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Sam Houston State University

DEEP LEARNING APPROACHES FOR FINGERPRINT VERIFICATION

Institute for Homeland Security

Sam Houston State University

Nikita Dalvi

Van Vung Pham

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1st Nikita Dalvi
Computer Science Department
Sam Houston State University
Huntsville, Texas, United States nxp059@shsu.edu

2nd Vung Pham
Computer Science Department
Sam Houston State University
Huntsville, Texas, United States
vung.pham@shsu.edu

Abstract—Fingerprint verification is vital because it provides a unique and permanent way to identify individuals. This technology is widely used in various areas like law enforcement, access control, and identity verification processes. Existing approaches for fingerprint verification tasks suffer from low accuracy due to training directly on low-quality and latent fingerprints. Therefore, this work proposes to utilize recent advancements in deep learning and computer vision to (1) enhance fingerprint image quality; (2) extract and verify that the minutiae are retained after enhancement; and (3) perform fingerprint verification tasks. Specifically, this work experiments with (1) Super-Resolution Convolutional Neural Network (SRCNN), Fast SRCNN, and Very Deep Super Resolution (VDSR) for fingerprint image enhancement; (2) Finger-Flow for minutia extraction; and (3) Siamese neural network for fingerprint verification. The experiment results indicate that among the experimented super resolution approaches, VDSR outperforms the others. Additionally, it can retain minutiae in the enhanced version and shows great potential to enhance latent fingerprints, which are less visible. Most importantly, the verification performances improve on the enhanced fingerprints versus low-resolution counterparts.

Index Terms—super-resolution convolutional neural networks, minutiae extraction, fingerprint verification

I. INTRODUCTION

Fingerprints are one of the most significant biometric traits used to identify individuals. However, it is difficult to classify fingerprints accurately. There are two main stages to classifying a fingerprint: extracting and comparing the image feature with the existing fingerprint image. These steps depend on the image quality of the collected fingerprints. In other words, using fingerprints as biometric traits to identify individuals includes three tasks: 1) improving image quality, 2) extracting features, and 3) classification. Existing approaches focus on utilizing traditional image processing techniques to perform these three tasks.

A few works in literature utilize deep neural networks for either one, two, or all three tasks. However, most of them work on one or a few individual small datasets, while deep neural networks often require a large amount of data to perform well. Therefore, this work proposes to fuse data from different sources to create a large benchmark fingerprint dataset and to optimize cutting-edge and recent advancements in deep neural networks to tackle tasks in this area.

Specifically, we would like to explore the impacts of using a Super-Resolution Convolutional Neural Network (SRCNN) and its variations to improve the input image quality (Task 1). Additionally, we would like to utilize Finger-Flow to extract minutiae from fingerprints to validate if the enhanced versions can keep key characteristics in the low-resolution counterparts (Task 2). Finally, we want to create a new neural network architecture to perform the classification fingerprints using the enhanced versions and validate if this could improve classification performance (Task 3). We synthesize that with a larger dataset and utilization of recent advancements in deep neural networks, the combined solution should beat the current results measured in terms of the Accuracy and Equal Error Rate (EER) for individual benchmark datasets. Therefore, this work has the following contributions:

- Using cutting-edge deep learning architectures for computer visions to improve the quality of fingerprints.
- Experimenting with deep neural networks for fingerprint verification tasks and validating the performance enhancement while applying these models to enhanced images versus applying them directly to low-quality fingerprints.
- Providing discussions and future directions to improve fingerprint verification tasks using deep learning approaches.

II. RELATED WORK

Super-resolution approaches are techniques to improve low quality images. They are useful in many fields, such as surveillance, medical image processing, and media production. Therefore, there are several families of techniques in this area. This field can be divided into single-image super-resolution (SISR) or multiple-image super-resolution (MISR) depending on the number of low-quality images used to construct the high-resolution counterparts. The former is more useful than the latter and is more suitable for this proposed work. Therefore, this section reviews techniques related to the SISR methods. These techniques can be broadly classified into two categories: traditional image processing techniques and deep learning techniques.

