2023 IEEE International Conference on Big Data (BigData) | 979-8-3503-2445-7/23/$31.00 ©2023 IEEE | DOI: 10.1109/BigData59044.2023.10386597

Improving Fingerprint Classification Accuracy Using Image Enhancement Deep Learning Models

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***Abstract*—Fingerprint verification is widely used to verify individuals based on their unique fingerprint patterns. However, existing fingerprint identification systems encounter challenges while dealing with poor-quality images, smudged or marked fingerprints, and variations in finger positioning. These issues are common for latent fingerprints. This work proposes to address these issues through a novel machine-learning model employing advanced image enhancement techniques. The model aims to enhance fingerprint image quality and minimize the impact of damage using machine learning, ultimately reducing the error rate in identification systems. Specifically, this work proposes to incorporate deep learning image enhancement techniques into the low-quality and latent fingerprints before passing them through another deep learning model to perform verification tasks. This work also provides insights as different experiments are made while applying different approaches to different real-life datasets.**

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

I. Introduction

Biometric authentication, which is used for automated personal identification, has gained significant interest in recent years. It involves using unique physical or behavioral characteristics like fingerprints, faces, retinas, and palm prints to identify individuals. Among these, fingerprint recognition is the most widely used and successful method, finding applications in various fields [1].

Fingerprint identification systems are crucial in law enforcement, access control, and personal authentication. They rely on a technique called feature-based image matching. Fingerprint identification systems compare the details of fingerprint features between two fingerprint images to determine if they match. However, existing systems face challenges in accurately recognizing fingerprints due to factors such as low-quality images, finger marks, or rotational differences. These challenges are common for latent fingerprints due to the intrinsic latent fingerprint collection process. These challenges result in a high error rate and incorrect identification of users' fingerprints, posing a security risk.

This work aims to address image quality issues and damages in fingerprint images using deep learning models such as Super-Resolution Convolutional Neural Network (SR-CNN) [2], Very Deep Super Resolution (VDSR) [3], and Super Resolution Generative Adversarial Networks (SRGAN) [4] models. We focus on enhancing the image quality and minimizing damage effects before feeding the images into the verification systems. Specifically, this work utilizes a Siamese model, and Scale-Invariant Feature Transform (SIFT) [5] key points matching model for the fingerprint verification tasks.

Siamese is a popular deep-learning model for image classification, and SIFT is a computer vision technique that identifies unique points or features in an image. These features are resilient to changes in scale, rotation, and other transformations. Image enhancement becomes crucial, especially with low-resolution images, as lower image quality leads to fewer detected key points, resulting in fewer matches. This is even more critical for low-quality and latent fingerprint images because the fingerprint key points are critical for the verification task. Therefore, besides the popular and common Siamese model, this work also tests the efficiency of image enhancement models using SIFT for latent fingerprints.

Additionally, this proposed approach is also applied to real-life fingerprint datasets called the SOCOFing [6] dataset, the NIST special fingerprint dataset 300a [7], and the FVC dataset [8]. This is a critical step in the development process, ensuring that the proposed models are robust, reliable, and applicable in practical scenarios beyond the controlled environment of training data.

II. Related Work

Computer vision deep learning models for modern vision tasks [9] are pervasive and might even be more accurate than human vision while dealing with low-quality and latent images [10], [11]. The fingerprint verification domain is no exception. Fingerprint enhancement techniques have been widely utilized in fingerprint-based authentication systems to improve the clarity of ridge and valley structures in input fingerprint images. Hong et al. [12] introduced an adaptive enhancement method that enhances the ridge and valley structures based on estimated local ridge orientation and frequency. Yang et al. [13] addressed limitations in traditional Gabor filter-based enhancement by proposing a modified Gabor filter.

Recent advancements in Convolutional Neural Networks (CNNs) have also been applied to fingerprint enhancement. Cao et al. [14] proposed a CNN-based method for orientation field calculation, while Jian et al. [15] presented a deep CNN-based enhancement scheme using multitask learning. Super-resolution (SR) techniques have also been explored, such as the ridge orientation-based coupled dictionaries by Singh et al. [16] and the sparse representation with ridge pattern prior by Bian et al. [17]. Zhu et al. [18] proposed FingerGan model was to enhance the quality of latent fingerprints. Additionally, Joshi et al. [19] proposed FDeblur-GAN, which deblurs low-quality images while still preserving fingerprint information.

Likewise, extensive research has been conducted on fingerprint image comparison employing deep learning computer vision models, which have also been employed in fingerprint comparison tasks. Werner et al. [20] improved the efficiency of a comparison algorithm using a neural network. Jea and Govindaraju [21] utilized a neural network to compare minutiae from partially overlapping fingerprints. These studies highlight the effectiveness of neural networks in fingerprint comparison tasks. Additionally, Li et al. [22] proposed Siamese Network with Convolutional Neural Network (CNN) and Multi-Scale Dilated Convolutions as an efficient method for fingerprint recognition, yielding promising results in measuring fingerprint similarity and verifying whether fingerprints belong to the same person. Similarly, the SIFT technology has also been investigated for matching fingerprint features. For instance, Bakheet et al. [23] proposed a robust minutia extraction and matching approach using SIFT features.

