FIGO: Enhanced Fingerprint Identification Approach Using GAN and One Shot Learning Techniques

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Abstract—Fingerprint evidence plays an important role in a criminal investigation for the identification of individuals. Although various techniques have been proposed for fingerprint classification and feature extraction, automated fingerprint identification of fingerprints is still in its earliest stage. The performance of traditional Automatic Fingerprint Identification System (AFIS) depends on the presence of valid minutiae points and still requires human expert assistance in feature extraction and identification stages. Based on this motivation, we propose a Fingerprint Identification approach based on Generative adversarial network and One-shot learning techniques (FIGO). Our solution contains two components: fingerprint enhancement tier and fingerprint identification tier. First, we propose a Pix2Pix model to transform low-quality fingerprint images to a higher level of fingerprint images pixel by pixel directly in the fingerprint enhancement tier. With the proposed enhancement algorithm, the fingerprint identification model's performance is significantly improved. Furthermore, we develop another existing solution based on Gabor filters as a benchmark to compare with the proposed model by observing the fingerprint device's recognition accuracy. Experimental results show that our proposed Pix2pix model has better support than the baseline approach for fingerprint identification. Second, we construct a fully automated fingerprint feature extraction model using a one-shot learning approach to differentiate each fingerprint from the others in the fingerprint identification process. Two twin convolutional neural networks (CNNs) with shared weights and parameters are used to obtain the feature vectors in this process. Using the proposed method, we demonstrate that it is possible to learn necessary information from only one training sample with high accuracy.

Index Terms—Criminal investigation, fingerprint image enhancement, automatic fingerprint identification system, image-to-image translation, conditional GAN, Pix2Pix model, Gabor filters, one-shot learning, convolutional neural network, forensic science.

1 INTRODUCTION

The presumption of innocence is a legal principle in democratic countries where all citizens are treated equally by the rule of law. In such countries, it is clearly articulated that "everyone is innocent until proven guilty". Proof of crime has vital importance for developing a fair decision-making mechanism. In this context, collecting clear evidence and presenting them to the competent authority is essential for the detection of crimes and criminals.

Although eyewitness identification has a long history of being used to uncover the truth about a crime, it can be considered an unreliable and problematic technique. That is because the nature of human memory is error-prone for remembering and interpreting a witnessed event. Additionally, a witness may intentionally lie under oath about a certain event in order to mislead authorities. In such cases, erroneous eyewitness identifications can lead to wrongful convictions [1]. These concerns have encouraged researchers to develop alternative solutions in the field of criminal identification for ages. As a result, experts in the criminal justice systems explored the use of biometric technology for forensic identification. Contrary to eyewitness identification, taking advantage of biometric information is more reliable and accurate since it is directly related to the unique characteristics of each individual. Behavioral characters (i.e. voice, signature), as well as physiological characters (i.e. fingerprint, iris, face), have been used for the identification and verification of criminals in the past decade.

While law enforcement agencies and intelligent communities make use of the state of the art biometric technologies for the purpose of identification, authentication, or investigation of individuals today, constructing a good biometric system has limitations and challenges. For instance, facial characteristics are typically standard and facial identification is influenced by expression, age, and observation angle to a different extent. Because of the instability of facial features, the accuracy of face recognition systems is low. When it comes to iris recognition technology, it requires advanced visual sensing cameras to capture the necessary features with sufficient details. On the other hand, fingerprints have distinctive patterns that make every fingerprint unique and more importantly they don’t change over time. Therefore, fingerprint-based criminal detection systems are the most widely used biometric technology compared to other biometrics [2].

The performance of the AFIS is heavily dependent on the extraction of the quality of relevant features. These features mainly consist of minutiae points that are set of points representing the distinctive character of a person and remain constant throughout a person’s lifetime [3]. Some common minutiae patterns are illustrated in Figure 1 [4].
In order to eliminate the manual intervention by a human expert in traditional methods, machine learning techniques can be used to automatically learn the valuable underlying implicit patterns of fingerprint images rather than hard-coded explicit features obtained by traditional methods so that it reduces the dependence on the knowledge domain [7]. However, machine learning models are data-driven approaches so they require large training examples for the application of even simple object detection tasks [8]. Unfortunately, collecting such large data samples to train a model is very challenging since every person is an unique example (fingerprint). Traditional machine learning models cannot effectively learn complex features when the model is fed with one supervised sample. In addition, retraining of the model is required when a new criminal’s record is incorporated into the system, resulting in low-level usability of criminal record applications. As a solution to the limitations of the traditional machine learning model’s effectiveness and usability, we present the one-shot learning approach, where the model is trained with only one sample. To achieve this goal, the proposed algorithm turns the classification problem into a difference-evaluation problem where the model attempts to learn similarity functions for image pairs instead of using manually designed features. In this way, the model gains the ability to learn from one example while also removing the need for retraining in a dynamic environment.

