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Survey on the convergence of learning techniques for precise pattern identification in fingerprint analysis

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Abstract Fingerprint analysis has been an essential component of forensic science and biometric authentication systems. The precise recognition of fingerprint patterns is critical for solving crimes, confirming identities and assuring the security of numerous applications. In recent years, the convergence of learning approaches, particularly machine learning and deep learning, has played an essential part in improving the accuracy and efficiency of fingerprint pattern recognition. In this paper, we discuss recent advancements in physiological-based biometric multimodalities, with a particular focus on the field of precise pattern identification in fingerprint analysis. Additionally, we assume the task of summarizing and examining a range of physiological-based biometric modalities, encompassing both traditional and deep learning approaches. A detailed review of several biometric measurements across many modalities is presented, encompassing various phases, including preprocessing, feature extraction and classification, which are thoroughly discussed. We provide a comprehensive analysis of the challenges and future developments associated with conventional and deep learning methodologies. The objective is to enable investigators to recognize these problems. A review is conducted to evaluate the standard and deep learning approaches employed in different physiological-based biometric systems. The comparative analysis of this review suggests that more advancement is necessary for the development of a reliable physiological-based approach to enhance and optimize the functionality of the fingerprint system.

Keywords: pattern recognition, fingerprint analysis, machine learning, deep learning

1. Introduction

Essentially, pattern recognition is used to extract patterns from receiving data to provide recognized evidence of observable elements and connections. These techniques are generally associated with image evaluation, considering the reality of the primary category of applications (Labati et al. 2019). The production of response problems in pattern recognition, such as those observed in drug usage prediction, text classification, image indexing, object discovery and visual monitoring, has necessitated the application of a wide range of supervised learning techniques, such as transfer learning, multi-instance learning and fascinating developments in deep learning strategies (Lian et al. 2018). Pattern recognition involves the creation and implementation of technologies that identify connections in evidence. A pattern recognition program's intention is to analyze an environment in reality and develop a description of the image that can be used to complete an assignment (das et al 2018). Sensors collect real-world observations that are classified or described by a pattern recognition system. A feature extraction technique computes quantitative or conceptual value from these experiences (Ehatisham-ul-Haq et al 2018).

The pattern recognition method comprises numerous techniques that ensure an effective representation of the patterns. Pattern recognition is required to ensure the correctness of pattern recognition technology (Dargan, and Kumar 2020). An analyzing machine learning-based pattern recognition technique is developed. Pattern recognition utilizes a variety of cutting-edge techniques to enhance performance and efficiency (Chugh et al 2018).

This complex procedure entails systematically examining and comparing fingerprint patterns to identify prospective connections between criminal incident information and current evidence (Tang et al 2017). This evaluation, provided by advanced technology such as automatic fingerprint identification systems (AFISs), plays an important role in criminal investigations, providing substantial information for resolving difficult crimes (Adam et al 2021). This has transformed the way in which government intelligence organizations approach criminal identification, improving the reliability and effectiveness of current investigation techniques. Fingerprint assessment, with its enormous effect on current criminality and law enforcement, is an essential instrument in the demand for equity. This research attempts to overcome the constraints of traditional fingerprint assessment by integrating current machine learning techniques, deep neural networks and pattern recognition approaches, providing a more accurate and comprehensive technique (Wang et al 2019 and Wang et al 2017).

The learning techniques for precise pattern identification and fingerprint analysis have generated significant achievements that have revolutionized the field of forensic science, providing a revolutionary approach to reliably recognize intricate patterns and analyze fingerprints with outstanding perfection by integrating superior machine learning algorithms and pattern recognition technologies. They provide individuals with opportunities to participate in different sectors, such as forensic science, biometric identification and security systems, by providing substantial advancements to the improvement of these industries.

2. Overview of biometric technology

When the prominent features of the pattern recognition that investigate images (the image that was obtained) are compared to the characteristics of the registration image (the image that was stored in a database), this is known as a biometric system. Image capture, feature extraction, comparison and pattern collection are the four basic components of any biometric system. The image of the biometric characteristic is gathered in the initial phase of a biometric system's image acquisition procedure; if the image quality is insufficient, a preprocessing algorithm is applied to improve it, and it is the image delivered to the system for analysis. After that, we take the implemented image and extract the most important feature. Third, a matching score is calculated by comparing the features of the investigated image with those of the registered image. Figure 1 is a graphical representation of four of these stages in action.