In contrast to previous approaches that relied on traditional approaches, where original images were considered ground truth values and image resolution deliberately reduced to simulate low-resolution images, our experiments took a different route. This work utilizes modified versions of images from the *SOCOFing* dataset, intentionally damaged with same resolution as original unaltered image, as low-resolution images. This is to simulate the real-world latent fingerprints collected from crime scenes, often of very low quality due to the intrinsic fingerprint collection process. Simultaneously, unaltered *SOCOFing* images are used to serve as high-resolution reference images. Additionally, this work pre-processed *NIST sd300* roll images to resemble the *SOCOFing* dataset, providing a validation of image enhancement on real-time data with human errors like marks, inks, and letters.

Additionally, instead of directly comparing images using the SIFT algorithm, this work first enhances the image quality using a deep-learning model tailored for image enhancement. Following this enhancement, the comparison of key points in the images exhibited a noticeable improvement in keypoint detection and matching, particularly for low-quality images. This innovative approach resulted in improved accuracy in fingerprint matching using the Siamese model and SIFT key points matching.

III. Datasets and Pre-processing

Datasets are important to test and validate to ensure that the proposed models are robust, reliable, and applicable in practical scenarios beyond the controlled environment of training data. This work utilizes three datasets, including the SOCOFing [6] dataset, the NIST special fingerprint dataset 300a [7], and the FVC dataset [8]. Specifically, various pre-processing steps are applied to these datasets to create five distinct datasets.

A. Dataset 1

The SOCOFing Dataset (Dataset 1) is divided into two main folders: ”real” and ”altered.” The ”real” folder contains original images, while the ”altered” folder contains images with alterations at three levels: easy, medium, and hard. These alterations come in three damage types: *Z-cut (Zcut)*, *circular rotations (CR)*, and *obliterations (Obl)* and three damage levels: *easy*, *medium*, and *hard*.

Fig. 1. Example of a real image (left) versus one of its damaged versions (right) in *SOCOFing* dataset. These can then be used as high-resolution and low-resolution inputs for the image enhancement models.

Figure 1 shows an instance of a real image and one of its damaged versions. Image enhancement models work on datasets with high-resolution and low-resolution images. Therefore, the “real” images are considered high-resolution images, and the “altered” images are low-resolution images. Since each real image is associated with nine different types of altered images, this work generates the same number of pairs (9) binding each real image with its altered versions. Specifically, these versions were named based on the original real image name from the original dataset, followed by the damage type (*CR*, *Zcut*, *Obl*) and the damage level (*easy*, *medium*, *hard*).

B. Dataset 2

Dataset 2 combines the *NIST* and *FVC* datasets. Furthermore, following the conventional approaches of generating high-resolution and low-resolution in the image enhancement community, this work considers the original images in these two datasets as the high-resolution one and resize the image (using conventional image processing method such as image interpolation) to 20% of its original size and then re-scale back. This resize and re-scale operation reduces the quality of the original image. This helps simulate the low-resolution fingerprints. Figure 2 shows an example of the original image from this dataset and its corresponding down-graded version using the conventional image resizing method. Observably, the image on the right is blurred compared to the original one on the left.

Fig. 2. Example of a real image (left) versus one of its down-graded version (right) in *Dataset 2* dataset. These can then be used as high-resolution and low-resolution inputs for the image enhancement models.

C. Dataset 3

The SOCOFing dataset is divided into two parts for training and testing a Siamese model, and the resulting dataset is named *Dataset 3*. Out of the 6,000 images in the real image folder, the first 5,000 images and their corresponding altered variations were used for training. The remaining 1,000 images were reserved for testing.

D. Dataset 4

This dataset (Dataset 4) aims to explore image super-resolution on a more realistic dataset. SOCOFing images are small and of standard size (103×96) but high resolution (96×96). They lack any other human errors such as letters, ink marks, or any other human errors. On the other hand, fingerprint databases and the latent fingerprints collected from crime scenes may vary in size and resolution and may contain things like ink marks or handwritten notes.

Therefore, this work proceeds with the *NIST Sd300a* dataset, which contains both roll and plain images, providing a more real-time scenario with various human errors like ink marks, letters, dust, etc. Notably, these images have various sizes and resolutions, representing the actual fingerprint databases in real life well. The next step is to produce the corresponding low-resolution fingerprints that can represent the low-quality and damaged latent fingerprints collected from crime scenes.

Figure 3 outlines the steps to produce the latent fingerprints. They include the following steps: (i) select 1000 roll images from the roll and plain images, (ii) resize all images to a uniform size of 512×512, (iii) randomly apply 2 to 3 alterations (damages) to the images generated in the previous step, and (iv) reduce the size of the images to 256×256. Finally, images resulting from Step (i) are used as high-resolution images, and those from Step (ii) are used as their low-resolution counterparts.

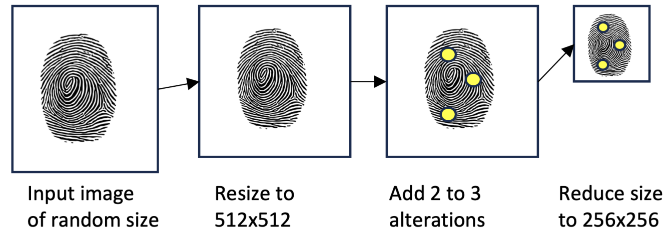

Fig. 3. Steps to generate low-resolution images that can simulate the latent fingerprints collected from crime-scene (right-most) from an original image (left-most).

