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Advancements and Challenges in Low-Quality Fingerprint Identification: A Comprehensive Survey

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Abstract
Low-quality fingerprint identification has played a significant role in the field of biometric identification. Especially for those who are experts in the use of sophisticated biometric technology in jail security and criminal identification in recent years. Many factors affect the accuracy of low-quality fingerprint identification, such as the quality of the fingerprint image, the accusation device, the extraction tools, etc. Many approaches have been proposed in this field to improve low-quality fingerprint identification. In this paper, we discuss the main factors of the low-quality fingerprint, the main approach of the human biometric data, as well as the main factors of the low-quality of the fingerprint data. Also, we list the state of the art, most recent machine learning and deep learning approaches that have been used recently in this field. As the end, this field of research is still in progress to improve the quality of the identification progress

Keywords: low-quality fingerprint, high-quality fingerprint

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1. Introduction

Reliable personal information is essential for person identification methods that aim to identify or verify the identity of individuals using various systems. Participants and users requesting services from the system in question rightfully place a high value on this information in some instances [1]. The scheme's goal is to prevent unauthorized parties from gaining access to the provided services, such as those involving person identification and verification tasks by Jain et al. [2]. The following systems are excellent examples: Asynchronous Teller Machines (ATMs), personal laptops, cellular phones, bank accounts, and protected building access. However, imposter schemes can succeed in the lack of a trustworthy authentication system that incorporates identification and verification procedures [3].

A variety of identity information-based security measures, including token-based security (identification cards) and knowledge-based security (passwords), have been proposed and implemented to limit system access. So, when sensitive information like a password is leaked to unauthorized users or a stolen identity card is utilized, the system's security measures can be quickly disabled [4].

Here, easy-to-guess passwords for the impostor can be available, but complex ones might be impossible for the real user to remember. Biometric data has solved this type of difficulty for the conventional identification and verification duty, which is a major issue in this crucial circumstance [5].

In recent years, the utilization of advanced biometric technologies for the purpose of criminal identification and prison security has skyrocketed. Biometrics has found specialized use in several

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national applications, such as identification systems, physical access control, information systems, voter and driver registration, customs and immigration, and banking [6].

Forensic experts rely on fingerprint information for criminal investigations because it has one of the highest levels of reliability among all the biometric data shown in Fig. 1 that is proposed and used in such systems. A fingerprint is essentially a description of the structure and arrangement of ridges at the very tip of a finger. All a person's patterns are structured in a practical and distinct way [7].