The traditional image processing category has a long development history with various interpolation techniques. However, the common and most successful methods in this area should include (1) nearest neighbor interpolation, (2) bilinear interpolation, and (3) bicubic interpolation. The nearest neighbor technique is simple but can generate a pixelated view in the high-resolution version of the low-quality image. On the other hand, the bilinear interpolation approach computes the new pixel value as the average of the four pixels closest to it. This technique produces smooth super-resolution images. However, it also blurs/smoothens the sharp edges due to the simple averaging of pixel values around the edges. Therefore, the bicubic interpolation technique produces a new pixel in the high-resolution by leveraging 16 neighbor pixels with different weights to create sharper images. The bicubic interpolation method is successful and used in many imageediting applications. Still, the conventional image processing techniques work well when the input image itself is clean, and it doesn't perform well if the input image is of low quality or altered (e.g., blurred or has noise). Therefore, our proposed work focuses on the deep-learning alternatives for this area.

Recent advancements in deep learning bring new potential in this area. Specifically, SuperResolution Convolutional Neural Network or SRCNN [1] is one of the first approaches that utilize deep learning in this area and achieved initial success. This model first uses bicubic interpolation to resize the input image to the expected output size. It then passes the resized image through three deep neural network layers (patch extraction and representation, non-linear mapping, and reconstruction layers) to produce the super-resolution output. This technique then became a benchmark for several deep learning approaches for this task. One variety of this approach is the Fast Super-Resolution Convolutional Neural Network (FSRCNN) [2]. FSRCNN improves SRCNN by (1) mapping the original low-quality image directly to the network by adding a deconvolution layer at the end, (2) shrinking the image features and later expanding them back, and (3) utilizing smaller filter sizes and with more layers.

At the same time, popular deep neural network architectures developed and succeeded in general image classification. These successful architectures include VGG (Visual Geometry Group), ResNet (Residual Neural Network), GAN (Generative Adversarial Networks), and Transformers. There are adoptions of these popular architectures for super-resolution image enhancement tasks too. Specifically, Very Deep Super-Resolution Convolutional Neural Networks (VDSR) [3] adopts the VGG style of developing a deep neural network with a skip connection to learn the residual of the high-resolution image out of the original input.

Similarly, Ledig et al. [4] utilize ResNet for this task and create SRResNet (SuperResolution ResNet). In this work, these authors also use the SRResNet as the base and propose

SRGAN, a generative adversarial network (GAN), for the image super-resolution (SR) task. SRGAN has a generator network and a discriminator network. The generator part of the first downsamples the input image to a low-resolution image with more channels to extract salient image features. It then up-samples the extracted features to generate the super resolution image. The discriminator has layers to distinguish the super-resolution images produced by the generator from the real ones. These modifications achieved new state-of-the-art at the released time for producing high-resolution images with large upscaling factors.

In the same direction, ESRGAN (Enhanced SRGAN) [5] enhances SRGAN by (1) introducing Residual-in-Residual Dense Block, (2) leveraging a discriminator to predict relativeness, and (3) modifying perceptual loss by using features before activation. These authors recently introduced Real-ESRGAN [6] attempts at blind super-resolution image enhancement. It is "blind" because it uses different degradation techniques to the input image and generates lowquality images for training (so the trained model is not biased over one or two simple methods of generating the training images, such as adding noises or blurring inputs). Another notable work in the GAN direction for image enhancement tasks is Generative Facial Prior GAN or GFPGAN [7], which focuses on enhancing facial images with the blind approach by utilizing different degradation techniques such as noise, blur, down-sampled, and image compression.

Recently, Transformers have achieved cutting-edge results in the computer vision field. Therefore, some works utilize Transformers for image-enhancement tasks too. A typical project in this direction should be Codebook Lookup Transformer (CodeFormer) [8]. This approach aims at the blind face restoration task, and it adds Generative Facial Prior (GFP) to the face restoration process and achieves a good balance of realness and fidelity.