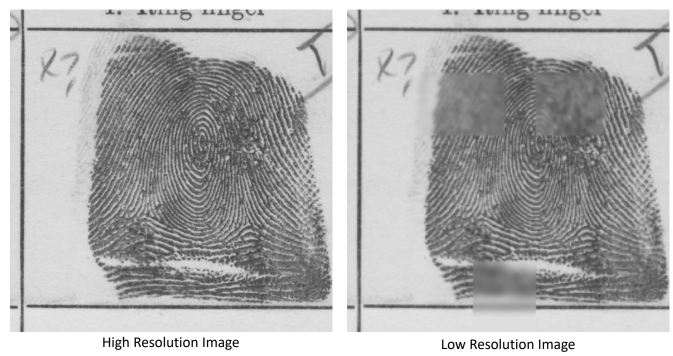

Fig. 4. An example of a high-resolution image (left) versus its low-resolution image (right) in *Dataset 4*.

Figure 4 shows an example of a pair of images for high-resolution (left) and low-resolution (right) input pair from *Dataset 4*. Notably, besides being low resolution, the image on the right also has several random areas being damaged. This is to simulate the common issues that happen to latent fingerprints due to their intrinsic collection process from crime scenes.

E. Dataset 5

Several ridge lines in fingerprints are thin, and due to the pixelated effects of the degrading process, some lines even change their patterns and become different lines, leading to wrong enhancement. Therefore, we attempt to create thicker ridge lines using image binary thresholding [8]. In other words, the darker grey parts next to a ridge line are combined with the ridge line to form a thicker line, and the rest becomes the background (white).

Thresholding is a key aspect of image processing as it facilitates the segmentation and extraction of vital information from an image. By segmenting an image into distinct regions based on pixel intensity or value, thresholding aids in distinguishing objects or features of interest from the background. While there are various thresholding techniques like Global, Adaptive Mean, and Adaptive Gaussian, the adaptive Gaussian method tends to yield superior results by reducing noise, as shown in Figure 5.

Notably, Adaptive Gaussian Thresholding produces more reasonable results. Therefore, we utilize this approach for this dataset. Specifically, this dataset is generated following steps

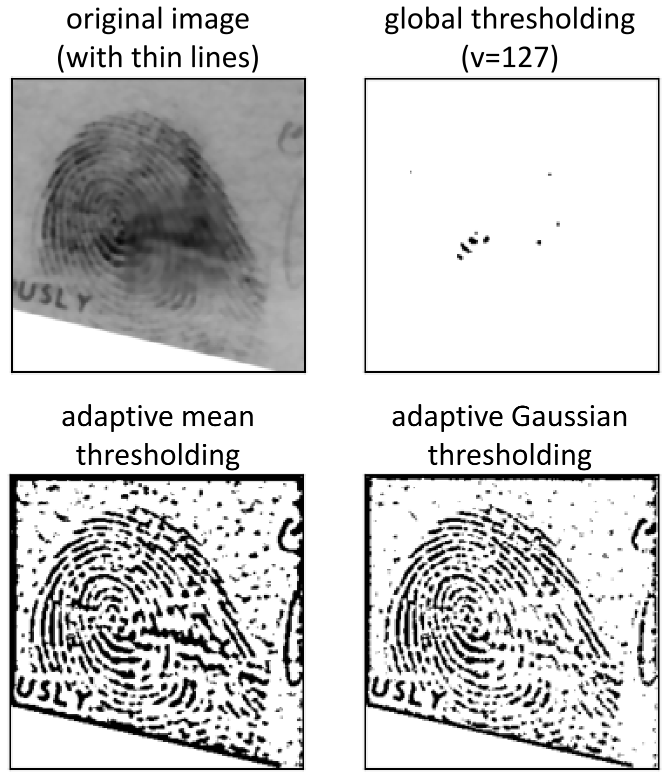

Fig. 5. The original image (top-left) and their corresponding outputs from different thresholding techniques.

specified for generating *Dataset 4*. The only difference is the application of Adaptive Gaussian Thresholding after Step (iii), followed by reducing images to low resolution. The instance of *Dataset 5* is shown in Figure 6.

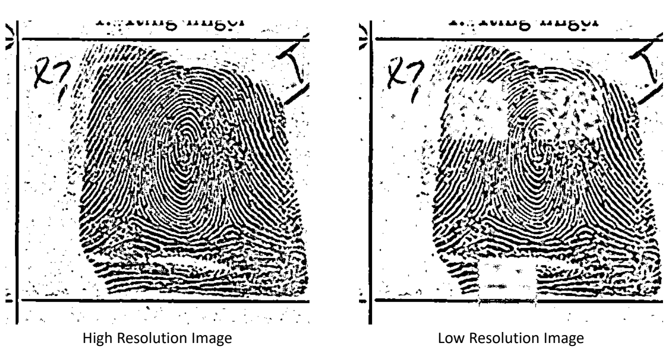

Fig. 6. An example of a high-resolution fingerprint (left) versus its low-resolution counterpart in *Dataset 5*.

IV. Model Training

A. Fingerprint classification model

The primary purpose of this model is to measure the similarity between two fingerprint images. This work aims to determine whether enhancing fingerprints can decrease the distance between pairs of fingerprints that match while increasing the distance between pairs of fingerprints that do not match. Therefore, a Siamese Model[1]. Specifically, this model is trained on the *Dataset 3* after splitting the 6,000 real images into 5,000 and 1,000 for training and validating accordingly. The validating set is used to select the best model trained on the training set.