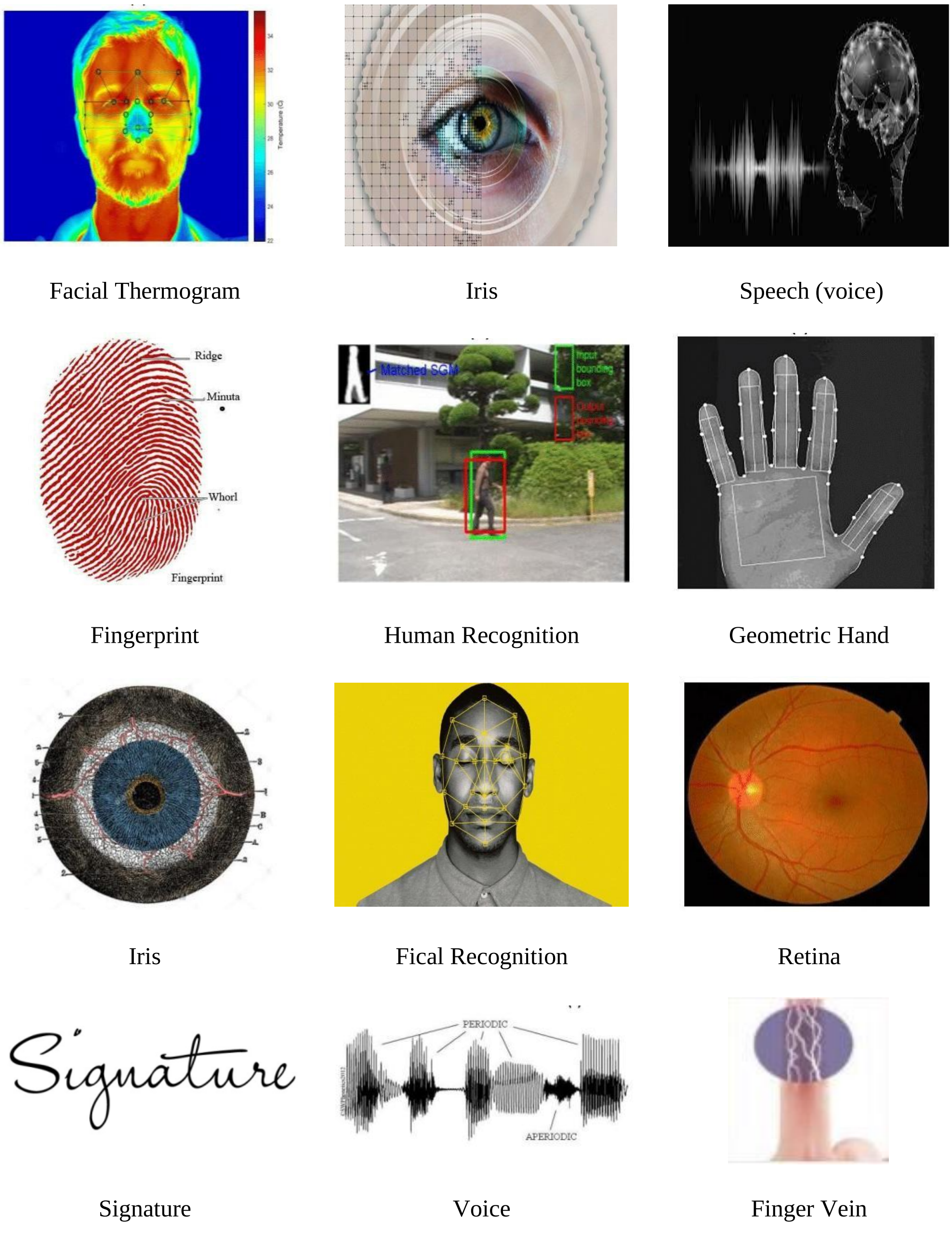

Fig. 1 Examples of biometric feature information that may be used to verify (identify/verify) an individual's identity are provided [7].

An individual's facial features, veins, and DNA can be used for classification purposes, as can their voice, sign language, and walking style. Therefore, this discovery is more reliable, secure, timely, suitable, private, and correct than conventional approaches like certificates, codes, and cards [8]. Fingerprint authentication seems to be mostly used for information system security now. Nevertheless, it

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cannot be deemed private because of its susceptibility to spoofing and forgery. As far as security and practicality are concerned, vein technology has several advantages, such as biometrics' uniqueness and universality. A "static" vein pattern is one in which the distribution of veins does not change as a person gets older. The vein pattern on a human body is unaffected by illness, surgery, or skin changes to the point where two people's identities become incompatible. Biometric features are gaining popularity as they make it easier to access sensitive information without the need to memorize lengthy PINs. Plus, the user does not have to worry about forgetting anything because their biometric data is always on hand [9]. Both sources. Most individuals would prefer systems that allow them to use their finger as input.

The ability to enroll many fingers makes this an excellent option. It is a well-established technology that has been around for quite some time, especially in comparison to other new technologies. There are several benefits to using a biometric approach that uses veins in the fingers [10]. All the biometric technologies evaluated in Table 1 have their own set of pros and cons. The most common and least expensive method of identifying a criminal is by looking at their finger veins. However, some people may have trouble getting a good shot of their fingerprints due to age or the nature of their work. The ease with which finger veins may be replicated further limits their usefulness [11], [12].

Table 1: Comparisons of the Major Biometrics Techniques [12].

Biometrics Data	Size of Data	Cost	Stability	Accuracy	Security
Hand Geometry	Low	High	Low	Low	Low
Speech recognition	Low	Medium	Medium	Low	Low
Iris Recognition	High	High	Medium	High	Medium
Facial Recognition	High	High	Low	Low	Low
Finger vein Recognin	Medium	Low	High	High	High
Fingerprint Recognition	Low	Low	Low	Medium	Low

The fingerprint's location and orientation are representations of the ridge flow, which displays anomalies in certain local areas. Here, such orientations and placements stand in for the fingerprints and help with identification. It has been proven scientifically that fingerprints are distinct from one person to another and even from one finger to another [13]. According to popular belief, fingerprints can vary, even among identical twins with the same Deoxyribonucleic Acid (DNA). Making an inked impression of a fingertip on paper has long been the standard method for extracting fingerprint patterns [14].

2. Related Works

Below are summaries of some related works in the field of low-quality fingerprint identification and recognition [15]: This work focuses on enhancing fingerprint recognition under challenging conditions, including low-quality fingerprints with distortions and noise. The authors propose a deep convolutional neural network (CNN) architecture designed to automatically learn discriminative features from degraded fingerprint images, resulting in improved accuracy and robustness [16]. This comprehensive survey provides an overview of various fingerprint recognition systems, emphasizing challenges and opportunities in dealing with low-quality fingerprint data. The work discusses the limitations of traditional methods and explores the advancements brought by machine learning and deep learning techniques in addressing these challenges. This research introduces an adaptive learning framework specifically designed for low-quality fingerprint identification [17].