Furthermore, latent fingerprints, collected from a crime scene, are rarely perfect for the purpose of identification. They are maybe corrupted or incompletely. In such cases, since the important information is lost, the model can not reliably extract discriminative features from fingerprint images, therefore, it fails to achieve an adequate level of performance. Hence, a pre-processing process to enhance the fingerprint information is a critical step for the model to deliver reliable results. Previous studies mostly have used Gabor filter algorithms for high-quality fingerprint images [9], [10]. Technically speaking, Gabor filter methods use a low-pass filter to connect the discontinuities in the fingerprint images to remove the noise and use a band-pass filter to create distinctive features to sharpen the images for the image enhancement process [11]. However, this process also generates unnatural (artificial) features that don’t exist in the original fingerprint samples so that it greatly impedes the applicability of a successful fingerprint identification system. In order to improve the identification process, we introduce a Pix2Pix model which is based on conditional Generative Adversarial Network (cGAN) [12] by capturing the relationship between original fingerprint images and constructed version. In this way, the images are automatically reconstructed as realistic as possible from distorted or incompletely ones.

This paper proposes a Fingerprint Identification approach based on a Generative adversarial network and One-shot learning technique (FIGO). The motivation of this paper, as illustrated in Figure 2, is to propose a sequential multi-model system where we synergistically bring two models together for improving image reconstruction and identification accuracy. Our research has the following contributions:

- We propose a novel combination of generic and automatic classification methods over a massive real-world fingerprint dataset. The proposed method enables effective learning from a single example in noisy environments for identification purposes.
- To the best of our knowledge, this paper is the first preliminary study to suggest creating a fingerprint identification model based on a one-shot learning approach for fully automatic feature extraction and fingerprint classification so that no human intervention is required. In spite of the fact that our proposed model eliminates the limitations of existing research on fingerprint classification, the model’s performance significantly degrades when low-resolution fingerprints are entered into the system as expected.
- In order to improve the quality of various levels of noisy fingerprint images, we develop a Pix2Pix model structure. Experimental results indicate that our proposed technique is better suited to reconstructing fingerprint images when compared with a conventional method (Gabor filter approach) and has shown substantial improvements in fingerprint classification accuracy when incorporated into the fingerprint verification system.

The rest of this paper is organized as follows: the literature review in the context of our work is discussed in Section 2. The background information relevant to our study is reviewed in Section 3. The proposed techniques are presented in Section 4. Section 5 describes the implementation of the reconstruction fingerprint and fingerprint classification approaches. We evaluate the models’ performances in Section 6. In conclusion, we finalize the paper in Section 7.
2 RELATED WORKS

The techniques of fingerprint identification and fingerprint feature extraction have previously been studied by several researchers. Wang et al. [13] proposed a fingerprint classification technique based on continuous orientation field and singular points. According to the authors, singular points on a fingerprint image, such as core or delta points, are important discriminative features, which were extracted using a modified Poincare index. The experiment was conducted using the FVC 2002 [14] and FVC 2004 [15] databases. The overall classification accuracy was found as 96.1%. Maio et al. [16] presented an automatic minutiae algorithm where the minutiae points were efficiently detected from the NIST fingerprint database [17]. The authors then showed that their proposed method outperformed some other solutions based on the image binarization approach in terms of efficiency and robustness. Since then, minutiae-based fingerprint recognition systems have become increasingly popular due to their uniqueness. Unfortunately, singularity or minutiae points don’t always exist in a fingerprint image due to the existence of noises or partial parts of the fingerprint availability. In such cases, the singularity-based or minutiae-based biometric techniques are more likely to fail to identify the target class.

