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REVIEW ARTICLE

A Systematic Review on Physiological-Based Biometric Recognition Systems: Current and Future Trends

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Abstract

Biometric deals with the verification and identification of a person based on behavioural and physiological traits. This article presents recent advances in physiological-based biometric multimodalities, where we focused on finger vein, palm vein, fingerprint, face, lips, iris, and retina-based processing methods. The authors also evaluated the architecture, operational mode, and performance metrics of biometric technology. In this article, the authors summarize and study various traditional and deep learning-based physiological-based biometric modalities. An extensive review of biometric steps of multiple modalities by using different levels such as preprocessing, feature extraction, and classification, are presented in detail. Challenges and future trends of existing conventional and deep learning approaches are explained in detail to help the researcher. Moreover, traditional and deep learning methods of various physiological-based biometric systems are roughly analyzed to evaluate them. The comparison result and discussion section of this article indicate that there is still a need to develop a robust physiological-based method to advance and improve the performance of the biometric system.

1 Introduction

Person identification system relies on knowledge-based (What he knows?) method and token-based (What he possess?) way to deal with perceive the people. In knowledge-based and token-based methods, an individual needs to recall the secret password (secret text) or keep the cards or both passwords and cards to authenticate his or her identity [69]. Both of these schemes are not secured, reliable and not user-friendly because passwords or ID cards can be easily forgotten/lost, guessed or shared. In those techniques, a user can conceal his or her original identity by providing duplicate identification records. Besides, these identification techniques were not offered any evidence at the crime scene for the identification of the suspect person. Therefore, token-based and knowledge-based methods are not adequate for stable identity management. Due to the drawbacks of knowledge and possession-based approaches, a rapid increase in the electronically linked user community, there is a need for accurate, simple, convenient user identification by automatic means for Human–Computer Interaction (HCI) approaches [149]. By computer algorithms, modeling the behavioural

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and psychological characteristics of a person has led to the utilization of biometrics in recognition scheme.

Biometric is a Greek word that implies bios (Life) and metric (measure). Biometric technology automatically recognizes and validates humans by his or her behavioral and psychological features such as finger vein recognition, face, iris, retina, gait, voice, etc. [158, 159]. Although the biometric method is not the best solution, but it provides several benefits over knowledge and token-based schemes in such a way that biometric attributes cannot be lost, forgot, and stolen. Furthermore, there is no need to remember long passwords and code by offering excellent security opportunities. The researcher community develops several biometric modalities inspired by the development of Bertillon's system in 1803 and Sir John Galton's fingerprint recognition system in 1903. Theoretically, the following are the measurement that needs to be satisfied for any psychological and behavioral attribute to qualify as a biometric trait [181]. Those measurements are given as follows.

- *Universality:* characteristic possessed by each person.
- *Distinctiveness:* any two humans have different features.
- *Invariance:* the ability of selected features should be sufficiently invariant over time.
- *Collectability*: biometric attributes should be easily collected and measured quantitatively.
- *Performance:* Imposition of the real constrained in term of data collection the required resource have to achieve the desired recognition accuracy and speed.
- *Acceptability:* the user extent to employ a particular biometric modality in everyday life.
- *Simplicity:* registration and transmission should be easy to use and error-prone.
- *Cost efficiency:* The process needs to be cost-efficient.
- *Circumvention:* the ability of the recognition system to detect an attack in case of a fraudulent attack against the regime.

In light of the above measures, biometric modalities can be tested and compared. In this research article, some recent psychological biometric traits are described and classified into three major categories: hand, face, and ocular regions, as shown in Fig. 1.

In recent years, there are in-depth and extensive research conducted. A few authors have reviewed different biometric modalities for personal authentication [15, 21, 25, 67, 154, 158, 159, 181]. Unar et al. [181] reviewed various unimodal and multimodal biometric traits and proposed prospects for person authentication. In another study [15], the authors explained the various ideas of biometric quality for three modalities, such as fingerprint, iris, and face. In [154], a review article was presented for different patterns while concentrating on the security and privacy issues of biometric. However, some researcher concentrates mainly on one specific biometric application [19, 130, 131, 151, 158, 159, 182]. 158,163 focused on finger vein recognition (FVR) technology. In that study, they comprehensively discussed the finger vein recognition algorithm via, image acquisition, preprocessing, feature extraction, and matching methods. Challenges and future research directions were also reviewed for the technology of FVR.

Borra et al. [19] have presented a survey on the fingerprint identification system. Considering the structure of fingerprint and studied different fingerprint approaches. However, none of them has compared and reviewed the new state-of-art algorithms for cognitive biometric authentication, including deep learning and traditional method. In this study [168] a deep learning algorithm was discussed, and some research gaps were highlighted. Since it was only described as a deep learning algorithm, and that was mainly focused on face and voice recognition systems. In this survey, the authors classify and comprehensively reviewed the new psychological-based biometric algorithms, primarily focused on deep learning and image processing algorithm for person authentication.

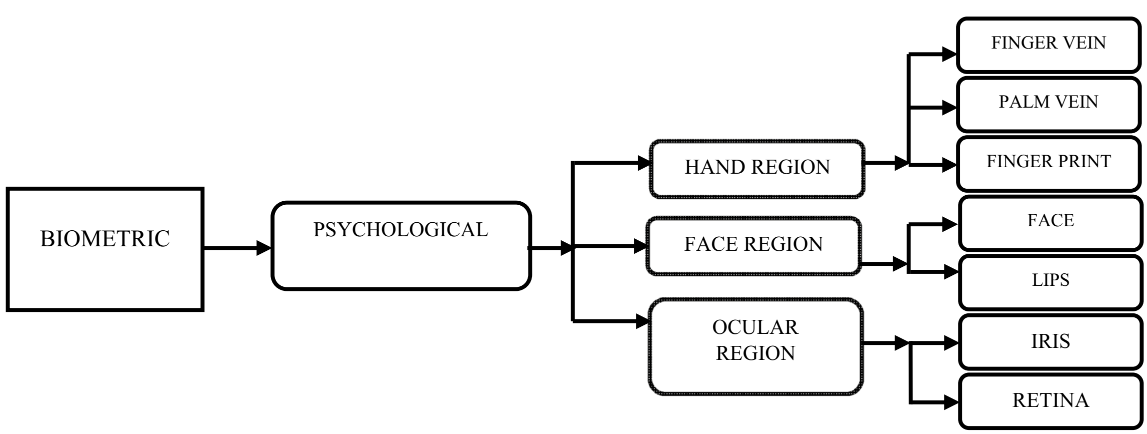


Fig. 1 State-of-the-art psychological-based multimodal biometric recognition systems

The authors have analyzed different kinds of threats and challenges related to the current biometric application. In view of the survey, further pointed-out several open issues and future research directions that are worthy for researchers. The contribution of this study can be illustrated as follow.

- We analyze the new conventional and deep learning scheme. The purpose of this study is to demonstrate and investigate the recent automated algorithms such as traditional machine and deep learning algorithms used in current psychological biometric technology for human identification.
- We comprehensively study the real work of cognitive-based biometric authentication by classifying them into three central body regions: hand region, face region, and ocular region. In our work, we considered traditional and deep learning approaches, compare them with proposed criteria to remark the pros and cons of each existing study.
- Finally, we figure out some open research gaps and propose some future research directions for secure, reliable, and efficient human authentication.

The rest of the article is organized as follows. Section 2 gives the steps engaged with the biometric system, operation of biometric technology, and the performance metric to evaluate the biometric application. In Sect. 3, a study about the traditional machine and deep learning-based algorithms of a new biometric system is discussed. Analysis and application prospectus of the biometric systems were highlighted in Sect. 4. A discussion, along with challenges and future research directions are given in Sect. 5. At long last, the article is concluded in Sect. 6.

2 Overview of Biometric Technology

A biometric system is considered a pattern recognition system that matches the salient feature of probe image (acquired image) with the features of the registered image (gallery image). To do so, each biometric system has four main steps, such as image acquisition, feature extraction, matching, and database template. In image acquisition steps, it is the first step of a biometric system in which image of the biometric trait is captured if the image quality is poor than the preprocessing algorithm are applied to improve the quality of acquired image otherwise forwarded directly to the system for further processing. Next, the salient Feature is extracted from the captured image. In the third step, the feature of the probe image (captured image) and register image (gallery image) are matched to obtain the matching score. Based on the matching score, decisions are made about the claimed identity, either verify or reject. Finally, the database contains the previously registered image termed is a template that is stored in the database. A visual example of all these four steps is graphically represented in Fig. 2.

A Biometric system has been operated in one of the modes, such as authentication (verification) or identification. In the authentication (Verification) step, it is considered a positive recognition. This kind of system seeks to answer the question, "Is this individual who they state they are? In this kind of mode, a person himself or herself present as a specific person. To find the match, the system needs to check the biometric template of that particular individual in the database and considered is a 1-to-1 matching system. Such kinds of modes applied in computer logins, access control, ATMs, identification of the user by mobile, and e-commerce [70]. Whereas in case of identification mode, it is a user biometric template is compared with all other enrolled models in the dataset by 1:N (one-to-many) comparison. This mode is essential in contrary recognition in which the user doesn't accept the particular identity. Negative recognition restricts

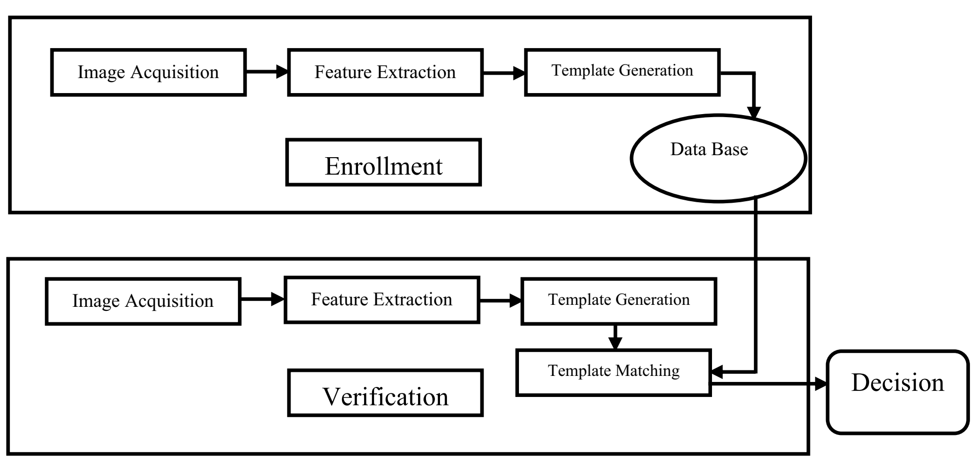


Fig. 2 An example of different steps for the development of state-of-the-art architectures of biometric systems

individuals to use one identity instead of multiple identities. The application in identification mode includes passport, ID card, welfare disbursement, and license of driving [181].

This section is about the metric used to evaluate the performance of biometric applications. The production of the biometric system mainly depends upon the data, which is affected by performance and environmental factor. Performance factor includes captured image quality, the time interval between enrollment and verification phases and strength of algorithm, while, and in environmental factor includes temperature, illumination condition around the system, humidity [70, 181]. The accuracy of the biometric system is measured in two terms, namely, sample acquisition error and Performance error. Acquisition error arises by the factor in the surrounding of the system. Thus, two kinds of errors generated in this way, such as failure to enroll (FTE) and fail to capture (FTC). FTE refers to the rate of the percentage of the user that is not successfully registered and then rejected a sample by the system due to noisy and poor quality image. FTA indicates the proportional of identification and verification attempt for which method are unable to acquire a sample. Typically, this kind of error occurs because of the uncleansed sensor surface.

Performance error measures the accuracy of the biometric system in a real environment. Below are the few terms used to represent the accuracy of the biometric system. False-Match-Rate (FMR): The rate to measure the incorrect positive matches of matching algorithm for single template comparison. False-Non-Match-Rate (FNMR): The standard to measure the false-negative events of matching algorithm for only template comparison.

- *False Rejection Rate (FRR):* FRR measures the incorrect rejection of the authentic user. If the genuine user makes one attempt, the false reject rate of that user would be:

$$FRR(A) = FTA + FNMR(A) \times (1 - FTA) \tag{1}$$

Here in Eq. 1, 'A' denotes the attempt of the authentic user. *False Acceptance Rate (FAR):* The ratio to measure the impostors accepted by the biometric system. If impostor attempt single time, the false acceptance rate would be:

$$FAR(A) = FMR(A) \times (1 - FTA) \tag{2}$$

- *Receiver Operating Characteristic Curve (ROC):* The graphical plot to show the FMR as well as FAR on the x-axis against the corresponding rate of FNMR as well as FRR on the y-axis at various threshold settings. Figure 3 represents the ROC curve.
- *Equal Error Rate (EER):* EER is the performance metric refers to the point where FAR and FRR become similar to each other and obtained from the ROC curve, which shows the tradeoff between FAR and FRR. The biometric system works well when the EER is low. EER is the measure of the accuracy of a biometric system. However, sample acquisition error is also essential, and the performance of the biometric system increases by providing excellent quality image and by decreasing the acquisition error.

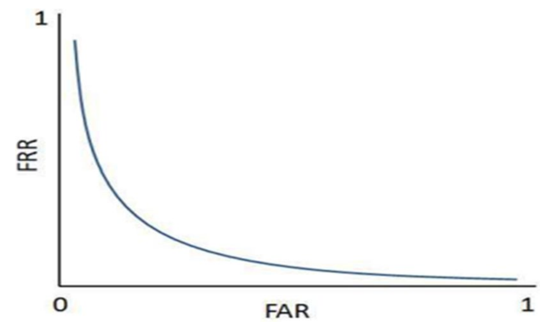


Fig. 3 ROC example: FAR and FRR

- *Identification Rate (IR):* The proportion of identification attempts by the enrolled user in a system and in which the correct user identifier is returned.
- *False-negative identification error rate (FNIR):* The proportion of identification attempts by an enrolled user in a biometric modality in which the correct user identifier is not returned. For one identification attempt made by an enrolled user against database size of N, it is defined as:

$$FNIR(A) = FTA + (1 - FTA) \times FNMR \tag{3}$$

- *False-positive Identification error rate (FPIR):* The Proportion of identification attempts by the user does not register in the system, where the identifier is returned. For one identification attempt made by a user against a database size of N, it is defined as:

$$FPIR(A) = (1 - FTA) \times (1 - (1 - FMR)^N) \tag{4}$$

- *Cumulative Match Characteristic Curve (CMC):* CMC is the graphical representation of identification results, plotting rank value on the x-axis, and the probability of correct identification on the y-axis.

3 Review Protocol

The review protocol defined the detailed layout, method that are plan to use in review. The protocol also defined the rules and instruction for conducting survey on the existing work on recent popular physiological biometric trait such as finger vein, palm vein, finger print, face, Lips, Iris and retina which offers assistance to research beginner in this domain. And, also provide enough information regarding traditional and deep learning based approaches in the mentioned biometric modalities. The review protocol exemplify sub-concepts namely review planning, research queries, study sources, data collection sources, standard for inclusion and exclusion and extraction of data. The survey also assist the user in regards of performance comparison of traditional and deep learning based physiological trait, the impact of deep learning technology on the recent physiological biometric trait, the kind of deep model are already implemented, and how the performance of the biometric system can be improved? Moreover, survey also provides help regarding the cost, data analysis and management, achieved result and also find the challenges related to both traditional and deep learning based biometric method.

3.1 Review Planning

The planning of review paper start with the intent and reason for the study of recent most commonly used physiological biometric technology. It should be relatively clear to our target audience. The success of review paper depends on the technique used to present the purpose of review, the aims, the questions produced and other related aspect. Review planning also show clearly the method that are used to reach target, standard for inclusion and exclusion and result comparison.

4 Research Questions

The fundamental core of the study of either the literature review or project is the research questions. This describe the methodological starting point scientific study in all discipline. Table 1 reveal the research queries linked with the physiological biometric trait and the motivation.