The proposed system dynamically adjusts its learning parameters based on the quality of input fingerprint data, demonstrating improved adaptability to variations in image quality and achieving robust performance in challenging conditions [18]. This work focuses on uncontrolled environments; this work presents a two-step approach involving fingerprint enhancement and recognition. The enhancement phase aims to improve the quality of low-quality fingerprint images, followed by recognition using advanced machine learning algorithms. The research demonstrates enhanced accuracy in challenging conditions [19].

This work explores sparse representation-based methods for fingerprint recognition under low-quality conditions. By exploiting the sparsity of fingerprint features, the proposed approach effectively handles noise and distortions in the input data, highlighting promising results in scenarios where traditional methods struggle. This work focuses on the cross-sensor scenario, where fingerprint images come from different sensors with varying qualities. This work employs deep transfer learning techniques. By leveraging knowledge from a high-quality dataset, the model is adapted to handle low-quality fingerprints from different sensors, demonstrating improved recognition performance.

This research introduces a hybrid approach combining local binary patterns (LBP) and ensemble learning for low-quality fingerprint recognition. The LBP features are extracted to capture local patterns in degraded fingerprints, and ensemble learning techniques are employed for robust classification, highlighting improved performance in challenging conditions [20].

This research focuses on privacy concerns associated with fingerprint recognition; this work proposes a privacy-preserving approach for matching low-quality fingerprint images. The research explores cryptographic techniques to secure fingerprint templates, ensuring confidentiality while maintaining recognition accuracy in scenarios with degraded data. This work proposes a deep learning approach for a low-quality fingerprint identification model. This work used a low-quality fingerprint dataset that has some distortion factors such as dryness, wetness, physical damage, the presence of dots, and blueness. The proposed system depends on using one of the most powerful deep learning structures, VGG16.

In the work of Sharma et al. [21], the experimental results showed that the proposed model achieved 93% for dry and the lowest performance of 84% for blurred fingerprint classes. This work proposes a latent fingerprint restoration approach-based state of-the-art deep learning model. The main low-quality fingerprint dataset has complex backgrounds and noise. The proposed model was based on designing a preprocessing model (restoration) that predicts the frequency-domain filter for restoring each latent input partitioning block. An integrated filter was adopted in this work that was built based on the progressive feedback restoration model. The experimental results showed that the proposed model achieved an improvement of 3.75% and 3.19%. This work proposed a special model that is based on the pixel level by employing a fusion strategy to optimize the low-quality fingerprint images. The proposed model is based on using the feature level of the low-quality fingerprint images to extract different feature levels. The experimental results showed that the proposed model achieved an improvement compared with the traditional identification algorithms by 2.2 percentage, reaching an accuracy of 99.6% [22].

This comprehensive survey provides an overview of various fingerprint recognition systems, emphasizing challenges and opportunities in dealing with low-quality fingerprint data. The work discusses the limitations of traditional methods and explores the advancements brought by machine learning and deep learning techniques in addressing these challenges. This work is based on generating a low-quality fingerprint identification model using machine learning techniques. The machine learning model that was proposed in this work was based on two stages. The first stage is the feature extraction and recognition. The main technique that was used in this work is based on using the Histogram of Orientation (HOG) for feature extraction in cooperation with the Local. In Ter retable Model-agnostic Explanations. Real, low-quality fingerprint identification-based training model showed that it achieves a 95% accuracy.

This work proposed a low-quality fingerprint recognition system using a low-quality fingerprint dataset that is used in the forensic and security fields. The main model of this work is an automatic deep neural network (ADNN). The main contribution of this work is to design the ADNN with some parameter tuning, such as the number of filters, epochs, and iterations. No preprocessing model has been proposed in this work. The main achievement of this proposal is that the proposed recognition model