In order to eliminate the limitation of minutiae-based algorithms in fingerprint recognition systems, machine learning-based solutions have been proposed by some other researchers. Militello et al. [18] demonstrated the performance of pre-trained CNN architectures (AlexNet, GoogleNet, and ResNet) over two different fingerprint databases. A Bayesian classifier was implemented in [19] while support vector machines are developed in [20] for fingerprint classification. Li et al. [21] introduced a fingerprint classification based on a deep learning approach to obtain global features. The optimum parameters of the neural network model were found through a genetic algorithm. Kouamo et al. [22] proposed a model to identify the users based on their fingers using a deep neural network. Ala et al. [23] proposed a dimensionality reduction technique based on the euclidean distance between the center point and their nearest neighbor bifurcation minutiae. By doing so, redundant and irrelevant features were eliminated. The remaining topmost features were then used to develop a fingerprint identification method based on a backpropagation neural network. Using the FVC 2002 database, they evaluated their methods and found that their results were superior to those of several other methods. In the literature, the primary problem with implementing an efficient fingerprint application using machine learning models is the lack of training samples since each individual has only one unique object. The above-mentioned studies attempted to circumvent this issue in some way by utilizing data augmentation techniques [24], [25]. However, augmented data created from existing data are often noisy. In many cases, machine learning models struggle to distinguish between noisy and noise-free data, which reduces the performance of the model [25]. Moreover, for each new sample, both state-of-the-art machine learning algorithms as well as transfer learning-based possible viable solutions are required to be retrained. Instead of synthesizing new fingerprint samples, we propose a one-shot learning approach to train the model with one training sample. Our proposed technique distinguishes fingerprints from each other more efficiently and eliminates the need for retraining the whole system.

As we outlined previously, fingerprints are rarely of good quality. Due to the presence of noise, they are distorted and corrupted. Therefore, it is essential to incorporate a fingerprint enhancement technique into the fingerprint identification system to make the system robust and increase identification accuracy. Barnouti et al. [27] proposed histogram equalization and compression methods in order to both increase the image quality and the processing speed. Using histogram equalization, the authors were able to increase the quality of the images while using principal component analysis to reduce the dimensions without losing much information in order to speed up the verification process. However, histogram equalization causes a change in the brightness of an image resulting in a considerable loss of image detail. Wang et al. [28] initially found an area that consists of a singular point then offered to use a bandpass filter in the Fourier domain for image enhancement. It is, however, difficult to extract singular points from a poor-quality fingerprint image.

3 BACKGROUND

In this section, we review background information related to our research.
3.1 CNN Model:

CNN is a special type of neural network which mostly applied to extract relevant features for the image content \([29, 30, 31, 32]\). Instead of extracting handcrafted explicit features by the classical image recognition system, a CNN model is able to learn the valuable features automatically for better classification \([33]\).

Technically speaking, a CNN model consists of input, output, and hidden layers. The hidden layer has three main components known as the convolutional layer, the pooling layer, and the fully connected layer \([34]\). While in the convolutional layer, raw pixel data is converted to a feature map that detects all different patterns in the input data, in the pooling layer the feature map is being downsampled to select the most valuable information. In the fully connected layer, this joint information content is used to classify the given image into various classes.

3.2 Overview of Fingerprint Recognition System:

The typical fingerprint recognition system consists of two stages, enrollment and identification \([35]\). Figure 3 demonstrates the traditional fingerprint identification system. The biometric device scans the individual’s fingerprints and converts them into digital images during the enrollment process. After that, the unique features of the fingerprint images are extracted and stored in a database. When a fingerprint is presented at the identification stage, it is subjected to the same process as at the enrollment stage in order to capture distinctive features and compare them against a database of known individuals. If any fingerprint pair is sufficiently similar, the identification is successful.

3.3 One-shot Learning Approach:

One-shot learning approach was firstly introduced in \([36]\). This technique is directly inspired by the ability of human beings to learn new tasks from the past gained knowledge by using particular models/algorithms. While traditional machine learning models require millions of training examples in the training process, the main idea of the one-shot learning approach is to reduce the number of training samples needed to perform machine learning tasks by learning the similarities and differences between object categories \([37, 38]\). Therefore, machine learning models can be generalized well without a need for a vast amount of supervised information (even with a single example) in the one-shot learning setting. In some cases, collecting sufficient data is infeasible or expensive. In such application scenarios, such as fingerprint matching applications, the implementation of a machine learning model via one-shot learning modeling would be more suitable to achieve remarkable learning results.

3.4 Conditional Generative Adversarial Network:

The Generative Adversarial Network (GAN) is a class of machine learning/deep learning models in which two neural networks compete in a zero-sum game \([39, 40]\). In this game theory, one network’s gain is another network’s loss. Although GANs were originally proposed as a form of generative modeling under the unsupervised learning paradigm, they have also proven useful under semi-supervised learning, fully supervised learning, and reinforcement learning.