The better quality of GFPGAN and CodeFormer in human face reconstruction tasks than general-purpose models such as ESRGAN indicates that models trained on a specific domain (e.g., faces in this case) work better than the generalized ones. This insight implies that specific models should be trained for the image quality enhancement of fingerprints. Concomitantly, specialized models (such as GFPGAN and CodeFormer) produce high-fidelity facial images, but the produced images lose special characteristics. Specifically, experiments show that, in several cases, the PSNR (peak signal-to-noise ratio) and SSIM (structural similarity index) of the images generated by these models may even be lower than those generated by simple methods such as traditional interpolation techniques (even though they look better).

In several cases, at low resolutions, two images can be correctly classified as one (e.g., from a single person), and they are miss-classified as two different ones when enhanced by these mentioned deep learning-based methods. This finding is critical in the fingerprint enhancement task because the final purpose of this task is not to make the fingerprints look better but to help classify them. Therefore, this project also experiments with deep-learning models to validate the fingerprint verification task to compare performance before and after enhancement.

Specifically, FingerFlow is utilized for the minutiae extraction task to verify if the enhanced image can retain the crucial characteristics in the enhanced version. Additionally, Siamese deep learning models [9] are utilized to perform the fingerprint verification task. The Siamese technique is a promising approach for image classification tasks. The fundamental principle behind these models involves training two identical neural networks with shared weights, or "Siamese twins," on pairs of images, one from each class. The networks learn to encode the images into feature vectors so that the distance metric between them reflects their similarity or dissimilarity. Siamese networks have proven effective in scenarios with limited labeled data, as they learn to compare and differentiate images directly, bypassing the need for extensive labeled datasets.

Moreover, Siamese models excel at one-shot or few-shot learning, where only a few examples per class are available. They have achieved impressive performance in various image classification tasks, including face recognition, object tracking, and similarity-based retrieval tasks. However, they might suffer from scalability issues in more extensive datasets due to their pairwise nature, and careful architecture design and regularization strategies are necessary to prevent overfitting. Thus, experiments with these models for fingerprint verification tasks are necessary before confirming whether the enhanced fingerprints improve classification performance.

III. DATA COLLECTION AND BENCHMARK DATASETS

Several datasets publicly available for minutiae fingerprints can be used for research and development purposes. The popular ones should be FVC (Fingerprint Verification Competition) series (FVC2002, FVC2004, and FVC2006), NIST Special Database 4, BioLab Database, PolyU Fingerprint Database, and IIT Delhi Fingerprint Database. Specifically, FVC2002 has four different subsets of fingerprints, and two are specialized for minutiae-based matching. FVC2004 and FVC2006 contain fingerprints from 800 and 400 individuals, respectively. Notably, NIST Special Database 4, BioLab Database, PolyU Fingerprint Database, and IIT Delhi Fingerprint Database contain many fingerprint images with minutiae annotations collected from different individuals in different settings. These datasets are publicly available and can be prepared and fused to train different neural networks for solving three different tasks (image quality improvement, minutiae feature extraction, and fingerprint classification using the extracted minutiae) while classifying fingerprints.

We used two different fingerprint datasets for two distinct tasks related to the fingerprint verification process. The first dataset we utilized is the FVC2000 dataset [10], employed for fingerprint image super-resolution. We experimented with two sets from the FVC2000 dataset. The first set comprised 66 images from the DB1 dataset of FVC2000. The second set included 246 images randomly selected from DB1, DB2, DB3, and DB4 datasets of FVC2000. Specifically, DB1 was collected using a low-cost optical sensor “Secure Desktop Scanner” by KeyTronic; DB2 was collected using a low-cost capacitive sensor “TouchChip” by ST Microelectronics; DB3 was collected using an optical sensor “DF-90” by Identicator Technology; and DB4 contains synthetic fingerprints.

This project uses image datasets like FVC2000 as high-resolution images, serving as ground truth values for the machine learning super-resolution models. A new subset of lowresolution images is created from these high-resolution images, with each image reduced to just 20% of its original size. These low and high fingerprint pairs are then used to train super-resolution deep learning models to enhance fingerprint images.