4.1 Data sources of Recognition method

(a) Finger Vein

- Shandong University MLA Finger vein dataset
- Tsinghua University Finger vein dataset
- University of Twente Finger vein dataset
- The Hong Kong polytechnic University Finger vein image database
- MMCBNU_6000
- Finger vein University Sains Malaysia data base

(b) Palm Vein

Table 1 Research question and motivations

Research question	Motivations
What is physiological biometric modalities?	To know more and study the recent approaches involved in this domain
What are the various approaches involved in physiological biometric trait?	To know what are the recent popular physiological biometric trait
What are the difference between physiological and behavioral biometric trait?	To study the research related to various biometric system
Does conventional deep learning approaches is time consuming?	To know and study the recent conventional approaches
What are the best deep learning model for biometric system?	To study various deep learning based physiological biometric identification process
Are deep learning based biometric approaches more efficient than conventional biometric traits in term equal error rate and accuracy of the system?	To study various deep learning and conventional biometric modalities and do comparison in term of equal error rate and accuracy of the system
Is deep learning based biometric scheme advance the biometric performance?	Experiment need to perform of selected method and compare
Does the dataset size of mentioned biometric technology facilitate the deep learning based method?	There is need to study various selected biometric technology and determine whether dataset is enough
Does existing deep learning and conventional based biometric method faces the challenges of poor quality dataset?	To investigate there is need to study the existing work related to deep learning and conventional method
Which application more suited?	Learning the importance and usefulness in real-time environment to make it more demanding
Data availability for research work?	Helps to analyze data for biometric trait that are discussed in literature
Does dataset size effect the accuracy of the system?	To know and compare the accuracies of biometric system of selected method
Are multimodal biometric approaches increase accuracy and decrease the error rate?	To study some of method involved multimodal approaches and analyze them for comparison

- Multi spectral near-infrared palm vein image dataset
- Multi-spectral Poly U dataset
- CASIA multi-spectral palm print Image dataset V.1
- Xian Jiao tong palm vein dataset

(c) Fingerprint

- Fingerprint verification competition (FVC2000) dataset
- Fingerprint verification competition (FVC2002) dataset
- Fingerprint verification competition (FVC2004) dataset
- Indian institute of technology (IIIT)-Delhi Latent Fingerprint database
- IIIT-D Multi-Sensor Optical and Latent fingerprint (MOLF)
- IIIT-D Multi-surface Latent fingerprint database (MSLFD)
- IIIT-D Multi-Sensor Optical and Latent fingerprint (MOLF)
  Poly U High-resolution fingerprint (HRF) database
- NIST D4 and D14

(d) Face

- Extended Yale dataset
- Face Recognition Technology (FERET) dataset
- Olivetti Research Lab (ORL) face dataset
- Essex Faces94 database
- Carnegie Mellon University (CMU) face database
- FEU face dataset
- AR face dataset
- Labelled Faces in the Wild (LFW) dataset
- CASIA NIR-VIS 2.0
- YouTube face (YTF) dataset
- Multi-Pie dataset

(e) Lips

- Cohn-Kanade Database
- Group of Digital signal Processing at the university of Las Palmas de Gran Canaria (GPDS-ULPGC)
- RaFD
- NITRLip V1 and V2

(f) Iris

- UBIRIS V1
- Multiple biometric grand challenge (MBGC) database
- CASIA Iris database
- IIT Delhi Iris dataset
- BATH dataset
- UPOL dataset
- Bio secure Iris dataset
- Cross-sensor NIR Iris dataset
- Mobile Iris Challenge evaluation (MICHE) dataset
- Noisy Iris Challenge evaluation (NICE) dataset
- ATVS_FIR dataset
- University of California Irvine dataset

(g) Retina

- VARIA dataset
- Digital Retinal Image Vessel Extraction (DRIVE) dataset
- Structure Analysis of Retina (STARE) dataset
- Retina Identification Database (RIDB) dataset
- Messidor
- DIARET database
- CHASE database

4.2 Standard for Inclusion and Exclusion

The inclusion and exclusion norm established with the set of rules which will define the research boundaries. In general, standard are considered after defining research question and before research process actually performed out. Here, for instance, irrelevant papers and out of concerned paper were denied. If the large field of study relate to our subject, we would consider the research. Published research manuscript from Top Journals (SCI and ESCI) and Top conference must always be acknowledged. And, also the research work of proficient scientist must be included in the stated work of review. The focus also should be on the qualitative and quantitative research that are presented in efficient way which must include last five to three years studies. However, old studies and research which do not fulfill our goal must be exempted.

4.3 Quality Evaluation

To pick appropriate papers and shortlisted papers for study, quality assessment method on nominated paper are performed after the process of inclusion and exclusion standard. As our research area is vast, and it comprises a variety of sub-areas of interest with huge number of reputed SCI and ESCI journals. Therefore, some procedure are required to choose research quality. So, according to quality assessment rule, our paper must include:

- Research paper with high quality
- The study selected with high quality dataset

- Paper with state of the art or comprehensive review studies
- Highly cited research work
- Study must include the approaches or method employed for biometric trait which are mentioned in this work
- Producing parameter for the comparison of conventional and deep learning approaches
- Sufficient data for analysis

4.4 Data Extraction

The final step after quality assessment is data extraction. The selected paper are interpreted for study and extract the significant and valuable data in transform into standardized data extraction form. This form provide the instruction for data extraction from existing research. Research assessment setup the foundation for data extraction. Quality assessment defined rule to include or exclude paper from study based on some standard. Data extraction technique find out the important data element that need to be certain, evaluated and investigated. Hence, following are the important element that needs to be considered carefully:

- Digital object identifier (doi)
- Reference data explain author name, title, years and source
- Journal name or conference proceedings from selected paper
- Research aim
- Image processing step (pre-processing, feature extraction, matching) involved in conventional and deep learning approaches
- Number of network, number of layer and parameter and identification rate in deep learning method
- Type of dataset used for specific physiological biometric trait
- Recognition performance or error rate obtained after experiments
- Reading carefully the already published state of the art review paper

Table 2 Biometric traits, major features and application

Modality	Major features	Application
Finger vein	Highly secure, reliable, highly accurate Not easy to copy and forge Required small sample size No requirement of physical contact with capturing device	Security system such house verification system ATM machine system Financial system and Access control
Palm Vein	Reliable and large variety of feature Recognition performance good even with low resolution camera	Door security system Financial system Access control
Fingerprint	Reasonably secure and reliable Fast matching process Need contact with the capturing system Required low memory space Economical biometric Open to copy and easy to copy Recognition can be effected by cuts, dirt, dust and scar	Driver-license authenticity Border control system/visa issues Access control system
Face	No physical contact required Template storage process easy Recognition process fast Facial identification change with time, age and accident happen Hard to find difference in twin Effect of lighting is consider important	General identity system Access control system Human–computer interaction system Criminal identification
Tongue	No physical contact with system Change with time, age and injury Required small sample size	Criminal cases Transaction authentication
Iris	Highly accurate and protective Required small sample size Fast processing but costly No physical contact required Accuracy can effect by disease	National ID card Google used for accessing data center Access control
Retina	Not easy to forged Low chance of error even twin have not same retina Highly secure and accurate Disease can produce error such as hypertensions and cataract Required direct contact	Security agencies such as, FBI,CID NASA Ophthalmological diagnostic

- Future prospect presented by the author of selected paper

5 Overview of Biometric Multimodalities

In this section, an in-depth overview of the different aforementioned psychological biometric modalities is depicted in detail. Physiological traits are consider physical traits of human and these modality are accepted because of uniqueness, permanence, collectability, inexpensive to achieve individual authentication. Table 2 represents various psychological biometric modality along with significant features (merit and demerit) and application. This article mainly focused on a psychological-based biometric recognition system and broadly divides into three regions i.e. Hand Region, Face Region and Ocular Region.

5.1 Hand-region Based Modality

Rich texture information in the human hand provided the foundations for different hand region-based biometric modalities. Among them, finger vein recognition is considered the most reliable, secure, and emerging biometric trait. A few hand-based biometric attributes have been identified and tested, such as palm print, hand geometry, finger knuckle print, finger vein, fingerprint, etc. In this article, we discussed the most popular hand region-based biometric modalities.

5.1.1 Finger Vein Recognition (FVR)

Compared to other biometric modalities, the finger vein recognition scheme is considered more robust, secure, and emerging biometric traits. Due to its unique characteristics such as live detection, anti-counterfeit, and need small portable capturing devices [160]. Figure 4 shows the process of the finger vein identification system. Among them, feature extraction is considered the essential step of finger vein recognition process.

5.1.1.1 Traditional FVR Methods Generally, the finger vein recognition process consists of three steps, preprocessing (region of interest, image enhancement, and normalization), feature extraction, and matching [192, 195, 196, 198, 199]. Indeed, the feature extraction step in FVR method is quite vital because of finger vein images can easily be imitated by various factors, like illumination, finger pose, occlusion, etc. Due to this FVR performance can degrade in such situations. Thus, effective feature approaches can overcome these challenges. At present, there are two kinds of traditional feature extraction methods proposed in FVR technique, i.e., vein image point-based and all image point-based methods [192, 195, 196, 198, 199]. Most of the vein point-based approaches were presented to segment the vein pattern from the image, viz, Gabor [17], repeated line tracking [121], curvature in radon space [143], an atomic structure analysis-based vein extraction [201], and maximum curvature [122]. Besides, some feature-based schemes are also developed from the vein point-based method to advance the performance of FVR system. These method include neighbor pattern coding (NPC) [193], Histogram of oriented gradient (HOG) [171], tri-branch structure [194, 197, 200], vein vector field [194, 197, 200] and Discretization [190]. [121] proposed a method called repeated line tracking to extract the finger vein pattern from unclear raw images and achieved an EER of 0.145%. However, the proposed method has low robustness and complexity problem. Efficiency and Robustness of repeated line tracking method relate to parameter p_n, which is the starting point for line tracking, a small mistake in selecting a suitable point according to the width of vein for different vein images, result in poor matching performance.

To robustly extract the vein feature, a method calculating the maximum curvature of the vein image was proposed in reference [122]. They obtain a highly accurate matching performance of 0.0009%. However, the finger vein width is not determined due to the fact, the texture direction of the finger vein image is not computed, which decreases the efficacy of FVR system. To improve matching performance, [201] proposed an FVR framework based on anatomical structure and imaging attribute for vein patterns. The proposed method

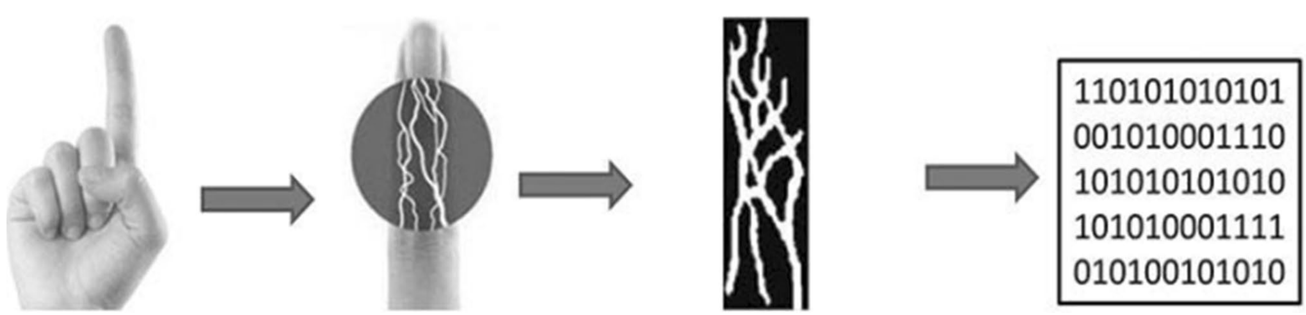


Fig. 4 Process of finger vein identification system [33]

achieved a low error rate of 0.38% and 1.39% on two datasets, respectively. However, the vein pattern is not efficiently detected from an ambiguous region affected by noise and irregular shadows. Therefore, Ye et al. [202] proposed a new point-based method, a Weber local descriptor (WLD) with variable curvature Gabor filters for finger vein identification. At first, the differential excitation operator and orientation operator in WLD was enhanced by computing the directional information. Finally, the variable curvature Gabor filter was introduced to extract the feature from the finger vein image, yielding EER of 0.6410, and 0.7862 on two different databases. The proposed method is robust to rotation and translation. However, the proposed curvature Gabor filter hasn't well suited to the curvature of a finger vein, which can degrade the recognition performance of FVR. Moreover, the vein point-based method is not robust to image quality because of the uniqueness of the finger vein vessel. To overcome these challenges, the second kind of feature extraction method was developed, called all image point-based methods. These method include competitive code [191], local binary code [90] discriminative binary descriptor [97, 101], discriminative binary code [187], polarized depth weighted binary direction code (PWBDC) [192, 195, 196, 198, 199], primary feature fusion with soft biometric [77] and personalized binary code (PBC) [102, 103]. To enhance the discriminative ability of local feature, Liu et al. [90] presented a method called, a discriminative binary descriptor (DFD) feature learning method, which reported low error rate of 0.0189% and 0.0069% on two different benchmarks. Another study [187], also advanced a learning-based scheme based on discriminative binary codes (DFC), to efficiently design feature learning based FVR system. They introduces a subject relation graph to establish associations among subject, and the acquire template are then used to depict the features of the subject. Low error rate of 0.0068% and 0.0030% were obtained on two dataset. However, both these learning method still not robust to occlusion, illumination and blur.

To address these issues, [192, 200, 201, 203, 204] introduced a novel all image point-based algorithm called polarized depth-weighted binary direction coding, to extract the vein pattern efficiently. The proposed work efficiently reduces the storage space by keeping a high identification rate of 98.8% on the established dataset. However, in extreme condition like significant finger rotation and apparent light variation resulted in some failed identification cases. Moreover, all image point-based approaches also extract non-vein points, which is not essential for robust person identification FVR application. To overcome these challenges, [192, 195, 196, 198, 199] proposed point grouping methods by incorporating the idea in a two-finger vein recognition algorithm, i.e., point grouping anatomy structure analysis-based vein extraction (ASAVE) and point grouping Gabor methods. The proposed method achieved impressive recognition performance by performing a low error rate of 0.43, 1.10, and 0.42 on three different datasets with less computation time. However, the configuration of the Gabor filter is complicated, which made the proposed work parametrically complex. Some methods aimed to address the image processing and enhancement problem in traditional finger vein recognition [204, 158, 159, 192, 195, 196, 198, 199]. Table 3 illustrates the conventional techniques, recognition performance, and public database available to finger vein identification modality.

5.1.1.2 Deep Learning-Based FVR Method Recently, a deep learning-based algorithm has achieved tremendous success in various applications, such as natural language processing, image recognition, and computer vision [162]. Some recent deep learning algorithm for finger vein recognition was featured in [47, 62, 71, 106, 144, 162, 165, 199, 209–211]. A deep learning-based finger vein recognition system has the challenge of high computation cost because of a great number of the learned parameter in the training process and storage space. Therefore, in [162] a local coding and convolution neural network (LC-CNN) method were proposed for finger vein recognition. The proposed method used the local coding layer instead of convolution to reduce parameter cost. Then, a pre-trained model was employed to extract the essential feature from a finger vein image. The proposed network architecture has three convolutional layers (CL), two max-pooling (MP), and two fully connected layers (FL), which achieved a classification accuracy of 100% and 98.7% on two different datasets. However, the method still has the problem of efficiency, consistency, and generalization.

Another study presented by [209–211] also addresses the high complexity, significant parameter, and slow computation process in the CNN model for finger vein authentication. Adaptive Gabor convolutional neural networks (AGCNN) were presented. The architecture of the system has eight Gabor convolution layers, five max-pooling, and three fully-connected layers with an accuracy of 84.95% and an AUC value of 0.9302%. This study somehow reduced the parameter size and improved the processing speed compared to the CNN model. However, the recognition performance of the finger vein recognition system deteriorates. Furthermore, the quality of the finger vein image is reduced because of many factors such as non-uniform illumination, the thickness of fat, low contrast, temperature, which resulted in the ambiguous region in the finger vein image. Therefore, Qin and Wang [144] proposed a finger vein pattern segmentation algorithm and supervised feature encoding scheme. First, sequence stacked convolutional neural networks with long short-term memory (SCNN-LSTM) and probabilistic support vector machine (P-SVM) are employed to predict the vein and background pixel in finger vein image. Then, a supervised feature encoding method is proposed to encode the vein pattern. The proposed SCNN model has two convolutional, two max-pooling, and one fully connected layer. The proposed work achieved an EER of 2.38%, which shows better recognition performance. However, the proposed method exhibits a high computation cost. In finger vein authentication, feature extraction is the critical step in the architecture of the finger vein recognition system.

The study in [62] presented convolution auto-encoder (CAE) and SVM for finger vein verification. First, CAE is applied to learn the features from finger vein images effectively, and then SVM is used to classify the learned feature code from finger vein images. EER of 0.12 and 0.21 on FV_USM and SDUMLA datasets were reported. The proposed CAE network model has three blocks, one flatten, one dense, three Re-block, and one convolution layer, which made the network parametrically complicated. Therefore, the proposed method has a high-cost time. Jalilian and Uhl [71] proposed three fully convolutional neural networks (FCN) architecture such as Unet, Refnet, and SegNet for finger vein authentication using automatic and manual labeling data. The result found that recognition performance significantly enhances with an automatically generated label.

However, the proposed model required a lot of training data, and the available finger vein dataset is limited [47, 106]. To address this issue and reduce the dependence on sizeable training data, [47] developed a CNN-based local descriptor named CNN competitive order (CNN-CO) by taking the first layer of the AlexNet network to exploit discriminative feature for finger vein recognition. EER of 0.74 and 2.37 were obtained from two datasets. However, the selections of CNN filter in proposed CNN-CO based on appearance and filter response, which haven't guarantee the performance improvement. The existed deep learning method employed difference of image is input to the network, and feature vectors were extracted from CNN. Difference images are exposed to noise as they are achieved by the difference in pixel value, and also the difference image was not applied to all network layers resulted in low accuracy. To address this issue in FVR technology, Song et al. [165] proposed a DenseNet 161 method that used composite two-finger vein images in input to the network and employed to the entire system. The DenseNet architecture used in the developed manner, have one convolution, max pooling, and average pooling layer, four dense blocks, three transitions, and one fully connected layer. High recognition performance of EER of 0.33% and 2.35% were achieved on two datasets. However, the proposed work is parametrically intricate. Information leakage in biometric is not acceptable because biometric data cannot be replaced and reset. To protect the biometric template, Yang et al. [199], proposed a biometric template protection algorithm called binary decision diagram multilayer extreme machine learning (BDD-ML-ELM). Table 4, highlight the recently developed finger vein recognition deep learning approaches and their performance on different available public finger vein datasets.

