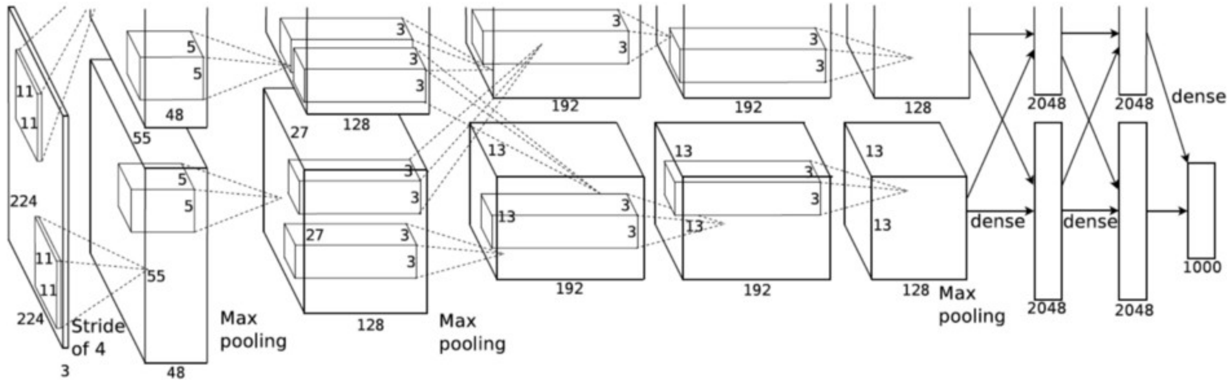


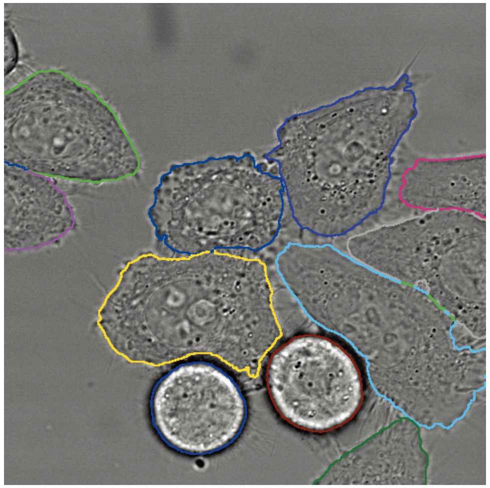
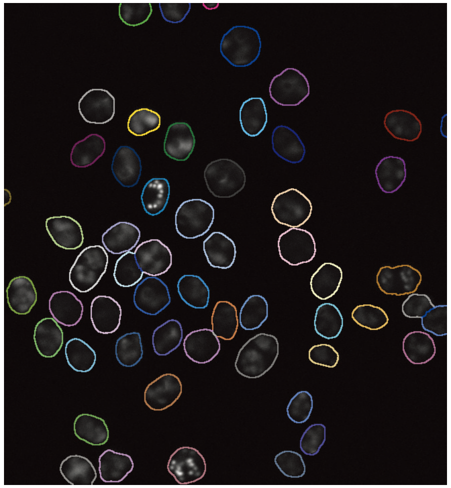
COMP9517: Computer Vision

Applications (Part 2)

Outlines

- Neural Architecture Search (NAS) for Cell Segmentation
- Generative Adversarial Networks (GAN) for Latent Fingerprint Enhancement

NAS for Cell Segmentation


Recap: several CNNs can be used for achieving cell segmentation

- Manually designing is time-consuming and labor-intensive
- Designing a network with excellent performance requires professional knowledge and expertise

NAS for Cell Segmentation

Goal: automatically design a deep neural network for a given task.

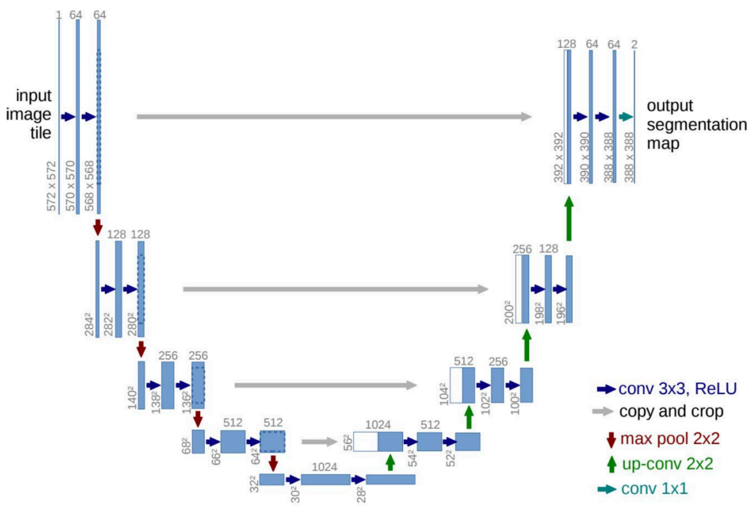
Neural Architecture Search (NAS)

- A subfield of automated machine learning
- Search space: defines which architectures can be searched
- Search strategy: details how to explore the search space
- Performance evaluation: estimates the performance of architectures

NAS for Cell Segmentation

Neural Architecture Search (NAS)

- **Search space**: defines which architectures can be searched
  - The backbone architecture of the outer network
  - The selection of basic operations, e.g., convolution, depthwise-separable convolution, max-pooling, average-pooling, etc.



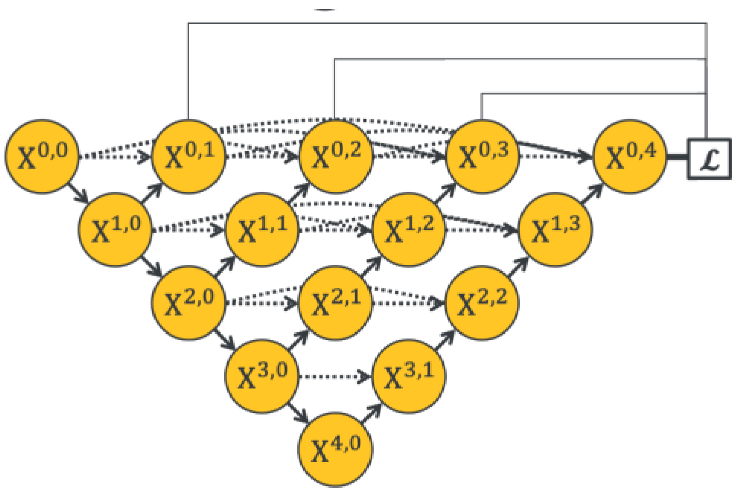


Figure from U-Net: Convolutional Networks for Biomedical Image Segmentation, Ronneberger et al, 2015
UNet++: Redesigning Skip Connections to Exploit Multiscale Features in Image Segmentation, Zhou et al, 2019

NAS for Cell Segmentation

Neural Architecture Search (NAS)

- **Search strategy**: details how to explore the search space
  - Evolutionary algorithms [1]
  - Reinforcement learning based methods [2]
  - Gradient-based methods [3]

[1] Lu, Zhichao, et al. "Nsga-net: neural architecture search using multi-objective genetic algorithm." *Proceedings of the Genetic and Evolutionary Computation Conference*. 2019.

