Biometric Based Recognition Systems - An Overview

Ahmed AK. Tahir and Steluta Anghelus

***Abstract*— Biometrics technology is gaining an important role in providing solutions to many issues in different applications that require person identification such as forensic sciences, security, finance, border screening, ministries and government offices. It is defined as the technique of analyzing physiological and behavioral traits such as face, fingerprint, iris, retina, voice, signature, etc., for person identification and authorization. At present, a lot of research work is being carried out to accomplish biometric recognition systems based on different types of human traits. To provide a comprehensive survey, this paper provides an overview of six biometric traits (iris, finger vein, fingerprint, face, voice and signature). The overview will cover acquisition method, preprocessing methods, features extraction methods, classification methods, application area, system evaluation and strength/weakness.**

***Keywords*—Biometrics, biometric recognition system, human traits, iris, fingerprints, finger vein, face recognition, voice recognition, signature recognition.**

I. Introduction

This The term biometrics refers to any human physiological or behavioral features (Human Traits) that can be measured and stabilized over time such as face, retina, fingerprints, finger vein, ear, palm vein, iris, voice, gait, keypresses, signature, etc., [1-3].

Nowadays, human traits are the main basis for security systems and have become the solution in many civil and government applications such as financial functions, border checks and government offices.

Biometric recognition systems have several advantages over knowledge-based systems that use a PIN, username, and passwords or token-based systems that use keys, magnetic or smart card and badge, [4,5]. They are based on features and properties that cannot be forgotten, stolen, shared, altered, lost or disclosed. However, biometric recognition systems are expensive and require sophisticated and automated methods for identifying and authenticating a person. In addition, they require measurements of the physiological or behavioral characteristics that exist with humans. Moreover, they require continuous developments to meet the demands of the society and specifically in the areas of e-government, e-banking, e-commerce, and to prevent fraudulent persons from passing and breaking the law, [6].

Biometric identification systems are usually designed either for identification or verification or both. In the identification system, which is referred to as one-to-many matching (Who the person is?), sample of individual biometric feature(s) is compared to a list of samples in the database in order to be sure that the individual is in the list. In the verification system, which is referred to as one-to-one matching, the checking operation is performed to conform whether a person is really who he\she claim, (Is the person is really what he claims?), [7].

Human biometrics are categorized into two types, physiological and behavioral. Physiological biometrics depend on the measurements of a specific individual's features for identity verification/authentication. This includes iris, fingerprints, face, palm vein, finger vein, etc., [8,9]. Behavioral biometrics are the measurement and analysis of human-specific behavioral traits such as voice, signature, handwriting, human interaction with computer parts such as mouse, keyboard, [10]. Physiological biometrics are commonly used for one-time authentication, whereas, for dynamic authentication, behavioral biometrics can be more effective.

Despite most of the security systems use physiological traits, behavioral traits still have some advantages over physical biometrics. For example, behavioral biometrics enable constant monitoring of users and deliver continual user authentication and is a powerful defense. In addition, its collection is not disturbing. However, it has some shortcomings. For example, its implementation is costly as it requires special hardware units and it requires the collection of huge personal data records to profile a user's typical behavior accurately. In addition, it is not adaptable when any change in the human behavioral happens.

The success of a biometric recognition system depends on the strength of the biometric trait and the purpose for which it was designed. Several studies have already been conducted to compare the performance of different types of biometric recognition systems. For example, [1-3, 5,7,11-13] compared different types of human traits including iris, fingerprint, face, palm vein, voice, signature, gait, ear, signature, DNA, and retina, etc. It was concluded that the performance of the human trait depends on the scope of application, cost, and how easy is to record it.

This paper presents an overview of the use of human biometrics to determine a person's identity. Six human traits are selected, four physiological traits (iris, finger vein,

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fingerprints, and face) and two behavioral traits (voice and signature).

The remaining parts of the paper are organized as follows: A description of biometric measurements is given in section 2. The main layout of biometric recognition system is given in section 3 and reviews of algorithms for all stages are given in subsections 3.1-3.5. Evaluation of biometric recognition systems is given in section 4 and finally the conclusions are given in section 5.

II. Biometric Measurements

There are many traits in the human body that can be considered biometric measurements. According to [14,15] there are seven pillars that must be available in the traits in order to be used as biometric measurements. These seven pillars are:

1. Universality: Each person should possess the same physiological traits such as fingers, iris, face, etc., and the same behavior traits such as voice, gait, signature, etc.
2. Distinctiveness: The trait must be unique enough to distinguish the person.
3. Permanence: The traits must be stable throughout a person's life.
4. Collectability: Biometric trait should be measured quantitatively and easily.
5. Performance: The trait must provide high recognition accuracy.
6. Acceptability: The way of acquiring of the traits must be accepted by the people. Usually, the people prefer to record the train in a non-invasive way.
7. Resistance to Circumvention: The system needs to be hard for any circumvent by fraudulent methods in order to provide efficient security.

