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A survey of Fingerprint Identification System Using Deep Learning

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Abstract: The integration of deep learning technologies, particularly Convolutional Neural Networks (CNNs), has profoundly transformed fingerprint identification, providing a more effective and accurate approach compared to traditional methods. These deep learning models, trained on extensive datasets of fingerprint images, excel in extracting intricate patterns and unique features essential for precise fingerprint matching, even amidst challenging conditions like varying image quality, orientation, or lighting. Notably, the adaptability of deep learning-based systems, continuously refining their accuracy and performance with additional data and fine-tuning, proves indispensable in dynamic environments with ongoing fingerprint data collection. Moreover, the convergence of deep learning with other biometric modalities, such as facial recognition or iris scanning, has led to the development of robust multimodal biometric systems, enhancing security through layered verification mechanisms. However, persisting challenges, such as the acquisition of large annotated datasets and the mitigation of bias in training data, underscore the importance of addressing these issues to further enhance the reliability and performance of deep learning-based fingerprint identification systems. This survey paper aims to comprehensively review and analyze the application of deep learning techniques in fingerprint identification systems, providing valuable insights into current advancements, challenges, and future directions in the field, thereby serving as a resource for researchers, practitioners, and enthusiasts seeking a nuanced understanding of this critical area in biometrics.

Keywords:Fingerprint, Identification, Deep learning, CNN, Biometric.

• INTRODUCTION

Biometric identification systems, leveraging distinctive physiological or behavioral attributes for individual recognition, have become indispensable tools in meeting heightened security demands. These systems utilize individuals' unique biometric features for flexible and highly effective identification [1]. Globally, numerous countries have adopted biometric technologies across various sectors, including criminal investigations, law enforcement, border control, citizen management, and voter registration, highlighting the versatility of these systems. Unlike traditional identification methods reliant on access cards and passwords, biometric systems offer a robust and reliable authentication approach, reducing risks associated with identity theft and credential loss. The richness of biometric identification is evidenced by various biometric identifiers, such as retinal scans, hand geometry, facial features, vocal patterns, and digital fingerprints [2], [3].

Fingerprint identification stands out as a cornerstone method within biometrics due to its established efficacy. By utilizing the unique ridge and valley patterns on fingertips, fingerprint identification systems undergo a

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comprehensive process involving image acquisition, feature extraction, template creation, and matching, resulting in a highly accurate and unobtrusive means of identity verification. This technology finds multifaceted applications in law enforcement, access control, mobile devices, and financial services, offering a secure and efficient biometric solution despite occasional challenges linked to environmental factors and privacy concerns [4], [5].

Fingerprint identification, characterized by the enduring features of friction ridges, has emerged as a focal point in the field of biometrics. These ridge patterns, unique to each individual and consistent throughout life, offer a reliable method of identification. The intricate nature of fingerprint patterns, consisting of curved lines known as friction ridges, etched into the skin's surface, highlights the distinctiveness of each person's fingerprint. The process of acquiring fingerprint images, which display dark ridges and light valleys, presents challenges due to environmental factors and user behavior, often necessitating image enhancement techniques [6], [7].

Fingerprint identification information can be categorized into three levels, as depicted in Figure 1. Level 1 focuses on macro details such as ridge flow and arrangement, while Level 2 includes more detailed characteristics like ridge minutiae. Level 3 encompasses a comprehensive set of dimensional attributes, including edge path deviation, width, shape, and other permanent details. Statistical analysis has revealed that Level 1 features, representing global fingerprint patterns, lack

Fig. 1. (➡) Level one, (▬) Level two, (◯) Level three

uniqueness. In contrast, Level 2 features, including individual minutiae points, possess sufficient discriminative power for fingerprint identification. Level 3 properties, comprising detailed structural features, are permanent, immutable, and truly unique [8], [9].

Fingerprint identification plays a crucial role in enhancing security and efficiency. The ongoing efforts to advance fingerprint identification techniques, classification methodologies, and explore new applications underscore its continued evolution and significance within the broader field of biometrics [10]–[13].