[2] Cai, Han, et al. “Efficient architecture search by network transformation." *Proceedings of the AAAI Conference on Artificial Intelligence*. Vol. 32. No. 1. 2018.

[3] Brock, Andrew, et al. "Smash: one-shot model architecture search through hypernetworks." *arXiv preprint arXiv:1708.05344* (2017).

NAS for Cell Segmentation

Neural Architecture Search (NAS)

- **Performance evaluation**: estimates the performance of the architectures
  - Estimate the performance of the candidate architectures to select an optimal architecture that achieves high predictive performance
  - Evaluate the optimal architecture for final performance

NAS for Cell Segmentation

Search Space

- Backbone architecture

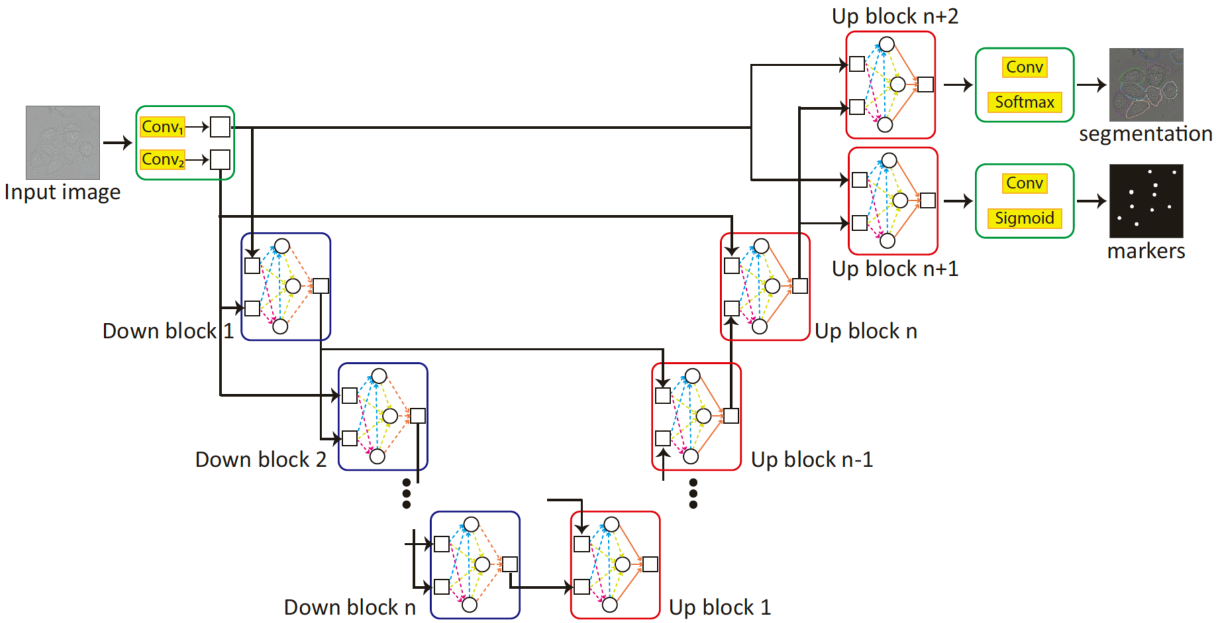


Figure from Automatic Improvement of Deep Learning Based Cell Segmentation in Time-Lapse Microscopy by Neural Architecture Search, Zhu et al, 2021

NAS for Cell Segmentation

Search Space

- Basic operation (BO) sets

BO set type	BO candidates
Temporal (T)	CLSTM
Down (D)	1. max-pooling 2. average-pooling 3. down conv 4. down atrous conv 5. down depthwise-separable conv 6. down squeeze-and-excitation
Up (U)	1. up conv 2. up atrous conv 3. up depthwise-separable conv 4. up squeeze-and-excitation
Normal (N)	1. none 2. identity 3. conv 4. atrous conv 5. shuffle conv 6. depthwise-separable conv 7. squeeze-and-excitation

Figure from Automatic Improvement of Deep Learning Based Cell Segmentation in Time-Lapse Microscopy by Neural Architecture Search, Zhu et al, 2021

NAS for Cell Segmentation

Search Space

- Define the fundamental computing unit (CU)

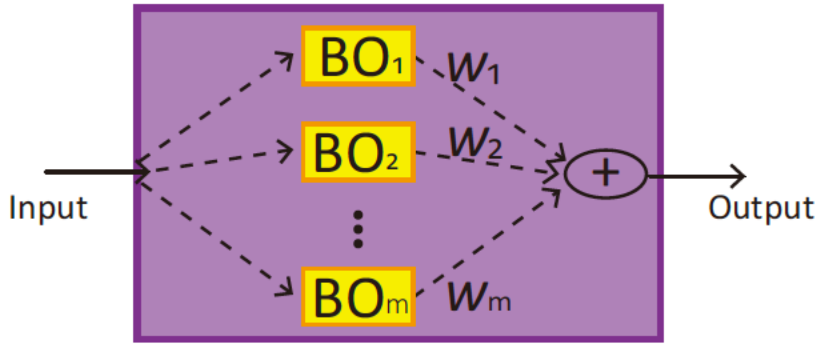
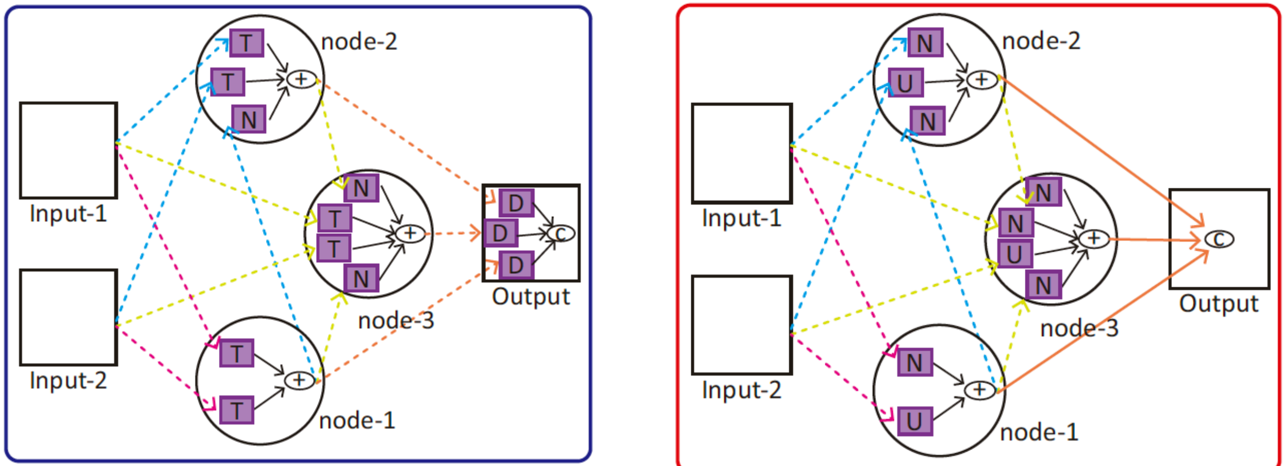


Figure from Automatic Improvement of Deep Learning Based Cell Segmentation in Time-Lapse Microscopy by Neural Architecture Search, Zhu et al, 2021

NAS for Cell Segmentation

Search Space

- Basic block structure



(a) Down block (b) Up block

Figure from Automatic Improvement of Deep Learning Based Cell Segmentation in Time-Lapse Microscopy by Neural Architecture Search, Zhu et al, 2021

NAS for Cell Segmentation

Search Strategy

- Two classes of parameters
- Gradient-based method

Performance estimation strategy

- Evaluate the performance of the architecture candidates without using a standard training and validation process to reduce the computation cost.