The strength of any biometric trait largely depends on the application for which it is used, [13,16]. There are applications that may accept some error rate such as highway tolls, whereas others may not such as banking system and criminal investigations. Besides, some application may require quick decision such as border controlling, whereas others may not such as criminal investigation. Table 1 shows comparisons between six biometric traits (iris, finger vein, fingerprints, face, voice and signature).

Table 1 Comparison of biometric traits for the seven Pillars

Criteria (Pillars) / Biometric Traits	Universality	Permanence	Distinctiveness	Collectivity	Performance	Acceptability	Circumvention
Iris	H	H	H	M	H	M	H
Finger Vein	M	H	H	H	H	H	M
Fingerprints	M	H	H	M	H	M	M
Face	H	L	M	H	L	M	M
Voice	M	M	M	H	M	H	H
Signature	M	L	L	H	L	H	H

III. THE MAIN LAYOUT OF BIOMETRIC RECOGNITION SYSTEM

The components and implementation of any biometrics system can be represented by the diagram in figure 1. The system implementation requires two modes, enrollment and operation. In the enrollment mode, the available traits of users are processed and the features are extracted and saved as a database to be used for comparison in the testing mode. In the testing mode, the trait of the user is acquired, processed and features are extracted and coded (if required) then compared to those in the database according to the purpose of the system whether identification or verification is, [1]. Descriptions of the system stages are given below. Also, for each stage, the requirements for the six biometric traits are tabulated.

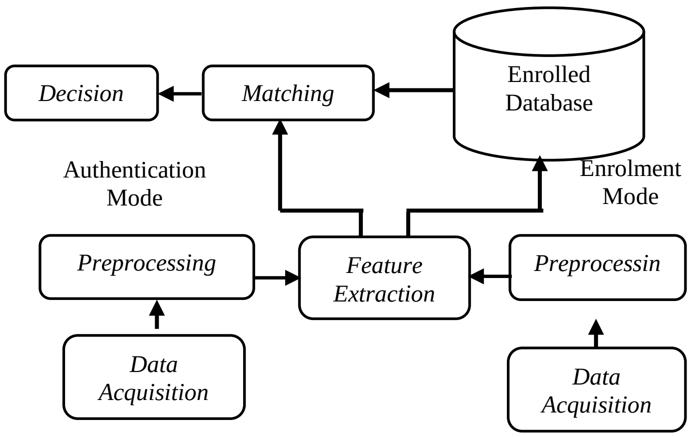

Figure 1 The layout of biometric recognition system

A. Data Acquisition

Human biometric trait data is usually acquired via a sensor, camera or recording devices depending on the nature of the trait. For iris and fingerprints, the data is in image form acquired by Infrared camera devices, whereas for voice, the data is a series of values representing the voice signal taken by voice recorders. The quality of the acquired image or signal is important for accurate identification/verification. To increase the performance of biometric systems, more than one image of the human trait is required to reach the best matching with the enrolled database [11,17]. Many devices including infrared camera, infrared sensor, voice recording, scanners and digitizers have already been developed for imaging the traits. These devices are available at reasonable prices. Also, many of the standard databases are available and have already been used for developing effective recognition systems, [17-19]. The quality of the data depends on the sensor specifications and the imaging conditions. For example, the optical fingerprint imaging, which captures a digital image of the fingerprints using visible light is affected by the quality of skin on the finger, while Ultrasonic sensors use very high frequency sound waves to penetrate the epidermal layer of skin. Also, thermal scanners can be used to sense the temperature differences between fingerprint ridges and valleys, so it is less affected by the skin quality. Usually, the digital representations of the biometric traits are stored either in a central database or in a card for further identification and verification tasks. Table 2 shows the data acquisition devices and the standard databases for the six biometric traits overviewed in this paper.