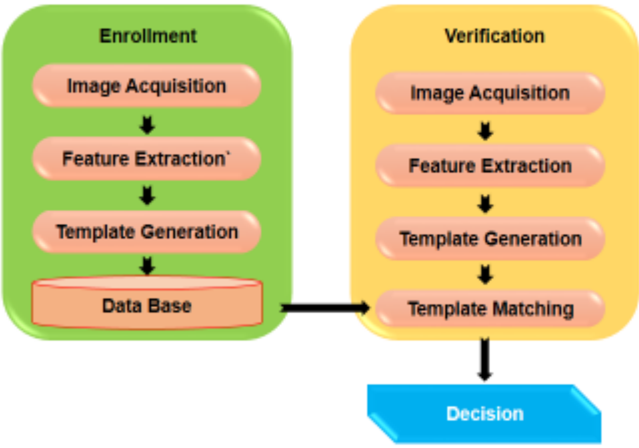

Figure 1 Biometric system.
Source: https://www.researchgate.net/figure/Research-and-development-procedures_fig2_367233392

The creation of biometric system information is affected by its efficacy and environmental context. The sustainability factors include the temperature, brightness surrounding the equipment, moisture and period during the application and confirmation stages, all of which affect performance (Rida et al 2020). Sampling, acquisition errors and efficiency errors are used to quantify the efficiency of the biometric system. Errors in the acquisition process might be caused by the system's environment. This causes two types of mistakes: “FTEs (failure to enroll)” and “FTCs (failure to capture)”. The fractional false alarm rate (FTE) is the proportion of users whose samples are rejected by the program because of background disturbance and restricted image resolution. Appreciation and acknowledgment proportion validation attempts for which techniques are struggling to obtain a sample. This type of mistake occurs when the sensor surface cannot be properly cleaned.

The effectiveness of a biometric system in a real-world setting is quantified by its performance error. Below, there are a few terms used to represent the efficiency of biometric technology. The frequency at which a matching algorithm returns false positives in a particular template comparison is known as the “false match rate” (FMR). The rate at which an algorithm is expected to produce false negatives during a template comparison is known as the “false-nonmatched rate (FNMR)”. Table 1 provides some examples of functioning pattern recognition models.

Table 1 Pattern recognition models.

Technique	Pattern equivalence	Probabilistic	architectural or semantic	Neural networks
feature identification	Correlation, distance measure	Discriminant function	Rules, grammar	Network function
fundamental condition	Classification error	Classification error	Acceptance error	Mean square error
Participation	Samples, pixels, curves	Features	Primitives	Samples, pixels, Features

False Rejection Rate (FRR): The false-rejection rate (FRR) quantifies how a factual user is dismissed. The percentage of false rejects made for an expected number of attempts by the authentic user is:

$$FRR(B) = FTA + FNMR(B) \times (1 - FTA) \qquad (1)$$

In this instance of Eq. 1, 'B' represents the genuine user's effort. The FAR is the proportion of fakes that were recognized by the biometric system. The percentage of fake acceptances due to single-attempt forgeries is:

$$FAR(B) = FMR(B) \times (1 - FTA) \qquad (2)$$

A receiver operating characteristic (ROC) curve is a histogram that compares the proportions of inaccurate, favorable and unfavorable results at different sensitivities with one another along two axes.

Equal Error Rate (EER): The compromise involving FAR and FRR can be observed in the efficiency evaluation ratio (EER), where FAR and FRR are identical. When the effective energy use rate (EER) is inadequate, the fingerprint technology functions optimally. A biometric system's performance is expressed as its EER. However, sampling collection, the reliability of fingerprint technology and the possibility of individuals improving when both high-quality images and moderate acquisition errors are provided.

Identification rate (IR): The percentage of occurrences in which a user connects to a system and receives accurate personal information.

False-negative identification error rate (FNIR): The percentage of instances in which an established user tries to identify themselves using a biometric modality where they do not receive their accurate user identity. The size of a database of size N is compared to a single recognition request made by a registered user as follows:

$$FNIR(B) = FTA + (1 - FTA) \times FNMR \qquad (3)$$

False-positive identification error rate (FPIR): In the system where the identifying is exchanged, the consumer's percentage of failed recognition efforts does not appear. If a user performs one ID request against a database of size N, the definition is:

$$PIR(B) = (1 - FTA) \times (1-(1 - FMR)^{M}) \qquad (4)$$

Cumulative Match Characteristic Curve (CMC): The CMC is a visual depiction of recognition accomplishments, including the position considered on the x-axis and the classification efficiency on the y-axis.