The core idea behind GANs as a model is that it is comprised of two networks, also known as Generator and Discriminator. The generative network generates candidates while the discriminator evaluates them. The generative network learns to map from a latent space to a data distribution of interest, while the discriminative network distinguishes candidates produced by the generator from the real data distribution. Generative networks are trained to fool discriminative networks by producing novel candidates that are as real as possible, such that the discriminator is unable to distinguish between real and synthetic samples.

The GAN is capable of generating quality synthetic data in a variety of situations, however, in some cases, it does not produce the desired outputs as there is no control over the types of data that are produced by the generator. To overcome the shortcomings of GAN, cGAN was introduced in \([12]\). Using this approach, auxiliary information can be used to guide the data generation process. Additional information may include supervised samples or partial parts of the data that learn a better representation of target images.

4 The Proposed Approach

In the following subsections, we first describe the proposed fingerprint reconstruction method using the Pix2Pix model to improve the pattern legibility that can help to enhance the fingerprint classification reliability. We then present another existing solution based on Gabor filters as a benchmark to compare with the proposed model by observing the fingerprint identification model’s accuracy. Last but not least, we discuss our unique and reliable method for fingerprint identification based on the one-shot learning approach. Note that Pix2Pix and one-shot learning models are the two essential components of the FIGO model.

4.1 Fingerprint Reconstruction Method Using Pix2Pix Model:

As we outlined earlier, latent fingerprints obtained from crime scenes are largely corrupted due to external factors such as the type of surface on which latents are found, the force of contact with the object, skin conditions, and so on. In order to improve the quality of latent fingerprint images, most latent fingerprint images must be preprocessed. In this regard, we propose a new fingerprint reconstruction framework based on the Pix2Pix model inspired by \([41]\). Our proposed Pix2pix model is based on cGAN where the model learns automatically how efficiently convert noisy/incomplete fingerprint images to enhanced fingerprint images by translating pixels to pixels. To this end, we adapt two neural network models based on CNN, labeled discriminator \(D\) and generator \(G\) to learn the translation function.

In the beginning, \(G\) takes low-resolution fingerprint images as input and produces output, which is then sent to \(D\). When \(D\) receives distorted fingerprint images and outputs from \(G\), it compares them with the same distorted fingerprint images and the original fingerprints. The two
Matching
No Record Found

Fig. 3: Illustration of the traditional fingerprint identification system.

Fig. 4: Example results of fingerprint image reconstruction using the proposed Pix2Pix model. The first column shows the noisy images while the second column demonstrates the real images. The third column shows generation of output images from noisy ones with proposed method.

Fig. 5: The left side image shows a noisy image while the right side one is reconstruction result using the Gabor filter.

models are trained simultaneously. The G attempts to not only fool the D, but also translate distorted images into the desired restored images, while the D is able to detect G’s fake samples. By fine-tuning G parameters, the real and fake distributions of data become highly similar. At this point, the enhanced fingerprint images are successfully produced from the noisy fingerprint images through the proposed translation model. As shown in Figure 4, the proposed Pix2Pix model successfully translates noisy images to enhanced counterparts.

4.2 Fingerprint Reconstruction Method Using Gabor Filters:

In [42], Dennis Gabor first introduced the Gabor filter, which was later extended by David Daugman in [43]. By taking into account its frequency-selective and orientation-selective properties, the Gabor function is a very useful technique for capturing both time and frequency information simultaneously from digital images. It has therefore been widely used in computer vision and image processing for the analysis of textures, the detection of edges, the extraction of features, and so on.

Hong et al. [44] assumed that periodic parallel ridge and valley patterns, which are the primary features of a fingerprint image for the extraction of minutiae points, could be described as sinusoidal plane waves. Since a Gabor filter is represented as a complex sinusoidal signal modulated by a sinusoidal plane wave [45], it makes them more suitable in the fingerprint image enhancement process based on their assumption. Therefore, the authors deployed the Gabor filters in an automatic fingerprint identification system to remove undesired noises and reported promising results. Since then, Gabor filters have become one of the most dominant approaches for addressing problems related to noisy or partial patterns in the literature of fingerprint enhancement methods. Figure 5 demonstrates how a noisy image is reconstructed to improve the image quality using the Gabor filter with our implementation.