NAS for Cell Segmentation

Architecture of the searched network

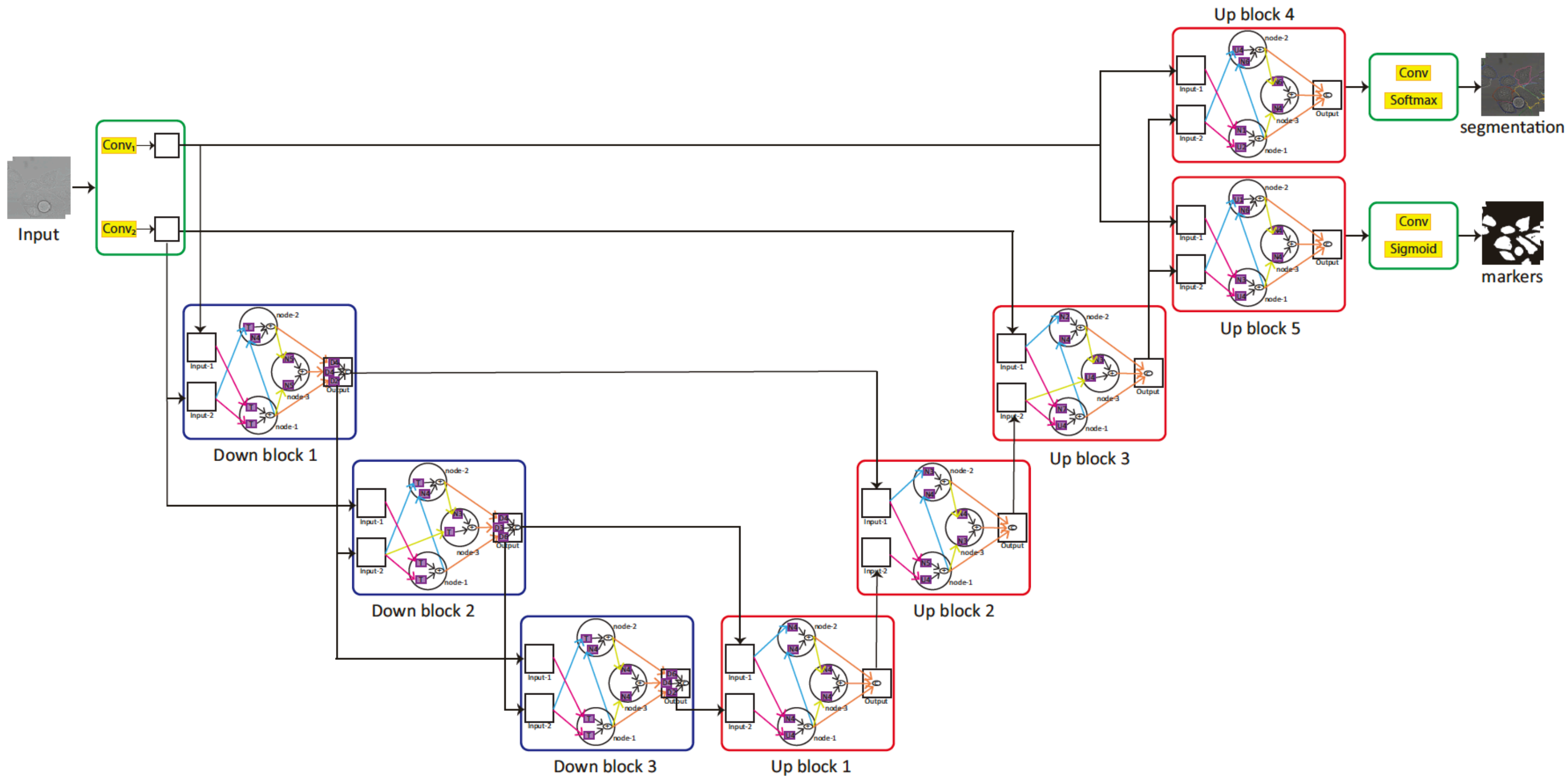


Figure from [Automatic Improvement of Deep Learning Based Cell Segmentation in Time-Lapse Microscopy by Neural Architecture Search, Zhu et al, 2021]()