Table 4 Performance comparisons of recent deep learning finger vein recognition methods

Cited	Method	No of network	Network layer	Parameter	Dataset(size)	Performance measure
[162]	LC-CNN	1	three Conv, Two max-pooling, Two fully connected	196(11×11)–(3×3)–128(5×5)–(3×3)–384(3×3)–4096–100	Datase(5000), SDUMLA-FV(600)	AC = 100%, AC = 98.7%
(Yakun [209–211]	AGCNN	1	eight Gabor Conv, five max-pooling, Three fully connected	64(5×5)–(2×2–)128(5×5)–(2×2)–256(5×5)–256(5×5)–(2×2)–512(5×5)–512(5×5)–(2×2)–512(5×5)–512(5×5)–(2×2)–1024–256–600	MMCBNU_6000(6000)	AC = 84.95%, AUC = 0.9302%
[144]	SCNN-LSTM + PSVM	1	2 conv, 2 maxpooling, 1 fully connected	24(5×5)–(3×3)–48(5×5)–(3×3)–100–128–2	Dataset(2520)	EER = 2.38%
[62]	CAE	1	3 block, 1flatten, 1 dense, 3 Reblock, 1 Conv	24×72×32–12×36×32–6×18×64–6 912–6×18×64–12×36×32–24×72 ×32–48×144×3–48×144×1	FV_USM (5904), SDUMLA(3816)	AC = 99.95% & EER = 0.12%, AC = 99.78% & EER = 0.21%
[71]	Semantic Segmentation CNNs	1	Unet, Refine Net, Segnet	Not reported	UTFVP(1440)	EER = 0.78%
[106]	CNN-CO	1	Not reported	Not reported	MMCBNU_6000(6000), SDUMLA-HMT(3816)	EER = 0.74%, EER = 2.37%
[165]	DenseNet-161	1	1Conv, 1maxpooling, 1averagepooling, 4 dense block, 3 transition, 1 fully connected	3(224×224–)96(112×112)–96(57×57)–384(57×57)–192(29×29)–768(29×29)–384(15×15)–2112(15×15)–1056(8×8)–2208(8×8)–2208(1×1)	PolyU-DB(1260) SDUMLA-HMT(3816)	EER = 0.33%

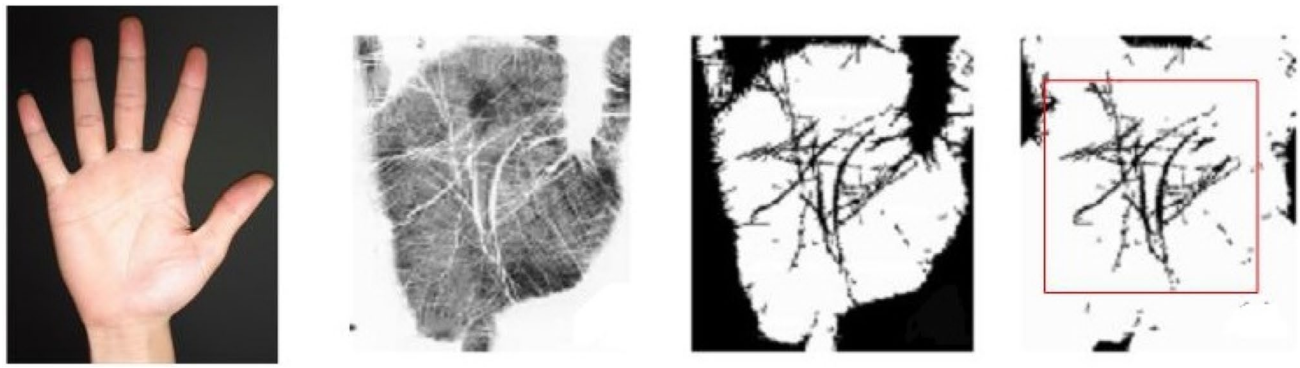


Fig. 5 The process involved in the palm vein biometric system [33]

5.1.2 Palm Vein Recognition

A palm vein is the new member of the biometric family which recently drawn the attention of the biometric community. Palm vein recognition system is already implemented in the ATM system of various banks in Japan and Taiwan [59] and considered the critical technology of biometric in 2006. Figure 5 demonstrates the process of the involved Palm vein recognition system.

5.1.2.1 Traditional Palm Vein Recognition Method Traditional palm vein recognition approaches also have three steps, (i) Image pre-processing (ii) feature extraction and (iii) Matching schemes [22, 59]. In recent times, most of the research focuses on the palm-vein feature extraction methods. Generally, feature extraction method can be classified into four categories, namely (i) geometry-based [10, 135, 155] (ii) statistical-based [4, 48, 94, 142] (iii) feature-based [164] (iv) coding based method [20]. We categorized these methods according to the feature image processing method that differentiates them from other approaches. The author in [10] proposed a geometry-based algorithm for palm vein pattern extraction based on the centerline of palm vein, and an error rate of 0.333 was reported. However, the method was not robust to translation and rotation problems. To address these issues, Parihar and Jain [137] used the SIFT feature to extract the key point from the extracted pattern of palm vein by image processing algorithm such as high pass filter and low pass filter and then SVM is employed to classify those images. A low error rate of 0.8875 and 0.925 was reported. However, the method has high computation cost and space complexity problem. Aglio-caballero et al. [4] introduced a statistical approach by presenting two texture descriptor method called Local Binary Pattern (LBP) and Uniform Local Binary Pattern (ULBP) methods. The author compared the palm vein verification performance of both methods, and they achieved a high error rate because the image acquires with high wavelength, which decreases the recognition performance. To improve the recognition performance, the study in [48], a proposed modified LBP method called diagonal cross local binary pattern (DCLBP) for palm vein feature extraction. The method achieved recognition accuracy of 96.6% on the CASIA dataset. However, the method was tested on a small dataset of 500 palm vein images, which hasn't guaranteed the robustness of proposed method. Moreover, geometry based and statistical based approaches often have poor discriminatory performance and highly sensitive to rotation, translation and changes. Therefore, Soh et al. [164] proposed a local invariant feature based method which do not depend on rotation, scale and translation changes. They used point feature matching by using single invariant feature transform (SIFT) and random sample consensus (RANSAC). The verification rate was significantly improved,EER and AUC of 7.7%, and 96.5% were achieved, respectively. Some research [20, 183] have employed coding based schemes to advance the performance of the palm vein identification system. They achieved high recognition rate. However, the feature extraction from single biometric source are consider not reliable and insufficient for robust palm vein identification application [141, 163, 189]. To investigate the performance of two feature biometric sources, Piciucco et al. [141] took two statistical based feature extraction approaches i.e. local binary pattern (LBP) and local derivative pattern (LDP) method. They reported a significant reduction in error rate compared to single feature technique. Another Study [189], also employed fusion approach by fusing the local Gabor histogram feature and achieved low error rate of 0.08% on CASIA palm vein dataset. Table 5, illustrate the recently developed traditional palm print approaches with their performances.

5.1.2.2 Deep Learning-Based Palm Vein Recognition method Deep learning has already been attracting the spacious attention of the researcher community because of his useful learning capability and a strong capacity for feature extraction in computer vision, multimedia tasks, and also in some biometric traits. However, in the palm vein recognition system, it's still a new research interest. Few authors implement a deep learning approach in the palm vein identification system. In [97, 101], an end-to-end Deep hashing Palm Vein Network (DHPN) was proposed to enhance the recognition performance of the palm vein system. First, the vein feature was obtained by Modified CNN-F architecture, then hashing code was used to represent the attributes of the image with a fixed-length binary code. The architecture of the proposed network has five convolutional, three max-pooling, and three fully connected layers. Finally, the hamming distance method was employed to measure the difference in two binary code of different palm vein images, an EER of 0.0222% were achieved using Poly U dataset. However, the method was tested on a small dataset. Training the network with limited data is an extremely challenging task. To address this issue, Thapar et al. [176] proposed a novel approach to design the end-to-end deep CNN framework, which consists of a convolution encoder–decoder network (CED) and a Siamese network. First, the CED network model was trained separately to learn texture code matrix (TCM) and Image Ray Transform (IRT) transformation, and then combine both the transformation model and train the end-to-end CED model from the original image. Afterward, the Siamese network was trained using triplet loss. Finally, the Siamese network was tested with transformed pictures obtained from the CED model and achieved EER of 0.66 and CRR of 98.78 using the Poly-U database. However, the architecture of the network is computationally complex, having 22 Conv, eight max-pooling, and four up sampling layers. To reduce the generalization error in the model, Dongyang et al. [41] proposed an end-to-end convolutional network. The proposed system has two convolutions, two pooling, and two fully connected layers. Initially, the convolutional and pooling layer was connected to extract image features. Mini-batch stochastic gradient descent algorithm was employed to minimize the classification error and achieved identification accuracy of 99% on the poly-U data-

Table 6 Performance comparison of deep learning palm vein recognition methods

Cite	Method	No of network	Network layer	Parameter	Dataset (size)	Performance measure
(J. L. C. [97, 101]	DHPN	1	5 conv, 3 maxpooling 3 fully connected	16(3×3)–(2×2)–32(5×5)–(2×2)–64(3×3)–128(3×3)–2048–2048–128	Poly-U(6000)	EER = 0.022%
[176]	CED and Siamese Network model	2	22 conv, 8 maxpooling, 4 upsampling	16(3×3)–(2×2)–32(3×3)–(2×2)–64(3×3)–(2×2)–128(3×3)–256(3×3) 128(3×3)–(2×2)–64(3×3)–(2×2)–32(3×3)–(2×2)–16(3×3)–256(1×1)	Poly-U(6000)	EER = 0.66 and AC = 98.78
[41]	end-to-end convolutional network	1	2 conv, 2 pooling 2 fully connected layer	116(4×4)–29(10×10)–20(4×4)–20(5×5)–7–7	Poly-U(6000)	AC = 99.9

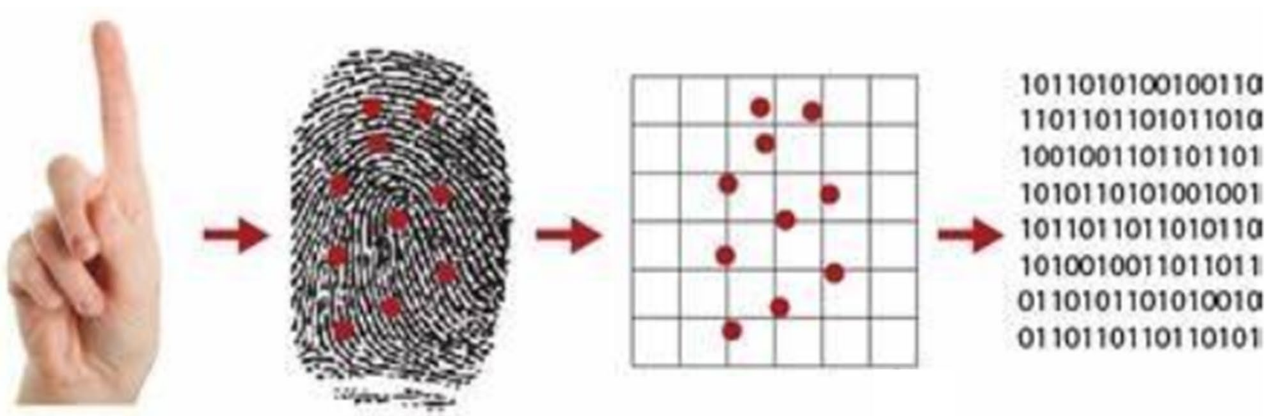


Fig. 6 Steps involved in the fingerprint recognition system [33]

base. Table 6 shows the performance of recent developed deep learning approaches for the palm vein recognition system.

5.1.3 Fingerprint Recognition

Fingerprint recognition is one of the most widely used biometric systems in critical and security applications. Fingerprint also has pre-processing, feature extraction, and matching stage. Figure 6 represents the step of the fingerprint recognition system.

5.1.3.1 Traditional Fingerprint Recognition Method Several conventional methods have been proposed and developed in fingerprint research. Sir Francis was the first one to defined Galton's point in the study of the fingerprint system, which has been used for identifying fingerprint in the late nineteenth century [54]. Galton's position is considered minutiae and has been employed to develop a mechanized fingerprint recognition system. Similar to other biometric modalities, fingerprint also refers to different tasks such as image preprocessing, feature extraction, matching/ classification. Image enhancement is commonly considered as image preprocessing techniques. The performance of automatic fingerprint recognition system is degraded due to the poor quality of fingerprint images. Various quality assessment and enhancement schemes were proposed recently [81, 111, 134, 161]. Panetta et al. [134] have proposed a quality measure called local quality measure (LQM), to evaluate the quality of images and localized quality measure enhancement (LQME), to enhance poor quality fingerprint images. The study in [111], presented an enhancement method based on a scale-invariant feature transform (SIFT) method for fingerprint image. Firstly, an intuitionistic type-2 fuzzy set was employed to enhance the contrast of the image. Secondly, the SIFT feature point was extracted from fingerprint images. Finally, the matching score was calculated by the Euclidian distance algorithm and good match score. Another research [161], low quality fingerprint images were identified using local phase quantization (LPQ) and classified into dry, wet, and good quality. The proposed method achieved a classification accuracy of 95.16% using an SVM classifier. However, the proposed method used a single texture feature for quality classification, which is not efficient for robust fingerprint identification.

Feature extraction plays a significant role in the performance improvement of the fingerprint recognition system. Generally, feature extraction in the fingerprint system was categorized into three classes [3]. In the first class, the minutiae point is extracted from fingerprint images [83, 88, 123, 126, 140, 157]. The fingerprint identification method in [157], was based on minutiae and invariant moment. First, the input fingerprint image was enhanced by the short-time Fourier transform (STFT). Afterward, minutiae points were extracted,then, a region of interest (ROI) was selected by the morphological transformation. Finally, the cosine similarity matrix was employed to compute the similarity,an average accuracy of 96.67% was reported.

However, the method requires high computation, which is not robust for fingerprint recognition. Another research [83], indexing algorithm were proposed which work on minutiae pair and convex core point to improve the identification performance of fingerprint system on large dataset. However, it needs to measure the similarity of each local feature pair from two fingerprint which need high computation cost, and degrade the efficiency of fingerprint authentication. To address this issue, Nachar et al. [126] proposed a hybrid minutia and edge corner point based method. In this work both ridges corner and minutiae point were considered is a feature, average recognition performance of 1.93%, 1.3% and 2.76% were achieved with average extraction time of 1.17 s. However, minutiae-based method have various problem such as false minutiae type, missing true minutiae, alignment method lacking, complexity of input image etc. Moreover, these methods haven't make use of available discriminatory information in fingerprint. The second class based on correlation between reference fingerprints image and pixel of test to calculate the likeness [52, 172]. The method proposed by Guo et al. [52], referred to reference point in fingerprint image. This work based on two folds, first a walking algorithm is proposed which detect the singular point directly without scanning the whole fingerprint image. Then, the local area around that point was enhanced by mean shift enhanced method, accuracy of 98.7% were reported on FVC2000 DB2 of 800 fingerprint images. However, these kinds of feature extraction can only be applicable to good quality fingerprint images. The third category refers to image-based system, in which local and global texture attribute is obtain from fingerprint pattern [8], 178, 188]. Correct and ideal invariance feature extraction enhances the performance of the fingerprint recognition system.

To achieve that invariance Ahmed and Sarma [8] proposed a feature extraction method based on the spatial relationship among minutiae points. Minutiae points were proposed based on a 4-dimensional feature vector, which satisfies the six desirable features vector properties to deal with the problem of missing and spurious minutiae in the fingerprint system. An average equal error rate of 0.0113 was obtained on the FVC 2002 dataset of 3200 fingerprint images. However, the proposed method has a non-linear distortion problem. To cope with the non-linear distortion problem in the matching algorithm, Tran et al., [178] proposed a local matching algorithm based on local feature representation for each minutia. In this work, a new method was proposed to calculate the adaptive matching threshold, and also an original similarity score was suggested. The proposed method achieved a low error rate of 0.49% on FVC2002-DB2A. Table 7 illustrates the performances of some of the recent fingerprint identification techniques.

In the fingerprint system, irrespective of recognition performance, another problem which recently is the growing concern is the vulnerability of the fingerprint security to presentation attack [198]. In 1998, the first ever research about fingerprint presentation attack was done by Mura et al. [125]. At present, various traditional [79, 136, 137] and multimodal methods [16, 50] were developed to detect the spoofing attack in the fingerprint system.

5.1.3.2 Deep Learning-Based Fingerprint Method Due to the significant development of deep learning algorithms in many research domains such as computer vision, multimedia, and recognition task, which motivate the biometric research community to implement deep learning-based approaches. In this section, we highlight the different developed deep learning schemes related to fingerprint recognition technology. The fingerprint recognition system process typically consists of three main modules, which involve fingerprint enhancement, feature extraction, and classification. Recently, researcher design a deep learning system to address the problem related to fingerprint enhancement and segmentation [76, 82, 92, 128, 170], feature extraction [23, 24, 34], 42, 72, 74, 129, 140, 185, 186] and classification [133, 175].

Inspired by the recent development of the Convolutional network, Li et al. [92] developed an enhancement based deep learning network called Fingernet. The proposed system has three central portions, one typical convolution and two deconvolution portions (enhancement and orientation branch). The network architecture of the proposed technique has four convolutions, two max-pooling, eight deconvolution, and four unspooling layers. The first features were extracted from fingerprint images by convolution network, and then the deconvolution enhancement branch was employed to remove the noise and enhance the image. Afterward, through orientation deconvolution branch guided the enhancement with a multi-class strategy and achieved an inference speed of 0.7 s. This method makes the matching time much more efficient. However, the matching accuracy was not high. The performance of fingerprint identification mainly depends on minutiae. But, reconstruction of the corrupt and missing pattern is a challenging task. Therefore, to denoise the visible minutiae and predict the disappeared ridge pattern, Svoboda et al. [170] proposed a fully convolutional autoencoder network. The encoding and decoding network have the same architecture comprises of 5 convolutional, and five deconvolutional layers achieved an accuracy of 78%. However, generated images have poor ridge structure and noisy background, which affects the performance of feature extraction,as a result fingerprint system had a poor matching performance. Therefore Joshi et al., [76] propose a generative adversarial network-based fingerprint enhancement algorithm. The comparable performance was significantly improved to 35.66% and 30.16% using rank-50 accuracy. However, a spurious feature was generated when the ridge information was limited, which challenge the identification performance of the proposed technique. In [82], a patch-based segmentation method was introduced using a convolutional neural network. The network of the proposed method is simple, having three convolution and two max-pooling layers and achieved a classification accuracy of 94.4%. However, their system has a simple structure and was not evaluated with challenging fingerprint settings.