Table 2 Biometric data acquisition devices and databases

Human Traits	**Data Acquisition Devices**	**Database [References]**
Iris	Infrared Camera	CASIA-1, CASIA-2, CASIA-3, CASIA-4, SDUMLA-HMT, UBIRIS, [17, 11, 20,21]
Finger Vein	Infrared Sensors Near-infrared LED CCD camera	SDUMLA, UTFVP, HKPU, MCBNU_6000 [17-19,22]
Fingerprints	Optical camera Ultrasound scanner Thermal scanners	CASIA, SDUMLA, Multi-Sensor Fingerprint Database, [17,23]
Face	Camera	SDUMLA-Face database part 1 and part 2. [17]
Voice	Voice Recorder + A/D Convertor	VoxCeleb, 2000 Hub5,Google Audiset, TIMIT database, [24]
Signature	Scanner digitizer	SVC and MCYT, CEDAR, MCYT-75, GPDS and UTSIG, SigComp2009, SigComp11, BHSig260, SVC2004 and ATVS, [26-35]

For iris, the most common databases are CASIA-1, CASIA-2, CASIA-3, CASIA-4, SDUMLA-HMT and UBIRIS. CASIA database was developed by the Chinese Academy of Sciences' Institute of Automation, [11]. The first version was CASIA-1 created in 2003 and the last version was CASIA-4 was created in 2010. SDUMLA-HMT is a multimodal database which was developed in 2010 by Shandong University, Jinan, China, [17]. It contains databases for five human traits, iris, finger vein, fingerprints, face part1, face part2 and gait. UBIRIS is another database created for iris [20,21]. For finger vein, the most common databases are HKPU, UTFVP and MMCBNU_6000, [17-19, 22]. CASIA and SDUMLA-HMT databases are available for fingerprints, [17,23]. For voice, the most common databases are VoxCeleb, 2000 Hub5, Google Audiset and TIMIT database, [24]. For signature, two main types of signature identification and verification systems exist, offline (static) systems and online (dynamic) systems. In the offline systems, signature is captured or scanned from a document. In the online systems, signature and additional information such as time, pressure, pen up and down, azimuth is captured using devices like tablets and smart phones, [25]. Many signature databases have been created for off-line and online signature recognition such as SVC and MCYT, CEDAR, MCYT-75, GPDS and UTSIG, SigComp2009, SigComp11, BHSig260, SVC2004 and ATVS [26-35]. Each of these databases contains genuine and signatures for each writer.

B. Preprocessing

This stage involves the removal of noise and any unwanted feature. For example, iris is preprocessed for the removal of specular reflection point, eyelash and eyelid, [36-38]. For finger vein, preprocessing includes the removal of black background and the extraction and enhancement of Region-Of-Interest (ROI) using various methods. Brindha, [39] used a combination of an open morphological operation and Neighborhood elimination technique to remove the noise and unwanted areas as the minutiae points that are not parts of the vein. For ROI extraction in finger vein, Mustafa and Tahir, [40] used image masking and alignment techniques for border detection and displacement correction. They used a combination of Contrast Limited Adaptive Histogram Equalization (CLAHE) and Modified Gaussian High Pass Filter for ROI enhancement. In fingerprints authentication systems, fingerprint images usually get degraded and corrupted due to variations in skin and impression conditions. Bansal and others, [41] used binarization, thinning and minutiae connection as preprocessing for fingerprints. Also, non-uniformity of the ink intensity, nonuniform contact with the sensors by users or changes in illumination and contrast during image acquisition process affect the quality of the image, [42]. Thus, image enhancement techniques are necessary prior to minutiae extraction. This may include the removal of noise and alignment. [42] used thresholding, binarization and thinning for the enhancement of fingerprint image before minutia points extraction.

Face recognition also reveals some issues with facial images due to variations in posture, position, occlusion, lighting, make-up, and noise. Shih and others, [43] used 2-D Gaussian skin-color model to differentiate between skin and non-skin regions by a 2-D Gaussian skin-color model. The same authors, used the mathematical morphology technique to remove noises and the region-filling technique to fill holes. For voice, the main source of noise is the background noise and recording device noise, which can be removed by various types of smoothing linear and nonlinear filters such as Kalman filter, maximum likelihood envelope estimation, wavelet analysis, mean filter, median filter, the normalized Gauss's filter, midpoint filter and the morphological filters, [24]. In signature recognition, image preprocessing is very significant stage to improve the signature data for both, online and off-line signature recognition systems. In image preprocessing, various operations are applied such as color image to gray image conversion, noise removal, thresholding, morphological operations, cropping, binarization, and signature size normalization [26]. Also, binarization and thinning by Otsu's method was used by [56] for signature preprocessing. Table 3 shows the most common per-processing methods for the biometric traits handled in this paper.