This study aims to provide a comprehensive examination of the significance of fingerprint biometric identification systems in enhancing security measures and validating individual identities. The exploration will encompass various biometric features, with a particular emphasis on the advancements and challenges associated with fingerprint identification. By delving into the intricacies of acquiring fingerprint images and the nuanced process of information extraction at multiple levels, this study aims to contribute to the development of more resilient and efficient biometric identification systems in the future.

The paper is organized as follows: Sections 2 through 5 will discuss the anatomy, functions, uniqueness, and applications of fingerprints, while Section 6 will present the most important related works. Section 7 will address challenges and gaps in the field, with Sections 8 and 9 discussing fingerprint identification algorithms and datasets. Section 10 will describe the evaluation methods used, and finally, Section 11 will present the paper's discussion and conclusions.

• FINGERPRINT ANATOMY

The human fingerprint stands as a remarkable biometric identifier distinguished by its intricate ridge patterns and specific minutiae points. The skin's surface exhibits a unique pattern comprising raised ridges and recessed furrows, as illustrated in Figure 2, with each ridge pattern bearing distinct characteristics such as ridge endings, bifurcations, and short ridges, collectively referred to as minutiae points. These minutiae points serve as primary features utilized by forensic scientists and fingerprint identification devices for individual identification. The anatomy of human fingerprints encompasses several elements:

A. Ridge Patterns:

The surface of a fingerprint is marked by raised, curving ridges and recessed furrows, forming distinctive patterns that vary among individuals [14].

B. Minutiae Points:

Minutiae represent the fine details within ridge patterns [15], encompassing key features such as:

- Ridge Endings: Occur when a slope abruptly terminates.
- Bifurcations: Points where a single ridge divides into two distinct ridges.
- Island: Small ridges running parallel to larger ones before re-joining.
- Dot: Tiny, isolated ridges that do not connect to nearby ridges.

C. Core:
Many fingerprint patterns exhibit a core, a central point where ridges flow in circular or spiral patterns [16].

D. Delta:
A delta denotes a point situated at or near the center of a ridge pattern, where three ridges converge [17].

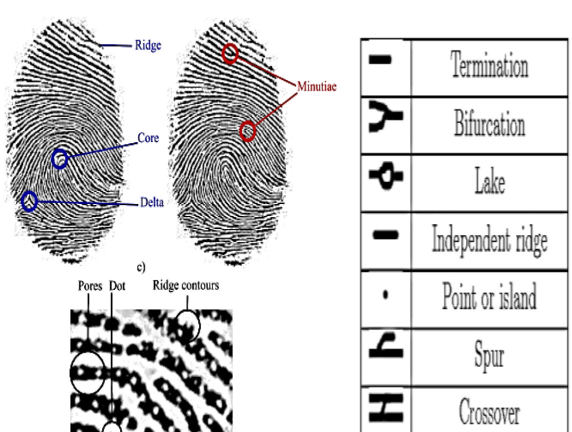

Fig.2. The anatomy of human fingerprints.

- **FINGERPRINT UNIQUENESS**

The concept of fingerprint uniqueness is a fundamental characteristic that underpins the reliability of fingerprints as biometric identifiers. The patterns and minutiae points present in each individual's fingerprints are distinct and remain unchanged over time, as depicted in Figure 3. This inherent uniqueness serves as the foundation for fingerprint identification and has been a cornerstone of forensic science. Even among identical twins, no two individuals possess identical fingerprint patterns. This level of uniqueness underscores the invaluable nature of fingerprints for personal identification and forensic investigations [18].