Feature extraction plays a vital role in the identification of system performance. In fingerprint technology, feature extraction is divided into three levels. Level 1 features (ridges, frequency, and orientation), Level 2 features (minutiae), and Level 3 features (sweat, pores, etc.) [42]. A lot of researchers implement level 1 and level 2 features extraction method for fingerprint identification. Nguyen et al. [129], developed a deep learning network CoarseNet, which extract minutia feature automatically from the fingerprint image. The coarseNet model has 20 convolution and eight pooling layers. Firstly, the CoarseNet model was used to compute the minutiae score map and minutiae orientation using CNN and fingerprint domain knowledge. Afterthat, the Fishnet-mintai classifier, based on the score map purify the candidate minutiae and get the result. The proposed method achieved 85.9% precision, 84.8% Recall, and 0.853% F1score. However, a small set of training data was used, and also, the process is computationally complex. To speed up the parallel processing, Jeon and Rhee [74] compare three classification models using VGGNet Structure. Model 3 achieved an average classification of 97.2% was consider the best model. However, the proposed method is not efficient in noisy data. The extraction of level 2 feature (minutia) is regarded as a challenging task because of the highly variable data of fingerprint. Darlow and Rosman [34] developed deep neural network-MENet to extract the minutiae feature from images. They used an automatic minutia point labeling method to train the MENet on a large dataset. A low error rate of 0.781 and 5.450 was reported using two datasets. However, the proposed method only shows the utility of the network in the feature extraction from images.

The study [24], combine the level 1 and level 2 feature to extract the ridge flow and minutiae descriptor extraction. In this work, an automated latent fingerprint recognition system was developed to address the issue of poor ridge quality, background noise, small friction, image distortion, and small ridge area in potential images. The experimental result has shown a significant improvement, rank one recognition performance of 74.4%, and 78.4% were achieved on two benchmark databases, i.e., NIST SD27 and WVU latent

DB. However, the feature extraction process of the proposed method was time-consuming and achieved poor performance on two datasets. According to the study in Labati et al. [42], level 3 features such as pore feature extraction boost the recognition performance of fingerprint technology. A pore extraction process is a demanding approach in automatic fingerprint identification. But, correct pore extraction is a tough task due to the dependency of pore shape on a person, region, and pore type. To solve this issue, Jang et al. [72] presented a convolutional neural network to extract the pore feature from images. The pore feature was detected by the CNN model, and then pore information was refined with different intensities in the fingerprint image. The actual detection rate R_T of 87.07% and false detection of 13.37% were reported on Higher Resolution Database (HRD). However, the proposed CNN method has many layers that use a lot of information such as ridge shape, pore surrounding from fingerprint image that affects the accuracy of the system. Another study [23] proposed a fingerprint indexing algorithm based on CNN. For fingerprint alignment, an orientation field for a dictionary was learned, and the CNN model was trained on a large dataset. The proposed method achieved a 97.8% rank-1 identification. Some deep learning fingerprint schemes were also implemented to detect the spoofing attack [29, 66, 84, 155, 166, 206, 207, 209–211]. Table 8, illustrate performance comparison of deep learning methods.

5.2 Face Region

Face region has always been the most appealing topic for research community because the facial region is a natural biometric trait used to identify human [181]. Facial recognition involved eyes location, shape and size of chin and jaw, nose, lips and cheek. Scanning device first read the face geometry and records it on grid, than, transferred to database in term of points. Afterward, matching technique performs face matching and come up with decision. Figure 7, demonstrate the steps involved in face recognition system.

5.2.1 Face Recognition

Face recognition is one of the most quickly developing biometric trait. In this section, we have discussed the biometric traditional and deep learning approaches related to the face region. There are several traditional, and deep learning face recognition schemes were developed at recent times.

5.2.1.1 Traditional Face Recognition Method Traditional face recognition process have four steps as face detection [139], image preprocessing [110, 185, 186], feature extraction [61, 173] and classification [108, 138], where the important one is feature extraction techniques. Several feature-based traditional face recognition method were proposed which are mainly classified into four main categories, descriptor/filter-based [46, 51, 53, 85, 86, 91, 93], representative based [49, 58, 65, 167], feature learning based [105] and template based [1, 26, 45]. Feature extraction becomes crucial when the quality of face image is poor because of various factor, i.e. acquisition devices, different face pose, noise, variances, un-even illumination etc. To address these issues, Král et al. [87] proposed a new descriptor method, based on enhanced local binary pattern (ELBP) which work on greater pixels and various neighborhoods to estimate the feature vector value. This work was evaluated on two datasets i.e. UFI and FERET face, which outperform the standard LBP method and recognition performance of 65.28% and 98.5% were reported. However, the proposed method is noise sensitive because the binary code of local pattern would change if the intensity of a single-pixel in the neighboring local pixel is change by image noise. Li et al. [93] presented a method based on structure Gabor wavelet for face identification. They employed Gaussian copula to design the dependence structure of Gabor wavelets and

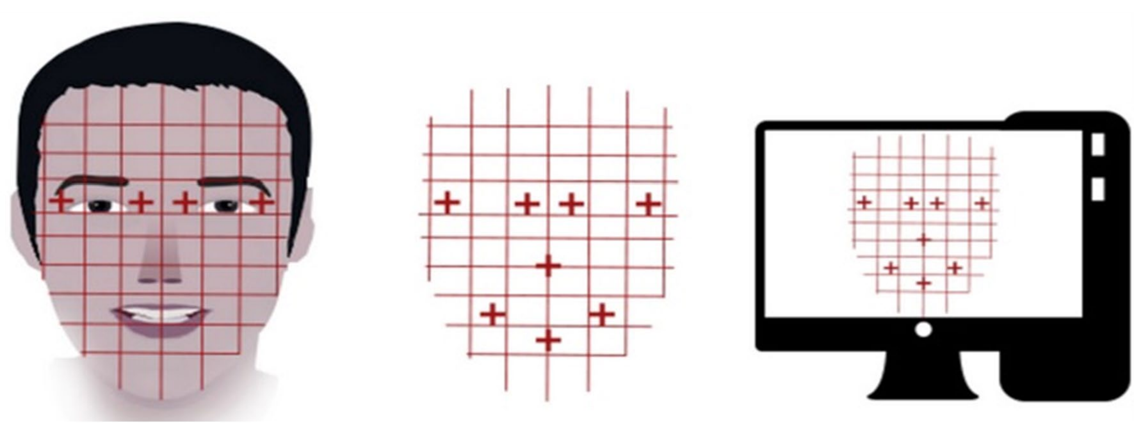


Fig. 7 Steps involved in face recognition system ("Biometrics—Quick Guide," n.d.)

achieved an accuracy of 99.9% on YEALB dataset. However, the copula model with Jeffery distance has high run time at classification/matching task. Recently, there are some other enhancement approaches [110, 185, 186] which also deal with image noise and non-uniform illumination problem. Hamdan and Mokhtar [53], present a descriptor based algorithm to extract the feature from face images. In this work, firstly moment-based angular radial transform (ART) was employed to obtain a feature vector. Secondly, SVM with polynomial kernel function was used for the classification task. The proposed method achieved good recognition rate (RR) of 97.5%, 85.2% and 87.4%, respectively on three different benchmark corpora, namely, ORL, Yale and face96. However, this method is less suitable for the inclined positioned face.

Heinsohn et al. [58] presented an approach for low quality face images called adaptive sparse representation (ASR). Two main tasks were performed in that work,firstly a new dataset was introduced called "AR-LQ" which include blurred images and low-resolution image in two separate databases. Secondly, a new bASR algorithm was presented to identify the low-quality images automatically. The proposed work achieved significant improvement in low resolution and blurred face images dataset. However, other kinds of degraded images problem such as pose, expression change and illumination are not tested. [65] presented a sparse representative approach, which combined Gabor wavelet transform and central symmetric local direction pattern (CSLDP) for robust face recognition. Gabor wavelet obtains multi-feature, and then apply to CSLDP for dimensionality reduction. Finally, the sparse representation classification method was employed and achieved a recognition rate of 0.98%, 0.98% and 0.97% on three datasets. However, most of these existing representative method and local descriptor approach required strong prior information and hard to design algorithm. Learning-based method [44, 105], was introduced which learn feature code from the raw pixel.

Duan et al. [44] have proposed a context-aware local binary feature learning (CA-LBFL) algorithm for face recognition. At first, pixel difference value (PDV) were obtained from face images, and mapping matrix was learned which project every PDV into a context-aware binary vector. Afterwards, a codebook was designed by introducing clustering method to learned binary code, and a histogram feature was extracted from face image with the learned codebook as the final face representation. Besides, to better use of local

Table 9 Performance comparison of recent traditional face recognition methods

Cite	Method	Image processing	Dataset (size)	No of subject	Performance measure
[93]	Gabor Wavelet	Gabor filter as a feature in face recognition and Gaussian capula describe the structure of gabor filter	Extended Yale-B(Not Reported), FERET(Not reported)	38,	AC = 99.92% AC = 95.36%
[53]	ART	Angular moment method are used to extract face feature	ORL(400), Yale(165), Face96(3040)	10, 15, 152	RR = 97.5%, RR = 85.2%, RR = 87.4%
[51]	ELBP	Histogram equalization are enhance the contrast, Viola and Jones algorithm are used to detect facial detection, Gabor filter and Zernike moment are employ to extract textual and shape feature	UFI(1210), FERET(14,051)	605, 1195	RR = 65.28%, RR = 98.5%
[75]	CPL	Collaborative probabilistic label	AR(2600), CMU PIE(100), Multiple PIE(3735) FERET = Extended Yale-B(414)	100, 66, 249, 38	RR = 72.2%, RR = 86.5%, RR = 93.8%
[58]	bASR	Blur sparse representation	AR-blur(500) AR-LR(500)	100, 100	RR = 87.17%, RR = 99.19%
[44]	CA-LBMF, C-CA-LBMFL	Context aware local binary multi-scale feature learning method are presented to explore specific information	LFW(13,233), YTF(5000) video pair, FERET(13,539)	5749, 1595 objects, 1567,	AUC = 95.67%, Accuracy = 83.3, Mean Verification Rate = 98.6% and 94.3%
[105]	SLBFE, C-SLBFLE	Simultaneous local binary feature learning and encoding method	LFW(13,233), YTF(5000) video pair, FERET(13,539), PaSC(9376), CASIA NIR-VIS 2.0 (725), Multi-PIE(337)	5749, 1595 objects, 1567, 293,	AUC = 92.00%, Accuracy = 92.7%, Accuracy 93.7%, Time = 216.4 ms

information from different scale and to make the proposed method applicable for heterogeneous face identification, a context-aware local binary multi-scale feature learning (CA-LBMFL) and a coupled (CA-LBMFL) method were developed. Experimental results of the proposed method achieved better performance for homogenous and heterogeneous face recognition. Lu et al. [105] have also presented a method for homogenous and heterogeneous face identification based on simultaneous local binary feature learning and encoding (SLBFLE). In the proposed method, single feature learning and encoding procedure were employed, which mutually acquire information from binary codes and dictionary (codebook) for face patches. This discriminatory information can be used for the identification of two different identities. For different face matching another method was proposed called coupled simultaneous local binary feature learning and encoding (C-SLBFLE). The author achieved significant results in six different benchmarks. However, these learning-based algorithms are computationally expensive, and, are more susceptible to noise. Table 9 illustrates the recent traditional face recognition method.

5.2.1.2 Deep Learning-Based Face Recognition Method Face recognition through deep convolution network is considered more robust than traditional facial identification methods. Several variants have already been developed to recognize a human face, which can broadly be classified into three classes. First-class relate to training data [39, 40, 55, 109], second class connect to network architecture [98, 99, 194, 197, 200] and third-class link to designing of loss function [37, 38, 208]. The performance of the deep learning model increases with the wider and deep network [109]. Face recognition system face the challenge of limited training data set for feature representation model training, which greatly degrade the identification accuracy. To deal with this issue, Lv et al. [109] developed five data augmentation method for face identification. These five data augmentation methods were evaluated by Multi Pie Database, and their accuracy rate of 99.3%, 100%, 100%, 96.6% and 97.95% were reported. Another Study in [55], also developed a face-specific data augmentation technique for unconstrained face identification. They focused on two key issues, i.e. to enlarge the dataset for appearance variation of training images and to reduce the dataset size for the appearance of test images. However, these methods perform only image-based recognition and also computationally complex. To this end, Deng et al. [39] presented a lightweight deep face recognition, which provides model compactness and efficient computation system. They proposed two large datasets namely, Deep Glint-Image with 1.8 M images and IQIYI-video with 0.2 M videos, and also introduce extensive comparison metric for the assessment of deep learning model. Verification Evaluation was done by true positive rate parameter concerning false positive rate, which was employed for four tracks such as Deep Glint light, Deep Glint large, IQIYI-Light and IQIYI-Large. YMJ and lhlh18 achieved the best performance on Deep Glint light and Deep Glint Large, however, Nothing LC and Trojans perform better on IQIYI.

Role of deep learning architecture can't be ignored regarding the performance advancement of face identification. [98, 103] developed a deep representation face recognition framework, called VIPLFaceNet, which include seven convolutional layers and three fully-connected layers. The proposed work obtained a mean accuracy of 98.60% on LFW benchmarks, and training time was significantly reduced by 80%. However, their method only evaluated by one benchmark. [194, 202, 205] proposed a joint collaborative representation with local adaptive convolutional feature (JCR-ACF) scheme to overcome the under-sampling problem in the training set. Initially, the adaptive local convolutional attribute was extracted. Then, joint collaborative representation (JCR) was introduced to efficiently use the local convolutional feature for small size sample problem (SSSP). The proposed network model consists of 9 layers, i.e. 4 convolution, 2 max-pooling and 3 fully connected layers. They achieved recognition accuracy of above 95% approximately on an almost different variation on AR dataset, 98.2% on CMU-MPIE database and 86.0% on LFW dataset. However, the proposed method considers different region point and some region don't contribute and even mislead the identification. Yin et al. [203], propose an interpretable face identification deep learning model, to learn more important structure features. This work based on two main parts, firstly, a spatial activation diversity loss, was proposed to learn face structure representation. Then, feature activation diversity loss to make these learn attributes more discriminative and robust. Identification rank 1 results of 93.7% and 90.3% are archived on IJB-A and IJB-C. However, this work mainly focuses on discrimination to occlusion part of the face for robust face recognition.

In deep convolutional neural network designing of the better and appropriate loss function, which can advance the discriminating power of face classes is a challenging job. In this regard, Deng [38] developed a method called, Additive Angular Margin Loss (ArcFace) to extract highly separable characteristic for face recognition. The proposed loss function was evaluated on ten different face recognition benchmarks which include large-scale images and videos datasets. However, angular margin destabilizes the network model. Another study [37] also presented marginal loss function for face recognition. In this work, Softmax loss was jointly used with a marginal loss to minimize the intra-class variation and maximize the inter-class distance of the deep features. However, they consider 256 batch size and 16 identities in one batch which increased the size of linear transformation

Table 10 Performance comparison of recent deep learning-based face recognition methods

Cite	Method	No. of layer	Network layers	Parameters	Dataset (size)	Performance measure
[109]	GoogleNet	1	27 Layer	Not Reported	Multi Pie Database	AC = 99.3%, AC = 100%, AC = 100%, AC = 96.50% AC = 97.95%
[55]	ResNet-101	1	Not Reported	Not Reported	IARPA Janus Benchmarks A (IJB-A) , IJB-B(21,798), YTF(500 videos)	CMC = 0.984%, AC = 99.0% AC = 95.86%, AUC = 97.8
[194, 197, 200]	JCR-ACF	1	4 conv, 3 maxpooling 2 fully connected	20(2 × 2)–20(3 × 3)–40(2 × 2)–40(3 × 3)–60(2 × 2)–60(2 × 2)–80(2 × 2)–160	AR(2600) CMU PIE(4731) LFW(1580)	AC = 95%, AC = 98%, AC = 86%
[203]	CASIA NET and ResNet-50	2	16 conv, 2 conv-upsampling, Hypercolumn Descriptor, Average Pooling	64(96 × 96)–64(48 × 48)–64(48 × 48)–128(48 × 48)–128(24 × 24)–96(24 × 24)–192(24 × 24)–129(12 × 12)–128(12 × 12)–256(12 × 12)–256(6 × 6)–160(6 × 6)–256(24 × 24)–192(24 × 24)–320(24 × 24)–192(24 × 24)–576(24 × 24)–1000(24 × 24)–1000	IJB-A(3134), IJB-C(3134)	IJB-A = 93
[98, 99]	VIPLFaceNet	1	7 conv, 3 pooling, 3 fully connected	48(9 × 9)–(3 × 3)–128(3 × 3)–(3 × 3)–256(3 × 3)–192(3 × 3)–192(3 × 3)–128(3 × 3)–(3 × 3)–4096–2048–10,575	LFW(13,233),	AC = 98.60%
[38]	MxNet	1	Not Reported	Not Reported	MegaFace (1 M), IJB-B = 10,270, IJB-C = 10,270, Trillion-Pairs = 1.5 M, iQIYI-VID = 565,372 videos clip,	AC = 99% AC = 94%, AC = 95%, AC = 81%, AC = 88%
[208]	BCNN	1	4 conv, 4maxpooling, 3 fully connected	32(3 × 3)–(2 × 2)–32(3 × 3)–(2 × 2)–64(3 × 3)–(2 × 2)–512–128–1	AT& T = 400, EURECOM Kinect Face Data-base(936)	AC = 96%, AC = 97%
[37]	Marginal loss in ResNet	1	27 conv,	Not Reported	LFW(4 M), YTF(4 M), CACD(4000), AgeDB(12), MegaFace(0.5 M),	AC = 99.48%, AC = 95.98%, AC = 98.95, AC = 95.75, AC = 92.6,

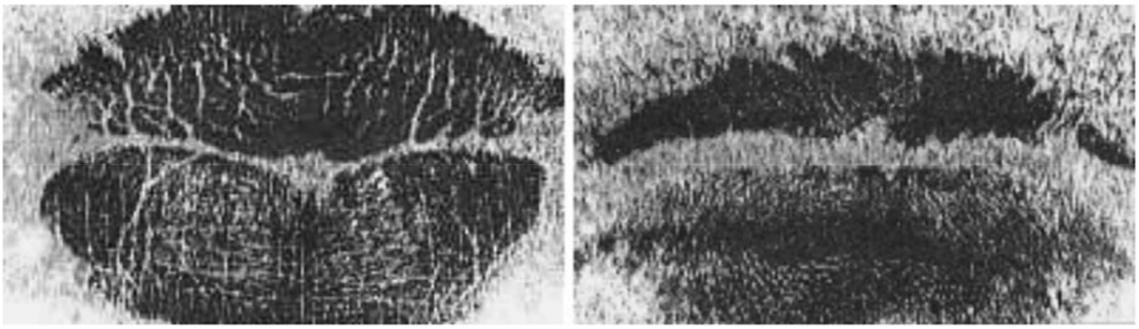


Fig. 8 Sample of lips used for forensic evidence [28]

matrix $W \in R^{d \times n}$. As a result, the discriminative power of the proposed network model becomes complex. Table 10 shows the performance comparison of deep learning method.