2.1. Review Planning

The purpose and rationale behind researching the most popular physical biometric technology of late should inform the remainder of the review outline. The intended population should have minimal trouble understanding. A review plan can either fail or succeed depending on the method utilized to represent the review's objectives, targets, inquiries and other associated aspects. Methods for achieving objectives and criteria, for instance, the acceptance and rejection of achievements, should be described in detail in the review plan.

2.2. Fingerprint

There are numerous datasets and databases pertaining to the field of fingerprint verification and recognition. These include the Fingerprint Verification Competition datasets, namely, FVC2000, FVC2002 and FVC2004. The "Indian Institute of Technology (IIT)" developed the Latent Fingerprint database, the "Multi-Sensor Optical and Latent Fingerprint (MOLF)" dataset and the "Multisurface Latent Fingerprint database (MSLFD)". Furthermore, the IIT-D has contributed to the "Multi-Sensor Optical and Latent Fingerprint (MOLF)" dataset. Other notable databases include the "Poly U High-resolution Fingerprint (HRF)" database and the NIST D4 as well as D14 datasets."

2.3. Standards for acceptance or rejection

The regulation that determines the scope of the study establishes criteria for acceptance or rejection. In the typical research process, standards are considered after the research matter has been established and before the research itself is conducted. For example, in this case, we eliminated unnecessary and unrelated papers. We evaluated whether the study fell within the broad scope of inquiry that is relevant to our topic. Research papers presented at prestigious conferences and published in high-impact journals (including SCI and ESCI) should be cited. The abovementioned review must incorporate the research of qualified scientists. Both qualitative and quantitative studies from the past few to five years should be included in the presentation. We must make an exception for outdated studies and research that do not contribute to our objective.

3. Fingerprint identification

The most commonly employed fingerprint technology used for safety and security purposes is fingerprint recognition. Figure 3 shows the fingerprint classification. The fingerprinting procedure consists of three steps: preprocessing, extraction of features and comparison. The fingerprint identification process is shown in Figure 2.

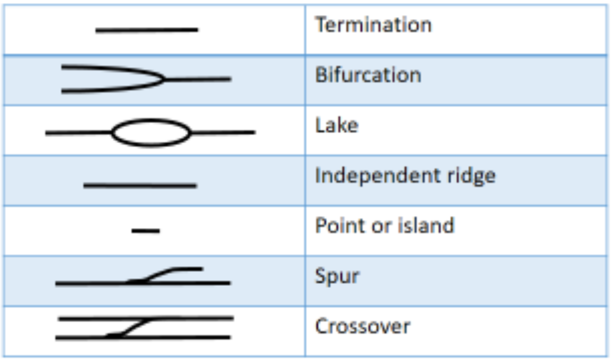

Figure 2 Fingerprint features.
Source: https://www.semanticscholar.org/paper/A-Novel-Approach-for-Fingerprint-Matching-Using-Patil-Zaveri/e1cee4bc0d607832f9bbbd9bfb9c554462dee817

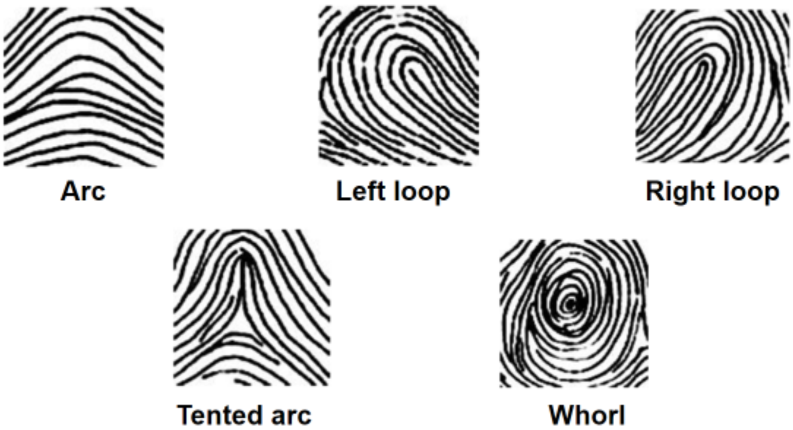

Figure 3 Fingerprint classification.
Source: https://bio.libretexts.org/Courses/Los_Medanos_College/Bio_30_Lab/Lab_4_Skin_and_Integument