B. Fingerprint enhancement models

1) Super-Resolution Convolutional Neural Network: Super-Resolution Convolutional Neural Network (SRCNN) model is designed to enhance image resolution and consists of three sequential convolutional layers (*l1*, *l2*, and *l3*) with specific filter counts and kernel sizes. A custom mean squared error (MSE) loss function for image comparison is used and the model uses the Adam optimizer with a learning rate of 0.001 and tracks performance metrics like PSNR (peak signal-to-noise ratio) and SSIM (structural similarity index). This model is essential for image enhancement and super-resolution applications. Figure 7 shows the architecture of SRCNN trained.

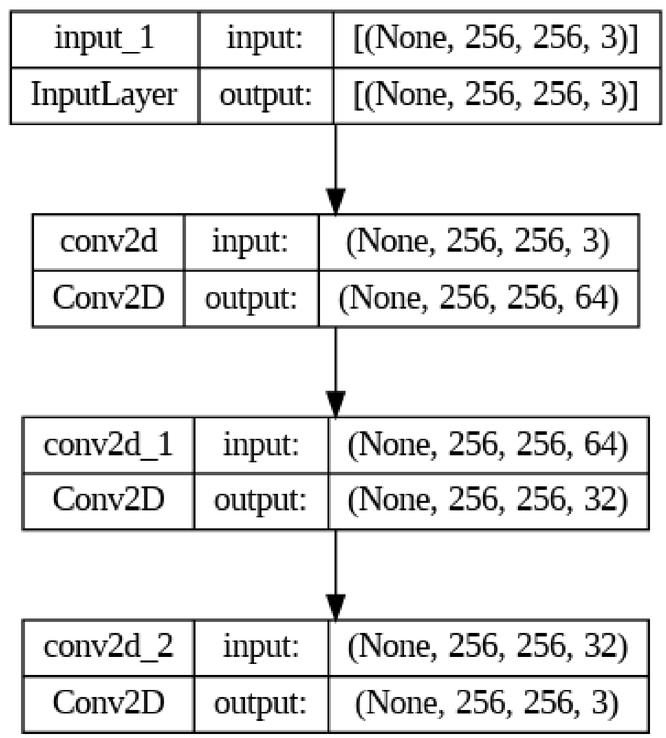

Fig. 7. Architecture of the trained Super-Resolution Convolutional Neural Network.

2) Very Deep Super-Resolution: A Very Deep Super-Resolution (VDSR) model specializes in enhancing image resolution, making it a vital component in a wide range of image processing applications. The model architecture begins with an input layer capable of handling images of various sizes and three-color channels. It proceeds to employ a sequence of convolutional layers, including an initial convolutional layer

[1]https://github.com/Abuzariii/Fingerprint-Matching-with-Siamese-Networks-Tensorflow.git

followed by 18 intermediate layers, each equipped with 64 filters and ReLU activation for feature extraction.

Significantly, the model incorporates a final convolutional layer with a single filter, creating a high-resolution image. However, the distinguishing feature of VDSR is its 'residual learning' mechanism. Rather than directly producing the enhanced image, it computes the difference between the high-resolution image and the input low-resolution image. This difference is then added back to the original image, emphasizing the model's focus on improving image quality.

3) Super-Resolution Generative Adversarial Network: This work also trained a Super-Resolution Generative Adversarial Network (SRGAN)[2]. The model in the article is designed so that the predicted image is four times the size of the low-resolution image. To align with this structure, the low resolution should be $1/16^{th}$ of the high resolution ($1/4^{th}$ for with and height respectively).

Dataset 5 is used to train this model, which has high-resolution images at 512×512 and low-resolution at 256×256, the low-resolution images were initially half of the high resolution. To fit the existing model structure, we further reduce the low-resolution image resolution to 128×128, maintaining the $4\times$-upscaling factor for width and height respectively.

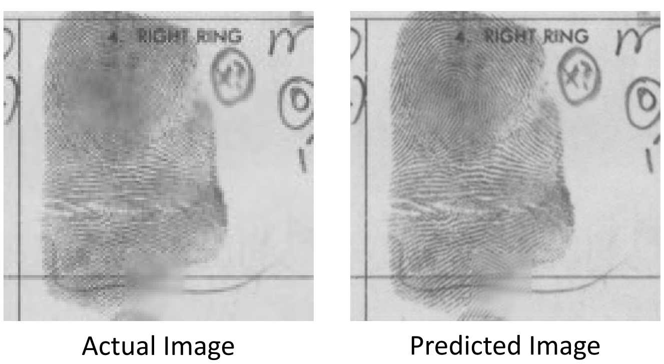

Fig. 8. An example of the actual image (left) and its predicted image from low-quality image (right) using Super-Resolution Generative Adversarial Network.

Additionally, SRGAN is more deeper than SRCNN, and training with image pairs at 512/128 resolutions requires higher GPU RAM. Therefore, due to GPU limitation, we adjusted the model structure, setting the upscaling factor to 2 instead of 4, and used 256×256 images as high resolution and 128×128 as low resolution. The factor of 2 is to avoid a very low-quality image ($1/4^{th}$ of 256 is 64), where fingerprint features would be excessively blurred. Figure 8 illustrates the outcomes of the SRGAN model predictions. Observably, SRGAN model can reconstruct the original fingerprint from the degraded one well.