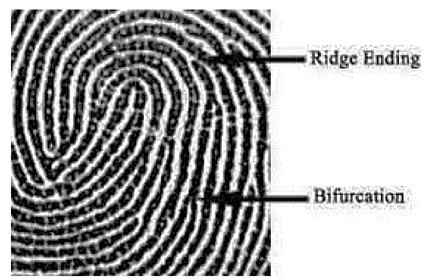

Fig.3. Simplified Fingerprint Uniqueness

Figure 4 illustrates the unique and intricate ridge patterns present on the surface of a fingerprint, along with minutiae points such as ridge endings and bifurcations. These minutiae points are distinctive to each fingerprint, and their arrangement and position contribute to the overall distinctiveness of the fingerprint. The permanence of these features, coupled with their uniqueness, forms the foundation for fingerprint-based identification and recognition systems [19].

Fig.4. An example of the uniqueness of fingerprints

- **FUNCTIONS OF FINGERPRINT**

Biometrics, which entails authenticating individuals based on their unique physical or behavioral attributes, holds significant relevance across a diverse array of applications, from securing digital devices to facilitating border control and aiding criminal investigations [20]. Among the various biometric modalities, fingerprint biometrics stands out as a widely employed methodology, encompassing a range of critical functions integral to diverse applications. These functions can be broadly categorized into key areas that significantly contribute to the security and efficiency of various processes. The multifaceted nature of fingerprint identification systems underscores their pivotal role in ensuring precision and reliability in identity verification and recognition, highlighting the broader implications of biometric technology in contemporary contexts [21].

Authentication is a primary function of biometrics, widely used to confirm an individual's claimed identity based on their biometric data. This function typically involves a one-to-one comparison, where an individual's biometric information is compared to a stored template to grant or deny access [22]. For instance, using a fingerprint scan to unlock a smartphone exemplifies an authentication function.

Verification, on the other hand, is a specific type of authentication that focuses on confirming whether an individual is who they claim to be. This process entails comparing a presented biometric sample to a single reference template associated with the individual. Verification is commonly employed in scenarios such as accessing a bank account or verifying identity at airport border controls [23].

Identification represents a broader function of biometrics, involving the identification of an individual's identity by comparing their biometric details to a database containing multiple stored templates. This process typically involves a one-to-many comparison and finds application in law enforcement for identifying suspects from a database of known individuals [24].

Recognition is yet another function of biometrics, encompassing the broader scope of identifying or recognizing an individual based on their biometric data, such as facial recognition in surveillance systems. Recognition may involve matching against a large database of individuals to determine a match or identifying a person's face, voice, or other biometric characteristics in real-time [25].

- **FINGERPRINTAPPLICATIONS**

Biometrics, the field that merges technology with identity verification, utilizes distinct physical or psychological traits to accurately identify individuals. Fingerprint identification, a prominent biometric method, capitalizes on the unique ridge patterns and minutiae points of fingerprints. The following are key applications that highlight the versatility and effectiveness of fingerprint identification across various domains:

a) Access Control: Fingerprint identification is extensively used in access control systems to ensure secure entry to restricted areas, buildings, and electronic devices. It offers a reliable and convenient method for authenticating individuals and preventing unauthorized access [26].

b) Mobile Device Security: Fingerprint identification plays a crucial role in enhancing mobile device security, providing a secure and user-friendly means to unlock smartphones, access applications, and conduct secure transactions. This biometric feature has become a standard security measure in modern mobile devices [27].

c) Financial Transactions: Fingerprint identification is employed in the banking industry to enhance the security of transactions, particularly in online banking and electronic payments. Users can securely access their financial information and authorize transactions using fingerprint authentication [28].

d) Government Services: Government agencies utilize fingerprint identification for identity verification in various services, including the issuance of passports, driver's licenses, and national identification cards. Fingerprint biometrics ensures the accuracy and authenticity of individuals' identities [29].

e) Border Management and Migration: Fingerprint identification is crucial in border regulation and immigration processes, where it verifies the identities of travelers. This application enhances security at international borders by preventing identity fraud and unauthorized entry [30].

f) Criminal Investigations: Law enforcement agencies leverage fingerprint identification in criminal investigations to match fingerprints found at crime scenes with those in criminal databases. This aids in identifying and apprehending suspects, contributing to the resolution of criminal cases [31].