NAS for Cell Segmentation

Architecture of the searched network

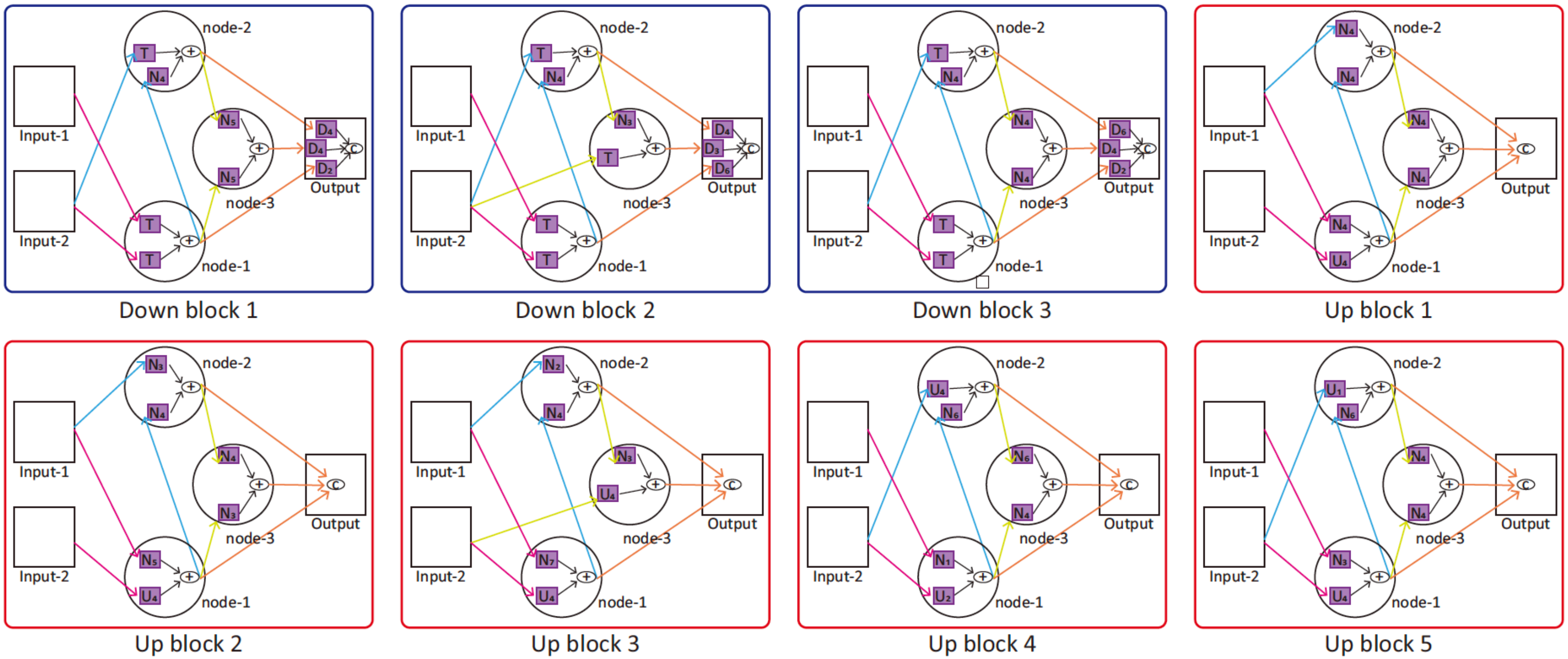


Figure from [Automatic Improvement of Deep Learning Based Cell Segmentation in Time-Lapse Microscopy by Neural Architecture Search, Zhu et al, 2021]

NAS for Cell Segmentation

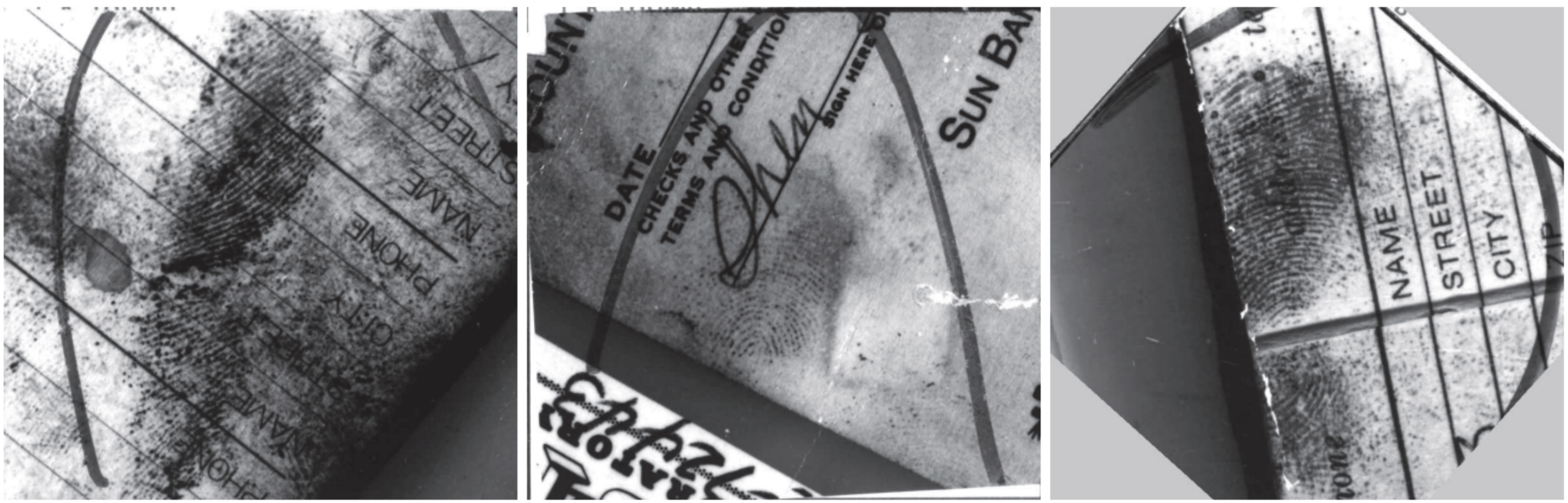
Performance of the searched network

Method / Dataset	State-of-the-Art	Our Networks	
	OP_{CSB} (#); SEG (#); DET (#)	OP_{CSB}; SEG; DET	Ranks / Count
BF-C2DL-HSC	0.905 (1); 0.818 (1); 0.995 (our)	0.893; 0.792; 0.995	3; 3; 1 / 14
BF-C2DL-MuSC	0.878 (1); 0.777 (1); 0.982 (2)	0.805; 0.644; 0.966	10; 11; 6 / 14
DIC-C2DH-HeLa	0.925 (3); 0.870 (3); 0.979 (3)	0.912; 0.863; 0.960	3; 4; 3 / 27
Fluo-C2DL-Huh7	0.843 (our); 0.752 (our); 0.935 (our)	0.843; 0.752; 0.935	1; 1; 1 / 5
Fluo-C2DL-MSC	0.761 (4); 0.687 (our); 0.876 (4)	0.760; 0.687; 0.832	2; 1; 3 / 32
Fluo-N2DH-GOWT1	0.952 (2); 0.938 (5); 0.980 (6)	0.948; 0.933; 0.963	2; 2; 5 / 43
Fluo-N2DH-SIM+	0.905 (7); 0.832 (7); 0.983 (4)	0.887; 0.807; 0.967	5; 6; 10 / 38
Fluo-N2DL-HeLa	0.954 (8); 0.923 (8); 0.994 (1)	0.951; 0.917; 0.984	3; 3; 13 / 41
PhC-C2DH-U373	0.959 (3); 0.927 (3); 0.991 (3)	0.954; 0.927; 0.982	3; 2; 7 / 31
PhC-C2DL-PSC	0.859 (1); 0.743 (1); 0.975 (1)	0.847; 0.733; 0.962	2; 2; 5 / 33

Figure from Automatic Improvement of Deep Learning Based Cell Segmentation in Time-Lapse Microscopy by Neural Architecture Search, Zhu et al, 2021

GAN for Latent Fingerprint Enhancement

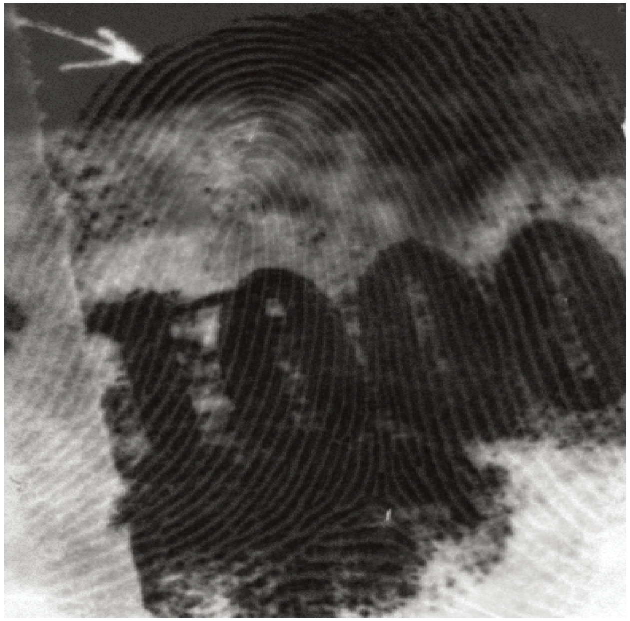
What is latent fingerprint?