[2]https://www.analyticsvidhya.com/blog/2023/06/srgans-bridging-the-gap-between-low-res-and-high-res-images/

V. Experiments

A. Experiment 1: SRCNN and Dataset 2

The trained SRCNN model is applied to *Dataset 2*, training it on 9,000 fingerprint images and achieving a PSNR of 36 decibels. Subsequently, this SRCNN model is used to improve input images before feeding to the trained Siamese model, which had been trained on *Dataset 3*. The diagram in Figure 9 provides an overview of this experiment.

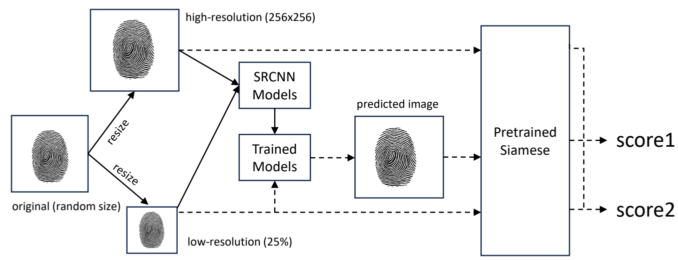

Fig. 9. Overview of Experiment 1. Solid arrows indicate training time (executed on the training set), and dashed arrows indicate inference time (executed on the test set). The difference between scores 1 and 2 shows the effect of image-enhancement models.

To have a deeper analysis, this work also conducts tests on 402 positive anchor pairs (matching pairs) and 402 negative anchor pairs (non-matching pairs). The aim is to investigate if SRCNN-based image enhancement could enhance the Siamese matching capability. For this, both the images in matching and non-matching pairs were initially enhanced using SRCNN and then fed into the Siamese model.

B. Experiment 2, 3, 4, and 5: VDSR/SRCNN and Dataset 1

Experiment 1 has a simple way of degrading the image quality by using image resizing. This is somehow simple and not realistic. In reality, latent fingerprints are damaged in different ways. Therefore, these experiments (*Experiments 2, 3, and 4*) attempt to analyze how image enhancement can improve prediction accuracy for the latent fingerprints that are partially damaged. Original SOCOFing has these damaged fingerprints (this explains why we name this dataset as *Dataset 1*). Figure 10 depicts an overview of this experiment.

In *Experiment 2*, the model is trained on 5,000 images of *Dataset 1*. We then assessed the trained model by testing the model on 402 positive anchor pairs (matching pairs) and 402 negative anchor pairs (non-matching pairs) to determine if SRCNN-based image enhancement could enhance Siamese matching.

The initial dataset of 5,000 images is relatively small, and we would like to evaluate the impacts of the training dataset size. Therefore, *Experiment 3* expands it to 15,000 pairs of images. This experiment also assesses the model using different SOCOFing alteration types, like *Obl*, *Zcut*, and *CR*.

Experiment 4 is similar to *Experiment 2*. However, instead of training the SRCNN model, we would like to analyze the impact of VDSR model instead (to compare the performance between these two architectures). Likewise, *Experiment 5* is similar to *Experiment 2* except that it utilizes SIFT as an evaluation metric instead of Siamese scores.

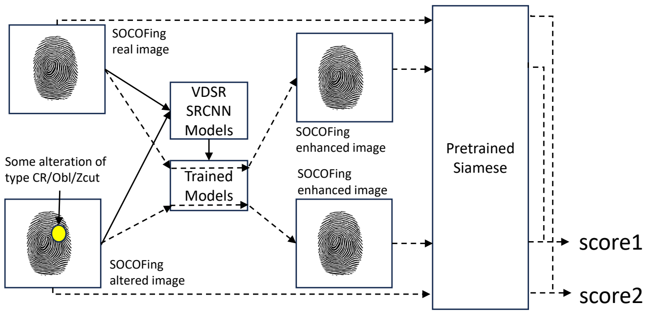

Fig. 10. Overview of Experiment 2. Solid arrows indicate training time (executed on the training set), and dashed arrows indicate inference time (executed on the test set). The difference between scores 1 and 2 shows the effect of image-enhancement models.

C. Experiments 6 and 7: SRCNN/SRGAN with Dataset 4

The purpose of these experiments is to evaluate the impacts of image super-resolution regarding fingerprint verification tasks utilizing more realistic datasets (*Dataset 4*) with different image sizes and resolutions (high and low) as described previously. For SRCNN training, dataset 4 is divided into 800 images for training, 100 for validation, and 100 for testing. After training the model, SIFT key-point matching is used to compare fingerprints. The comparison focused on three categories for positive and negative anchor pairs:

1) Comparison 1 (High & low resolution): High-resolution image (512×512) paired with a low-resolution image (256×256) from *Dataset 4*.
2) Comparison 2 (High & resized low resolution): High-resolution image (512×12) paired with a low-resolution image (256×256) resized to 512×512.
3) Comparison 3 (High & enhanced resolution): High-resolution image (512×512) paired with a 512×512 size image predicted by SRCNN.

Experiment 7 is similar to that of *Experiment 6*. However, instead of SRCNN, we train SRGAN instead. Additionally, due to GPU limitation and SRGAN's complexity, we use 256×256 and 128×128 for the high and low image sizes, respectively.