5.2.2 Lips Recognition

Identification based on Lips is a relatively new biometric modality which qualifies the criteria for being a recognition system. Lip based work is not only used for detection and recognition but also employed in various other image processing, signal processing and machine learning tools [107]. Lip-print features have also been used in forensic experts and criminal activities Fig. 8 The feature of Human Lips were considered unique by Kazuo Suzuki and Yasuo Tsuchihasi at Tokio University (1968–1970) [27]. Therefore, lips are used by some of the researchers for the biometric task. In this section, we will highlight some of the new traditional lips recognition methods. Chorus et al. [27], developed an automatic lip recognition method to identify the person based on their extracted lips shape and color features. In this work, color feature was computed for the masked lips, then shape feature of binarized lips were merged to color feature of masked lips and 76% rank1 accuracy were reported on best selected feature of lips. Lips detection become a challenging task when the partial part of the face in image.

Liu et al. [100] presented Fast Box Filtering (FBF) lips recognition method to identify human. At first, the box filtering approach employed to get a noise-free source. Secondly, on the proposed method, five different corners of the mouth were detected, which able to combat the beard, rotation and shadow issues. Finally, for feature extraction, two geometric and ten parabolic parameters for recognition through SVM. However, the recognition performance of the proposed method decreases with the increase in the number of subjects. Mir et al. [120], used texture and color based features of lips to identify humans by lips. In this work, the author used the Spatial Gray Level Dependence Method (SGLDM) for feature extraction and SVM for classification. However, the experimental work was not well presented. To improve the performance of a lip biometric system, Travieso et al. [179] proposed a lip-shaped correction based algorithm. Firstly, lip correction preprocessing method was applied on static lip shape, and then data is transformed to classify by Hidden Markov Model (HMM) [180] and SVM. Accuracy of 100% and 99.76% were achieved on GPDS-ULPG (Group of Digital Signal Processing at the University of Las Palmas de Gran Canaria) and (RFD) Radboud Faces Database respectively. The study in [35], focuses on the template design of lip security scheme using steganography. Initially, a contrast enhancement method is used to enhance the local point of an image. Then the SIFT approach was employed to extract the local point feature to identify the person. Finally, the modulation technique of spatial steganography is used to embed the critical details of lip images. Accuracy of 92% was reported with stenography method. However, in this method, recognition performance was little effected using steganography algorithm. There is no deep learning method implementation in lip biometric. Table 11 illustrates some of the new lip based biometric schemes.

5.3 Ocular Region

The ocular region is also considered one significant region for biometric modality. The eye is the highly protected organs of the human body, as shown in Fig. 9. In this section, the study of conventional and deep learning approaches of the two most active ocular region-based biometric system, i.e. Iris and Retina biometric trait has been presented.

Table 11 Performance comparison of recent lip based conventional recognition methods

Cite	Method	Image processing	Dataset (size)	No of subject	Performance measure
[27]	Feature-based	Color feature is calculated and merge with a shape feature of binarized lips	Database (114)	38	Rank1 = 76%
[95]	FBF	Viola and Jones algorithm used to detect face region, Fast box filtering histogram stretching used to enhance and smooth the image, corner search region and lower search used to detect the corner of lips	Database (8795)	97	FAR = 0.148%, CAR = 85.9%
[179]	HMM + SVM	Viola and Jones detect face region, a heuristic approach used to extract mouth region, RGB transformation used to enhance lips region, Otsu binarization method is used to segment the lips in the enhanced image, lips contour is obtained by dilating segmented lips by a morphological operator, polar grid feature used to extract feature,	GPDS-ULPG (510) RaFD (540)	100	AC = 100%, AC = 99.76%
[180]	Discrete Hidden Markov Model Kernel	Viola jones used for facial image extraction, color transformation technique to detect lips region, lips region are normalized then, contour lips are extracted by image binarization method	GPDS-ULPG (510) PIE (748) RaFD (540)	100, 68, 60	AC = 99.8%, AC = 97.1%, AC = 98.1%
[35]	SIFT + Stenography Modulation technique	Contrast Enhancement to enhance the lips image, Feature is extracted by SIFT method	NITRLipV1 (109) NITRLipV2 (100)	15, 20	AC = 92%

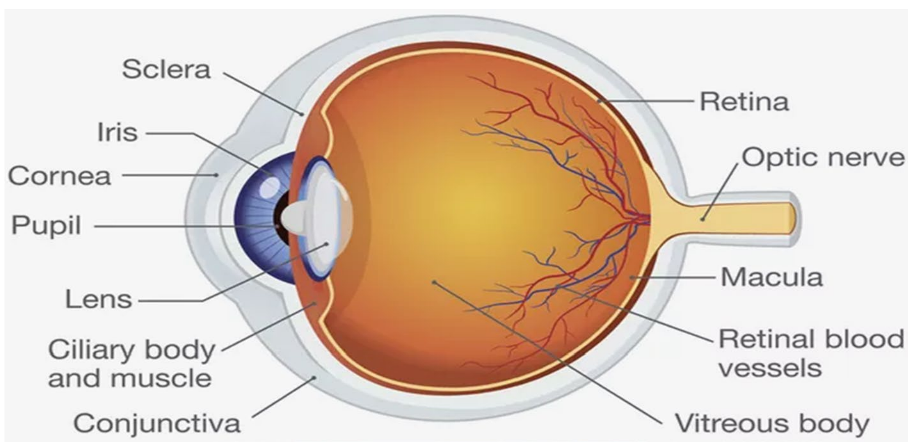


Fig. 9 Human eye

5.3.1 Iris Recognition

Iris recognition is an automatic biometric approach, which used for personal identification. Iris structure of the human eye is complex and differ from eye to eye [14, 145–147]. The unique structure of iris resulted in a meagre false match rate on extensive dataset under constraints scenario [130, 131]. The concept of introducing iris pattern in human identification was initiated in 1936 by Frank Burch. However, later in 1987, Leonard Flom and Aran Safir patented this concept [89].

5.3.1.1 Traditional Iris Recognition method The first-ever automatic Iris recognition system was developed in 1993 by Dougmann [177]. Afterwards, based on the dogman model, various traditional iris recognition system was designed. The traditional iris recognition techniques are broadly classified into three folds: pre-processing (iris segmentation) [11, 96, 104], feature extraction [32, 73, 78, 150, 152, 156 and matching/classification [6, 64, 98, 99, 127, 209–211]. Iris recognition system affected by the images taken from the different sensor device. To fulfil this gap, in [104] a multi-sensor iris recognition method with the fused method at the segmentation stage were presented, which shows performance improvement in a non-cooperative environment. However, the proposed work is computationally expensive because of the involvement of two segmentation method. Another study present performance improvement segmentation method

[96], which developed an algorithm that is sufficient for iris recognition. However, the proposed work haven't designed well-balanced precise segmented iris, and, the image still has noise, i.e. eyelashes. Feature extraction module in iris biometric modality also considers important like other biometric modality. The nature of extraction would be global or local, or region based depends upon particular research domain. In [32], a local texture-based binarized statistical image feature (BSIF) with domain-specific iris recognition method was proposed. They designed the domain-specific BSIF filter, which improved the statistical result of the iris identification system, and outperform the default BSIF feature method. However, this work only focuses on BSIF feature performance rather than identification performance of iris system. Barpanda et al. [13] employed a tunable bi-orthogonal filter to extract region-based feature from non-cooperative iris images. The performance of the proposed method was tested on three benchmarks dataset, i.e. CASIAv3, UBIRISv1 and IITD and accuracy of 91.6%, 90% and 89.7%, were achieved respectively. However, the proposed method not robust to noise which decreases the identification accuracy. To effectively improve the recognition performance, the study in [156], also develop an algorithm called, a density-based spatial clustering technique (DBSCAN) and key point reduction method which are applied on phase intensive local pattern (PILP) based dense feature extracted from the image. The proposed method speeds up the match up to five times. However, the method was mathematically complex. To improve storage requirement and authentication speed, Rathgeb et al. [152] proposed an improved SIFT based Iris recognition system. However, the proposed method is a computational complex. Hu et al. [64] proposed a matching method based on a weight map to advance the performance of iris recognition in a less constrained scenario. However, the performance of the model is not consistent on single-sensor, and cross-sensor captures, which effect iris recognition. To match different images in less constraint application, a [98, 103] presented a code level method for heterogeneous iris recognition. First, the nonlinear relationship between feature codes of composite iris images is model by the Markov model, which transform the number of iris template from a probe into homogenous iris template. Secondly, a weight map is derived from the iris template from the proposed model. The proposed method significantly improved the recognition of performance and achieved an accuracy of 98.74%. Some of the traditional Iris methods also address the problem of presentation attack [30, 92, 136, 137, 209–211]. The study in [31], suggest that presentation attack detection for iris recognition is not yet a solved problem. Table 12 suggest the performance of new traditional iris recognition methods.

5.3.1.2 Deep Learning Iris Recognition Method Application of deep learning biometric iris recognition recently hot research domain in the biometric research community. We can broadly classify the existing deep learning work in four categories, namely Image preprocessing (Image Segmentation and Enhancement) [5, 12, 60, 80, 102, 103, 174], Feature-based method [119, 130, 131, 148], 184, 212, classification [7] [43] and architecture based deep learning frameworks proposed by Marra et al. [113] and Zhao et al. [213]. Iris recognition system based on a particular texture area of the iris, which is considered as a base attribute for identification and authentication purpose. Hence, accurate detection of iris boundary is essential even in an acute condition, i.e., off-angle, motion blur, noise, hairs, glasses, eyelashes and specular reflection. Therefore, to address this anomaly, Arsalan et al. [12] developed a two-staged iris segmentation framework based on convolutional neural network. At first, the image processing algorithm was used to define the ROI of the iris image. Then, CNN model ResNet is applied to the data obtained from ROI, and two features was provided by the CNN output feature. Finally, iris and non-iris points are classified based on output features to find the exact iris boundary. Average segmentation rate of $E_i = 0.0082$ and $E_i = 0.00345$ were obtained on two datasets. However, the proposed method was computationally expensive.

Hofbauer et al. [60], introduces the parameterization of Iris based on CNN segmentation for the first time, to make the Gap small between CNN based segmentation and the rubber sheet-transform. The proposed method works well on low-quality iris images. However, the performance of the method is poor on high-quality iris dataset, specifically on the frontal acquisition and open eyelids images compared to another traditional approach. Moreover, the iris pattern after segmentation for training may lose information. Therefore, [102, 107] proposed a fuzzified image enhancement operation for deep learning iris recognition. Initially, the pupil and iris boundary was detected. Then, the region outside the detected iris boundary is blurred. Two deep learning frameworks, F-CNN and F-capsule were trained using fuzzified images, the accuracy of 86.8% and 89.2% were reported on two different datasets. However, the proposed method has an over-fitting problem. Deep learning approaches are also used in feature representation/feature extraction task of iris recognition.

Minaee and Abdolrashidi [121] have presented ResNet 50 network model having 17 convolutions, 1 average pooling and 1 fully connected layer. This model jointly represents a feature and perform recognition and achieved an accuracy of 95% on IIT Delhi dataset. [130, 135], introduced off-the-shelf features which are effecting on an excellent representation of iris images in iris recognition. In this work, 5 network model (AlexNet, ResNet, Google inception, VGG

Table 12 Performance comparison of recent traditional iris recognition methods

Cite	Method	Image processing	Dataset (size)	No of subject	Performance measure
[104]	Modified Laplacian Pyramid based fusion method	Two iris segmentation algorithm are applied to localized and obtain inner and outer iris boundaries,Daugman algorithm normalize the processed images,	CASIA-V3-interval = 2644, CASIA-V4-interval(5000), UBIRIS-V1(1500), MGC V2(2000),	249, 249,	EER = 0.81, EER = 8.82, EER = 0.22, EER = 2.6,
[96]	Haar, Daubechies, Biorthogonal, Reverse-Biorthogonal	Four wavelet Harr, Daubechies, Biorthogonal, Reverse-Biothogonal use to feature vector	Dataset(20)	10	FAR = 0.08%, FAR = 0.06%, FAR = 0.02%,, FAR = 0.06%
[32]	BSIF	Binarized statistical image feature (BSIF)	Dataset (1900)	330	Median Value = 6.7%
[13]	Tunable Bi-Orthogonal Filter Bank	Daugman's integrodifferential operator (IDO) to localize iris region, Normalization of iris region is done by Daugman's rubber sheet model, the feature is extracted by proposed tunable filter bank and Canberra distance method used for similarity	CASIA v3(22,035), UBIRIS v1(1877), IITD(1120)	700, 241, 224	AC = 91.87%, AC = 90.51%, AC = 89.72%
[156]	PILP + DBSCAN	PILP method to obtain key point, These points are clustered by Density-based spatial clustering of application with noise for feature vector	BATH(32,000), CASIAv3-Lamp(16,212)	800, 411	AC = 96.3%, AC = 97.3%
[78]	Discrete Orthogonal Moment	Canny edge detector used for binary edge map, Circular Hough Transform is applied to localized pupil-iris boundary, Daughman homogenous rubber sheet model is employed to normalize iris pattern, Discrete orthogonal moment is used to extract iris texture feature, Manhattan Distance matching method	CASIA Iris V4(2639), IITD.v1(1120), UBIRIS.V2(1860),	249 224 372	AC = 99.80%, AC = 99.90%, AC = 97.50%
[152]	SIFT	Rubber sheet model to transform iris to normalized texture, CLAIHE is applied to enhance iris texture, SIFT method extract key point feature	CASIA v1(756), CASIA v4(1332), BioSecure(840),	108, 198, 210	EER = 0.232, EER = 0.225, EER = 2.223,
[64]	Weight Map Method	Matching method	CASIA 4(5037), UBIRIS2(1000), CSIR(7787), MICHE(1479),	Not reported	EER = 0.0343, EER = 0.0981, EER = 0.0447, EER = 0.1440,
[6]	MLPNN-ICA	GLDM method used to extract feature	CASIA Iris V3(Not Reported), UCI(1027),	Not Reported	AC = 99.99%, AC = 99.66

and DenseNet) are used to extract the feature from normalized images. The different model achieves peak accuracy its different layers, among 5 network model DenseNet model achieved peak accuracy of 98.7% at layer 6, while Alex Net model performs poorly for iris recognition. However, the method is computationally complex, and domain adaptation is also required to work for iris recognition. Another study [148], developed multi-patch deep features employing deep sparse histograms to extract robust feature for iris recognition. The proposed method achieved higher actual match rate (GMR) on two datasets. However, the work involves lot image processing, computation and complexity. For accurate

Table 13 Performance comparison of recent deep learning-based iris recognition methods

Cite	Method	No of network	Network layer	Parameters	Dataset (size)	Performance measure
[12]	CNN-based Segmentation	1	13 conv, 4 pooling, 3 fully connected	64(224 × 224)–64(224 × 224)–64(112–122)–128(112 × 112)–128(112 × 112)–128(56 × 56)–256(56 × 56)–256(56 × 56)–256(56 × 56)–256(28 × 28)–512(28 × 28)–512(28 × 28)–512(28 × 28)–512(14 × 14)–512(14 × 14)–512(14 × 14)–512(14 × 14)–512(7 × 7)–4096–4096–2	NICE-II(1000),Mobile Iris Challenge Evaluation (MICHE)	$E_i = 0.0082$, $E_i = 0.00345$
[60]	Multi-path RefineNet	2	4 RefineNet Unit, 8 Residual convolutional Unit	Not Reported	IIT Delhi Iris Database(Not Reported), CASIA Iris V4(Not Reported), ND-0405(837), Protect Multimodal(Not Reported)	EER = 0.368%, EER = 0.023%, EER = 0.8%, EER = 0.711%, \
[102, 103]	F-CNN and F-capsule	2	6 conv, 3 maxpooling, 2 fully connected	96(11 × 11)–256(5 × 5)–384(3 × 3)–256(3 × 3)–4096–4096 256(9 × 9)–128(9 × 9)–16(9 × 9)–16	CASIA(20,000), Cogent(1163) ATVS(800),	AC = 75.4% & 83.1%, AC = 86.8% & 83.3%, AC = 86.8% & 88.4%, AC = 85.8% & 89.2%,
[119]	ResNet 50	1	17 conv, 1 pooling, 1 average pooling, 1 fully connected	64(7 × 7)–64(3 × 3)–64(3 × 3)–64(3 × 3)–128(3 × 3)–128(3 × 3)–128(3 × 3)–128(3 × 3)–256(3 × 3)–256(3 × 3)–256(3 × 3)–256(3 × 3)–256(3 × 3)–256(3 × 3)–512(3 × 3)–512(3 × 3)–512(3 × 3)–512(3 × 3)–2048	IIT Delhi(2240),	AC = 95%
[130, 131]	CNN encoding deep features	5	Not Reported	Not Reported	ND-cross sensor(116,564), CASIA Iris 1000(20,000),	AC = 98.8%, AC = 98.0%
[148]	Multi patch deep sparse histogram features	Not Reported	Not Reported	Not Reported	MICHE-I(200), MICH-II(60),	EER = 0.37% and 0.66% EER = 6.55% and 0.00%,
[184]	DRFNet	1	4 conv, 6 Tanh, 2 Pre_conv, 2 Imnorm	16(3 × 3)–32(1 × 1)–32(1 × 1)–64(1 × 1)–64(3 × 3)–1(3 × 3)	ND-IRIS-0405 Iris Image dataset (64,980), CASIA V4(2,446), WVU Non-ideal database(3,042)	EER = 7.14%, EER = 10.7%, EER = 27.4%,
[7]	RBFNN and GA	1	Not Reported	Not Reported	CASIA-Iris V3(Not Reported), UBIRIS(1877),	AC = 99.99%, AC = 99.98%
[213]	Capsule Network + fully connected decoder network	2	Not Reported	Not Reported	JluV3.1(1780), JluV4(114,904), CASIA-V4 Lamp iris dataset(16,215),	AC = 99.37%, AC = 99.42% AC = 93.87%