Yang et al. [46] demonstrated that fingerprint images do not always follow the ideal sinusoidal plane wave shape (see Figure 5) in which case the technique does not improve the quality of these images. Thus, Hong and others’ assumption is not valid in all circumstances. This technique has another disadvantage in that Gabor filters are parametric solutions that require a set of parameters to be tuned, such as the standard deviations of the Gaussian function, the convolution mask size, etc. Its denoising performance is dependent on parameter values, and these values can only be determined through experience. For example, larger standard deviations tend to make the method more robust to noise, but it is also more likely to generate spurious minutiae. On the other hand, a large number of real minutiae points would be ignored with smaller values of the standard deviation. Consequently, the technique leads to an image-dependent solution due to the parameter selection process.

To provide a more robust noise reduction algorithm while preserving the true ridge and valley structures without depending on fingerprint images, we propose a Pix2Pix model. Our experimental results demonstrate that our
Pix2pix model is more powerful than traditional Gabor filters in reconstructed fingerprint images. In Section 3, we analyze the model performances in detail.

4.3 Fingerprint Identification Using One-Shot Learning Approach:

To develop a fully automated fingerprint classification system, we propose a similarity-based learning approach in which the model attempts to learn similarity functions for image pairs as opposed to using manually designed features. This idea is inspired by the Siamese network structure [47]. The proposed model consists of two twin CNN networks connected by a similarity layer at the top. To put it another way, these two identical networks have the same configuration (i.e., the same number of layers and nodes) that share weights and parameters. The tying of the weights ensures that similar images will map close together in the feature space while dissimilar pairs will fall apart since each network in the architecture computes the same function.

In order to develop a model for fingerprint image classification, we generate all possible fingerprint image pairs from original samples and label them either as ‘positive’ or ‘negative’. If two images are the same, then the image pair is labeled as ‘positive’, otherwise, it is labeled as ‘negative’. During training, matching and non-matching image pairs are fed to CNN models to extract unique features from labeled examples. After that, the Euclidean distance is calculated between all image pairs. As a result of these calculations, a loss function is derived. The loss function is designed to minimize the squared Euclidean distance between positive samples and maximize for negative samples. In this way, the proposed approach gains discriminative and generalization ability. With its discriminative ability, the model can efficiently differentiate a fingerprint from the others. On the other hand, due to its generalization ability, the proposed model properly identifies the person even if there is variations in the fingerprint image due to the presence of structured noise. The training process of the proposed fingerprint identification method is depicted in Figure 7.

Mathematically speaking, let M be our fingerprint identification model, x represents any fingerprint image and Y represents the corresponding ground-truth output label (negative (0) or positive (1)) of each x * x pair. C(M, x, y, Y) is the cost function used to train the fingerprint classification model as shown in the equation below. The aim is to minimize error if any pair of inputs belong to the same class while maximizing error, otherwise.

\[
\text{objective} \begin{cases} = \text{minimize} & c(M, x1 * x2, Y), & \text{if } Y = 1 \\ = \text{maximize} & c(M, x1 * x2, Y), & \text{if } Y = 0 \end{cases}
\]

The distance metric is calculated based on element-wise absolute difference:

\[
d(x1, x2) = |M(x1) - M(x2)|
\]

The design of this proposed fingerprint identification algorithm using the one-shot learning approach differs considerably from traditional machine learning techniques. The advantages of the proposed approaches are twofold. Firstly, traditional machine learning models require a huge amount of training samples whereas this model can be trained with a single training sample. Another notable advantage of this method is that when a new user joins/leaves the fingerprint database there is no reason to retrain the model because the model is trained to distinguish between fingerprints based on pairwise similarity. However, with a typical machine learning classification model, the system has to be retrained with each new user, reducing the usability of such systems.

5 MODEL IMPLEMENTATION

In this section, we describe the dataset used to build the fingerprint identification model using generative adversarial networks and one-shot learning techniques, along with an explanation of how the FIGO model is implemented.