D. Experiment 8: SRCNN with Dataset 5

Due to the thin fingerprint line pattern, the image degradation and enhancement may produce wrong line patterns. Therefore, *Experiment 8* experiments with the pre-processing steps to generate thicker ridge lines before degradation and enhancement (as described in the generation of *Dataset 5*). Due to the limitation of GPUs, we only experiment with the SRCNN model using *Dataset 5*. Specifically, this dataset is divided into 800 training images, 100 validation images, and 100 test images for training, model selection, and testing, respectively.

VI. Evaluation Metrics

The evaluation of the results of the first four experiments is based on the following criteria: (1) For matching pairs (positive anchor): If the enhanced images yield a reduced distance between matching pairs, it is considered successful and failed otherwise. (2) For non-matching pairs (negative anchor): If the enhancement results in an increased distance, it is regarded as successful and is failed otherwise.

VII. Results

A. Experiment 1: SRCNN and Dataset 2

The purpose of *Experiment 1* is to evaluate the image enhancement applied to SOCOFing images. Unfortunately, this step reduces the accuracy of verification tasks, as shown in Figure 11. The outcomes of the Siamese matching are as follows: 48% the enhancement helps improve the results (increase similarity distance for negative pairs and reduce similarity distance for the positive pairs). In simpler terms, this means that after image enhancement, the Siamese model produced better results in 48% of cases but provided unsatisfactory results in the remaining 52%.

Fig. 11. Actual image (left) versus predicted image (right) using SRCNN model trained on *Dataset 2*.

The poor results may happen because the model was trained on a different dataset containing NIST and FVC images and then tested on SOCOFing images. The NIST/FVC dataset has images with higher resolution and less ink intensity, whereas SOCOFing images are lower in resolution and have more ink intensity. As a result, the model might not be able to work well with the lower-quality SOCOFing images because it didn't learn the characteristics of low-resolution, high-ink-intensity images during its training.

B. Experiment 2: SRCNN trained on Dataset 1

SRCNN model trained on 5,000 images of *Dataset 1* improves image quality, as shown in Figure 12. The outcomes of the Siamese matching indicate the improvements in the image enhancement process to the accuracy of fingerprint verification tasks.

Specifically, Table I shows the percentages of the cases in which the trained SRCNN model can help with fingerprint verification tasks. Notably, the enhancement helps significantly

Fig. 12. Actual image (left) versus predicted image (right) using SRCNN model trained on *Dataset 1*.

Fig. 13. Actual image (left) versus predicted image (right) using VDSR model trained on *Dataset 1*.

in the case of Z-cut damages to the fingerprints (81.41%) and does not help much with obliterations (63.6%). This is explainable since SRCNN can only enhance the resolution and cannot re-generate the damages made by obliterations.

Alternation Type	Improvement
CR (circular rotations)	75.00%
Obl (obliterations)	63.60%
Zcut (Z-Cuts)	81.41%

TABLE I
PERCENTAGE OF THE CASES THE SRCNN MODEL CAN HELP IMPROVE FINGERPRINT VERIFICATION TASKS.

C. Experiment 3: SRCNN trained on extended Dataset 1

Table II shows the results of this experiment. Observably, increasing training size does not help (and even hurt) the verification performance. This may be explained that the SRCNN model is simple and cannot help to accommodate a huge amount of information from a larger dataset.

Alternation Type	Improvement
CR (circular rotations)	69.00%
Obl (obliterations)	50.24%
Zcut (Z-Cuts)	50.24%

TABLE II
PERCENTAGE OF THE CASES THE SRCNN MODEL CAN HELP IMPROVE FINGERPRINT VERIFICATION TASKS WHEN INCREASING DATA SIZE FOR TRAINING.

D. Experiment 4: VDSR trained on Dataset 1

The results of Experiment 4 indicate that there wasn't a notable improvement in image quality and the repair of damaged areas, as illustrated in Figure 13. Specifically, this experiment demonstrates that VDSR didn't perform well, achieving only a 52% as improvement cases.

E. Experiment 5: Matching using SIFT

Results of Experiment 5 show that image enhancement increased the number of key points detected significantly, leading to more key point matches. For instance, let's consider one of the matching cases from Figure 14: on the original image, there were only 32 good matches, but after enhancement, this number jumped to 1,147. Additionally, nearly all the key points from the image were detected, except for the altered part.

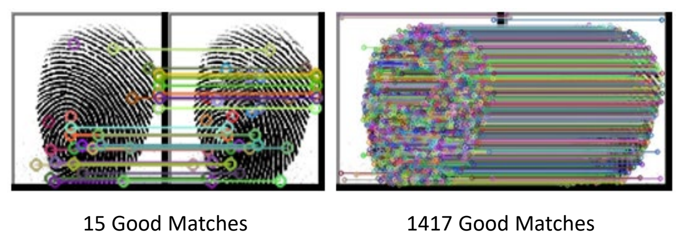

Fig. 14. An example of how the image enhancement process helps increase the matching key points for a pair of fingerprints. This matching pair only has 15 pairs of good matching points before enhancement. The same pair has 1,417 matching pairs after enhancement.

This significant increment in the number of matched key points after the enhancement process demonstrates that image enhancement can be an effective technique for improving key point-based image analysis and feature matching, especially in cases involving low-quality or altered images. More importantly, most of the fingerprint verification techniques are based on key-point matching.

F. Experiment 6: SRCNN with Dataset 4

The results from Experiment 6 suggest that SRCNN resolution shows promising outcomes in all comparisons, as illustrated in Figure 15. The first comparison (between the original image and its low-resolution counterpart) has the least number of good matching points, the second (between the original one and its resized version) outperforms the first, and the final comparison (between the original one and its enhanced version) produced the highest matching points. This characteristic holds for all test images, as depicted in Figure 23.