3.1. Conventional Techniques for Fingerprint Identification

Several traditional fingerprint analysis approaches have been presented and developed. Galton's point in the investigation of fingerprints was originally defined by Sir Francis, and since the late nineteenth century, fingerprints have been utilized as a means of personal identification (Harish et al 2017). Galton's perspective is believed to be of minor importance and has been used in the creation of automated fingerprint identification systems. Compared to various fingerprint techniques, fingerprinting is associated with a wide range of processes, including image preparation, feature extraction, comparison and categorization. Preprocessing techniques are considered when referring to image improvement. Due to insufficient image quality, automatic fingerprint identification systems operate inadequately. Recently, a number of different plans for evaluating and improving quality have been proposed. Panetta et al. (2019) suggested an image quality evaluation metric called the local quality measure (LQM) and an improvement metric for low-resolution fingerprint scans called localized quality measure enhancement (LQME). Manickam et al. (2019) introduced a scale-invariant feature transform (SIFT)-based technique for fingerprint image improvement. First, the image contrast was improved with the use of a Type-2 imprecise collection with intuition. Second, the fingerprint images were processed to remove the SIFT feature points. Finally, the Euclidean distance technique and the number of acceptable matches were used to determine the matching score. In another study (Sharma and Dey 2019), through the use of local phase quantization (LPQ), substandard fingerprint images were discovered and categorized as dry, moist or good. The proposed method, which relies on a support vector machine classifier, achieved an accuracy of 95.16%. However, for quality classification, the proposed method uses one texture characteristic, which is inefficient for accurate fingerprint identification.

The efficiency of the fingerprint identification system can be enhanced by the use of feature extraction. There are three main types of feature extraction using fingerprints as evidence. Forensic information comprises the initial session. Scans are broken down into their finest components (Krish et al 2019). The forensic fingerprint analysis by De Santis et al. (2017) was based on constants and specifics. The short-time Fourier transform (STFT) was used to improve the input fingerprint image. After the fine-grained points were retrieved, a structural modification was used to focus on a target area (ROI). Finally, Gaussian resemblance matrices were applied to determine the similarity, and an optimum efficiency of 96.67% was achieved.

This technology demands extensive computing power and is unreliable for fingerprint recognition. In several investigations (Khodadoust J and Khodadoust AM 2017), to enhance the recognition efficiency of the fingerprint system on significant datasets, an indexing technique was developed that operates on topographical combination and convex fundamental points. On the other hand, a significant amount of computational resources is required to evaluate the resemblance of individual regional characteristic pairs between two fingerprints, reducing the effectiveness of confirmation with fingerprints. To address this issue, Nachar et al.'s (2020) strategy combines the use of edge corner points and minute details. In this work, optimum identification percentages of 1.93%, 1.3% and 2.76% were attained with an average extraction time of 1.17 seconds. Problems with minutia-based approaches include the presence of fake minutiae, the absence of actual minutiae, the absence of an alignment method, and the complexity of the input image. In addition, these techniques do not take advantage of the discriminatory data that are present in fingerprints. In the second type, similarity is determined by comparing the reference fingerprint image to the test pixel (Guo et al. 2018). The procedure recommended by Jinich et al. (2019) and fingerprint image reference points were referred to. This study is twofold. First, a walking technique is used to locate the single recognition without examining the complete fingerprint image. The proximate region around that point was extended using the maximum movement-enhanced methods, producing a reliability of 88.6% on the FVC2000 DB2 of 700 biometric images. This method of feature extraction requires high-quality fingerprint images. Image-based systems with localized and global texture attributes are derived from a fingerprint pattern, making up the third type (Ahmed and Sarma 2018). Fingerprint identification effectiveness is enhanced when ideal consistency features are extracted.

To accomplish this invariance, a technique for extracting features depending on the geographic connection between particulate positions was developed. A four-dimensional characteristic matrix that satisfies the six necessary component attributes was created as a means of addressing the challenge of misplaced and misleading minutiae in fingerprint systems. On the FVC 2002 dataset of 3200, an aggregate identical mistake incidence of 1.1224 was found in the fingerprint images. The proposed technique suffers from nonlinear distortion. The corresponding algorithm's nonlinear distorting condition requires a solution to the problem (Tran MH et al. 2017), who suggested a matching process based on individual detail's local feature representation. There is increasing concern about the susceptibility of fingerprint protection to attacks. Hence, a revolutionary technique was proposed in this research to determine the corresponding adaptable level independently of identification effectiveness (Yang et al. 2019). Investigators have explored fingerprint representation attacks (Mura et al 2017). There are many conventional methods (Park et al 2018) for identifying deception attempts in fingerprint systems, and multifunctional techniques (Gomez-barrero et al 2018) have been created.