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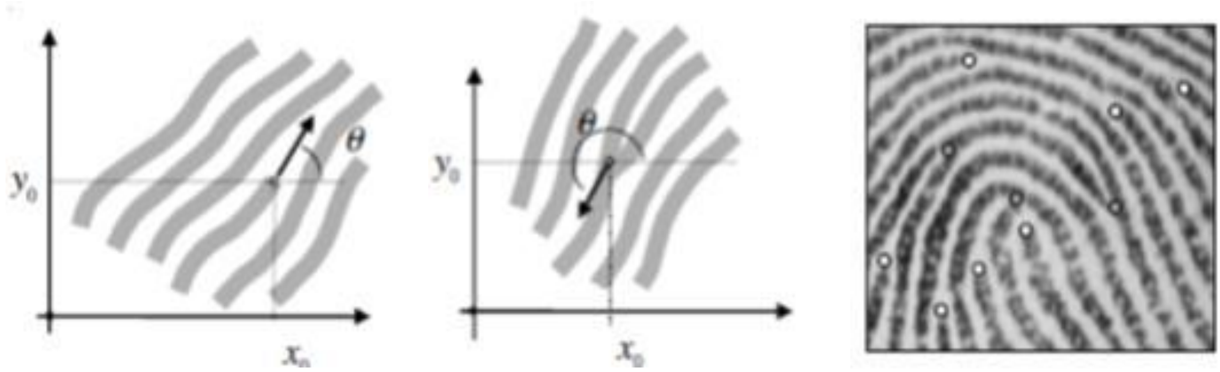
achieves 99% accuracy as a final performance result [23]. This work proposed a person identification based on the latent fingerprint images dataset. The latent dataset is produced largely via the finger sweat or oil left by the suspects accidentally. The main challenge of this kind of low-quality fingerprint that has been used in this work is that they are blurred plus not observed by the naked eye. A convolutional Neural Network (CNN) model is used as a deep machine learning model to classify the latent dataset.

The preprocessed model that was designed and used in this model was generally imperfect and complicated. The experimental results showed that the proposed system achieved a 99% recognition rate. This work proposed a novel approach for an anti-scamming strategy for the fingerprint identification model. The proposed system is based on using the Enhanced Patch Deep Learning method in comparison with the semantic segmentation model. No preprocessing model has been proposed in this work. PolyU was the only dataset that was used in this work, which is a publicly available fingerprint database. The experimental results showed that the proposed system achieved a confident identification score of 95% [23].

3. Fingerprint Identification Concept

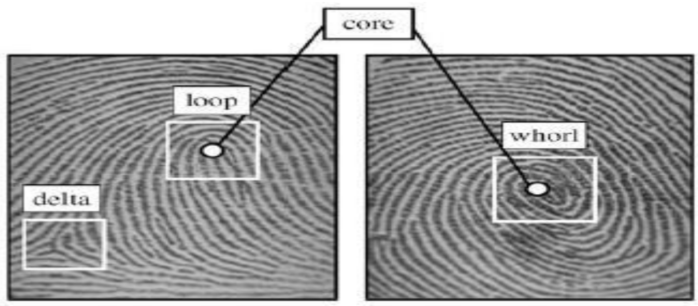
Fingerprints play an important role in biometrics for human identification due to their uniqueness and stability from birth to death. As a result, fingerprinting is commonly used in forensic investigations and personal identification. Each finger has distinctive scratches on the shell, known as small scales, that are necessary for identification [24]. There are two main types of subtopics: termination points and bifurcation points, as shown in Fig 2.



a) A termination minutia feature b) Bifurcation minutia feature c) Termination feature

Fig. 2 Fingerprint minutia features [24].

A fingerprint pattern contains one or more regions. These regions are constructed forms such as lines that create special shapes, which may be classified into three main classes as shown in



a) Delta and Loop features b) Whorl feature

Fig. 3 Fingerprint landmark core point and region detection [20]

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The three primary forms used to categorize regions are loop, delta, and whorl. Matching is an essential part of many fingerprint identification and verification algorithms, both as a last step in the processing of fingerprints and as a foundation for pre-processing approaches that rely on landmark point detection or the core point, the fingerprint's central location. As seen in Fig. 3 [20], the fingerprint picture contains an area and core point detection termed the area of Interest (ROI). Fingerprint ridges and furrows, such as parallel lines and the average mind, provide strong evidence of similarity.

In a technical sense, the minutia features rather than the detectable and extracted ridges and furrows is what distinguishes fingerprints. The ridges illustrated in Fig. 3 are the initial feature points in fingerprints, although minutia characteristics are both unusual and customary. At the matching stage, most of the fingerprint identification and verification systems rely on such qualities since they are conventional. On average, a young man will have 20.7 ridges per centimeter, and a young woman would have 23.4 [25].