Table 3 Methods of preprocessing

Human Traits	Preprocessing Methods and [references]
Iris	The removal of specular reflection point is done inclusively via the process of iris localization technique, [45] Eyelid detection and removal: the technique of Canny edge detector and edge map refinement is developed and used by [38] and the techniques of Canny edge detector followed by Hough transform were used by, [46-52]
Finger Vein	Noise removal: removal of unwanted areas by Neighborhood elimination technique [39]. Removal of peaks introduced by background noise using open morphological operation, [39] ROI extraction: Border detection and displacement correction using image masking and alignment techniques and ROI enhancement by the technique of CLAHE and modified Gaussian high pass filter and image alignment, [40,53,54],
Fingerprints	Noise removal, alignment [55], Noise Removal +binarization and thinning, [42] Binarization, thinning and minutiae connection and Gabor filters as preprocessing to facilitate the extraction of minutiae points in fingerprints, [41].
Face	Noise removal by morphological techniques, [43] Detection of skin and non-skin regions by a 2-D Gaussian skin-color model, [43].
Voice	For noise removal various types of filters are used such as Kalman filter, maximum likelihood envelope estimation, wavelet analysis, mean filter, median filter, the normalized Gauss's filter, midpoint filter and the morphological filters, [24].
Signature	Noise Removal, Color-to-gray conversion, cropping, rotation, binarization, thinning and normalization, [26]. Binarization and thinning by Otsu's method, [56].

C. *Feature Extraction*

Feature extraction represents a crucial stage that has great impact on the performance of the developed system. It involves the extraction of the most unique feature from the biometric traits. Much of research has already been done for feature extraction. In iris, the most effective feature is the texture of the iris region, which is extracted using various methods of iris extraction such as Canny edge detector, Hough transform or Integro-differential operator and Gabor filter for coding, [44,56-58]. For finger vein, the most effective feature is the coded vein patterns using LBP, LDP, CLBP, Gabor filters, histogram concatenation by [40,53,54]. For fingerprints, the most effective features are the minutia points which include Bifurcations, ridge endings and islands, core and delta, [59]. These minutia features are can be classified into three classes, [41]. Level-1 features, which show macro details of the ridge flow shape. Level-2 features, which include minutiae points that are discriminative enough for recognition. Level-3 features, which are the pores. For face, the most effective features are shape outlines, size, mouth and nose, which can be extracted using various methods of feature extraction. [60] used the Active Shape Model (ASM) and the Active Appearance Model (AAM) for feature extraction. The ASM includes the landmarks of the face such as the areas of the eyebrows, cheeks, eyes, mouth, and nose, while the AAM includes include detailed texture (pattern of intensity or color). [61] used Gabor filter and PSO technique for detecting the shape outlines such as the size of mouth and nose. PSO is used to select the best features of Gabor results. Shih and others, [43] used the shape, size and PCA information to verify face candidates. They established an ellipse model to locate the area of interest (AOI) of eyes and mouths. Then they applied automatic thresholding and morphological opening to discard non-facial feature pixels. Also, LBP coding technique is used by [62].

For voice, the most effective features are the Voice characteristics, also called as voiceprint or voice template. Several methods of feature extraction have already been developed for voice recognition system. Examples are, Linear Prediction Coefficients (LPC),), Line Spectral Frequencies (LSF), Discrete Wavelet Transform (DWT), Mel Frequency Cepstral Coefficients (MFCC), [63]. For signature, the features depend on the acquisition method, off-line, which are called static features or online, which are called dynamic features. Off-line signatures are recorded on a paper by an ordinary pen, and then transferred into a digital file by scanning. Online signatures are captured with digital devices such as electronic pens or tablets, where the real-time features (like pressure, vertical and horizontal position, azimuth, and time) are captured [64].

Static features are mainly divided into local features and global features, [65]. Local features include texture features and gradient features. Texture features include end points, crossing points and branch points. End points are the starting and ending points of the signature stroke. Gradient features include spatial coordinate, inclination of letters and writing order. Dynamic features are divided into parameter-based features and function-based features. Parameter-based features include the duration of the signature and the number of pen-tips across the paper. Function-based features include signature trajectories such as pen pressure data, pen up/down. Dynamic features based on functional features; therefore, they produce better results [66]. Also, Beresneva and others, [67] described the more informative parameters of signature such as size, shape, velocity, pressure and the extracted methods such as Wavelet transform, discrete Radon and Fourier transforms, Signature features can be, categorized into global, mask, and grid features. Global features give wavelet coefficients and Fourier coefficients. Mask features give information about the signature lines' directions. Grid features give information about the overall appearance of a signature, [68]. Table 4 shows the most common methods of feature extraction for the six biometric traits selected in this paper.