Figures from [National Institute of Standards and Technology Database SD27]

GAN for Latent Fingerprint Enhancement

Goal of the latent fingerprint enhancement.



Figures from [FingerGAN: A Constrained Fingerprint Generation Scheme for Latent Fingerprint Enhancement, Zhu et al. 2022]

GAN for Latent Fingerprint Enhancement

Recap: GAN

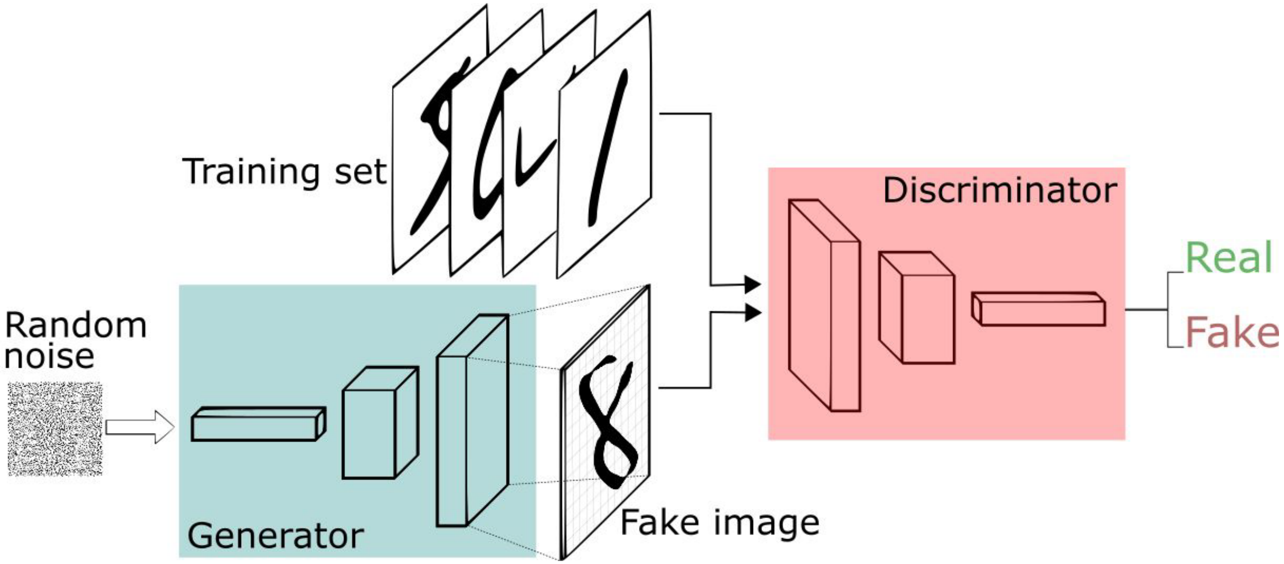


Image from https://wiki.pathmind.com/generative-adversarial-network-gan

GAN for Latent Fingerprint Enhancement

Framework of the FingerGAN

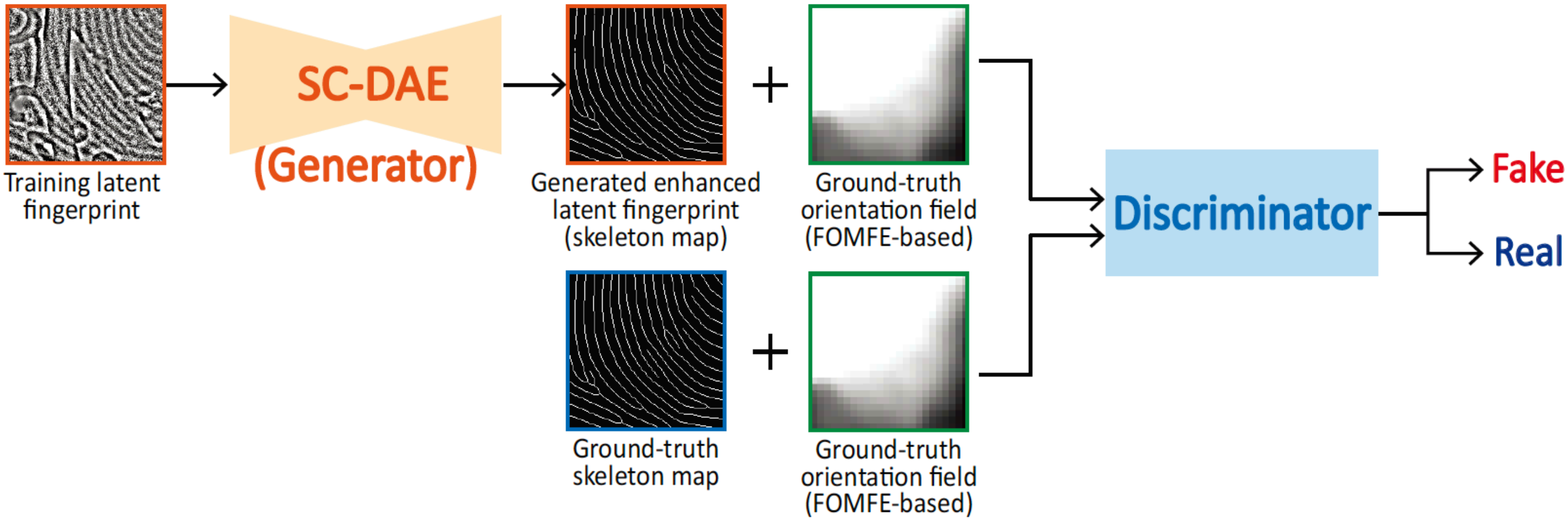


Figure from [FingerGAN: A Constrained Fingerprint Generation Scheme for Latent Fingerprint Enhancement, Zhu et al. 2022]