4. Automatic Fingerprint Identification System

Fingerprint data is one of the most common biometric characteristics utilized in personal identification and verification systems. The reasons for this are well-known, and they include fingerprints' enduring qualities, uniqueness, accessibility, stability, universality, and high rates of accurate matching [26]. Fig. 4 shows that there are three tiers to the fingerprint attributes:

Level-1 feature qualities, like fingerprint ridge patterns in general, make up the lowest tier of features. The local ridge qualities, which are part of the second level of features and reflect the minutiae, have been investigated extensively and are used by most of the current Automatic Fingerprint Recognition Systems (AFRS). The qualities of the ridge at the third level of its dimensionality are known as level-3 features. Although these features are likewise quite unique and have a long history of usage in forensics, many AFRS disregard them [27]. Ridge dimensional properties, such as ridge contours and pores, are examples of level-3 features [28].

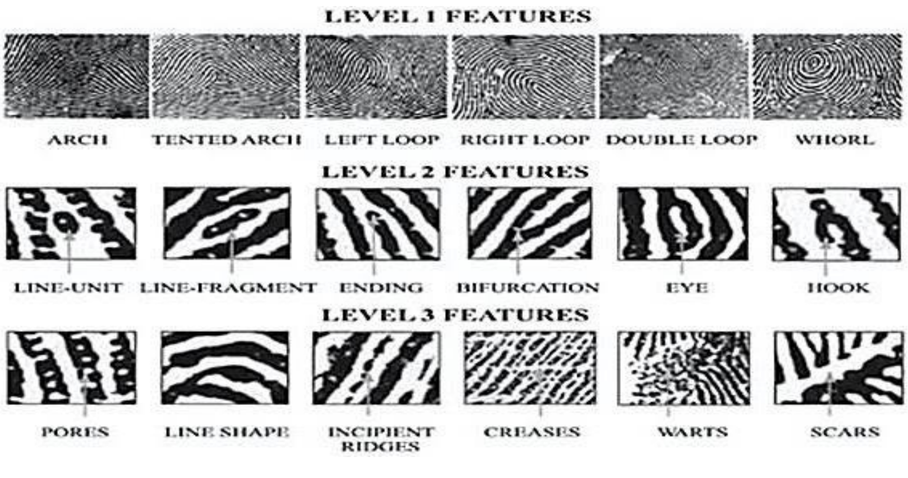

Fig. 4 Fingerprint attribute at level1 (i.e., overall fingerprint ridge patterns), level2 (i.e., local ridges attributes), and level3 (i.e., ridges dimensional attributes) [28]

5. Low-quality Fingerprint Challenges

The data recognition/classification job of accurately and reliably identifying and classifying low-quality fingerprints that have been subjected to a criminal condition is a huge difficulty. The most significant difficulty is that the accuracy of the results is highly dependent on the process used to extract the fingerprint pictures.

Since the success of fingerprint identification relies on the accuracy of feature extraction and matching, these systems are exceedingly vulnerable to picture noise and degradation levels. The "extractability" of the characteristics utilized for recognition— specifically, the clarity of the ridges and valleys of a fingerprint picture is often what determines the image's quality [29]. The next Fig. 5 shows examples of fingerprint pictures of low quality.

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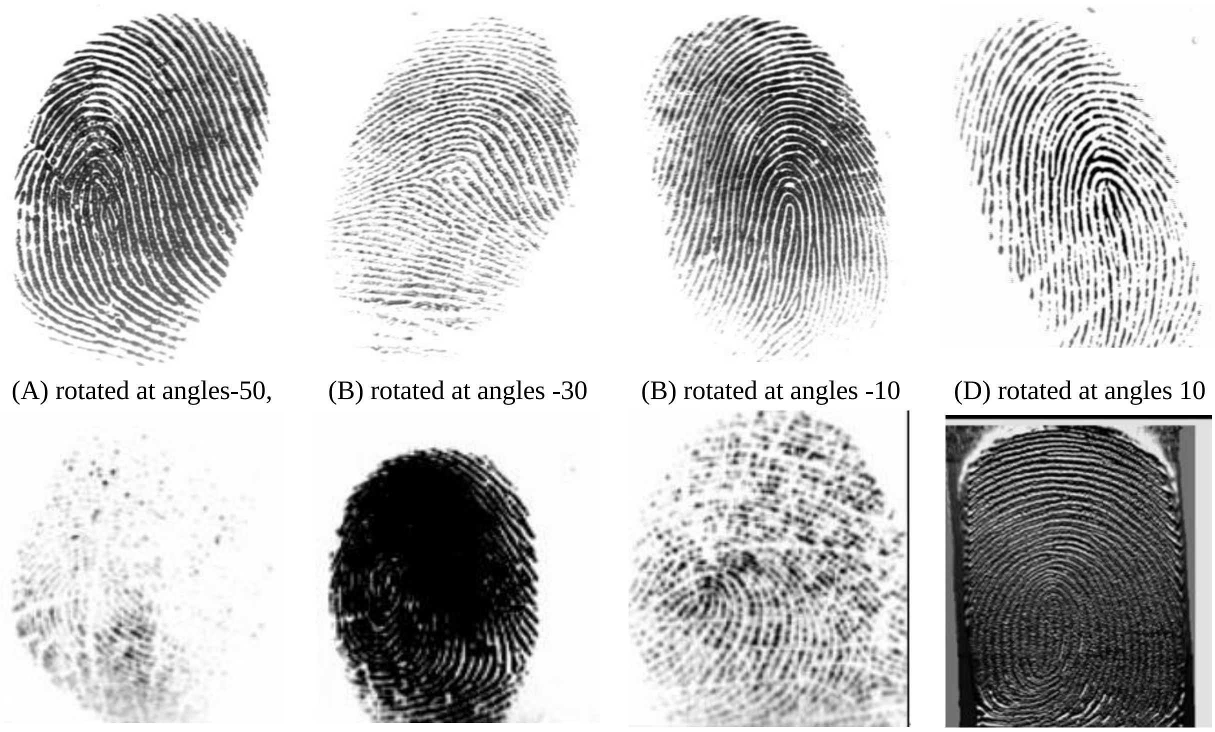