Table 4 Methods of feature extraction

Human Traits	Features	Method of Feature Extraction/References
Iris	Iris texture	Iris extraction: Hough Transform, [57] and Integro-differential Operator, [58] Pupil boundary detection: morphological operations and two-directional scanning method, [45]. Limbus boundary detection: Hough transform, [45] Eyelid detection: refine-connect-extend-smooth (R-C-E-S), [38] Iris Coding: Gabor filter with near-horizontal orientation by [59], Binary Pattern (LBP) and Local Phase Quantization (LPQ) by [69] and wavelet by [70]. Gabor Filter with near-horizontal orientations by [59].
Finger Vein	Coded finger vein net	LBP, CLBP and LDP by 40,53] Histogram concatenation of LBP images by [54]
Fingerprints	Minutia points: Bifurcations, ridge endings islands, core and delta.	Extraction of minutia points: Wavelet + pseudo-Zernike moments (PZMs) by [71], thinning + Crossing Number CN by [42] and Gabor filter by [41].
Face	Face landmarks and outlines such as shape, size of mouth and nose, locations of eyes, nose and eyebrows	Detection of face landmarks: Active Shape Model (ASM) and the Active Appearance Model (AAM) by [61], Gabor filter and PSO by [62] and PCA information to verify face candidates and detection of Area-Of -Interest (AOI) + automatic thresholding and morphological opening to discard non-facial feature pixels, [43]. Also, Local Binary Patterns (LBP) was used by [63]
Voice	Voice characteristic s (Voiceprint).	Linear Prediction Coefficients (LPC),), Line Spectral Frequencies (LSF), Discrete Wavelet Transform (DWT), Mel Frequency Cepstral Coefficients (MFCCs), [64]
Signature	1. Static features 2. Dynamic features:	Wavelet transform, discrete Radon and Fourier transforms, [67], Wavelet transform by [72-74], Contourlet transform by [30], Gabor wavelet transform by [75], Discrete Radon transform by [76,77] and Fourier transform by [74].

D. Enrollment

Enrollment is a mode where the coded features are stored in the system to be used in the testing mode. However, when deep learning approach is used, the system needs to be trained and the features are extracted most often inclusively. The most recent method of deep learning approach is the Convolutional Neural Network (CNN). However, the use of CNN must be done with some considerations related to the selection of the network layers and the hyperparameters, which have significant impact on the performance of the system. A proper selection may prevent the problems of overfitting and underfitting, [78]. Also, the optimization method is another important key in improving the CNN performance, [79].

E. Classification and Matching

This stage is implemented in testing mode. In this stage, a comparison is done between the coded features of the test image and the templates of the enrolled features. When the system is designed for person authentication, the features of tested trait is compared to all of the enrolled data (one-to-all comparison) and the decision is made by taking the trait with highest match as the identified trait. When the system is designed for verification, the features of tested trait is compared only to those of the claimed person (one-to-one comparison) to verify if the user claim is correct or not. For iris, Hamming Distance is the most common measure for iris classification, [44,57,58]. Recently the approach of Convolutional Neural networks (CNNs) has been used, [80,81]. In finger vein recognition, Hamming Distance (HD), Phase Only Correlation (POC) and Histogram Difference have been used [40,52,53] as matching measures. In addition, the approach of CNN has been used recently, [82-84]. For fingerprint recognition, K-Nearest Neighbor Minutiae Clustering is used, [85], See [86] for a comprehensive study on fingerprints matching algorithms. For face recognition, [61,87] used deep learning approach such as the convolutional neural network (CNN). Shih and others, [43] performed the SVM classification on the AOI of eyes and mouths. In addition, other methods were used for the Face Recognition such as Karhunen-Love transform, [88] which is known as Principal Component Analysis (PCA), and eigenface vector technique was used by [89]. In voice recognition, the speaker talks to the program which will analyze the voice and compare it to the enrolled data using either the template matching approach or feature analysis approach, [90]. Voice recognition could be speaker dependent or speaker independent. In speaker dependent system, the speaker talks to the program and the program analyze the voice and compare it to the enrolled data. Speaker independent system does not require training to analyze the voice. The most popular recognition models are vector quantization (VQ), dynamic time warping (DTW), and artificial neural network (ANN) [91]. In addition, a hybrid framework based on hidden Markov models and K-nearest neighbors was used by [92]. For signature recognition, several classifiers have been used such as Templet Matching by [26], Artificial Neural Networks, Support Vector Machine by [68], Hidden Markov Models by [93], K-Nearest Neighbour by [77], Deep learning algorithm [35] and Gaussian Mixture Model by [Sanda, and Amirisetti, 2017 94]. Table 5 shows the most common measures used for matching for each of the six biometric traits selected in this paper.