g) Time and Attendance Management: Fingerprint identification systems are widely used for time and attendance management in corporate settings. Employees use their fingerprints to clock in and out, ensuring accurate and secure attendance records while minimizing time fraud [32].

h) Healthcare Access and Patient Identification: In healthcare, fingerprint identification enhances access control to medical records, medications, and restricted areas within healthcare facilities. It contributes to accurate patient identification, improving the overall security of sensitive healthcare information [33].

i) Educational Institutions: Educational institutions deploy fingerprint identification for various purposes, including secure campus access, attendance tracking, and exam verification. This technology ensures the integrity of academic processes by accurately verifying the identities of students and staff [34].

j) Smart Home Security: Fingerprint identification is integrated into smart home security systems, allowing residents to securely access their homes, control smart devices, and monitor security. This application enhances the overall security and convenience of smart home environments [35].

6. Related work

The main aim of matching fingerprints is to determine the level of similarity that exists between the fingerprint being examined and a fingerprint in the database.Matching algorithms aim to improve accuracy while decreasing variances. We will discuss previous works, and review more details about them in Table 1. According to this goal, previous research papers and studies can be classified as follows depending on the quantity of features identified in fingerprint samples:

6.1Level 1

Although there are few studies based on this method, various studies at the foundational level of fingerprint matching have made strides in improving accuracy and minimizing disparities in the process. Aritonang et al. [36] used fingerprint pooling and a convolutional neural network (CNN) algorithm to solve the problem of distinguishing unique and identical fingerprint patterns, achieving an accuracy of 95.64% and a verification accuracy of 98.76%. This method laid the groundwork for improving fingerprint data matching accuracy.

6.2 Level 2

Researchers refined their approaches to fingerprint identification after building on the foundational work. Praseetha et al. [37] proposed a pre-verification filter that uses deep convolutional neural networks to screen out bad or malicious fingerprints, with a 94% accuracy rate. Kim et al. [38] developed novel deep neural network algorithmsfor producing artificial fingerprints and identifying fake ones, the average identification error rate was 1.57%.Xun et al. [39] improved driver fingerprinting by combining CNN and support vector field description (SVDD), achieving high AUC values.

With the introduction of Slim-ResCNN, a lightweight yet robust network architecture, Zhang et al. [40] refined the fingerprint liveness detection process. This method improved the efficiency of fingerprint vitality determination, with an overall accuracy of 95.25%. Belmonte-Hernández et al. [41] made a significant contribution to the field by developing SWiBluX, a comprehensive multimedia tracking system that improved fingerprint positioning accuracy by up to 45%. Agarwal et al. [42] developed adaptive stacking and bagging versions to improve algorithm performance and adapt to data set similarity, resulting in competitive results.After using more than one method and data set, the accuracy results varied According to the datasets and methods used. The accuracy with the LivDet data set was 73.45%, 73.71% using A-Stacking and A-Bagging, respectively.

Deshpande et al. [43] demonstrated improved first-order identification rates using the "Nearest Neighbor Classification Index (CNNAI)" model for detailed-based local convolutional neural network (CNN) matching.The overall accuracy with the FVC2004 and NIST data sets was 80% and 84.5%, respectively. Chowdhury et al. [44] created an entirely new Siamese convolutional neural network, achieving high precision in detailed point location.It achieved the highest accuracy with FVC-2000, reaching 83% as a partial result.

The application of deep learning techniques is a notable trend in this domain. Deep neural networks were used by Lee et al. [45] and Goal et al. [46] to revolutionize fingerprint identification. While Lee et al. focused on fingerprint recovery using machine learning and structural image features, Goel et al. presented a patch-learning look at for segmented line estimation based on CNN, which challenges traditional hand-crafted features in fingerprint detection.