GAN for Latent Fingerprint Enhancement

Training data generation for the FingerGAN

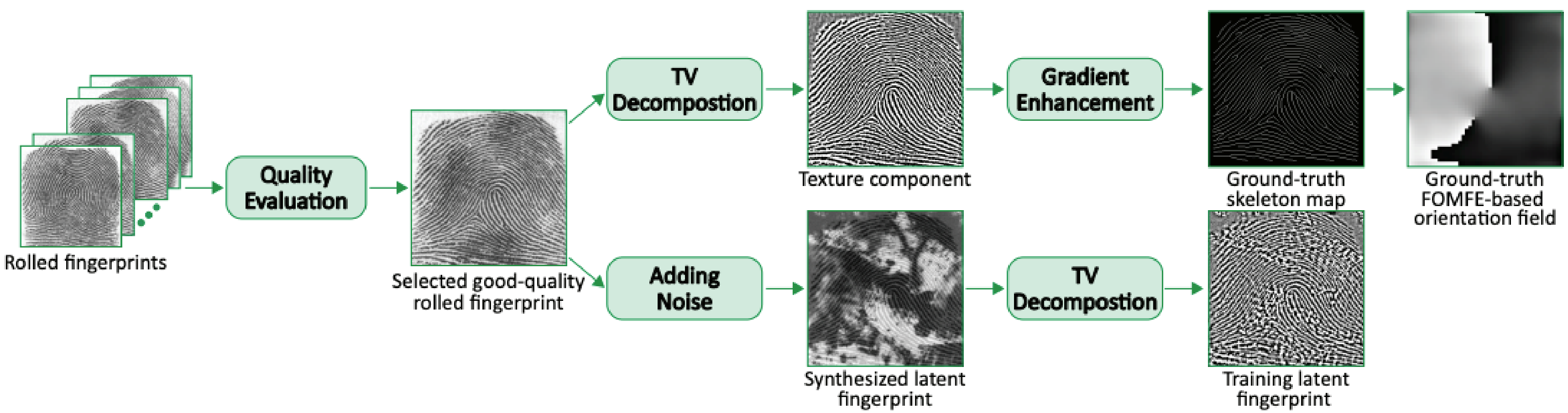


Figure from [FingerGAN: A Constrained Fingerprint Generation Scheme for Latent Fingerprint Enhancement, Zhu et al. 2022]

GAN for Latent Fingerprint Enhancement

Detailed architecture of the FingerGAN

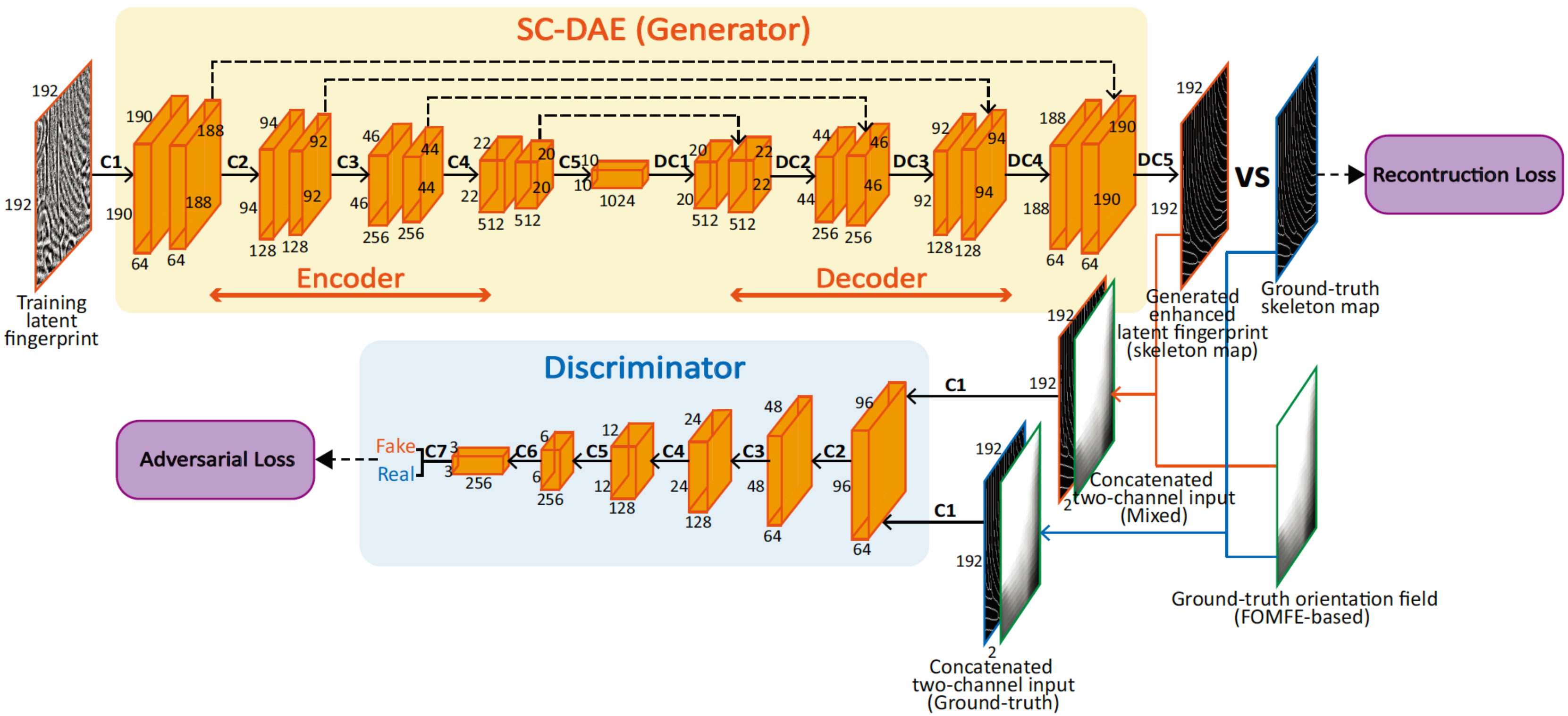
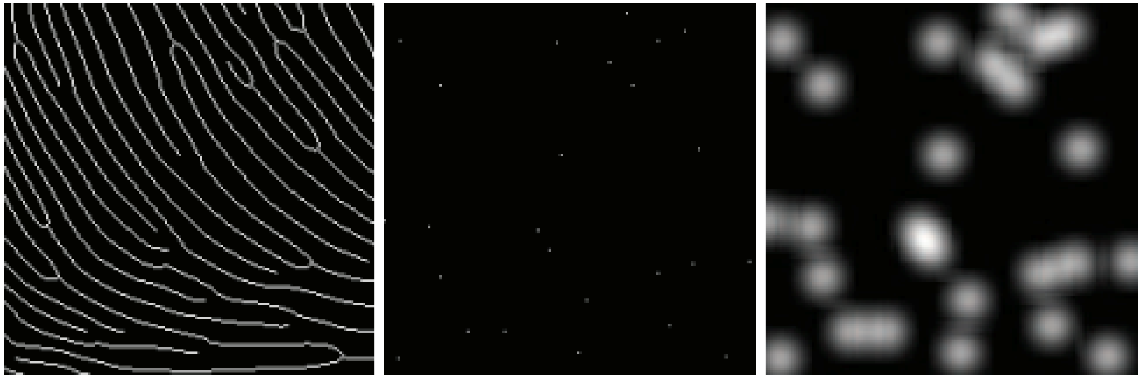


Figure from FingerGAN: A Constrained Fingerprint Generation Scheme for Latent Fingerprint Enhancement, Zhu et al. 2022

GAN for Latent Fingerprint Enhancement

Constraint: Gaussian-based Minutia weight map for forcing the generator in the FingerGAN to optimize minutia information.