Table 5 Methods of classification and matching

Human Traits	Preprocessing Methods and [References]
Iris	Hamming Distance, [44; 57,58] Classifier: Convolutional Neural networks (CNNs), [80,81]
Finger Vein	Matching measure: Hamming Distance, [40], Phase Only Correlation, [52] and Histogram difference [53], CNN, [82-84]
Fingerprints	Artificial Neural Networks with Back-propagation on minutia template, [42] and K-Nearest Neighbor Minutiae Clustering, [85]
Face	Support Vector Machine, [43], deep learning algorithms, [61,87], Karhunen-Love transform, [88], eigenface vector, [89]
Voice	Support Vector Machine and multilayer perceptron by [63], Template matching approach by [90], artificial neural network, [91], Hybrid framework based on hidden Markov models and K-nearest neighbors, [92]
Signature	Templet Matching, [26], Artificial Neural Networks and Support Vector Machine, [68], Hidden Markov Models, [93], K-Nearest Neighbor, [77], Deep learning algorithm, [35] and Gaussian Mixture Model, [94]

IV. Evaluation of pattern recognition systems

There are several criteria upon which the evaluation of biometric recognition system can be done. These criteria are: system performance, application area, strength and weakness, etc. System performance is derived from some criteria such as True Acceptance Rate (TAR), False Acceptance Rate (FAR), True Rejection Rate (TRR) and False Rejection Rate (FRR), which can be used to provide the ROC curves of the system. The best performance is achieved when FAR equal FRR, that is when ERR is minimum. Also, the areas for which the system is used, is another important criterion when evaluating the system. Some areas do not need high security, so a very high performance may not be necessary and the system could be made cheaper in term of software. In addition, some human traits have some strength points over other human traits. For example, iris is more stable and secure compared to other traits such as face and fingerprints. Table 6 shows the evaluation of biometric recognition systems for the six traits. According to this table, iris recognition system is the best since it provides better accuracy and it is more secure and therefore it can be used for the applications that require high security.

V. Conclusion

A In this paper, a review of the Human biometrics systems based on iris, finger vein, fingerprints, face, voice and signature has been made. The major advantages and disadvantages of each of them were presented and summarized in tables. In addition, the most common techniques and algorithms for the various stages of them were given. Finally, an evaluation table, which shows the performance and limitation of each of these traits was given. According to this table, iris and finger vein are the most effective traits since they provide highest accuracy, and at the same time they are difficult to be replicated, despite they are expensive and may encounter resistance from the users. Thus, the paper is useful in finding gaps in the research and giving room for improvement.

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Table 6 Evaluations of the biometric recognition systems for the four physiological traits

Human Traits	Application Areas	Advantages	Drawbacks
Iris	1. Border Checking 2. Government Offices 3. Banking security	1. Provides high accuracy 2. Difficult to be replicated	1. Expensive in term of speed and processing Methods 2. Encounter resistance from the user.
Finger Vein	1. Border Checking 2. Government Offices 3. Banking security	1. Provides high accuracy 2. Difficult to be replicated	Expensive in term of speed and processing methods.
Fingerprints	1. Forensic 2. Border Checking 3. Government initiatives such as national ID, voter registration, passport. Banking security	1. Provides medium accuracy 2. Very Familiar, acceptable, cheap and easy to use	Easy to replicate and spoof and wear away with age
Face	1. Forensic 2. Border Checking.	1. Provides medium accuracy 2. Very Familiar, acceptable, cheap and easy to use 3. The identification can be performed from a distance and can be used in static (image) and	1. Requires well lighting conditions. 2. The face of a person changes over time 3. Facial expressions and sunglasses may affect the accuracy.

		dynamic (video) applications .	

Table 7 Evaluations of the biometric recognition systems for the two behavioral traits

Human Traits	Application Areas	Advantages	Drawbacks
Voice	1. Forensic 2. Telephone services.	1. Provides medium accuracy 2. Inexpensive and require less hardware. 3. *Easy to use as well as no special instructions are needed.*	1. The voice quality is very sensitive to noisy environments. 2. The emotional and health conditions of the users affect the voice. 3. *The size of the voice database is large and it can impact the matching speed.*
Signature	1. Government Offices 2. Banking security 3. business validation for transaction contracts and agreements	1. Difficult to mimic the behavioral patterns which are inherent in the process of signing 2. Noninvasive, and user-friendly.	1. Provides low to medium accuracy 2. It has large intra class variability 3. Not stable over time. 4. Affected by user health, position 5. Affected by environmental conditions such as writing surface and writing pen 6. Language dependent,

REFERENCES

[1] G. Kaur, and C. K. Verma, “Comparative Analysis of Biometric Modalities”, International Journal of Advanced Research in Computer Science and Software Engineering, Vol. 4, issue 4, 2014, pp. 603-613.

[2] D. Fronitasari, Basari, and D. Gunawan,” Palm Vein Feature Extraction Method by Using Optimized DVH Local Binary Pattern”, International Journal of Computer Science and Information Security (IJCSIS), Vol. 17, No. 5, 2019, pp. 8-12.