5.1 Dataset:

In our project, we use the SOCOFing dataset in [48]. The dataset contains 6,000 fingerprints taken from 600 Africans. A fingerprint sample is taken from each finger of each individual. The noise was created using three different alteration techniques, including obliteration, central rotation, and z-cut, using the STRANGE toolbox [49]. Based on parameter settings in this toolbox, the authors generated different levels of noise and categorized them as ‘easy’, ‘medium’, and ‘hard’. The output of this phase is shown in Table 1 as an example. As seen in Table 1, the original image is slightly
Table 1: Sample illustration for all three alteration categories along with original sample

```
001_M_Left_little_finger_Obl.bmp
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Fig. 8: Format of the fingerprint used in the dataset.

Distorted by noise in the 'easy' category. When the level of noise is increased in the 'medium' category, the quality of the image is reduced. In addition, the more additive noise corrupts the real image to a great extent in the 'hard' category. In this case, the fingerprint image will lose much of its most important information.

The image file format is illustrated in Figure 8 where:
1) identifies each individual from 1 to 600.
2) indicates the gender of the individual, such as F-female, M-male.
3) indicates which hand is being used, i.e., left or right hand.
4) specifies the finger name; thumb, index, middle, ring, little.
5) displays the type of alteration (only for noisy samples): CR - central rotation, Obl - obliteration, or Zcut.
6) filename extension: " .bmp" for each image.

5.2 FIGO implementation:
As previously mentioned, the FIGO model consists of a Pix2Pix model and a fingerprint identification model. During the training process, each model is trained separately. Once the models are completely trained, they are linearly stacked one on top of another into a pipeline where the output of the Pix2Pix model is fed to the proposed automated fingerprint identification model for the identification.

We implement both models using Python programming language and the Tensorflow library. The SOCOFing dataset is randomly divided into three parts as training, test, and verification. We use 80% of the dataset to train the models, 10% of the dataset for testing, and the remaining is reserved for evaluation of the FIGO’s performance. The Python code runs on Google Colab equipped with NVIDIA GPU Tesla P4 [50].

To develop a denoising framework based on the Pix2Pix model, we utilize the same architecture and parameters for both the discriminator and generator except for types of loss functions. A “Mean Absolute Error” is used to measure the error of the generator, whereas a “Mean Square Error” is used to measure the error of the discriminator. Table 2 shows the fine-tuned system parameters for the Pix2Pix model experiment.

Table 2: Experimental parameters for the Pix2Pix model

| System Parameters       | Value                                |
|-------------------------|--------------------------------------|
| Embedding Layer Size    | 17                                   |
| Learning Rate           | 0.0002                               |
| Epoch Number            | 10                                   |
| Optimizer               | Adam Optimizer                       |
| Loss Function           | Mean Squared Error (for Discriminator)|
|                         | Mean Absolute Error (for Generator)  |

We also implement a novel one-shot learning approach for the identification of criminals. A fine-tuned set of system parameters is provided in Table 3. As a brief summary, in our scenario, we are using only real (undistorted) samples in order to train a fingerprint identification model using a one-shot learning technique. The assumption is regarded as more realistic for crime scene investigation, since the fingerprint information of every or almost every citizen is stored in the fingerprint database and is always available to authorities. The use of this approach can also help ease the burden of collecting or generating large quantities of fingerprint information. In the process of training the model, negative and positive pairs of data are created, which are then used to train the model based on triplet loss [51]. The purpose of the triplet loss is to ensure that the distance between positive samples is as small as possible while the distance between negative samples is as large as possible. In this way, the proposed fingerprint identification model is able to effectively distinguish latent objects from each other.

Table 3: Experimental parameters for the fingerprint identification model

| System Parameters       | Value                  |
|-------------------------|------------------------|
| Embedding Layer Size    | 2                      |
| Similarity Layer Size   | 6                      |
| Learning Rate           | 0.001                  |
| Epoch Number            | 10                     |
| Optimizer               | Adam Optimizer         |
| Loss Function           | Binary Cross Entropy    |

Once the FIGO model is trained, the model is tested on unseen data. During testing, the Pix2Pix model takes an unseen noisy fingerprint image as an input and produces
Fig. 9: The fingerprint identification model’s recognizing accuracy under various corruption level without incorporating fingerprint enhancement algorithms.

Fig. 10: The fingerprint identification model’s recognizing accuracy under various corruption level by integrating fingerprint enhancement algorithms.

Fig. 11: The fingerprint identification model’s recognizing accuracy under various corruption level by combining Gabor filter and Pix2Pix fingerprint enhancement algorithms.