The second dataset we employed is the NIST 300a pair dataset, which was used for fingerprint matching. This dataset contains images with a resolution of 500 pixels and consists of two impression types: “roll” and “plain.” Rolled fingerprint images are captured by rolling a finger from one side to another (“nail-to-nail”) to capture all ridge details. Plain impressions are captured when the finger is pressed down on a flat surface without rolling. All the images in this dataset are in .png file format. Each image in the dataset is named following the pattern: SUBJECT IMPRESSION PPI FRGP.EXT, where:

- SUBJECT is a unique identifier for an individual’s fingerprints.
- IMPRESSION represents the type of fingerprint capture (e.g., roll or plain).
- PPI indicates the scanning resolution of the image, measured in pixels per inch.
- FRGP is the ANSI/NIST-ITL 1-2011 Update:2015 friction ridge generalized position code, which corresponds to the finger position as listed in Table I.
- EXT is the file format extension.

FRGP	Description	FRGP	Description
1	Right Thumb	8	Left Middle
2	Right Index	9	Left Ring
3	Right Middle	10	Left Little
4	Right Ring	11	Plain Right Thumb
5	Right Little	12	Plain Left Thumb
6	Left Thumb	13	Plain Left Four Fingers
7	Left Index	14	Plain Right Four Fingers

Table 1. FRGP (FRICTION RIDGE GENERALIZED POSITION) CODE MAPPING

The “roll” directory contains images with friction ridge positions 1 to 10, scanned from the top of the card. The “plain” directory contains simultaneous captures of plain images and segmented, rotated versions of the distal joints of the fingers from the simultaneous capture plain images [11].

To create labels for the images based on SUBJECT and FRGP values from both the “plain” and “roll” datasets, we identified matching pairs as those with the same SUBJECT and FRGP in both folders (“plain” and “roll”), and labeled them as “1.” For non-matching pairs, we randomly selected an image from the “roll” folder with different SUBJECT and FRGP values from the “plain” image, and labeled them as “0”.

IV. EVALUATION METRICS

There are two tasks to experiment with: image quality enhancement and verification accuracy. For image quality enhancement, there are common evaluation metrics such as PSNR (Peak Signal-to-Noise Ratio) [12] and SSIM (Structural Similarity Index) [13]. There are also specific quality evaluation metrics for fingerprints, such as the NFIQ2 tool provided by NBIS (NIST Biometric Image Software) [14]. The NFIQ2 tool provides quality scores ranging from 1 to 100 regarding how easy it is to verify an image based on its quality. However, a fingerprint might be easily verified (with high quality) but may also be misclassified due to artificial artifacts generated during the enhancement process. Therefore, we still base our final evaluation metric on verification Accuracy and Equal Error Rate (EER).

Equal Error Rate (EER) and Accuracy are two different performance metrics used to evaluate the performance of binary classification systems, such as spam detection, fraud detection, or medical diagnosis. Each metric has its strengths and weaknesses, and the choice of which one to use depends on the specific context and requirements of the problem. Equal Error Rate (EER) is used when the cost of false positives and false negatives is roughly the same, and you want to evaluate a biometric or security-related system. While, Accuracy is used when the class distribution is balanced, and there is no significant difference in the cost associated with different types of misclassifications. Additionally, we have a balanced dataset; thus, we do not need to use evaluation metrics for imbalanced scenarios like Precision, Recall, F1-score, or Area Under the ROC Curve (AUC-ROC) to gain better insights into the model’s performance.