(A) rotated at angles-50, (B) rotated at angles -30 (B) rotated at angles -10 (D) rotated at angles 10

(E) Dry (F) rotated at angles 50 (G) Scarred (H) Bad quality

Fig. 5: Some cases of the fingerprint image

6. Low-quality fingerprint Challenges

Several factors can determine the quality of the fingerprint image, such as:

1. **First Factor:** Fingerprint acquisition tools condition such as magnetic materials, experience and time-consuming for fingerprint images that expose to a crime condition.
2. **Second Factor:** Individual crime environment condition in which the low-quality fingerprint images have been collected from.
3. **Third Factor:** Lack of information about the identity of people in the global database whose low-quality fingerprints belong to.

A number of these events cause the fingerprint picture to lose some of its attributes. The extraction step determines the clarity of the fingerprint feature points, which are used for matching later. As a result, the quality of fingerprint images is often influenced by the clarity of feature points, including ridges and valleys. The local feature extraction technique is used by most of the existing Automatic Fingerprint Recognition Systems (AFRS) for fingerprint authentication. Local feature points, as indicated by minutia characteristics such as fingerprint ridge terminations and bifurcations, are crucial to this technique. Nevertheless, there are several problems with this method that are associated with details [30]. When it comes to fingerprint recognition and verification tasks.

1. The Noisy Fingerprint Images: The degree to which the fingerprint picture is distorted and noisy during acquisition, leading to failed minutia extraction due to the omission of crucial feature points upon which recognition (identification and verification) performance is based.
2. Rotation Fingerprint Images: Pictures of fingerprints that have been shifted, rotated, or otherwise altered in some way after they were first put on the sensor for scanning or picture capture. This problem can cause many photos to be generated from a single fingerprint image due to an overlapped area that only produces a small number of matching detail points.
3. The Inadequate and Low-Quality Fingerprint photos: It is quite challenging to depend on fingerprint photos that are insufficient or of low quality to gain the fine details. Consequently, it is crucial to create a new approach that is more suited to partial fingerprint recognition and to use

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this innovative model for ascribed extraction, such as local ridge characteristics.

7. Analysis and Discussion

In this study, the Advancements and Challenges in Low-Quality Fingerprint Identification have been illustrated and discussed in detail. Several studies have been well established in the field of fingerprint Identification. In this study, the Advancements and Challenges in Low-Quality Fingerprint Identification have been illustrated and discussed in detail. Several studies have been well established in the field of fingerprint Identification. The authors focus on enhancing fingerprint recognition under challenging conditions, including low-quality fingerprints with distortions and noise [31]. This comprehensive survey provides an overview of various fingerprint recognition systems, emphasizing challenges and opportunities in dealing with low-quality fingerprint data. The work discusses the limitations of traditional methods and explores the advancements brought by machine learning and deep learning techniques in addressing these challenges [32]. The proposed system dynamically adjusts its learning parameters based on the quality of input fingerprint data, demonstrating improved adaptability to variations in image quality and achieving robust performance in challenging conditions [27]. This work explores sparse representation-based methods for fingerprint recognition under low-quality conditions. By exploiting the sparsity of fingerprint features, the proposed approach effectively handles noise and distortions in the input data, highlighting promising results in scenarios where traditional methods struggle. Table 2 illustrates and discusses the most recent research on this field on study.