an enhanced version. Each image from the real dataset is paired with this enhanced image one by one and fed into the fingerprint identification model. For each match, the fingerprint identification model computes a similarity score. The system determines the user’s identity with the highest score according to this comparison.

6 EVALUATION AND RESULTS

To assess the proposed FIGO model’s overall performance in terms of image quality enhancement and recognition accuracy, we have conducted several experiments. In the first set of experiments, fingerprint enhancement algorithms are not applied. Once the fingerprint identification model is trained with only real samples, the model is tested with samples under three different corruption levels along with real ones. Figure 9 illustrates the unimodals’ recognition accuracies at different noise levels. In our study, we found that the model classifies each real (reference) fingerprint image almost precisely. However, when the images are distorted by small alterations, the accuracy rate of the model drops to 85.93%. The reason for this is that the amount of distinctive information included in the images is limited. Furthermore, when the fingerprint image degeneration is severe to a certain extent, it leads to very poor accuracy. In cases of heavy noise contamination in images, since most of the valuable rich information from clean samples is lost, the model’s identification performance is significantly reduced with an accuracy rate of 22.8%.

In the second set of experiments, we extend the experiment for a more comprehensive evaluation by integrating the fingerprint enhancement algorithms (Pix2Pix model and a Gabor filter) with the fingerprint verification model in order to eliminate the adverse effect of low-quality samples. As shown in Figure 10, both enhancement methods help improve the recognition accuracy under actual sampling conditions and the Pix2Pix model gets a bit more encouraging result than the Gabor filter method, which are 100% and 99.6% respectively. The slight advantage of the Pix2Pix model over the Gabor filter algorithm could probably be explained that the Pix2Pix model brings out more discriminative information of the disguised latent fingerprint images.

In the case of the existence of different levels of corruption, the multimodal system including with Gabor filter method performs worse than the unimodal fingerprint identification system that has the accuracy of 75.2%, 27.8%, and 14.39 for easy, medium, and hard categories respectively. This consequence mainly results from the fact that although the Gabor filter algorithm helps suppress the undesired noises, a significant number of spurious features are generated, which leads to unsatisfactory accuracies. On the other hand, the multimodal system including with Pix2Pix model (FIGO model) helps speed up fingerprint detection in all three different noisy scenarios due to its effective noise reduction method. As can be seen from Figure 11, the proposed FIGO model increases the recognizing accuracy nearly by 12% and 17% for easy and medium groups respectively. When the fingerprint image distortion is severe to a great extent, it is the most challenging for unimodal fingerprint identification to detect useful information whereas, the designed FIGO approach boosts the accuracy of fingerprint identification by approximately 40%.

In the last set of experiments, we combine the Gabor filter method and Pix2Pix model to enhance fingerprints, where the output of the Gabor filter technique is fed to the Pix2Pix model before the input images are entered into
the fingerprint verification model. As it can be observed in Figure [11] the matching performance of the fingerprint recognition system is slightly increased with the combined scenario for noise-free images. While the design model performs worse than unimodal recognition in the case of noise, the accuracy of fingerprint identification has improved compared to Gabor-based enhancement. Due to the fact that the Gabor filter method unexpectedly generates artifacts and does not provide sufficient enhancement in some areas of the fingerprint images, this leads to a degradation of the accuracy of fingerprint identification.

Overall, the results of the experiments indicate that the accuracy of the proposed fingerprint verification system based on the one-shot learning approach is very high with high-quality fingerprint images, but its performance decreases more or less with distorted images. In our empirical study, the Gabor filter method is not a desirable approach for the image enhancement process. Moreover, the proposed Pix2Pix model is an effective way of handling different levels of noise and is more powerful than Gabor filter approaches for enhancing fingerprint images, so that it can be incorporated into the identification process as a complementary tool.

7 Conclusion

When a decision is made regarding a quilt, the criminal justice system relies heavily on forensic evidence. The use of false or misleading forensic evidence contributes to erroneous convictions that lead to the breakdown of trust and injustice. Latent fingerprints are one of the most important pieces of evidence that have primarily been used for forensic purposes. However, in practice, a large percentage of fingerprint images obtained are of poor quality and require significant restoration. In addition, the accuracy and reliability of the fingerprint identification system are dependent upon the expertise of the latent print examiners. The FIGO model is designed to ensure robust feature extraction and accurate feature matching without the involvement of a human expert. The FIGO is multimodel where the Pix2Pix model is added to the proposed fingerprint classification model based on the one-shot learning approach. According to the results of numerous experiments, the proposed image enhancement algorithm significantly improves the performance of the proposed biometric system, resulting in remarkable identification accuracy.

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