Figures from [FingerGAN: A Constrained Fingerprint Generation Scheme for Latent Fingerprint Enhancement, Zhu et al. 2022]

GAN for Latent Fingerprint Enhancement

Loss function: the sum of two losses: 1) the adversarial loss and 2) the reconstruction loss.

$$\min_G \max_D L = L_a + \eta L_r$$

The adversarial loss:

$$\min_G \max_D L_a(G, D) = \mathbb{E}_{g \in \mathcal{G}, g_F \in \mathcal{G}_\mathcal{F}}[log(D(g, g_F))] + \mathbb{E}_{l \in \mathcal{L}, g_F \in \mathcal{G}_\mathcal{F}}[log(1 - D(G(l), g_F))]$$

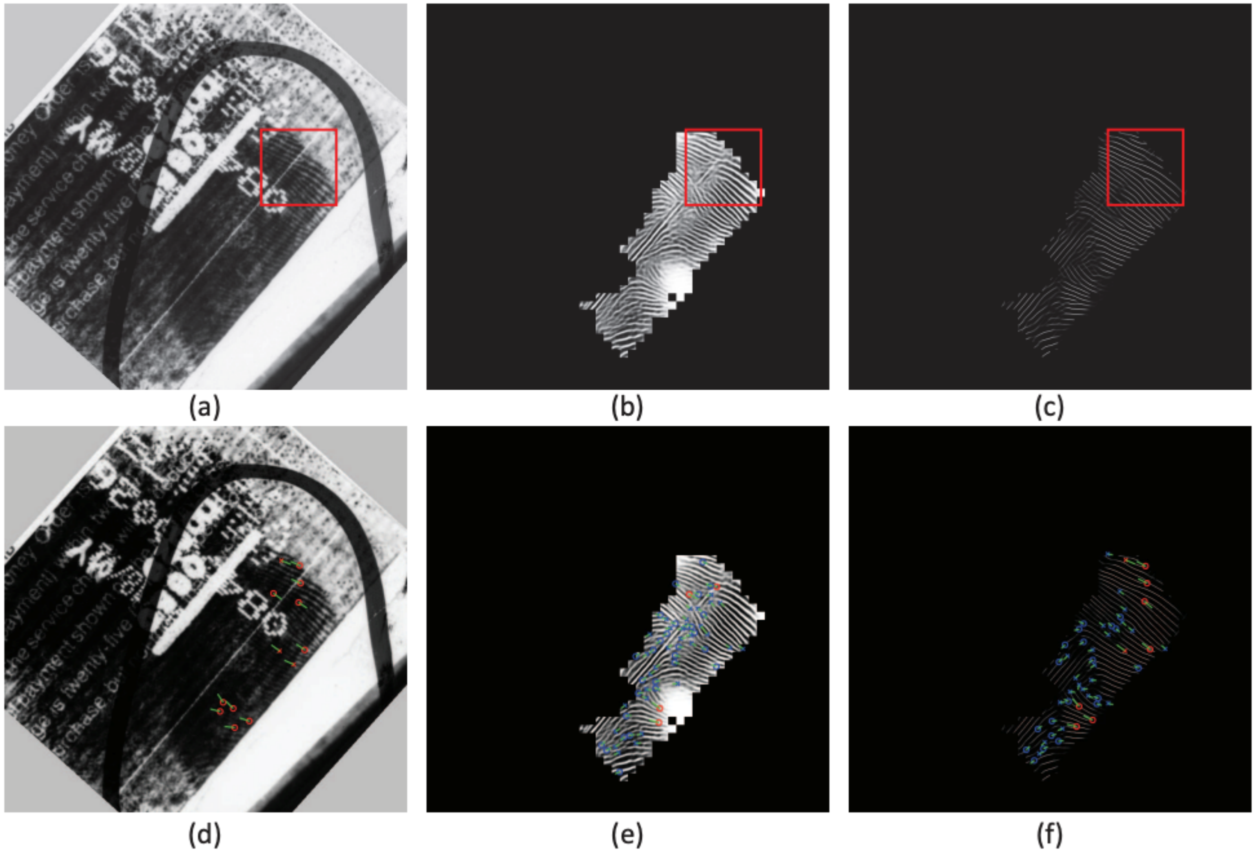
The reconstruction loss:

$$L_r(G) = \mathbb{E}_{l \in \mathcal{L}}[||w \odot (g - G(l))||_1]$$

Equations from FingerGAN: A Constrained Fingerprint Generation Scheme for Latent Fingerprint Enhancement, Zhu et al. 2022

GAN for Latent Fingerprint Enhancement

Visual inspection of the enhanced latent fingerprint by the FingerGAN



Figures from [FingerGAN: A Constrained Fingerprint Generation Scheme for Latent Fingerprint Enhancement, Zhu et al. 2022]

GAN for Latent Fingerprint Enhancement

Quantitative evaluation through comparing the recovered minutiae extracted from the enhanced latent fingerprint with the manually labeled minutiae by FBI experts.