[3] T. Sabhanayagam, V. P. Venkatesan, and K. Senthamaraikannan, “A Comprehensive Survey on Various Biometric Systems”, International Journal of Applied Engineering Research, Vol. 13, No. 5, 2018, pp. 2276-2297

[4] A. Achban, J. Y. Sari, and Sutardi, “The Implementation of Local Binary Patterns for Biometrics System Based on Dorsal Hand Vein Image “, Indonesian Journal of Information Technology, online ISSN 2599-295, Vol. 2, Issue 2, 2018, Pag. 18-26.

[5] C. B. Tatepamulwar, and V. P. Pawar, “Comparison of Biometric Trends Based on Different Criteria”, Asian Journal of Management Sciences Vol. 2, No. 3, Special Issue, 2014, Pp. 159-165.

[6] J. Galbally, S. Marcel, and J. Fierrez, “Image Quality Assessment for Fake Biometric Detection: Application to Iris, Fingerprint, and Face Recognition”, IEEE Transactions on Image Processing, Vol. 23, No. 2, 2014, pp. 710-724.

[7] H. Srivastava, “A Comparison Based Study on Biometrics for Human Recognition”, Journal of Computer Engineering, Vol. 15, Issue 1, 2013, pp. 22-29.

[8] M. Guermoui and M. L. Mekhalfi, “A sparse representation of complete local binary pattern histogram for human face recognition”, 2016 pp. 1–4, arXiv:org/abs/1605.09584v1.

[9] M. Sarfraz and N. Alfialy, “Introductory Chapter: On Biometrics with Iris”, Recent Advances in Biometrics, IntechOpen, edited by Muhammad Sarfraz, OPEN ACCESS PEER-REVIEWED CHAPTER, 2022, pp. 1-22, doi:10.5772/intechopen.105134.

[10] M. Sharma and H. Elmiligi, “Behavioral Biometrics: Past, Present and Future”, Recent Advances in Biometrics”, IntechOpen, edited by Muhammad Sarfraz, OPEN ACCESS PEER-REVIEWED CHAPTER, 2022, pp. 1-20, doi:10.5772/intechopen.102841.

[11] J. Phillips, K. Bowyer, W. Transactions, and P. J. Flynn, “Comments on The CASIA Version 1.0 Iris Data Set”, IEEE on Pattern Analysis and Machine Intelligence, Vol. 29, No. 10, 2007, pp. 1869-1870.

[12] R. Saini., and N. Rana, “Comparison Of Various Biometric Methods”, International Journal of Advances in Science and Technology (IJAST) Vol. 2, Issue 1, 2014, pp. 24-30.

[13] C. Otti, “Comparison of Biometric Identification Methods”, 11th IEEE International Symposium on Applied Computational Intelligence and Informatics, May 12-14, 2016, Timişoara, Romania, pp. 339-344.

[14] P. Sareen, “Biometrics – Introduction, Characteristics, Basic technique, its Types and Various Performance Measures”, International Journal of Emerging Research in Management &Technology, Vol. 3, Issue 4, 2014, pp. 109-119.

[15] Yadav A. K., and S. K. Grewal, “A Comparative Study of Different Biometric Technologies”, IJCSC, Vol. 5, No. 1, 2014, pp. 37-42.

[16] K. Mali, and S. Bhattacharya, “Comparative Study of Different Biometric Features”, International Journal of Advanced Research in Computer and Communication Engineering, Vol. 2, Issue 7, 2013, pp. 2776-2784.

[17] Y. Yin, L. Liu, and X. Sun, “SDUMLA-HMT: A multimodal Biometric Database’, In Biometric Recognition by (Sun, Z., L., J., Chen, X., Tan, T. (Eds.)), Springer Berlin Heidelberg, 2011, pp. 260-268.

[18] M. Vanoni, P. Tome, L. El Shafey, and S. Marcel, “Cross-Database Evaluation Using an Open Finger-vein Sensor”, IEEE Workshop on Biometric Measurements and Systems for Security and Medical Applications (BIOMS) Proceedings, Rome, 2014, pp. 30-35.

[19] Y. Lu, S. J. Xie, S. Yoon, Z. Wang, and D. S. Park, “An Available Database for the Research of Finger-vein Recognition”, the 6th International Congress on Image and Signal Processing, 2013, pp. 410-415.

[20] H. Proença, L. A. Alexandre, “UBIRIS: A Noisy Iris Image Database”, In: Roli, F., Vitulano, S. (eds) Image Analysis and Processing – ICIAP 2005. ICIAP 2005. Lecture Notes in Computer Science, Vol 3617, 2005, Springer, Berlin, Heidelberg, pp. 970-977, https://doi.org/10.1007/11553595_119.