Likewise, when examining negative anchors representing non-matching images, the number of good matching points stayed consistently low and aligned across all three comparisons, as demonstrated in the right column of Figure 15 as

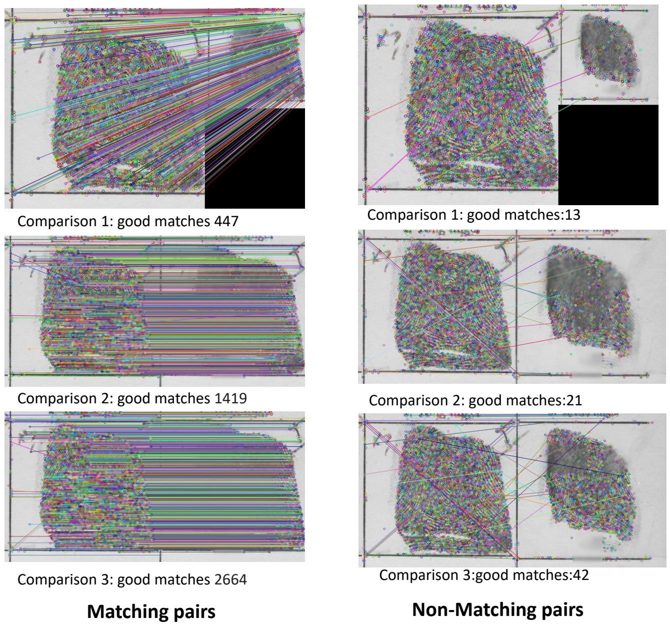

Fig. 15. Image enhancement process with SRCNN helps increase matching key points for matching pairs and still keep that as low for non-matching pairs. Comparisons 1, 2, and 3 are the comparison between the original file with its low-resolution, resized resolution, and enhanced resolution, respectively.

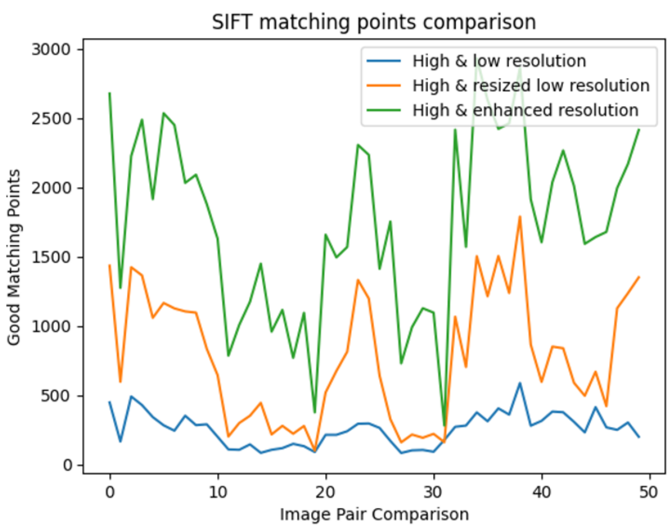

Fig. 16. Image enhancement process with SRCNN helps increase matching key points for all testing matching pairs.

one instance. This characteristic also holds for all other testing cases for non-matching pairs, as shown in Figure 17.

G. Experiment 7: SRGAN with Dataset 4

The improved predicted image from SRGAN exhibited superior results compared to the first two comparisons. Figure 18 graph further highlights that the first comparison had the fewest good matching points, the second outperformed the first, and the final comparison yielded the highest matching points for all test images.

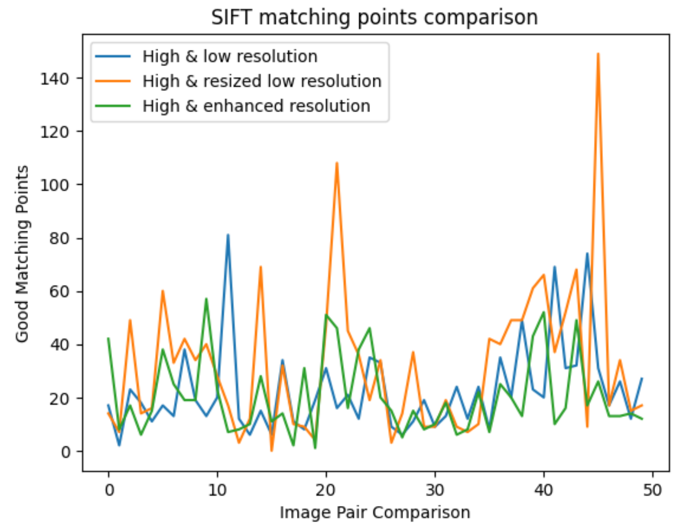

Fig. 17. Image enhancement process with SRCNN keeps matching key points relatively and consistently low for non-matching pairs.