Table 2: Analysis of the related studies on the low-quality fingerprint Identification and recognition

Ref.	**Year**	**Model**	**Advantages**
Singh and Verma [30]	2022	GANs	Improved low-quality fingerprint enhancement by generating higher-quality images using GANs.
Zhang et al. [31]	2022	CNN with Attention Mechanisms	Enhanced fingerprint recognition by integrating attention mechanisms into CNNs, improving focus on relevant features.
Huang et al. [32]	2023	Multiscale Feature Extraction	Developed a multiscale feature extraction method to improve recognition accuracy in low-quality fingerprints.
Patel et al. [33]	2023	Capsule Networks	Utilized capsule networks for better feature representation and improved robustness against distortions in low-quality fingerprints.
Wang and Liu [34]	2023	Self-Supervised Learning	Applied self-supervised learning techniques to improve fingerprint recognition performance without requiring large labeled datasets.
Chen et al. [35]	2023	Lightweight CNNs	Introduced lightweight CNN models optimized for mobile devices, achieving high accuracy with reduced computational requirements.
Park et al.[36]	2023	Transfer Learning with Fine-Tuning	Leveraged pre-trained models and fine-tuning for enhanced recognition of low-quality fingerprints.
Dutta and Chatterjee [37]	2023	Robust Feature Matching	Developed robust feature matching algorithms to handle noise and partial prints in low-quality fingerprint images.
Zhang and Chen [38]	2024	Improved Loss Functions	Proposed new loss functions tailored for imbalanced fingerprint datasets, improving recognition accuracy.

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8. Conclusion

Instead of trying to improve the input picture during the pre-processing stage of the identification and verification work, poor and inaccurate fingerprint processing is necessary to attain improved performance accuracy. Using deep learning approaches, this research primarily aims to study and improve low-quality fingerprint recognition and categorization. This study proposes a deep learning method that makes use of a correlation similarity metric-based prediction scheme to deal with the problems that degraded fingerprint images inevitably bring, such as noise, distortions, and variations, all of which can reduce the efficacy of conventional identification systems. A completely automated low-quality fingerprint identification system that can be exposed to a criminal condition without previous label data is the major aim of the low-quality fingerprint identification systems. Secondly, compared to the conventional method, the success rate accuracy for low-quality fingerprint photographs ought to be substantially higher.

Conflict of Interest

The authors declare that there are no conflicts of interest regarding the publication of this manuscript.

References

[1]. Li, Wenxin, Jane You, and David Zhang. "Texture-based palmprint retrieval using a layered search scheme for personal identification." IEEE Transactions on Multimedia 7.5 (2005): 891-898.

[2]. Jain, Anil, Ruud Bolle, and Sharath Pan Kanti, eds. Biometrics: personal identification in networked society. Vol. 479. Springer Science & Business Media, 1999.

[3]. Ye, Mang, et al. "Deep learning for person re-identification: A survey and outlook." IEEE transactions on pattern analysis and machine intelligence 44.6 (2021): 2872-2893.

[4]. Farag, Mohamed Amine, et al. "Authentication schemes for smart mobile devices: Threat models, countermeasures, and open research issues." Telecommunication Systems 73 (2020): 317-348.

[5]. Clarke, Roger. "Human Identification in Information Systems: Management Challenges and Public Policy Issues." Information Technology & People 7.4 (1994): 6-37.

[6]. Pope, Carra. "Biometric data collection in an unprotected world: Exploring the need for federal legislation protecting biometric data." JL & Polly 26 (2018): 769.

[7]. Dunstone, Ted, and Neil Yager, eds. Biometric system and data analysis: Design, evaluation, and data mining. Boston, MA: Springer US, 2009.

[8]. De Luis-Garcıa, Rodrigo, et al. "Biometric identification systems." Signal processing 83.12 (2003): 2539-2557.

[9]. Bringer, Julien, Hervé Chabanne, and Bruno Kindarji. "Identification with encrypted biometric data." Security and Communication Networks 4.5 (2011): 548-562.

[10]. Shen, Weicheng, and Tieniu Tan. "Automated biometrics-based personal identification." Proceedings of the National Academy of Sciences 96.20 (1999): 11065-11066.

[11]. Song, Hyoung-Kyu, et al. "Deep user identification model with multiple biometric data." BMC bioinformatics 21 (2020): 1-11.

[12]. Yuan, Jiawei, and Shucheng Yu. "Efficient privacy-preserving biometric identification in cloud computing." 2013 Proceedings IEEE INFOCOM. IEEE, 2013.