This trend was continued by Nur-A-Alam et al. [47], who proposed an intelligent fingerprint verification algorithm that combined Gabor filtering and CNN. Their approach achieved an impressive 99.87% accuracy. These studies show the growing importance of deep learning to enhance reliability as well as accuracyof fingerprint identification.

Althabhawee et al. [48] presented a deep CNN-based fingerprint authentication model using deep learning methods. This model, which had fifteen layers and a two-stage approach, performed well, achieving 100% accuracy during both the training and validation stages. Althabhawee's use of deep CNNs reflects a shared emphasis on leveraging advanced neural networks for improved fingerprint identification.

Hung et al. [49] extended fingerprint identification applications by proposing an identification algorithm that incorporates a CNN, a multi-class avaricious auto encoder, and a variation auto encoder. This microprocessor-optimized approach achieved an impressive overall accuracy of 99.67%. Hung et al.'s study fits with the theme of innovation and versatility in fingerprint identification, pushing the limits of what these systems can do.

Li et al. [50] introduced a compact processing images using an algorithm centered on the Siamese cat's neural network, expanding on the theme of flexibility. This novel approach recognizes fingerprint images from a variety of sources without the need for a pre-built image database. This method outperformed traditional fingerprint matching in key evaluation metrics, demonstrating high accuracy.

The detection of liveness is one aspect of fingerprint identification. nelzkiper et al. [51] investigated this aspect, focusing specifically on Support Vector Machine (SVM) and CNN methods. CNN emerged as the best deep learning classifier, with the highest accuracy rate in liveness detection (51.45% in the Crossmatch dataset). This research provides to the broader effort to improve the safety and dependability of identification using fingerprint systems.

Zhu, et al. [52] provides a holistic framework for performing latent fingerprint enhancement While optimizing minutia data. This wear substantially enhances latent identification of fingerprints performance. Experiments conducted on two public hidden fingerprint databases show an accuracy of 76.36%.

6.3 Level 3

Researchers have focused on specific attributes within fingerprints to advance the fingerprint identification process. DeepPoreID, a deep feature learning approach for individual pores within fingerprints, was introduced by Liu et al. [53]Diarra et al. [54] focused on deeplearning methods for fingerprint identification, achieving remarkable accuracy rates by combining different network architectures and pre-processing techniques.

TABLE 1. details of previous studies .

Seq.	Ref.	level	Authors	Algorithm	datasets	Performance Metrics
1.	[36]	1	2020	CNN	Private data	Accuracy= 98.76%
2.	[37]	2	2020	CNN	ImageNet	Accuracy= %94
3.	[38]		2019	GAN	LivDet	Error rate 1.57%
4.	[39]		2020	CNN	Private data	AUC= 0.973 , 0.997
5.	[40]		2019	CNN	LivDet	Accuracy = 95.25%
6.	[41]		2019	CNN	Private data	Improve accuracy by 45%
7.	[42]		2020	A-Stacking , A-Bagging	LivDet	Accuracy = 73.45% , 73.71%
8.	[43]		2020	CNN	FVC2004 , NIST SD27	Accuracy = 80% , %84.5

9.	[44]		2019	CNN	CASIA FVC-2000	Improve accuracy
10.	[45]		2021	GAN	NIST	Accuracy = 90%
11.	[46]		2020	CNN	FVC2002 , MCYT-Fingerprint-100 ,	EER = 1.75%; zeroFMR= 3.93% zeroFNMR= 11.76%
12.	[47]		2021	CNN	NIST , FVC	Accuracy =%99.87
13.	[48]		2022	ConvNet	Private data	Accuracy =%100
14.	[49]		2021	CNN , AE , VAE	Private data	Accuracy = %99.67
15.	[50]		2022	SNN	ImageNet	Accuracy = %92
16.	[51]		. 2022	CNN+SVM	LivDet2015	Accuracy = 86% - 98%.
17.	[52]		2023	GAN	NIST SD14	Accuracy = 76.36%
18.	[53]	3	2020	CNN	FVC-2000	Improve accuracy30% - 35%
19.	[54]		2021	ResNet-50 , DenseNet-201	SOCOFing	Accuracy = 99.53%