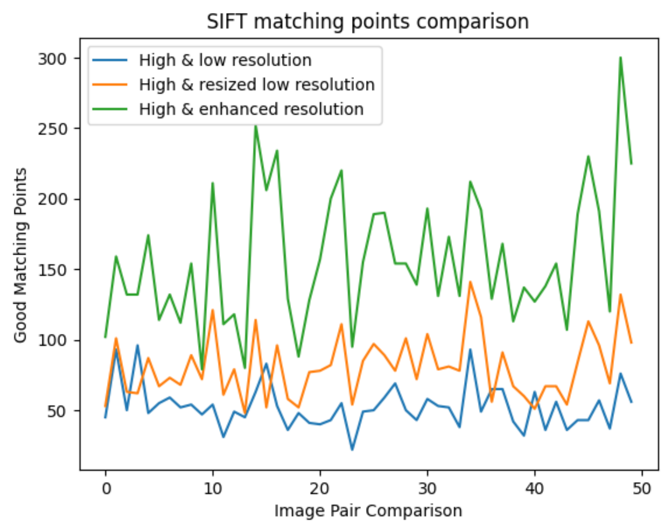

Fig. 18. Image enhancement process with SRGAN helps increase matching key points for all testing matching pairs.

Similarly, when analyzing negative anchors representing non-matching images, the number of good matching points remained consistently low and aligned across all three comparisons, as demonstrated in Figure 19.

H. Experiment 8: SRCNN with Dataset 5

Additionally, there's a noteworthy observation about the SRGAN model. After enhancing the image, it tends to enhance its appearance. However, if fingerprint ridges are in very low resolution, during prediction, it might generate clear but incorrect ridges. As depicted in Figure 20, the low-resolution image (LR) has a very low resolution, and the predicted super-resolution image shows clear ridges. However, they are distinctly different from the original high-resolution (HR)

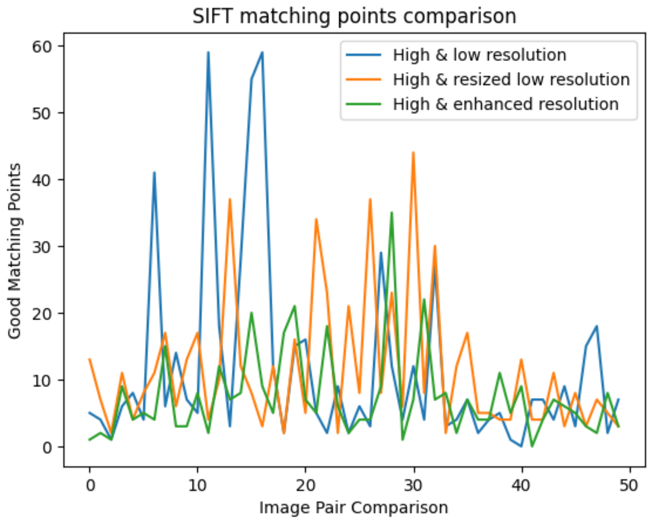

Fig. 19. Image enhancement process with SRGAN keeps matching key points relatively and consistently low for non-matching pairs.

image. This impact might be caused by the degradation process itself.

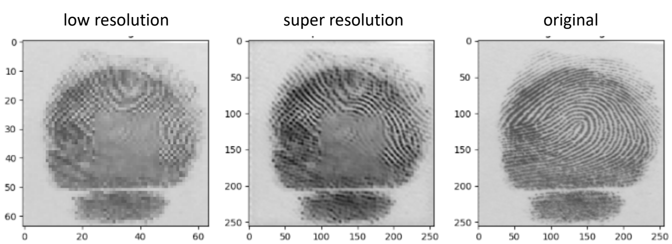

Fig. 20. SRGAN may generate wrong pattern if the image is too low quality.

Therefore, this experiment attempts to thicken the ridge lines before applying degradation process and verification process as described in *Dataset 5*. However, our initial experiment shows that this attempt still does not help improve the verification accuracy.

VIII. Discussions

The following observations should be further explored in the future: (1) applying the approach used in *Dataset 1* experiments, where SOCOFing altered images were treated as low resolution. This methodology can be further explored with SRGAN, emphasizing a consistent upscaling factor of 1; (2) instead of relying solely on Gaussian blur in *Dataset 4*, we also explore 'blind' image degradation approach; (3) conducting Experiment 7 using SRGAN could yield improved results by utilizing high GPU RAM during model training for processing lower resolution images of superior quality; and (4) enhanced outcomes may be achieved in Experiment 6 and 7 by training the model with a larger set of images.

IX. Conclusion

In conclusion, this project aims to enhance fingerprint classification accuracy by utilizing machine learning enhancement models, namely SRCNN, VDSR, and SRGAN. Departing from the traditional super-resolution approach, this work experimented with damaged images from the SOCOFing dataset at the same resolution as low-resolution counterparts. This novel method significantly improved fingerprint matching accuracy, especially with SRCNN, achieving a 73% accuracy rate across all damage types, with an exceptional 81% accuracy for Zcut damage.

The extension of this experiment to the NIST roll sd300a dataset, with preprocessing to simulate real-world conditions, demonstrated the versatility of the approach. Despite differences between the datasets, SRCNN and SRGAN yielded remarkable results, providing enhanced images that, when matched using SIFT key points, outperformed damaged low-resolution counterparts. Notably, SRGAN occasionally produced clear but incorrect ridges when dealing with very low-resolution images.

These findings emphasize the potential of employing machine learning enhancement models for fingerprint recognition, showcasing improved accuracy even in diverse and realistic datasets. Further exploration and refinement of techniques, especially addressing occasional inaccuracies like those observed with SRGAN, will contribute to the ongoing advancement of fingerprint recognition technology.

X. Acknowledgement

We express our profound gratitude to the Institute for Homeland Security at Sam Houston State University for their unwavering support for our project.

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