V. EXPERIMENTS

A. Fingerprint Image Enhancement

The experiments in this section focus on improving the quality of fingerprint images for the verification process. Machine learning models like SRCNN [1], FSRCNN [2], and VDSR [3] were utilized for image enhancement. The experiments were divided into two stages:

Stage 1: SRCNN and FSRCNN models were tested on a subset of 66 fingerprint images. These images were split into three sets: training set (55 images), test set (6 images), and validation set (5 images). SRCNN: The performance of the 3-layer SRCNN model was evaluated using evaluation metrics like PSNR (Peak Signal-to-Noise Ratio) and SSIM (Structural Similarity

Index). The model was trained for 20 epochs with a ReLU activation filter. The FSRCNN model was tested with two different setups. In the first setup, the activation filter used was ReLU, and the stride factor was set to 1. The activation filter was set to PReLU in the second setup, and the stride factor was set to 2. Both setups of FSRCNN were evaluated based on the PSNR and SSIM metrics, and each setup was trained for 100 epochs.

Stage 2: FSRCNN, SRCNN, and VDSR models were tested on a larger subset of 246 fingerprint images. The dataset was divided into three sets: training set (182 images), validation set (32 images), and test set (27 images). Each set contained images from all four databases of FVC2000. Specifically, with SRCNN, the 3-layer SRCNN model was trained with a ReLU activation filter and evaluated based on PSNR and SSIM values. The model underwent training for 100 epochs. Similarly, the FSRCNN model was trained with a PreLU activation filter, a stride factor of 2, and a kernel size of 9. The model had 9 layers, with the first 8 being convolution layers and the last one being a convolution transpose layer. The model was trained for 100 epochs and evaluated based on PSNR and SSIM.

The VDSR model was trained with a ReLU activation filter and had a deeper network with 20 layers. The layers included the first layer as a convolution layer, 18 intermediate convolution layers, and one last image reconstruction convolution layer. The model employed residual learning, where the residual image difference between high-resolution and low-resolution images was used. The model was trained for 80 epochs, starting with a learning rate of 0.1, and the learning rate was decreased by 10% after every 10 epochs. The performance of the VDSR model was evaluated based on PSNR and SSIM values.

B. FingerFlow and Minutia Comparison:

While improving the quality of fingerprint images using deep learning super-resolution networks, preserving fingerprint details and features is essential. To verify that the enhanced fingerprint image retains the necessary information and minutiae, a pre-trained FingerFlow model is used. FingerFlow is a Python framework based on deep learning designed to manipulate fingerprint minutiae. It offers several modules:

1) Extractor module: This module is responsible for extracting and classifying minutiae points from fingerprints. It can also detect fingerprint core points.
2) Matcher module: This module handles the matching of extracted minutiae feature vectors.

The FingerFlow model minutia extractor is applied to both the original and enhanced images generated by the VDSR model. This process helps to locate the minutiae points accurately. The predicted minutiae points are then marked on both the original and enhanced images for qualitative evaluation of whether the enhanced images can retain the crucial image features in the low-quality counterparts.

C. Fingerprint Matching Using Siamese Model

For fingerprint matching, a Siamese model was used. This model was evaluated using the NIST sd300a paired preprocessed labeled dataset. In this experiment, a total of 4,000 pairs of fingerprint images were selected. Among these pairs, 2,000 were matching pairs labeled as 1, and the other 2,000 were non-matching pairs labeled as 0. The dataset was divided into three parts:

training, validation, and testing, with the split criteria being 70% for training, 20% for testing, and 10% for validation. Before splitting the data, the dataset was shuffled to ensure that all the sets (train, test, and validation) had a balanced number of matching and non-matching fingerprint image pairs. This balancing step ensures that the model can learn effectively from both types of pairs.

The Siamese model was trained using the Adam optimizer with a learning rate of 0.001, and the training was done for ten epochs. The loss function used during training was binary crossentropy, which is commonly used for binary classification tasks. A prediction threshold of 0.9 was set during the model's prediction phase. This threshold means that if the model predicts a value above 0.9 for a test image pair, it is considered a matching pair; otherwise, it is classified as a nonmatching pair. The model was tested on the NIST sd300a test dataset in two scenarios: without any image enhancement and with image enhancement using the VDSR model (because VDSR has better fingerprint enhancement results as the results shown in the following section).