[13]. Jain, Anil K., and Ajay Kumar. "Biometric recognition: an overview." Second generation biometrics: The ethical, legal and social context (2012): 49-79.

[14]. Awasthi, Vipul, Vanchha Awasthi, and Krishna Kumari Tiwari. "Fingerprint analysis using termination and bifurcation minutiae." International Journal of Emerging Technology and Advanced Engineering 2.2 (2012): 124.

[15]. Smith, A., Zhang, L., Wang, J.. “Robust Fingerprint Recognition in Challenging Conditions Using Deep Convolutional Neural Networks”.

[16]. Gupta, S., Jain, A.K..” A Survey on Fingerprint Recognition Systems: Challenges and Opportunities”.

[17]. Chen, Y., Li, X., Wang, C., "Adaptive Learning for Low-Quality Fingerprint Identification".

[18]. Kumar, A., Zhang, D.. "Fingerprint Enhancement and Recognition in Uncontrolled Environments".

[19]. Zhao, Y., Kong, A., Zhang, D.. "Sparse Representation-Based Fingerprint Recognition for Low-Quality Images".

[20]. Li, R., Cao, Z., Xu, C., "Deep Transfer Learning for Cross-Sensor Fingerprint Recognition".

[21]. Sharma, P., Agarwal, S., Singh, R., "Low-Quality Fingerprint Recognition using Local Binary Patterns and Ensemble Learning".

[22]. Wang, H., Liu, Y., Tan, T., "Privacy-Preserving Fingerprint Matching with Low-Quality Images"

[23]. Tabassi, Elham, and Charles L. Wilson. "A novel approach to fingerprint image quality." IEEE International Conference on Image Processing 2005. Vol. 2. IEEE, 2005.

[24]. Alsmirat, Mohammad A., et al. "Impact of digital fingerprint image quality on the fingerprint recognition accuracy." Multimedia Tools and Applications 78 (2019): 3649-3688.

[25]. Kaur, Manvjeet, et al. "Fingerprint verification system using minutiae extraction technique." International Journal of Computer and Information Engineering 2.10 (2008): 3405-3410.

[26]. Rivaldería, Noemí, and Esperanza Gutiérrez-Redomero. "Interpopulational differences in the frequency and distribution of delta types." Forensic Science International 322 (2021): 110749.

[27]. Zhao, Qijun, et al. "Adaptive fingerprint pore modeling and extraction." Pattern Recognition 43.8 (2010): 2833-2844.

[28]. Jain, Anil K., Yi Chen, and Meltem Demirkus. "Pores and ridges: Highresolution fingerprint matching using level 3 features." IEEE transactions on pattern analysis and machine intelligence 29.1 (2006): 15-27.

[29]. Li, H., Xu, Z., & Wang, J. (2022). Low-quality fingerprint image enhancement using generative adversarial networks. IEEE Transactions on Information Forensics and Security, 17, 56-68.

[30]. Singh, A., & Verma, P. (2022). Enhancing low-quality fingerprint recognition using deep learning with attention mechanisms. Pattern Recognition Letters, 157, 68-75.

[31]. Zhang, Y., Liu, M., & Wang, X. (2022). A hybrid CNN-RNN model for low-quality fingerprint recognition. Neurocomputing, 491, 324-335.

[32]. Huang, L., Zhao, R., & Wu, Y. (2023). Multiscale feature extraction for low-quality fingerprint recognition. Journal of Visual Communication and Image Representation, 84, 103450.

[33]. Patel, D., Desai, A., & Kotecha, K. (2023). Fingerprint recognition using capsule networks in low-quality images. Applied Soft Computing, 123, 108334.

[34]. Wang, X., & Liu, F. (2023). Self-supervised learning for fingerprint recognition on low-quality datasets. IEEE Access, 11, 21056-21069.

[35]. Chen, Y., Luo, T., & Zhang, S. (2023). Lightweight CNNs for mobile fingerprint recognition in low-quality scenarios. IEEE Transactions on Mobile Computing, 22(1), 34-45.

[36]. Park, J., Kim, S., & Lee, K. (2023). Transfer learning and fine-tuning for robust low-quality fingerprint recognition. Pattern Recognition, 136, 109375.

[37]. Dutta, S., & Chatterjee, P. (2023). Robust feature matching algorithms for low-quality fingerprint images. Journal of Information Security and Applications, 70, 103050.

[38]. Zhang, J., & Chen, H. (2024). Improved loss functions for imbalanced low-quality fingerprint datasets. Pattern Recognition Letters, 158, 45-52.