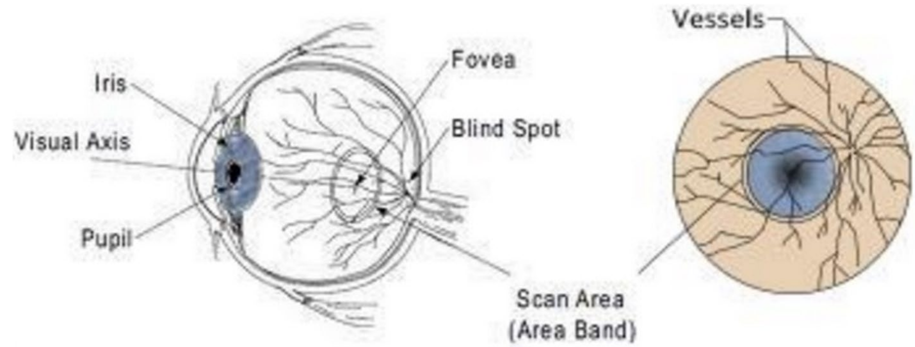


Fig. 10 Retina anatomy ("Biometrics—Quick Guide," n.d.)

and simple deep learning framework for iris recognition, Wang and Kumar [184] incorporate the dilated convolutional kernel and residual learning in deep learning framework for accurate matching. However, there is still some failure in the matching of genuine class iris sample. Ahmadi et al. [7], proposed a learning-based matching method called hybrid radial basis function neural network (RBFNN) with genetic algorithm (GA) for the classification step. The proposed work achieved an accuracy of 99.9% and 99.8% on two datasets CASIA-Iris V3 and UBIRIS V1. However, this work has a memory space problem. Table 13 demonstrate some recent deep learning-based iris recognition methods.

5.3.2 Retinal Recognition

The retina is one of the safest biometric modality because of protection inside the eye, as shown in Fig. 10. The anatomic structure of retina offers different characteristic and retinal components such as the macula, the fovea, and optic disk. Also, the retina has a blood vessel which is unique in each eye. These vascular patterns of the eye provide us with a high level of security. Besides, the retina is unique for everyone and remains the same for a person's lifetime. Thus, retina based identification is considered more secure biometric identification trait.

In this section, we will discuss some recently developed traditional methods [2, 9, 36, 56, 57, 112, 114, 115, 117, 118, 124, 169, 205] and deep learning retina based identification techniques [18, 68, 132, 153].

5.3.2.1 Traditional Retina Identification The first traditional based retina identification study was proposed by Eye Dentify Company in 1976 [2]. Recently, several normal retina based identification method was proposed. Yuan et al. [205], presented a method based on structure similarity (SSIM). The proposed work aims to improve performance with less computation involved. However, the method hasn't considered the feature extraction, which can advance the performance of the system. Mazumdar and Nirmala [116] proposed texture feature based retina identification approach. Local configuration pattern and randon transform method were used to extract the textual feature. The performance of the proposed method was evaluated on seven. However, the computation time of the method was high. Meng et al. [118], introduces a method based on Improved Circular Gabor transform (ICGF) and SIFT method to reduce the difficulty of feature extraction and mismatch problem. However, there is still a good feature extraction which is robust to image deformation challenge in retina image. Aleem et al. [9], proposed fast and accurate retinal recognition system. First, a hybrid segmentation method was used to efficiently balance the wavelet response between thick and thin blood vessel. Next, a PCA feature extraction was applied, which reduce the time cost and accelerate the matching process. However, the identification performance was degraded because of severe pathological noise in the retinal image. Another study [124] deal with the correct identification of the crossing points. The author proposed a method based on vascular skeletal of a fundus image. This work achieved promising results. However, there is still need a wider validation of significant points to boost the performance further. The study in [117], developed a parabolic model based on retinal authentication system. Average accuracy of 99.39% and processing time of 5.46% were reported. However, there is a need to address the latency issue, which can improve the processing time. Table 14 illustrates the performance of modern traditional methods.

5.3.2.2 Deep Learning Retina Identification There are a few recent articles about deep learning-based retina identification. Bhukya [18] proposed method based on template security to enhance biometric security. The proposed adaptive weighted neighbor (AWN) classifier and achieved recognition accuracy of 94.3%. However, they waste memory space because of template storage. Oliveira et al. [132] proposed a retina vessel segmentation method based on fully convolutional neural network (FCN). In this work, multiscale analysis and multiscale fully convolutional neural network to overcome the different structure problem in a vessel. The proposed method was tested on

Table 14 Performance comparison of recent traditional retina identification methods

Cite	Method	Image processing	Dataset (size)	No of subject	Performance measure
[205]	SSIM	CLAHE method used to normalize the image intensity and increase the contrast, Gaussian filter to smooth the processed image. Morphological opening operation are applied to make the background more consistent	VARIA(233)	139	AC = 99.97%, EER = 0.09%
[124]	Hit or miss Transformation	Morphological operator, stochastic watershed transformation and Hit and Mist transformation are used to extract centerline in retinal images	DRIVE STARE (Not Reported)	Not Reported	Predict positive rate = 0.908%
[118]	ICGF + SIFT	Improved Circular Gabor Transform used to process the image, and SIFT for feature extraction	VARIA(233)	139	EER = 0
[9]	PCA	CLAHE enhancement method employ to maximize the contrast between a blood vessel and background,	Biometric retinal identification database (BRDB) (1800)	200	AC = 99.46
[117]	Parabolic Model	Parabolic model is used to extract feature and Euclidean distance used to do Matching	DRIVE, HRF, Messidor, RIDB, VARIA and images from local hospital (1143)	Not Reported	AC = 99.39%

Table 15 Performance comparison of recent deep learning retina based identification methods

Cite	Method	No of network	Network layer	Parameters	Dataset (size)	Performance measure
[18]	Adaptive Weight Neighbor	–	Not Reported	Not Reported	DRIVE (40)	AC = 94%
[68]	Capsule Neural Network	1	1 convolution section and 1 vector section	Not Reported	Face 95 and CASIA-Iris 1000 (1440)	AC = 99.2%
[153]	Deep Neural Nets	3	9 convolution block, 9 convolution transpose block	Not Reported	DRIVE (40)	AC = 95.5%
[132]	FCN	1	5 conv, 2 maxpooling, 2 up sampling, 1 fully connected	32(88 × 88)–32(44 × 44)–64(44 × 44)–64(22 × 22)–128(22 × 22)–128(44 × 44)–64(44 × 44)–64(88 × 88)–32(38 × 38)–32(32 × 32)–2(32 × 32)	DRIVE (40), STARE(20), CHASE_DB1 (28),	AC = 95.7%, AC = 96.9%, AC = 96.5%,

three databases and achieved average of 0.9576, 0.9694 and 0.9653, respectively. However, the proposed method has limited training data which restrict the CNN model to perform well. To deal with a limited dataset, Jacob [68] proposed a capsule network-based biometric retinal identification. The work showed an accuracy of 99% on two combined datasets. However, the method requires high computation time. Roy and Biswas [157] designed a framework which deals on a large amount of data with high-speed computation using deep learning neural net. They proposed three different neural network model for segmentation, bifurcation point and center of object detection, respectively. The method achieved an average accuracy of 96.89% and 95.63% on training and test data respectively. Table 15, demonstrate deep learning methods.

6 Trends of Psychological-Based Biometric system

In this section, we discuss the impact and recent trend of deep learning-based psychological biometric trait and also present the comparison of the traditional and deep learning-based approach of existing work. Biometric modality is significant for the advancement of different biometric recognition technology. However, the biometric traits always depend upon system performance.

6.1 Deep Learning Architecture

Recently, deep learning has widely been researched in various biometric systems. Therefore, many related methods have developed. Mostly, deep learning method is derived from a basic model which can be divided into five models, i.e. Convolution Neural Network, Recurrent Neural Network, Restricted Boltzmann Network, Deep Belief Network, and Stacked Auto-Encoder. Some of these deep learning algorithms are already discussed in the above section.

6.1.1 Convolution Neural Network

Currently, one deep learning model, i.e., convolution neural network has done in outstanding performance in various biometric traits [41, 42, 130, 131, 162, 208]. The most important algorithm related to physiological biometric modality. E.g. finger vein, palm-vein, fingerprint, face, lips, iris and retina are described in Tables 3, 5, 7, 8, 12, and 14. Finger vein and palm vein biometric technology perform outstandingly and achieved average accuracy greater than 96% using a learning algorithm. The accurate comparison is complicated because of the different dataset used in existing work.

Normally, the common deep learning scheme (CNN) mainly consists of convolutional, pooling and fully connected layers. These layers play a different role to train robustly. Each layer of CNN has neurons with weight and biases that can be learned and process the input data. Each neuron has the aim to extract pattern in the local region of input image [82]. Generally, the convolution layer consists of a learnable filter, F with kernel size l, against the small set of x images of size AXB, with weight matrices w. The convolution operator, V for n local connection, and one dimensional can be computed by Eq. (5),

$$V_j = \sum_{i=1}^{l} w_i + x_{i+j-1} j = n \tag{5}$$

Figure 11 represents the basic structure of the CNN model.

CNN model is approved by the research community, because of immense potential, i.e. It operates shared weighting mechanism in convolution layer to locate every pixel of an image using a single filter. The CNN model has various benefit such as it needs a small number of preprocessing steps, human interaction and past information are not required to train the CNN model. Moreover, CNN is considered to be more computationally effective than other networks, due to the fewer number of parameter use in hidden layers to run multiple experiments. Gradient descent and back-propagation are frequently applied to train CNN to make the convergence and learning process fast. The main disadvantage of the CNN model is that it required a tremendous amount of memory space. Some of the other architecture of CNN networks, like ResNet [119], AlexNet [130, 131], DensNet 161 [165], GAN [76], GoogleNet [109], and Capsule Neural Network [68] was implemented recently by the researcher and found efficient in biometric applications with an impressive result.

6.1.2 Recurrent Neural Network

Recurrent Neural Network (RNN) is a type of Neural Network where the output from the previous step are fed as input to the current step. The RNN has the potential to operate real data sequences in stages. After, the first step of data sequence processing, a new sequence is brought into existence by the prediction made on training data. Practically, RNN design a new sequence based on the hidden layer using a fuzzy rule to evade long sequences. Hence, RNN models are the perfect choice of network optimization. It is because that standard RNN is not able to keep previous input for a long duration. The advantage of the RNN network over other network is that the prediction of the RNN network is not based on a few inputs. And, also not affected by increasing the size and sample of the network. On the other hand, other networks cannot predict past input when the network size and sample size is increase. Therefore, the RNN network is robust to noise in the training process. Figure 4 shows an example of the RNN model.

Table 3 Performance comparisons of recent traditional finger vein recognition methods

Cite	Method	Image processing	Dataset (size)	No of subject	Performance measure
[192, 195, 196, 198, 199]	PWBDC	Polarized direction extraction construct the feature on two most in-depth directions in the image, Extended normalized angular binary coding for each direction feature maps, self-adaptive depth-dependent weight adaptively weight the two deepest directions in matching	Dataset (210)	55	AC = 98.89%and EER = 1.3%
[17]	Gabor filter	The difference of binarization and Sobel edge detecter is applied to segment ROI, Local histogram used to enhance the ROI image, the feature is done by Gabor filter, and multi-orientation Gabor filter and morphological operation are used to enhance vein structure	Dataset (6264)	156	EER = 0.43%
[143]	Curvature in Radon Space	Vein image is transformed to radon space by radon transformation, and curvature is computed for vein pattern, then, the contrast of vein pattern are enhanced	Poly U(2520) NTU(680)	PolyU (105) NTU(85)	PolyU EER = 0.48% NTU EER = 0.69%
[192, 195, 196, 198, 199]	Anatomy Structure Analysis-based Vein Extraction (ASAVE)	Vein network extraction is done by Orientation map-guided curvature and thining process, to remove displacement problem in finger vein network calibration are applied, and for matching elastic match, the approach is used	HKPU (1872) SDU(3816)	Not Reported	HKPU EER = 1.39 SDU EER = 0.38
[122]	Maximum Curvature	Center position of the vein is extracted, then these positions are connected, and image are labeled	Not Reported	200	FAR = 0, FRR = 1
[193]	Neighbor Pattern Coding Scheme	Edge of the vein is detected by a Sobel edge detector, and coding strategy are applied to extract 8-neighbor pixels, flooding algorithm is performed on coded edge map to improve the robustness of matching	Dataset(440)	220	EER = 1.28%
[171]	Enhanced Maximum Curvature & Histogram Oriented Gradient	Pattern normalization model is used to remove misalignment the from image, ROI dectector is applied to detect ROI, and Contrast adjustment and high-pass filtering enhancement approach used to enhance the image finally increased the maximum curvature and histogram orientated method used to extract feature	PKU(1576) SDU(636)	PKU(197) SDU(106)	PKU EER = 0.33 SDU EER = 0.14
[194, 197, 200]	Tri-branch Vein Structure	Thining and denoising, Bifurcation detection, and morphological dilation	HKPU(1872) SDU(636)	Not Reported	EER = 0.86 EER = 3.46

Table 3 (continued)

Cite	Method	Image processing	Dataset (size)	No of subject	Performance measure
[202]	WLD	Optimize gradient magnitude is applied to the pixel of the image to increase discrimination, to reduce the translation and rotation double Gabor orientation is used, and finally, cross-matching algorithm used to improve the recognition rate	FV-TJ(960), FV-USM (2952)	Not Reported	AC = 100% AC = 99.45%
[90]	Local Binary Pattern and Local Derivative Pattern	Modified Gaussian high-pass filter used to enhance the feature of the image, the LDP method is applied to extract feature, and hamming Distance matching method measures the similarity	Dataset (2400)	30	EER = 0.13%
[97, 101]	Discriminative Binary Descriptor	Multi-directional pixel difference vectors (MDPDV) and DBD method used	SDUMLA-FV(3816), PolyU(936)	106, 156	AC = 99.08%, AC = 99.98%
[102, 103]	PBC	Multiple-directional pixel difference vector, PBC learning method, representation of finger vein image	SDU(3816), HKPU = (3132)	636,	AC = 99.41%

6.1.3 Restricted Boltzmann Machine

Restricted Boltzmann Machine (RBM) network model is un-directional graphical models developed by Hilton [168]. RBM model can be defined using graph comprise of a single layer of observable variable v and hidden layer variable $\boldsymbol{h}$. RBM is energy-based models with energy function

$$E(v, h) = -b^T v - C^T h - v^T Wh \tag{6}$$

In the above equation, W represents the weight between hidden and visible layers, b and c are the biases of the visible and hidden layer. The joint probability distribution is defined below

$$P(v, h) = \frac{1}{A} e^{(-E(v,h))} \tag{7}$$

A denotes the partition function $p(v, h)$ could be factorized that made the calculation sampling easy. But. A is still intractable. Therefore, RBM like Contrastive Divergence algorithm used approximate method. Salakhutdinov and Hinton designed Deep Boltzmann Model by stacking various RBMs. Figure 12, example DBM with three hidden layers.

6.1.4 Deep Belief Network

Deep Belief Network (DBN) is an unsupervised probabilistic deep learning network, proposed by Hinton. DBN is considered highly complex, graphical model, which is composed of staking restricted Boltzmann Machine (RBM) architecture. The two high-level layers of both the network, i.e. DBN and RBM are connected without directions while the low layer is connected with direction as shown in Fig. 12.

DBN can be trained by RBMs using layer by layer, and it can be rapidly trained through contrast divergence algorithm, in training process training complexity of DBNs are evaded, which made the training process easy to train each RBM. Past literature on DBN depicted that it can solve the problem of low convergence speed and optimum local problem in traditional backpropagation scheme in training multilayer neural network.

DBN model has the advantage of learning the optimal parameter instantly trained by greedy algorithm layer by layer, no matter how large the network is parametrically and layer-wise. Moreover, DBN employs pre-train unsupervised algorithm even though for large unlabeled datasets. The drawbacks of DBNs involve the limitation of approximate inference method to a single bottom-up pass. The greedy algorithm can learn the feature of one layer at a time, and it never rearranges the other parameters and layer of the network. Also, developing a DBNs involve various RBM training model. Therefore it is a computationally expensive job.