VI. RESULTS

A. Fingerprint Image Enhancement

We use PSNR and SSIM values to evaluate the image enhancement models. The evaluation results for stages 1 and 2 are shown in Tables II and III, respectively. Higher PSNR values indicate better quality, and PSNR is typically reported in decibels (dB). Similarly, an SSIM value closer to 1 indicates better quality. Based on the data in Tables II and III, we found that the VDSR model performed better in terms of both PSNR and SSIM than other experimented models like FSRCNN and SRCNN. Therefore, we selected the VDSR model for further experiments.

Model	PSNR	SSIM
SRCNN	23.333 db	0.918
FSRCNN first setup	24.161 db	0.932
FSRCNN second setup	22.149 db	0.903

Table 2. Fingerprint Enhancement Evaluation with 66 images

Model	PSNR	SSIM
SRCNN	20.992 db	0.763
FSRCNN	19.410 db	0.716
VDSR	21.229 db	0.777

Table 3. Fingerprint Enhancement Evaluation with 246 images

B. FingerFlow and Minutia Comparison

When we examine the visualized results (Figure 1 as an example), we can observe that the minutia points present in the original image are preserved in the enhanced image produced by the VDSR model. This characteristic indicates that the VDSR model has successfully improved image quality while retaining important minutia information. Additionally, there is an additional minutia point at the top-left corner of the enhanced image detected. This additionally detected minutia point is the result of the image enhancement process that helps add more details about fingerprint information that was not visible due to out-of-ink region. Though this region does not have ink, it does leave fingerprint information on the collected plane as a latent fingerprint region and is visible only after enhancement. This result indicates that deep learning models can greatly improve latent fingerprints. As a result, we can confidently proceed with further experiments using the VDSR model for image enhancement.

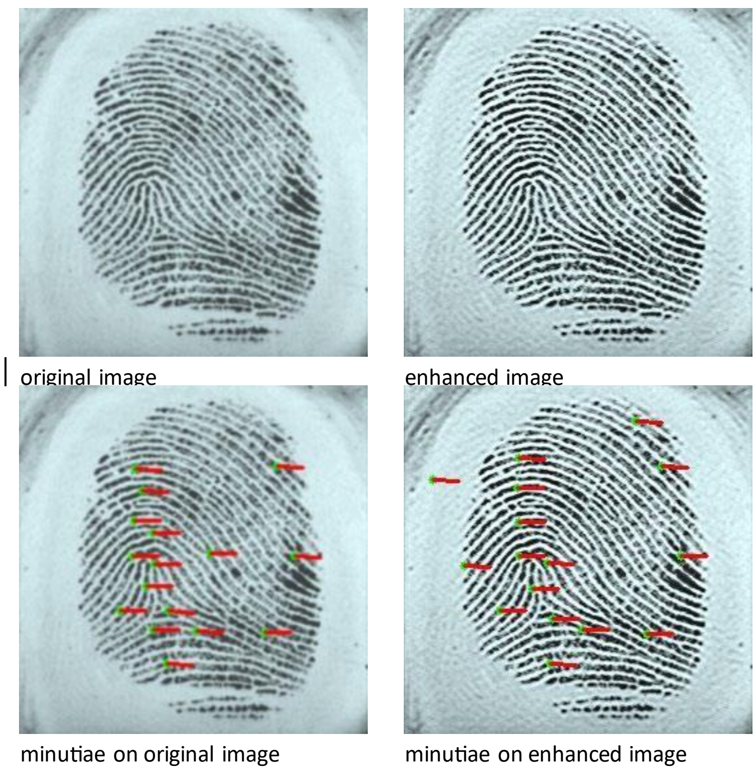

Fig. 1. Minutiae extraction for original fingerprint and VDSR (very deep super resolution) enhanced counterpart.

C. Fingerprint Matching Using Siamese Model

We assessed the Siamese model using accuracy and EER (Equal Error Rate), calculated on the original and VDSR-enhanced images. A higher accuracy value, closer to 100, indicates better performance, while a lower EER value signifies better results. The data in Table IV shows that the Siamese model performed better when using the VDSR-enhanced images. The accuracy was higher, and the EER was lower, which indicates that the Siamese model's performance improved significantly with the enhanced images produced by VDSR.