3.2. A Fingerprinting Technique Focused on Deep Learning

The academic population of biometrics is inspired to embrace deep learning-based strategies due to the rapid growth of the application of these methods to disciplines such as computer vision, multimedia and identification tasks. Here, we summarize the many deep learning algorithms that have been implemented in fingerprint identification technologies. Fingerprint improvement, feature extraction and classification are the three key components of a fingerprint recognition system workflow. To solve the issues of fingerprint enhancement and classification, researchers have developed deep learning methods (Nguyen et al 2018), feature extraction methods (Peralta et al 2017) and classification methods.

Motivated by the discovery of convolutional networks, Li et al. (2018) created a deep learning network using fingerprint data called a fingernet. There are three main parts to the proposed system: one conventional convolution and two deconvolutions. The proposed method employs a network design of four convolutional layers with a maximum of 8 pooling layers, four unpooling sections and two max pooling tiers. Convolutional neural networks were used to extract initial fingerprint image attributes; subsequent noise cancellation and enhancement were achieved by deconvolution enhancement expansion. The inference time was reduced to 1.8 seconds using a multiclass approach and orientation deconvolution branch guidance. The matching process is streamlined with this strategy. The matching efficiency was minimal. Fingerprint identification quality is highly granular. However, recreating defective and incomplete patterns is difficult (Svoboda et al 2018). A "fully convolutional autoencoder network" was proposed. The identical structure of 5 convolutional and five deconvolutional layers was employed for the encoding and decoding networks, leading to an efficiency of 78%. However, the identification ability of the fingerprint technique was inadequate since the generated images had substandard ridge architecture and a noise background. Therefore, to improve fingerprint quality, Joshi et al. (2019) suggested an approach based on a synthetic artificial network. Using rank50 efficiency, the results improved to 35.66 percent and 30.16 percent, respectively. The detection effectiveness of the proposed method is compromised by the generation of a false feature when the ridge information is sparse. Using a convolutional neural network, a patch-based segmentation method was presented by Khan and Wani (2019). The proposed method has a straightforward structure, with three convolutions and two max-pooling

levels, and it has an 85.5% performance rate in classification. Their approach is fundamental and has not been tested in a realistic fingerprinting environment.

The determination of a system's performance depends heavily on feature extraction. In fingerprint technology, there are three tiers of feature extraction. There are three tiers of physical information: level 1, level 2 and level 3 (DonidaLabati et al, 2018). Numerous experiments use the extraction of features at levels 1 and 2 for fingerprint recognition. Coarse-Net, a deep learning system, can reliably identify microscopic features from fingerprint images. The coarse-Net architecture consists of 20 convolution sections and eight pooling elements. The initial stage was to determine the specifics using the Coarse-Net model, which included CNN and fingerprint category information value structure and minutia alignment. The potential minutiae are filtered and refined using the Fish-net-mintai algorithm, which is based on the achieved pattern. A precision of 76.81%, a recall of 75.92% and an F1-score of 1.942% were attained by the proposed approach. However, a small proportion of the data were used for education, and the overall procedure is operationally intensive. As a means of accelerating parallel computing, Jeon and Rhee (2017) examined three different VGGNet structure-based categorization models. Model 3 was deemed superior since it obtained an aggregate classification rate of 86.3%. The proposed strategy performs spectacularly when dealing with noisy data. Due to the varied nature of fingerprint data, level 2 feature extraction is a difficult task. Darlow and Rosman (2018) created a deep neural network named MENet to detect microscopic features in images. To train the MENet, they used a computerized approach of categorizing incredibly small samples. Using two datasets, the stated error rates were very small: 1.892 and 6.561. However, the suggested technique demonstrates that the system performs well in extracting features from images.