7. Challenges and Gaps in Fingerprint Identification

The field of fingerprint identification faces complex challenges that require innovative and exploratory approaches. One such challenge is the variation in fingerprint features, which makes distinguishing an individual fingerprint from thousands difficult due to differences in shape, size, and depth among individuals. Additionally, overlapping areas in fingerprints pose a challenge for identification systems. The effectiveness of first-level features in these systems is limited, as many techniques rely on distinguishing distinct points in a fingerprint image. However, second and third-level points, such as curves, grooves, and fine details, can significantly enhance accuracy and reliability. Another challenge is the representation of pores in fingerprints, which are small gaps between the grooves and dots in a fingerprint that present difficulties in the identification process. Moreover, reducing false error rates in identification systems is critical. Furthermore, fingerprint identification systems must balance scalability and efficiency, as well as conduct extensive testing on small fingerprint image sizes, which can result in the loss of fine details. Despite these challenges, ongoing research in fingerprinting is helping to develop advanced technologies and systems, necessitating the use of modern technologies such as deep learning and artificial neural networks for analyzing fingerprints and extracting distinguishing features [36] - [54].

8 . Algorithms for Building Fingerprint Identification Systems

Fingerprint identification algorithms play a crucial role in various stages of fingerprint system identification. Traditional fingerprint matching methods can be categorized into three groups: linkage-based comparison, detail-based comparison, and vague feature-based matching. Linkage-based matching algorithms, such as Generative Adversarial Networks (GAN), Stacked Autoencoders (SAE), and Deep Belief Networks (DBN), establish connections between small fingerprint points and their surrounding features. These algorithms utilize small fingerprint dots to indicate specific points on fingerprint ridges, using their relative orientation and position to determine fingerprint similarity [12].

Detail-based matching algorithms are capable of handling complex fingerprint details and employ various techniques to capture and compare small details. Some common examples of these algorithms include:

- Restricted Boltzmann Machine (RBM): A method used for deep learning and feature extraction from complex data.

- Recurrent Neural Network (RNN): This is utilized for processing sequential data and analyzing its correlation.
- Radial Basis Function Network (RBFN): Radial basis functions are used for nonlinear data processing and classification.
- Probabilistic Neural Network (PNN): This algorithm utilizes probabilistic modeling for processing and categorizing probabilistic data.
- Convolutional Neural Network (CNN): CNNs are employed for extracting features from spatially structured data, such as images, with a focus on 2D data.
- Single-Layer Perceptron (SLP): SLP is a simple and linear data classification algorithm.

Fingerprint thinning is a crucial preprocessing step in fingerprint image classification, aimed at extracting the basic structure of the fingerprint and eliminating unnecessary pixels. Two main thinning strategies exist: iterative boundary removal methods and non-iterative separate transformation methods. Iterative approaches, including both sequential and parallel methods, continuously remove boundary pixels to achieve a pixel-wide thin image. On the other hand, non-iterative methods, such as mean axis transformations, offer alternative thinning techniques, although they are less powerful and less suitable for certain applications [56].

It is important to note that the relationship between algorithms at various stages of recognition systems is complementary, aiming to achieve highly efficient systems.

9. Fingerprint Datasets

Fingerprint datasets consist of collections of fingerprint images or templates assembled for diverse purposes, including research, algorithm development, and system testing within the field of fingerprint identification. These datasets play a pivotal role in training and evaluating fingerprint identification algorithms, assessing system performance, and conducting experiments in the domain of biometrics. The details of these datasets are summarized in Table 2. Commonly employed fingerprint datasets include:

- The Fingerprint Verification Competition (FVC) databases are widely recognized benchmark datasets in the fingerprint identification community, comprising multiple editions (FVC2000, FVC2002, FVC2004, FVC2006, FVC-onGoing). Each edition contains fingerprint images captured under varying conditions [57] - [59].