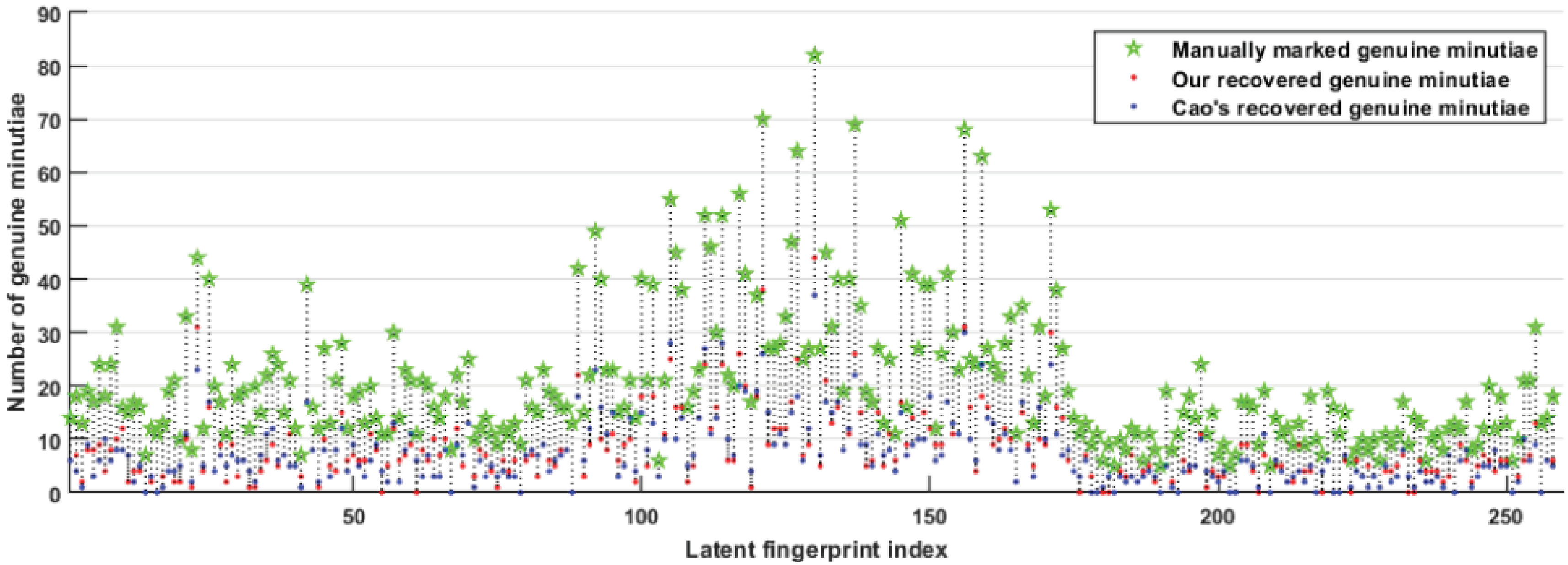
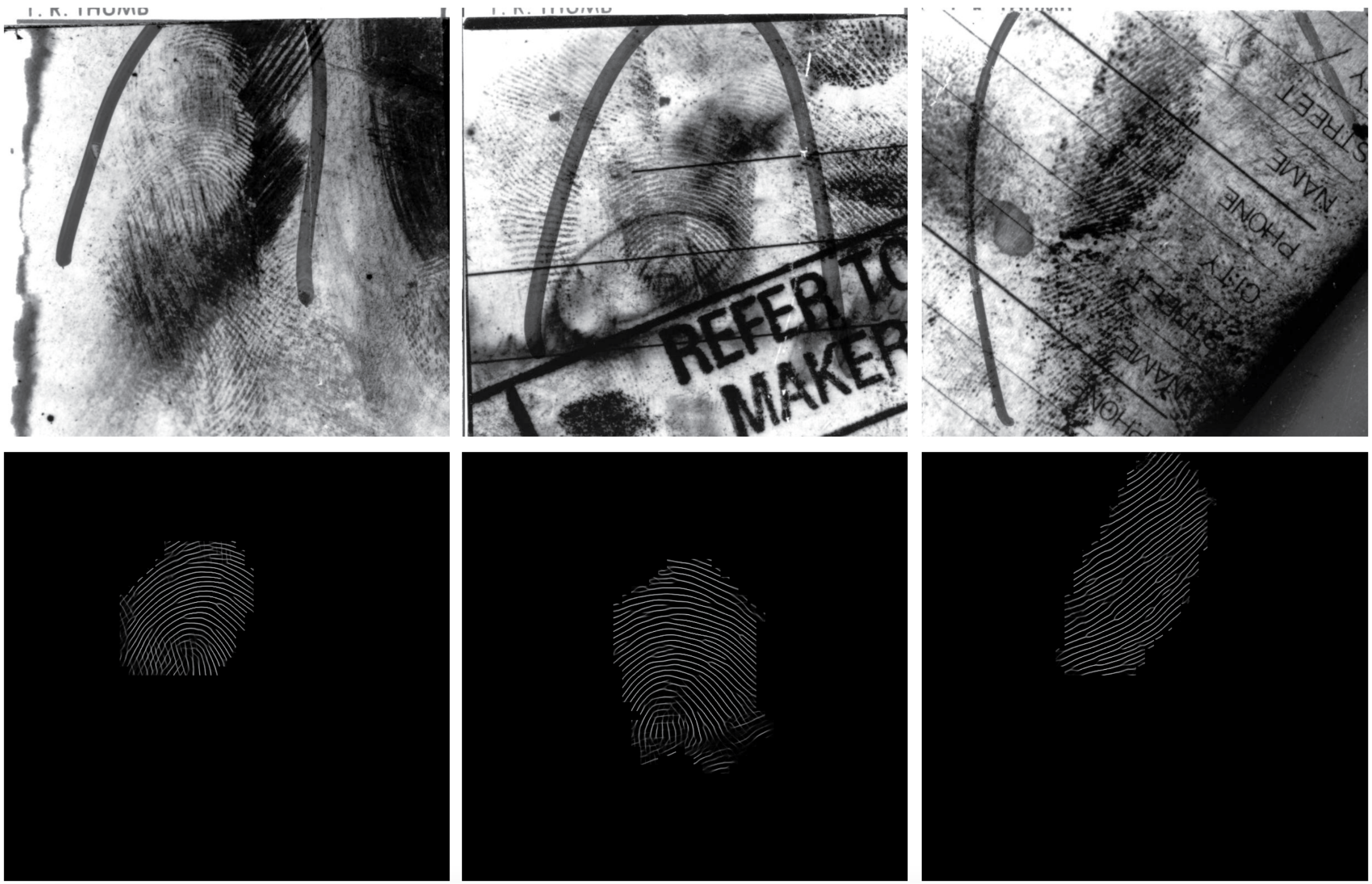


Figure from [FingerGAN: A Constrained Fingerprint Generation Scheme for Latent Fingerprint Enhancement, Zhu et al. 2022]

GAN for Latent Fingerprint Enhancement



Figures from [FingerGAN: A Constrained Fingerprint Generation Scheme for Latent Fingerprint Enhancement, Zhu et al. 2022]

GAN for Latent Fingerprint Enhancement

Quantitative evaluation through fingerprint identification performance achieved using the enhanced latent fingerprint.

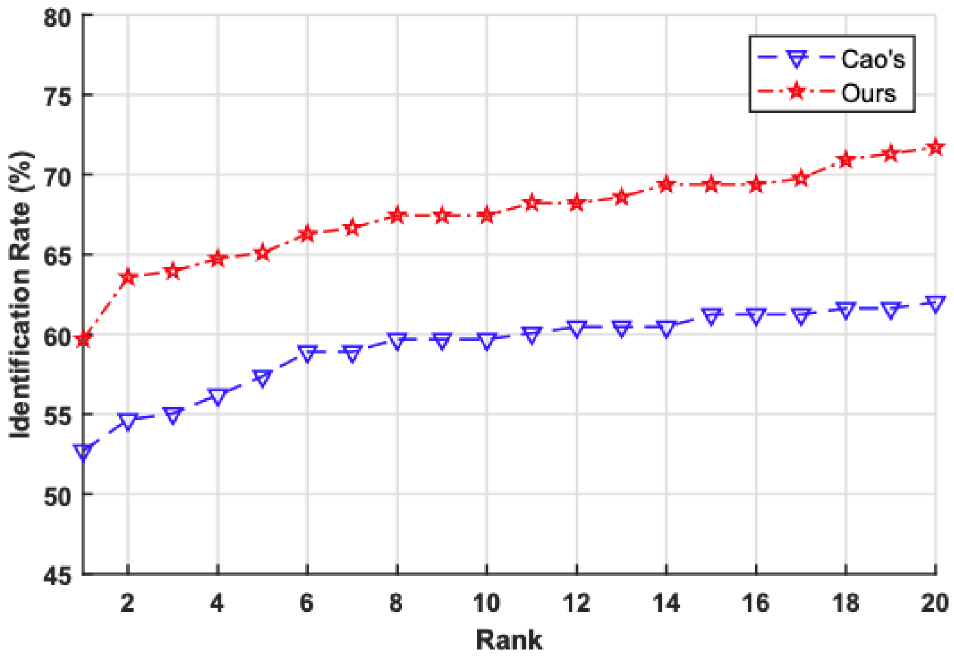


Figure from [FingerGAN: A Constrained Fingerprint Generation Scheme for Latent Fingerprint Enhancement, Zhu et al. 2022]

Any Questions?