Image Type	**Accuracy**	**EER**
Original	61%	0.384
Enhanced by VDSR	62%	0.376

Table 4. Siamese Model Evaluation for Original and Enhanced Fingerprints

VII. DISCUSSIONS AND WAY FORWARD

This work set the ground experiments for deep-learning approaches for enhancing fingerprint verification tasks. The results show great initial success in this task. One critical observation that can be seen from the enhanced fingerprint, as shown in Figure 1, is that the improved version does show the latent fingerprint regions that were out of the inked area and provides more fingerprint information. This result indicates that latent fingerprints (those collected on crime scenes on the objects that mark fingerprints) would greatly benefit from image enhancement techniques as these fingerprints will reveal more fingerprint information following the enhancement process.

Besides initial success, this work still has some limitations, such as the qualitative evaluation of the retainment of minutia points is time-consuming. Therefore, it would be better to devise a technique to evaluate this automatically. Furthermore, we have utilized only a few available fingerprint datasets due to limited time and computation resources. In contrast, many more fingerprint datasets can be used for fingerprint enhancement tasks (as these images do not require labels for training). Additionally, separate models are being trained for image enhancement, minutia extraction, and classification. We could devise a deep learning model to incorporate these three models and perform the fingerprint verification task. In this way, the minutia part of the network helps to enforce the retainment of the minutiae points during the enhancement process and thus helps improve the final classification performance.

For instance, Joshi et al. [15] propose a GAN-based architecture to deblur fingerprint images called FDeblur-GAN. This architecture uses the Gaussian blur method to generate low resolution images for training. It also considers the loss when extracting ridge from the enhanced fingerprints and the loss while performing fingerprint classifications. FDeblur-GAN is interesting but still has limitations, such as being a non-blind method and not paying attention to the key points in the fingerprints. First, it is non-blind because the only degradation approach is Gaussian blur. In reality, latent fingerprints collected from crime scenes may be altered in various ways, and a blind approach is required. Second, FDeblur-GAN cares about a loss regarding ridge extraction rather than the key points of the fingerprints. Several fingerprint classification methods utilize key points, such as minutiae, for classification purposes. The ridge has a large amount of information, and many of them are not key points. Therefore, the high score for ridge similarity may not correlate with a high score for key-point matches. For instance, the two fingerprints may have many matching regions for ridge extractions (high similarity score). Still, they are not matched at the key points (such as minutiae), leading to the missed classification.

Toward this end, He et al. [16] propose Mask R-CNN (Region-based Convolutional Neural Network) architecture that achieves top results in person key point detection from COCO (Common Objects in Context) dataset. We hypothesize that similar architecture can be applied for detecting minutiae and can be used to constrain the fingerprint enhancement neural networks to keep these minutiae as key points. Therefore, this should be an important future direction for this project.

VIII. CONCLUSION

This work experiments with (1) Super-Resolution Convolutional Neural Network (SRCNN), Fast SRCNN, and Very Deep Super Resolution (VDSR) for fingerprint image enhancement; (2) FingerFlow for minutia extraction; and (3) Siamese neural network for fingerprint verification. The experiment results indicate that among the experimented superresolution approaches, VDSR outperforms the others. Additionally, it can retain minutiae points in the enhanced version and shows great potential to enhance latent fingerprints, which are less visible in the low-resolution counterparts. Most importantly, the verification performances improve on the enhanced fingerprints. Though these experiments show initial successes, they help provide insights about current limitations and important future directions. First, we should devise a neural network combining the three neural networks: one for enhancing the images, another for constraining the retainment of the existing minutiae, and the last to ensure the verification performance. Second, more techniques (such as blind approaches or generative artificial intelligence approaches for image degradation) should be explored to generate datasets for latent fingerprints, as this fingerprint data type is rare in the current literature.

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