- The NIST Special Database 27, provided by the National Institute of Standards and Technology (NIST), includes fingerprint images collected via optical and capacitive sensors. This dataset encompasses images from multiple fingers and is commonly used for biometric research evaluation [60].

- Another contribution from NIST is the NIST Special Database 4, which contains fingerprint images from multiple fingers captured using high-resolution scanners. It is frequently utilized for evaluating minutiae-based fingerprint identification algorithms [61].

- The Fingerprint Verification Competition 2006 (FVC2006) is a part of the FVC series, offering datasets for fingerprint verification. It comprises four databases, each containing fingerprint images captured using different sensors and under varying conditions [62].

- The PolyU Fingerprint Database (PolyU-FP) contains fingerprint images captured using optical sensors. This dataset includes a substantial number of images from various fingers and is often utilized for research and algorithm testing [63].

- NIST Special Database 9 consists of fingerprint images acquired using live-scan technology, encompassing flat and rolled fingerprint images. This dataset is employed for testing fingerprint identification algorithms [64].

- Lastly, the SDUMLA-HMT Fingerprint Database is a high-resolution dataset containing fingerprint images captured under diverse conditions. It is commonly used for evaluating fingerprint identification algorithms in challenging scenarios [65].

TABLE 2.details about the most famous fingerprint dataset.

Seq.	name	Num. images	year	quality	Type
1	FVC2000	880	2000	Mixture	JPEG
2	FVC2002	2960	2001	Mixture	JPEG
3	FVC2004	880	2003	Mixture	JPEG
4	FVC2006	1800	2006	Mixture	BMP
5	NIST 4	4000	1992	Mixture	JPEG
6	NIST 9	2700	2008	Mixture	JPEG
7	NIST 27	258	2000	Mixture	lff
8	PolyU	1800	2014-2016	Mixture	JPEG
9	SDUMLA-HMT	25,440	2010	Mixture	BMP

10. Evaluation

A variety of evaluation metrics are utilized to comprehensively assess biometric fingerprint identification systems, providing quantitative measures that offer insights into various aspects of system performance. These metrics play a crucial role in evaluating the effectiveness of these systems. Key evaluation metrics include, but are not limited to:

Sensitivity: This metric measures the system's ability to accurately identify actual positive cases. It is calculated as the ratio of genuine positives (TP) to the total of true positive results and false negatives (FN) (Equation 1). A higher sensitivity indicates that the system can identify a greater proportion of true positives.

$$\text{Sensitivity} = \frac{TP}{TP+FN} \quad (1)$$

Accuracy: this metric refers to the overall correctness of the method's predictions. It is computed by dividing the total number of actual positives and actual negatives (TN) by the sum of actual positives, true negatives, false positives (FP), and false negatives (FN), then multiplying the result by 100 (Equation 2). A higher accuracy score indicates a more reliable system.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FN+FP} * 100 \quad (2)$$

F1-Score: The F1-Score combines accuracy with recall to offer a balanced evaluation of system performance. It is computed as the harmonic average of recall and precision, where precision is the proportion of actual positives to the sum of accurate positives and false positives, and recall is equivalent to sensitivity (Equation 3). The F1-Score ranges from 0 to 1, with a higher value indicating better performance [66].

$$\text{F1 - score} = \frac{2*TP}{2*TP+FP+FN} \quad (3)$$

Genuine Acceptance Rate (GAR): GAR assesses the system's ability to correctly accept genuine users. It is calculated by dividing the number of correctly accepted genuine cases by the total number of genuine cases and multiplying by 100 (Equation 4). A higher GAR signifies a more dependable system that correctly accepts genuine users.

$$\text{GAR} = \frac{\text{Number of Cases Accepted Correctly}}{\text{Total Number of Genuine Cases}} *100 \quad (4)$$

