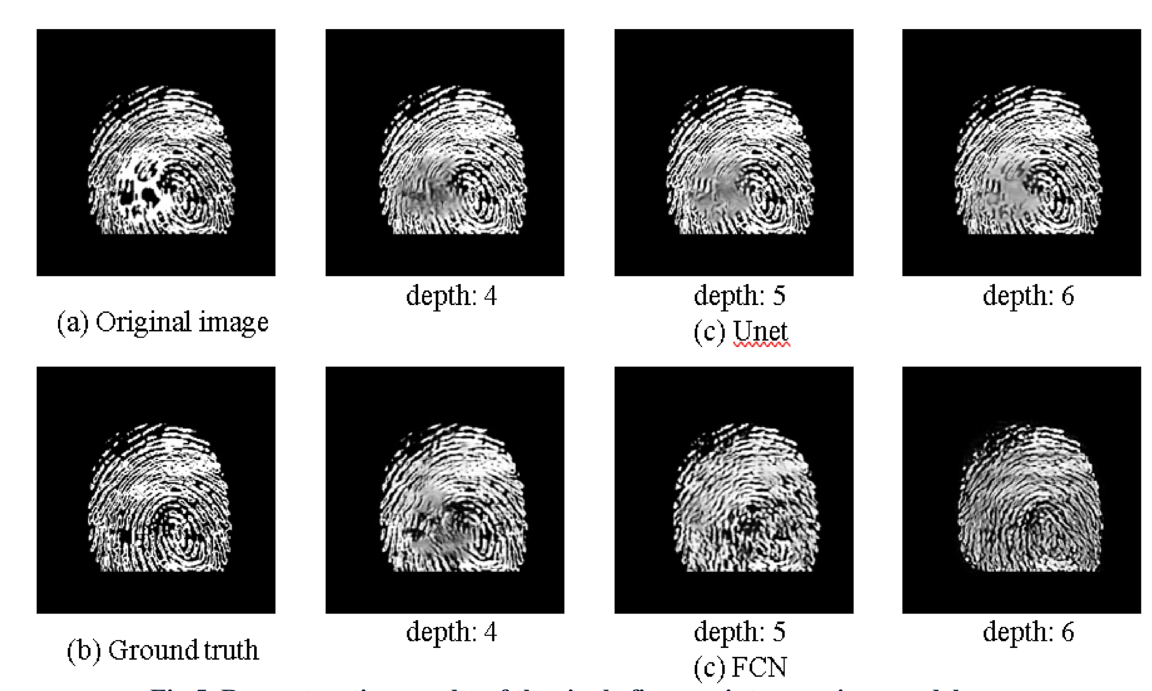

Fig 5. Reconstruction results of the single fingerprint on various models

According to the results, the segmentation metrics for U-Net were superior to those of FCN. For U-Net, the highest values for accuracy, Jaccard Index (JI), Dice Similarity Coefficient (DSC), and sensitivity were observed at a depth of 6, while specificity peaked at a depth of 5 (Table 2). In contrast, the segmentation metrics for FCN generally exhibited the highest values at depth 5. The reconstruction metrics related to error rate, Mean Square Error (MSE), and Mean Absolute Error (MAE) were lower for U-Net (Table 3).

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MATERIALS & METHODS

Segmentation and Reconstruction are closely related to the architectures of FCN and U-net models. U-Net has a U-shaped architecture and uses skip connections between the convolution and deconvolution layers to obtain high-resolution feature maps. FCN extracts important features of the image using convolutional layers (filters). In the pooling layer, important information is summarized, and Max pooling is mainly used (segmentation). Then, through the up-sampling process called deconvolution, the image is restored to its original size (reconstruction).

A single layer that includes the processes of convolution, pooling, and deconvolution is referred to as depth. In this study, various models with different depths were used to find the most efficient depth.

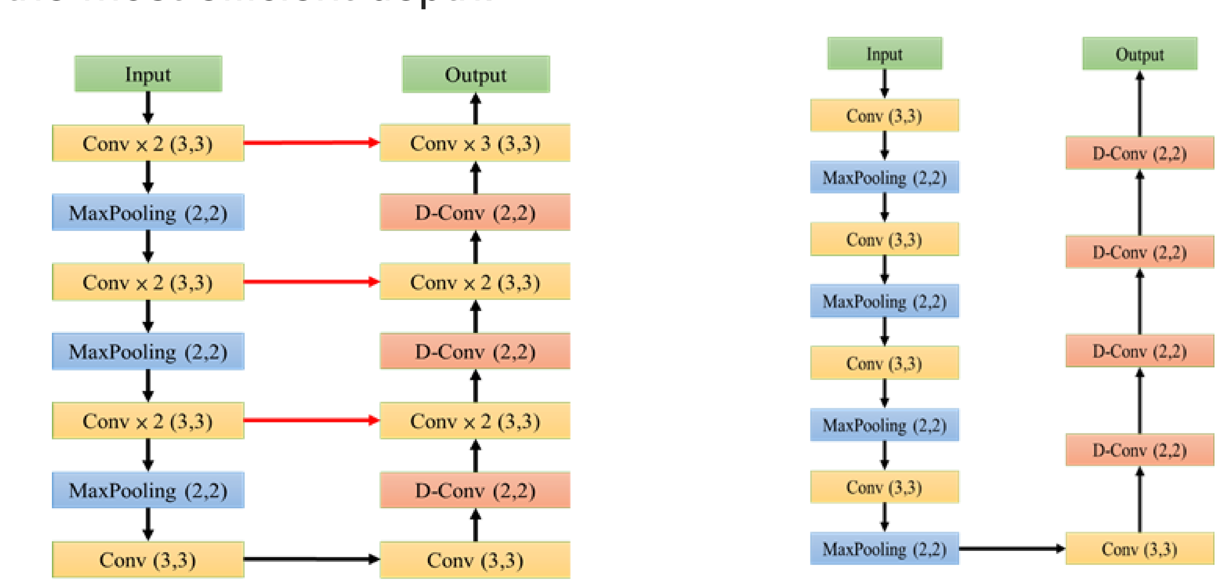

Fig. 3 Architecture diagrams of U-net(left) and FCN(right)

CONCLUSIONS

This study proposed methods using FCN and U-Net to segment and reconstruct fingerprint images.

The experimental results showed that:

- The U-Net model outperformed the FCN model in segmentation performances in all five indicators.
- In the evaluation process for reconstruction, U-Net model demonstrated lower error rate than FCN model in both MSE and MAE.
- The results show deep learning technologies can potentially be used to process traditional physical pattern evidence.

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