Table 5 Performance comparison of recent traditional palm vein recognition methods

Cite	Method	Image processing	Dataset (size)	No of subject	Performance measure
[183]	Discriminative correlation analysis feature level fusion method	Discriminative correlation analysis feature level fusion method	Dataset (6000)	500	ACC = 99.80%
[22]	Gabor based palm vein recognition	CLAHE used to amplify contrast, Gaussian filter and the median filter used to remove noise and preserve vein pattern in the image, Multiple Gabor filters used to extract feature and Hellinger distance as a matching method	Dataset(63)	21	FAR = 0.32, FRR = 1.58 and EER = 1.44 and Time 1.5 to 2 s
[10]	Centerline	Image enhanced by gray intensity, contrast stretching and median filter to remove noise, post-processing by morphological operation and cleaning operation is done to remove undesired pixels; centerline feature are extracted by applying distance from boundary and thining morphological operation	PolyU multi-Spectral Palm print database (6000)	250	EER = 0.333%
[135]	SIFT	Discrete Wave transform (DWT) improves the brightness, High-pass gain low detain frim image, and low-pass generates last computed image, SIFT used to extract feature, and SVM is used for classification	Not Reported	Not Reported	EER = 0.8875
[4]	LBP and ULBP	Gauss filter used to segment hand, ROI is extracted using the meaningful points, LBP and ULBP used to remove the feature, and distance-based matching method is used	Not reported	Not reported	EER = 7.33
[164]	SIFT + RANSAC	Low Pass Gaussian filter applied to remove noise, Morphological filter implemented to remove the white area of the pixels in palm region, Histogram equalization, and contrast limited adaptive histogram equalization applied to enhance the image. ROI extracted with limited and uniform contrast, SIFT method computes the feature from the image and RANSAC used to calculate mismatching	CASIA Multi-Spectral Palm Print(20)	Not reported	EER = 7.7 and Area Under Curve (AUC) = 96.5
[20]	2D Gabor filter + Competitive Coding	2D Gabor filter and Competitive Coding method used for feature extraction and Jaccard distance to measure the similarity matrix between feature map	MS-Poly U(6000)	250	AC = 99.50
[183]	Competition code and DPL	Competitive code is applied to feature extraction and learned by DPL for classification	Multispectral palm vein database(6000)	500	AC = 99.05%

Table 5 (continued)

Cite	Method	Image processing	Dataset (size)	No of subject	Performance measure
[141]	Fusion LBP and LDP	Non-linear image enhancement method is applied to remove uneven illumination and non-uniform background, the feature is extracted by LBP and LDP	Data Set(1032)	86	EER = 2.96%
[163]	MRDCT	MRDCT and Frequency Partition Discrete Cosine are fused to extract fine detail	CASIA(600)	100	EER = 5.53% and AUC = 98.1%
[189]	Local Gabor Histogram	ROI and CLAHE to normalize image, then local Gabor histogram method is fused to represent the image	CASIA(7200)	100	EER = 0.08%

And, it is tough to optimize the model. Example of DBNs, as shown in Fig. 12.

6.1.5 Stacked Auto-Encoder

These model are broadly used in the unsupervised learning task. The network is trained to redesign the input by using some constraints. This kind of architecture consists of two components: an encoder and a decoder. Given an input x, an encoder component learns representative information $h = f(x)$, and, by using decoding component input is reconstructed as $g(h) = x$ using decoder. To decrease the reconstruction loss, encoder and decoder are jointly trained using back-propagation.

$$M(x) = \|g(f(x)) - x\|_2^2 \tag{8}$$

Figure 12 shows the auto-encoder model with one hidden layer. These models can also be designed with a more hidden layer.

- *Impact and future trend of Deep Learning in a biometric system*

Mainly, deep learning method involves in the advancement of biometric system, by solving a variety of issues in biometric modality such as image quality improvement [102, 103, 144], extracting discriminative feature [42, 82, 140] computational complexity [39, 74, 162] and system performance enhancement [81, 134, 144]. Due to the strong ability of feature depiction, the investigator has brought deep learning in to the biometric field. The popularity of deep learning in a biometric domain has three main reasons: (I) advancement in the chip processing system, i.e., graphical processing unit (GPUs),(II) Capability of extracting low-level pattern detail from a noisy image,(III) hardware availability with low cost,(IV) incredible innovation in machine learning approaches [168]. Biometric modality employ supervised learning approach for the recognition process. Implementation of deep learning algorithm based on hierarchical feature and data representation with practical optimization approaches and potent computer resources are studied useful tool in biometric systems. Because of these benefit deep learning algorithm are going to replace traditional biometric approaches. Without a doubt, deep learning approaches are considered efficient in supervised learning and trained discriminatively to learn delicate feature from a database, which is well capable of handling the intra-class variation problem in noisy data. Various deep learning architecture that contributed to the development of biometric are CNN, Capsule Network, CNN with other learning models, and DNN auto-encoder. Figure 13 shows the percentage of deep learning architecture that is studied in this article.

Table 7 Performance comparison of recent traditional fingerprint methods

Cite	Method	Image processing	Dataset (size)	No of subject	Performance measure
[134]	LQM and LQME	LQM quality measure is proposed which consider sharpness, orientation, contrast, ridge structure (minutiae)	DB1(80) DB2(80) Db3(80) DB4(80)	Not reported	EER not reported
[161]	LPQ	Image are segmented block wise by Local phase Quantization,	DB1 of FVC 2004(800)	Not reported	AC = 95.16%
[111]	SIFT	A grayscale image is converted to binary by binarization method, and Ridge Thining are introduced to decrease the darkness of ridgeline, ridgeline enhancement is done by intuitionistic type-2 fuzzy set, SIFT method used to extract feature and matching is done by Euclidean distance	DB1(150) and DB2 (150)	15	Match score = 124 and 122
[157]	STFT	Image is enhanced by STFT, Minutiae feature is extracted, and ROI is extracted using morphological transformation, Consine similarity are used to measure the similarity matrix	FVC2002(80)	10	AC = 96.67, FAR = 0.0328, and FRR = 0.0338
[83]	Indexing	Gabor filtering method used to enhance the fingerprint image, Enhanced thining algorithm are presented to extract minutiae feature, Orientation field used to detect single point. Indexing algorithm is proposed to improve recognition	Dataset(5140)		True Positive Rate = 2.18
[126]	Minutiae and Corner feature points	Gabor filtering is used to increase the contrast between ridge and valley; edge detector is employed to extract ridge edges, edge cornet is detected by edge corner detecter, ridge primitive is introduced with edge corner, the affine model used to match	FVC2000(800) FVC2002(800) FVC2004(800)	100 100 100	EER = 1.93% EER = 1.3% EER = 2.76%
[52]	WEMS	A walking algorithm is used to extract singular point in fingerprint image, Means shift method used to remove reference point to improve performance	FVC2000DB1(800) FVC2000DB2(800)	100	AC = 98.75 and average EER = 4.30
[8]	Minutiea Triplet	MINDTCT are used to check the ridge flow direction, low contrast, low ridge flow and high curvature	FVC 2002(3200)	32	EER = 0.0113

Among all, CNN is most frequently used and efficient architecture that helps in achieving high recognition accuracy in a recent biometric trait, as shown in Fig. 14, compared to other deep learning architecture. Many researchers proposed CNN architecture for a various biometric task, i.e. image enhancement and segmentation task, feature extraction and classification, achieved impressive work.

Despite, the deep learning algorithm advancement in biometric systems, there is some research direction that needs to be addressed for the designing of the influential deep learning network. Various deep learning variant is employed to advance the performance of recognition in the biometric method. However, there are some challenges with a different biometric modality such as model complexity, computation cost and limited dataset for training model. Therefore, the following important steps are required for the development of deep learning compared to the conventional method.

Table 8 Performance comparison of recent deep learning fingerprint identification methods

Cite	Method	No network	Network layer	Parameters	Dataset (size)	Performance measure
[92]	FingerNet	1	4 Conv, 2 maxpooling, 8 Deconv, 4 unpooling	(9×9)–(5×5)–(3×3)–(2×2)–(3×3)	NIST special Database 4(2000) NIST special Database (258) NIST special Database14(27,000)	Inference speed = 0.7
[170]	Fully Convolutional autoencoder	2	5 conv, 5 deconv	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(1046)	AC = 78%
[76]	GAN	1	9 conv, 2 deconv, 9 Resnet Blcok,	64(512×512)–128(256×256)–256(128×128)–256(128×128)–256(128×128)–256(128×128)–256(128×128)–256(128×128)–256(128×128)–256(128×128)–256(128×128)–128(25×256)–64(512×512)–164(256×256)–128(128×128)–256(64×64)–512(32×32)–1(32×32)	IIITD Multi-Optical Latent Fingerprint (MOLF) (4400) & IIITD Multi-Surface Latent Fingerprint Database(551)	AC = 35.66% and 30.16%
[82]	Patch Based CNN	1	3 conv, 1 subsample, 2 fully connected	64(16×16)–(2×2)–64(8×8)–256–256	IIIT-D(1045)	ACy = 94.44, MDR = 10.5% FDR = 4.7%
[42]	CNN_D and CNN_R	2	7 conv, 5 maxpooling,	(5×5)–(3×3)–(15×!5)–(3×3)–(1×1)–(10×10)–(3×3)–(25×25)–(3×3)–(250×250)–2–2	DB Touch based(30) DB Touchless(44) DB Latent (36)	$R_T = 84\%$, $R_F = 15\%$ $R_T = 51\%$, $R_F = 11\%$ $R_T = 52\%$, $R_F = 24\%$
[24]	ConvNets	1	4 conv, 2 maxpooling, 1 fully connected	96(11×11)–96(3×3)–128(5×5)–128(3×3)–256(4×4)–128–128	NIST SD27(258) WVU(449)	Rank 1 identification = 74.4% and 78.4%
[72]	CNN_{DP}	1	d conv, d batch normalization,	64(3×3)d	HRF(30)	$R_T = 87.07\%$ $R_F = 13.37\%$
[23]	ConvNet	1	Not Reported	Not Reported	NIST SD4(2000), NIST SD14(27,000)	EER = 0.75%, EER = 0.26%
[34]	MENet	1	5 conv, 2 pooling, 2 fully connected	32(5×5)–32(5×5)–32(5×5)–32(5×5)–32(5×5)–1024–1024	Database(7920)	EER = 0.781
(H. [185, 186]	Unet	1	6 conv, 2 pooling	256(3×3)–128(3×3)–128(2×2)–128(3×3)–64(3×3)–64(2×2)–3(1×1)	HRF(100)	$R_T = 83\%$, $R_F = 13.89\%$
[74]	CNN, Ensemble and batch Normalization	1	13 conv, 13 Batch Norm, 4 Pooling, 3 fully convoluted	64(224×224)–64(224×224)–64(112×112)–128(112×112)–128(112×112)–128(56×56)–256(56×56)–256(56×56)–256(56×56)–256(28×28)–512(28×28)–512(28×28)–512(28×28)–512(14×14)–512(14×14)–512(14×14)–512(14×14)–512(7×7)–4096(1×1)–4096(1×1)–5(1×1)	Database(888)	AC = 97.2%
[129]	MinutieaNET CoarseNET FishNET	3	20 conv, 8 pooling	64(5×5)–128(3×3)–128(3×3)–128(3×3)–256(3×3)–256(3×3)–256(3×3)–512(3×3)–512(3×3)–512(3×3)–64(3×3)–64(3×3)–64(3×3)–64(3×3)–128(3×3)–128(3×3)–256(3×3)–256(3×3)–256(3×3)–256(3×3)	FVC2004(3200)	Precision = 85.9% Recall = 84.8% F1 score = 0.853%

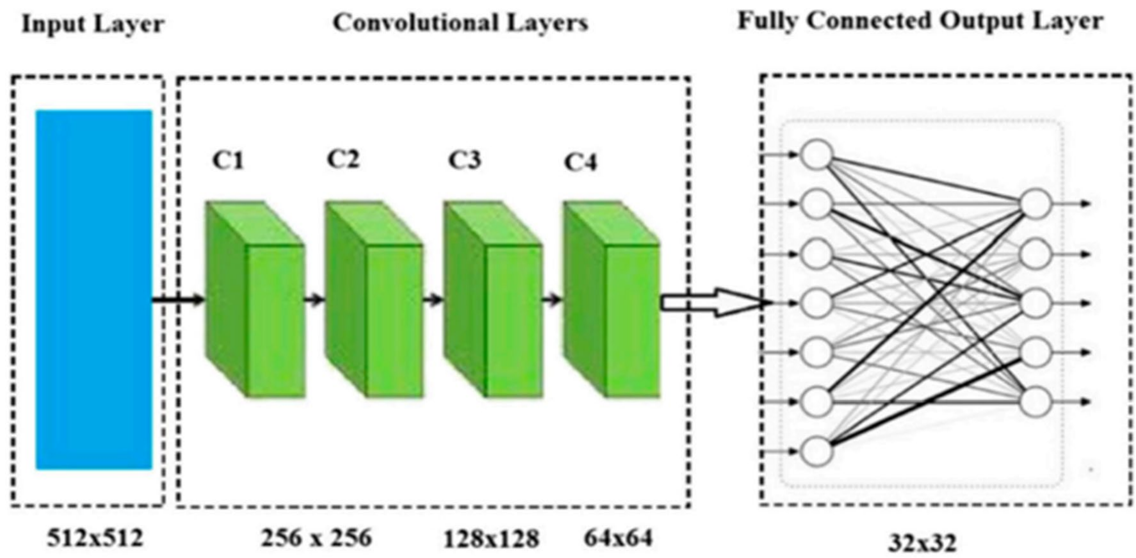


Fig. 11 Primary Taxonomy of CNN model [146, 147]

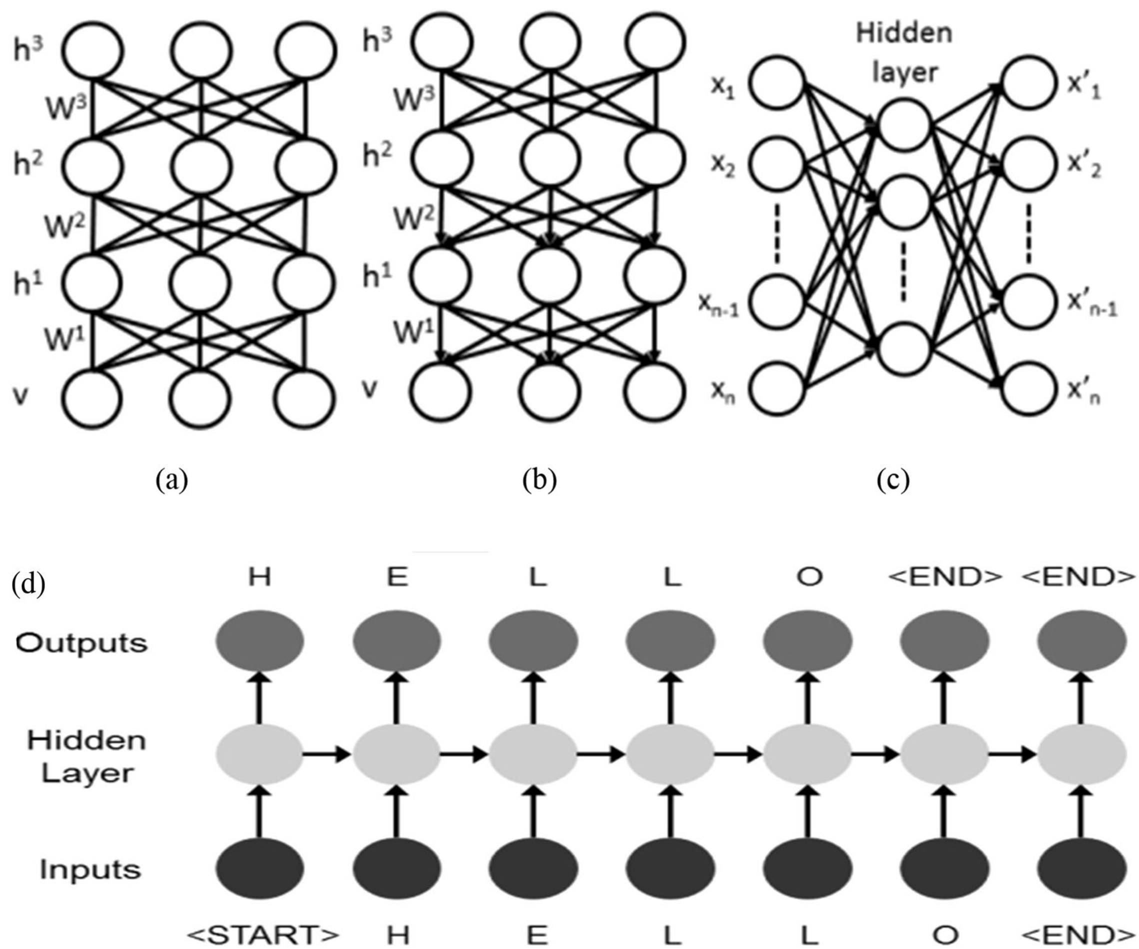


Fig. 12 **a** Deep Boltzmann machine, **b** deep belief network, **c** auto-encoder and **d** RNN network [168]

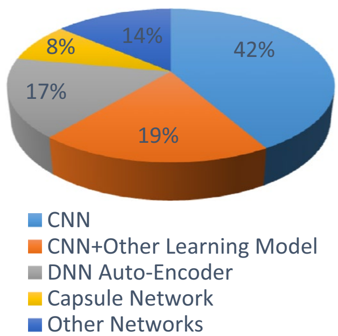


Fig. 13 Recent deep learning architecture used in this survey

(a) To improve the generalization ability of deep learning model, there is a need to add more layer in a network.
(b) Currently, deep learning model based on the pre-trained model, the focus is required to design an application-based model, which advance the recognition performance.
(c) Integrating hand crafted feature and non-hand crafted feature to obtain better network model.

Besides, the performance of new deep learning could be improved by incorporating the dynamic size of deep learning architectures with their result in a cascaded way. Hence, this will reduce the considerable processing time, and training of each deep learning network requires to execute task separately. For example, Sun et al. [167] developed a three-class CNN model for face identification. The facial point initially was computed by first class, and then second class were employed to fine-tune the initial prediction. Labati et al. [42], designed a two-class CNN model for fingerprint recognition. First-class CNN model, detect the pore from the fingerprint image. And, then the second CNN model removes and estimate the error from initially computed pores.