False Acceptance Rate (FAR): FAR represents the rate at which impostors are incorrectly accepted by the system. It is calculated by averaging the FAR and the False Rejection Rate (FRR) (Equation 5). A lower FAR indicates a more secure system with fewer false acceptances [67].

$$FAR(k) = \frac{FAR(k)+FRR(k)}{2} \quad (5)$$

Recognition Rate (RR): The Recognition Rate (RR) denotes the percentage of correct identifications made by the system. It is computed by dividing the total number of correctly recognized instances by the overall number of instances and multiplying the result by 100 (Equation 6). A higher RR indicates a system that is more accurate at recognizing individuals [68].

$$\mathrm{RR} = \frac{\text{Num. Correctly Recognized}}{\text{the overall number Instances}} * 100 \quad (6)$$

Total Success Rate (TSR): The Total Success Rate (TSR) evaluates the system's overall performance in successful identification. It is calculated by dividing the number of effective instances by the total number of instances and multiplying by 100 (Equation 7). A higher TSR signifies a system with a higher rate of successful identification [69].

$$\mathrm{TSR} = \frac{\text{Num. of Successful Instances}}{\text{Total Number of Instances}} * 100 \quad (7)$$

Specificity: Specificity assesses the system's ability to accurately identify true negative cases. It is determined as the ratio of true negatives to the sum of actual positives and false negatives (Equation 8). A higher specificity indicates a system with a lower rate of false negatives [70].

$$\text{Specificity} = \frac{TN}{TP+FN} \quad (8)$$

Root Mean Squared Error (RMSE): RMSE calculates the difference between expected and actual values. It is computed as the square root of the mean squared variance between the actual and predicted values (Equation 9). A lower RMSE indicates that the system is more accurate and has smaller prediction errors [71].

$$\mathrm{RMSE}(X, h) = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(h(Xi) - yi)^2} \quad (9)$$

Mean Absolute Error (MAE): MAE describes the average magnitude of errors in the system's predictions. It is calculated as the average unconditional difference between the actual and predicted values (Equation 10). A lower MAE suggests that the system has smaller average prediction errors [72].

$$\mathrm{MAE} = (1/n) * \Sigma|yi - xi| \quad (10)$$

The Receiver Operating Characteristic Curve (ROC Curve) illustrates the trade-off between true positive results and false positive rates, aiding in the analysis of system performance [73].

Fingerprint Image Distortion (FID) quantifies the extent of distortion in fingerprint images, contributing to the assessment of the captured fingerprint data's quality and reliability [74].

Likelihood Ratio Test (LRT) is a statistical method used in biometric systems for decision-making. It calculates the likelihood ratio between two competing hypotheses to inform decisions [75].

$$\mathrm{LRT} = -2 * (\ln(L1) - \ln(L0)) \quad (11)$$

The mean error (ME): ME computes the average of the system's prediction errors (Equation 12). It provides insights into the average deviation between predicted and actual values [76].

$$\mathrm{ME} = (1/n) * \Sigma\,(y - \hat{y}) \quad (12)$$

These evaluation metrics are formulated mathematically and collectively contribute to a comprehensive evaluation of biometric fingerprint identification systems. Their combined use ensures that system performance is assessed from various angles, enabling informed enhancements and adaptations to improve the accuracy and reliability of these technologies in real-world scenarios.

10. Conclusion

This paper offers a comprehensive exploration of recent research in fingerprint identification, delving into methodologies, techniques, and databases to uncover key factors influencing accuracy and performance efficiency. Emphasizing second-level features such as ridge ends, spurs, bifurcations, and statistical attributes, the study reveals critical trends in fingerprint feature extraction crucial for biometric identification. Additionally, a detailed analysis of deep learning techniques in fingerprint identification underscores their effectiveness, despite varying accuracy linked to different models and database complexities. The findings highlight deep learning as the most promising approach in fingerprint identification, showcasing its adaptability across diverse applications. This survey not only underscores the transformative potential of deep learning in biometric authentication but also sets the stage for future advancements and innovations in fingerprint identification technologies.

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