Cao and Jain (2019) extracted ridge flow using the level 1 and level 2 characteristics of fine-grained descriptors. Inadequate ridge effectiveness, environmental noise, inadequate struggle, blurring of the image and a lack of usable ridge area are the problems that this work attempts to solve through the creation of an automatic implicit fingerprint recognition system. A position on identification of 85.6% and 88.5% was attained on two benchmarking databases, demonstrating a considerable improvement in the experimental results. However, the proposed method's feature extraction was difficult and yielded substandard performance across the two datasets. Level 3 features, such as pore feature extraction, are said to improve the efficiency of fingerprint recognition. Automatic fingerprint recognition using a pore extraction procedure is difficult. To prevent this situation, Jang HU et al. (2017) demonstrated that a CNN could automatically detect pores in images. The CNN model identified the pore features, and the fingerprint image was improved to emphasize the pore information at varying intensities. The efficiency of the system is impacted by the multiple layers of the proposed CNN method, which employs a great deal of information, including ridge shape and pore surrounds, from the fingerprint image. Another study (Cao and Jain (2018)) developed a CNN-based fingerprint indexing system. The fingerprint-matching CNN model was trained on a substantial dataset, and an introduction vector for a vocabulary was generated. The proposed technique was able to identify samples with a rank-1 accuracy of 97.8%. To further detect impersonating assaults, several deep-learning fingerprint algorithms have been implemented (Chugh et al. 2018). Table 2 presents a performance evaluation of various deep learning techniques.

Table 2 Deep learning comparison of fingerprints.

Author with year	Technique	Networks	Layers	Metrics	Dataset	Performance Measure
(Svoboda et al 2018)	Fully Convolutional Autoencoder	2	5 Convolution, 5 Deconvolution	128(11×11)–256(7×7)–512(5×5)–1024(5×5)–1024(7×7)–512(9×9)–256(11×11)–256(13×13)–128(5×5)	Dataset (2157)	AC = 78%
(Khan, Wani (2019).	Patch Based CNN	1	3 Convolution, 1 Subsample, 2 Fully Connected	74(17×17)–(3×3)–74(9×9)–367–367	IIIT-D (2156)	ACy = 85.55%, MDR = 11.6%, FDR = 5.8%
(Joshi et al. 2019)	GAN	1	9 Convolution, 2 Deconvolution, 9 Resnet Block	74(612×412)–138(356×356)–356(148×148)–456(158×158)–656(168×168)–156(178×178)–856(168×168)–756(178×178)–556(158×158)–656(168×168)–356(138×138)–148(35×176)–74(612×612)–174(266×356)–188(168×168)–456(74×74)–612(42×42)–2(33×33)	IIITD Multi-Optical Latent Fingerprint (MOLF) (5500), IIITD Multi-Surface Latent Fingerprint Database (672)	AC = 35.66% and 30.16%

(Li et al. 2018)	FingerNet	1	4 Convolution, 2 Maxpooling, 8 Deconvolution, 4 Unpooling	(8×8)–(6×6)–(4×4)–(3×3)–(1×1)	NIST Special Database 4 (2000), NIST Special Database (258), NIST Special Database 14 (27,000)	Inference Speed = 1.8
(DonidaLabati et al 2018)	CNN_D and CNN_R	2	7 Convolution, 5 Maxpooling, (6×6)–(4×4)–(16×16)–(2×2)–(5×5)–(11×11)–(6×6)–(35×35)–(7×7)–(360×260)–3–3	DB Touch based (40), DB Touchless (54), DB Latent (46)		RT = 86%, RF = 37% RT = 73%, RF = 33%

4. Final considerations

Fingerprinting remains an essential part of forensic technology and fingerprint identification structures, performing a significant role in the protection of crime, the confirmation of individual identities and the protection of numerous technological systems. The combination of machine learning and deep learning techniques has contributed to substantial improvements in fingerprint structure identification in subsequent generations. With a focus on specific pattern recognition in fingerprint evaluation, this study examined current developments in physiological-based fingerprint multimodalities. Multiple fingerprint techniques, influencing preprocessing, feature extraction and classification stages, have been examined while emphasizing the difficulties and potential of traditional and deep learning approaches. The findings provide important perspectives for academics and operators in the field, highlighting the need for further improvements in physiological-based techniques to improve and optimize fingerprint technologies. Ineffective fingerprint identification and compromised fingerprint technology reliability have been caused by manual evaluation, individual error, a lack of expansion and time-consuming procedures, which require more sophisticated technical interventions. More accurate, adaptable and guaranteed fingerprint structures can be developed for employment in fields such as law enforcement, border control and specific instrument protection if technology, actual time identification, and artificial intelligence and machine learning connections are further developed.

Ethical Considerations

Not Applicable.

Conflict of Interest

The authors declare no conflict of interest.

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