- Comparison between traditional and deep learning methods

Figures 15 and 16 describe the recognition accuracy of a various biometric trait between state-of-the-art conventional and deep learning algorithm. We have computed the average accuracy roughly for a biometric trait that is discussed in the literature because of the different dataset were used. These figures represent that deep learning outperforms the traditional approaches in terms of recognition

Fig. 14 Average accuracy of recent deep learning architecture used in this article

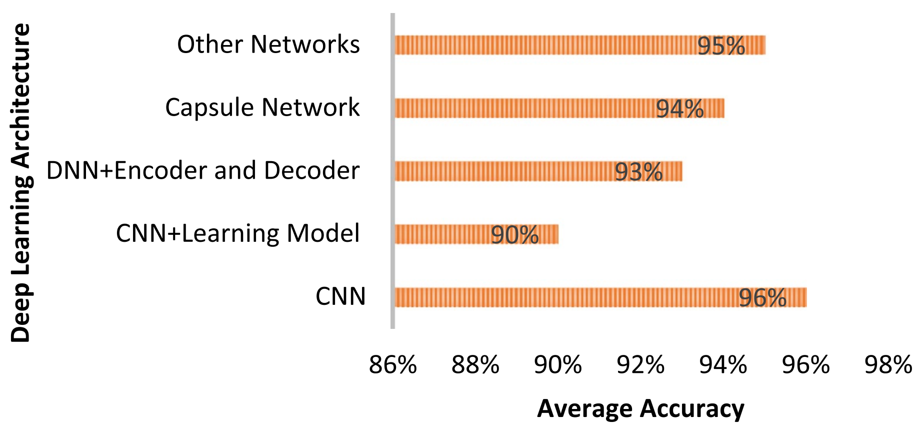
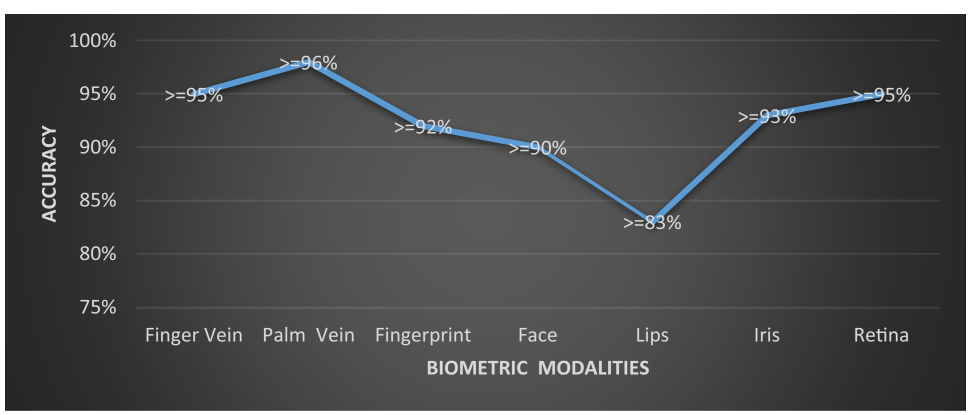


Fig. 15 Rough accuracy of traditional physiological biometric system



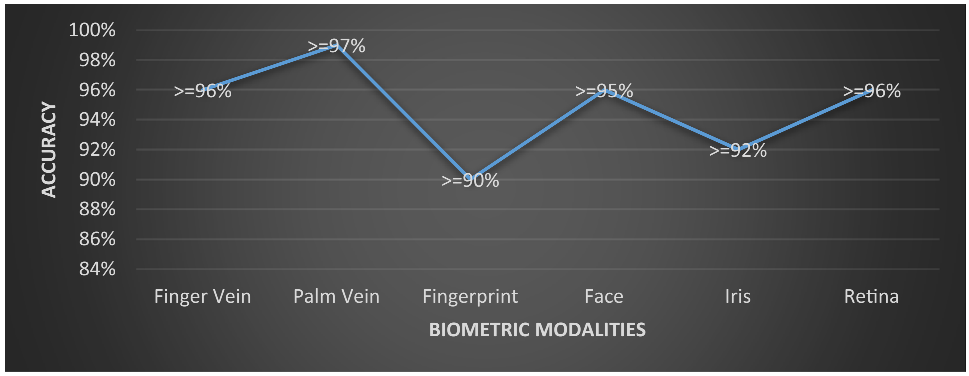


Fig. 16 Rough accuracy of deep learning-based physiological biometric system

Table 16 Comparison of traditional and deep learning-based biometric approaches

Traditional based biometric method	Average EER	Deep learning method based	Average EER
Finger vein	0.92%	Finger vein	0.76%
Palm vein	1.17%	Palm vein	0.34%
Fingerprint	2.06%	Fingerprint	1.5%
Face	Not reported	Face	Not reported
Iris	0.65%	Iris	0.45%
Retina	0.04%	Retina	Not reported

rate. Moreover, in Table 16, a performance comparison between conventional and deep learning approaches as shown to show the supremacy of deep learning method over traditional techniques in term error rate.

Current literature illustrates that deep learning-based techniques have been well used and improved the performance of biometric modalities. A deep learning-based method is robust to acquire feature precisely from the raw image, without the involvement of a handcrafted feature, which significantly enhances the matching method [41, 60, 150, 165]. However, in the traditional method, handcraft descriptor (Gabor wavelet, Statistical feature, BSIF, SIFT, etc.) are used to obtain the attribute from images [32, 91, 136, 137, 152]. Moreover, deep learning can reduce the computation time of biometric authentication. Whereas, traditional biometric trait requires much processing time and effort to process different stages of biometric recognition [164, 171, 179]. Identification accuracy is the prime concern in biometric applications. The handcrafted biometric method requires complex preprocessing, with the massive effort required to clear noise, glean and enhance feature ahead of matching algorithm. In such cases, a small mistake can decrease recognition performance [111, 192, 195, 196, 198, 199]. Wherein, deep learning scheme does not require over-complex image processing and preprocessing. Besides, deep learning method is robust to image processing problem such as noise, misalignment, segmentation [12]. Although the deep learning model is parametrically complex, now the development of powerful GPUs improves complex network problems [203].

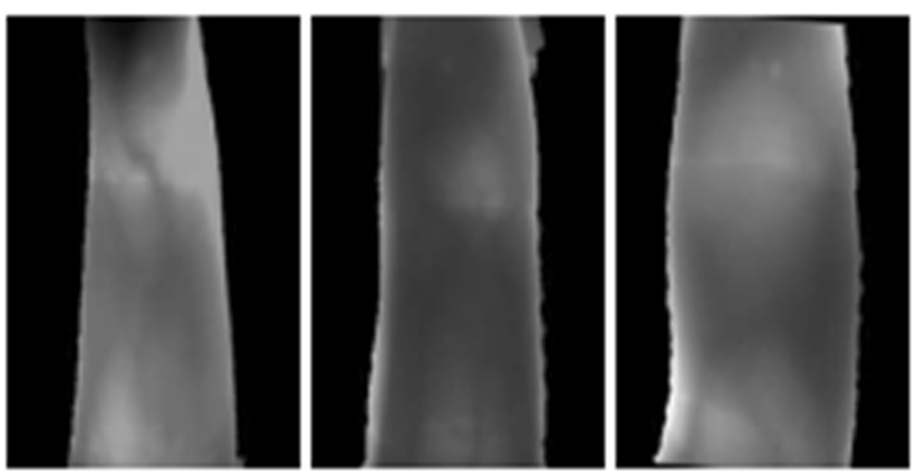


Fig. 17 Low-quality images

7 Discussion

In this article, we study and discuss the recent traditional and deep learning research work of psychological biometric traits, i.e., finger vein, palm vein, fingerprint, face, lips, iris, and retina. This section focuses on how the psychological-based biometric method can be advanced by the traditional and deep learning method. Also, we highlight the potential research gaps that exist in the current conventional and deep learning biometric system.

- Challenges related to Traditional Psychological Biometric System

In hand-based biometric traits, we have discussed finger vein, palm vein, and fingerprint biometric trait. In VFR, we primarily focus on modern handcrafted feature extraction method of the VFR system and discuss image point-based feature and all image-based feature extraction techniques. Both of these feature extraction algorithms have advanced VFR, and achieved promising recognition performance. However, there are some challenges faced by these feature extraction strategies. Vein point-based feature extraction techniques are not robust to image quality. The quality of finger vein image is mostly reduced because of noise, low contrast, and non-uniform illumination. As shown in Fig. 17, the amount of vein vessel is small, and it's not easy to extract these thin vessels and low contrast region. Therefore, there is a need to improve the image quality before using the the vein-point feature extraction method.

All image point feature extraction method: These approaches extract the feature from all image, extracting the non-vein point from the finger vein image. The optical attribute of subcutaneous tissue and skin revealed by near-infrared light, which degrade the performance of FVR system. However, [192, 200, 201, 203, 204] proposed a point grouping methods (point grouping anatomy structure analysis-based vein extraction (ASAVE) and point grouping Gabor methods) which also consider all image point to extract discriminatory information from finger vein image. However, this method is parametric complex because of the configuration of the Gabor filter, which is difficult. Hence, there is still a need to develop a simple, efficient feature extraction method that can boost the traditional finger vein system's recognition performance.

In this article, we have reviewed recent traditional feature extraction methods for palm vein recognition. We have classified these feature-based method into four categories, namely, geometry-based statistical-based, feature-based, and coding based approach. The vast majority of these methods are not robust to translation, rotation, and scale changes, which can degrade the recognition performance of the palm vein system [164]. Moreover, some feature extraction methods has high computation costs and complexity problems [135, 189]. Therefore, there is a need to design robust feature extraction methods, which can efficiently extract discriminative features to boost palm vein recognition performance with less computation. Moreover, most palm vein images have poor quality,hence, there is a need to employ an enhancement technique that can improve the quality of palm vein images.

This review has studied various recent traditional fingerprint identification approaches that mainly focused on the feature extraction step of the fingerprint system. Although, the performance of most the conventional fingerprint identification scheme was quite impressive. But, several open issues still exist in the traditional method, which needs to be solved. (1) Appropriate preprocessing methods is required to obtain the better quality image. (2) It's challenging to counter a large fingerprint datasets with acceptable time. (3) An efficient feature extraction method is needed to extract relevant discriminatory information. Therefore, there is still need a domain-based, cost-effective and robust conventional feature extraction method that can advance the performance of fingerprint system and be easy to implement in real-time applications.

In this article, we have discussed various feature extraction methods for face recognition and lips recognition—several challenges are faced by these recognition methods. Face recognition from multiple stylistic sketches is still an open issue and challenge for face-based identification method. In [139], multiple stylistic sketches face recognition scheme was proposed. However, the performance was still far from a satisfactory result.Another challenging problem is a single sample per person (SSPP), which still needs to be overcome in the face recognition method. In [138], a decision pyramid classified method (DPC) was proposed to address the SSPP in extreme variation. However, the pixel feature was not proper for the DPC method. Therefore, there is another proper feature needed for DPC. In addition, a human face is not unique various factor changes the face appearance such as age, pose variation, low-resolution, and illumination variation. Moreover, traditional methods have high computation costs, which is still a great challenge for traditional approaches. Hence, there is an effort required in a preprocessing step to design a perfect traditional human face recognition method. In this work, we also discussed a few conventional recent lips based identification methods. Lips based recognition method is a relatively new biometric trait. There is still a research gap to improve the recognition performance and security of conventional lips based biometric algorithm. Extracting good features still required, which advances the lips recognition method. In [35], a biometric template security-based lip identification technique was proposed. However, this work decreases the recognition rate. Therefore, the security and recognition of of both aspects together should be considered in the future. We have discussed several recent conventional iris recognition methods. Various traditional methods have achieved promising recognition results in the iris recognition system. However, there is still some possible direction that needs to be addressed to design a powerful iris identification system. Most of the well-known segmentation method of iris recognition scheme faces the challenge of poor image quality and high computation time. In a traditional retina identification systems, noise, low contrast, and iris image between blood vessels and backgrounds affect the recognition accuracy. A segmentation algorithm was proposed in [9] But, the proposed work fail to extract features from pathological disorder images. Therefore, there is a need to improve the image quality of these severe noisy retinal images. There is also a need to use image de-noising algorithm such as eyelid occlusion and eyelashes to improve the iris recognition system performance. In addition, most research used bifurcation point and blood vessel as a feature parameter which are not enough for reliable person identification system. Therefore, there is a need to use some good feature in fundus retina images such as optic disc, computing macula position and other unique features that need to be extracted for designing a reliable and robust biometric retinal identification scheme. Moreover, the recent traditional methods are time costly and complex. Hence, a fast, accurate, and simple traditional retina identification system still needs to be researched.

- Challenges related to Deep learning Psychological Biometric System

In hand-based biometric trait,, we have discussed finger vein, palm vein and fingerprint biometric trait. Deep learning-based finger vein recognition still faces the challenge of computation cost, complexity in network parameter, and system performance decrease. Although several methods were proposed to address these issues [162, 209–211]. However, computing cost, parameter complexity are still unsolved issues in deep learning-based finger vein system. Hence, a robust learning-based finger vein scheme is necessary to develop. Moreover, finger vein has a limited dataset available, which is also one of the challenges for training deep learning model. In [47], a CNN-CO deep learning algorithm was proposed to deal with limited data problems in a finger vein recognition system. However, the proposed method have low recognition accuracy because data are labelled based on the appearance of finger vein image, which haven't guarantee the performance improvement. Therefore, a limited dataset still in an open problem that needs to be addressed. Also, there is a need to implement automatic labeling approaches to train models, advancing the finger vein system performance. In addition, the quality of finger vein image is poor which effect the recognition performance of finger vein system. Hence, there is a need to give attention and develop deep learning-based enhancement algorithm to boost overall system performance. In palm vein identification system, very little research have been done using deep learning scheme. Learning based palm vein authentication technology have the challenge of limited data and architecture complexity. There is a need to incorporate deep learning based research considering these challenges to boost the performance of palm vein authentication technology.

In this article, we have discussed various recent deep learning based fingerprint algorithm based on enhancement, feature extraction and classification task. Various existing learning-based enhancement and segmentation approaches have done a great job to improve the fingerprint pattern. However, the developed enhancement and segmentation method still faces the challenge of poor quality image and high computation cost. Therefore, there is still a research gap to develop efficient and robust learning-based enhancement and segmentation method. Moreover, we have studied various feature extraction based deep learning model for fingerprint authentication. We observe that the performance of most of the recent feature-based learning technique is poor. Hence, there is a need to design a method that enhances the overall performance of the fingerprint system. Following are the important steps required to develop robust deep learning strategies.

i. There is a need to extract level 3 features such as sweat pores, ultra-thin ridges, and incipient ridges.
ii. Investigating a different kinds of ConNet architecture such as GoogleNet, ResNet. These kinds of Deep Learning model contain many layers which are significant to improve identification accuracy.
iii. There is a need to develop an application based model which do not need on existing model. The current deep learning model based on already developed model.

In this work, we have studied the published work based on training data of deep learning model, network architecture, and designed loss function of a deep learning model for face authentication. However, the impact of deep learning on the Lips is still unclear. Indeed, much research has been done on face recognition technology. There are some issues still worthy to be addressed. (1) First, there is need of model adaptation to subject-list and how to tune the model if new subject enrolled in the subjected list. (2) Weighting strategies required which can identify the role of a discriminative region or not a discriminative region in human face automatically. (3) Designing of the suitable loss function is necessary for deep learning model to improve the discriminating power of the network model.

In this work, we also studied deep learning-based iris recognition system and classified it into four main categories, namely, preprocessing, feature extraction, matching, and architecture of deep learning model. There are various challenges and open queries when applying deep learning schemes to an iris authentication problem. First, the computational complexity of the deep learning model is very high during the training phase because of a large number of parameters used in a network. Therefore, model reduction methods such as pruning, removal of redundant neurons, and layers are needed to solve complexity problems. Thus, this can remove the high computation cost. The second issue is about domain (Iris) based feature extraction and fine-tuning of the deep learning model. Fine-tuning can only select few layers to adapt the representation capability (iris specific features) of the deep learning model to iris images, which opposed the generic image attributes. In addition, there is some other deep learning architecture such as unsupervised Deep Belief Network (DBN), Recurrent Neural network (RNN), and Stacked Auto-Encoder (SAE) can be useful to use in feature extraction task from iris images to enhance the representation capacity of iris template.

Deep learning-based retina identification also faced some challenges. In [18], a method was proposed to address the template security issue. However, there still need of efficient and reliable method which focuses on memory wastage problem during storing process of template for user authentication. Another problem relates to an available limited dataset, the performance of the deep learning method proposed in [132] was affected by the limited training dataset. Therefore, there is a need to used the advance deep learning data augmentation technique. Moreover, computation cost problems and lack of domain knowledge are two key challenges faced by the existing deep learning method. Hence, there is a need to combine domain knowledge with the deep learning method, which will boost the retina identification performance.

8 Conclusions and Future work

In this article, a comprehensive review is conducted about recent conventional and deep learning algorithm of various biometric modalities, namely: finger vein, palm vein, fingerprint, face, Lips, Iris, and Retina from over 215 research manuscripts, which also outline the challenges and performances of the existing physiological based biometric system. Initially, the biometric architecture, operation mode, and performance metric are described in detail. Next, the recent current state-of-the-art traditional and deep learning biometric modalities were discussed in depth to gain an understanding of their framework for the pre-processing, feature extraction, and classification/matching performance using non-publicly and publicly available datasets. Afterwards, a deep learning trend and rough performance analysis of recent traditional and deep learning algorithms were presented in terms of of recognition rate and error rate. The deep learning method shows significant improvement over conventional biometric methods. Finally, in the discussion section the main challenges of the mentioned biometric modalities are demonstrated along with the possible solutions. To a developed a robust biometric authentication system in the future, the issue described in the discussing section for finger vein, palm vein, fingerprint, face, lips, iris, and retina, need to be addressed. In conclusion, this work would be useful, starting research point for novel schemes and a general field for extensive work in physiological biometric authentication and recognition.

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Compliance with Ethical Standards

Conflict of interest The authors declare that they have no conflict of interest.

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