[21] H. Proença, S. Filipe, R. Santos, J. Oliveira, and L. A. Alexandre, “The UBIRIS.v2: a database of visible wavelength images captured on-the-move and at-a-distance”, IEEE Trans Pattern Anal Mach Intell 32(8), 2010, pp. 1529–1535.

[22] A. Kumar and Y. Zhou, “Human identification using finger images,” IEEE Transactions on Image Processing, Vol. 21, No. 4, pp. 2228–2244, 2012.

[23] CASIA-Fingerprints, “Note on CASIA-FingerprintV6”, 2023, pp. 1-70, http://biometrics.idealtest.org/downloadDB.do?id=?#/datasetDetail/7, Visiting date: 01/30/2023.

[24] E. Fedorov, T. Utkina, and T. Neskorodeva, ”A Voice Signal Filtering Methods for Speaker Biometric Identification”, Books: Recent Advances in Biometrics, IntchOpen, edited by Muhammad Sarfraz, OPEN ACCESS PEER-REVIEWED CHAPTER , 2022, pp. 1-29, doi: 10.5772/intechopen.101975.

[25] Y. M. Al-Omari, S. N. H. S. Abdullah, and K. Omar, “State-Of-The-Art In Offline Signature Verification System”, International Conference on Pattern Analysis And Intelligence Robotics (Vol. 1, 2011, pp. 59-64). Ieee.

[26] N. H. Al-Banhawy, H. Mohsen, N. I. Ghali, “Signature identification and verification systems: a comparative study on the online and

offline techniques", Future Computing and Informatics Journal, Vol. 5, issue 1, 2020, pp. 28-45.
[27] R. Tolosana, R. Vera-Rodriguez et al., "SVC-onGoing: Signature Verification Competition", Pattern Recognition Vol. 127, No. 5:108609, 2022, pp. 1-14, http://dx.doi.org/10.1016/j.patcog.2022.108609.
[28] M. H. Sigari, M. R. Pourshahabi, and H. R. Pourreza, "Offline Handwritten Signature Identification and Verification Using Multi-Resolution Gabor Wavelet", International Journal of Biometrics and Bioinformatics, Vol. 5, No. 4, 2011, pp. 234-248.
[29] R. Kumar, J. D. Sharma, and B. Chanda, "Writer-Independent Off-Line Signature Verification Using Surroundedness Feature", Pattern Recognition Letters, Vol. 33, No. 3, 2012, pp. 301-308.
[30] S. Sthapak, M. Khopade, and C. Kashid, "Artificial Neural Network Based Signature Recognition & Verification", International Journal of Emerging Technology and Advanced Engineering, Vol. 2, No. 8, 2013, pp. 191-197.
[31] P. Babita, "Online Signature Recognition Using Neural Network", Journal Of Electrical & Electronics, Vol. 4, No. 3, 2015, pp. 1-5, doi: 10.4172/2332-0796.1000155.
[32] Z. Chen, X. Xia, and F. Luan, "August). Automatic Online Signature Verification Based on Dynamic Function Features", In 2016 7th Ieee International Conference on Software Engineering and Service Science (Icsess), pp. 964-968, Ieee.
[33] S. Dey, A. Dutta, J. I. Toledo, S. K. Ghosh, J. Lladós, and U. Pal, "Signet: Convolutional Siamese Network for Writer Independent Offline Signature Verification", Arxiv Preprint 2017, Arxiv:1707.02131.
[34] S. Kurnaz, and A. Al-Khdhairi, "Offline Signature Identification System to Retrieve Personal Information from Cloud." Journal of Computer Engineering (IOSR-JCE), Volume 20, Issue 1, 2018, pp 56-64.
[35] N. Çalik, O. C. Kurban, A. R. Yilmaz, T. Yildirim, and L. D. Ata, "Large-Scale Offline Signature Recognition Via Deep Neural Networks and Feature Embedding", Neurocomputing, Vol. 359, 2019, pp. 1-14, https://doi.org/10.1016/j.neucom.2019.03.027.
[36] A. AK. Tahir, and A. I. Bindian, "Localizarea Irisului Pentru Sistemul Biometric De Identificare A Ersoanelor", The XVIII International Conference on Multidisciplinary, "Professor Dorin Paul - Romanian hydropower founder", June-2016 vol. 30/2016, AGIR Edition, ISSN 2067-7138, pp. 215-224. (Conference Proceedings in Romainan and English Languages).
[37] A. AK. Tahir, and S. Anghelus, "A New Method of Eyelid Detection for Iris Recognition System", The XVIII International Conference on Multidisciplinary, "Professor Dorin Paul - Romanian hydropower founder", June-2018, Cluj, Romania, Vol. 33/2018, ISSN 2067-7138, e-ISSN 2359-828X, 2018, pp. 171-184.
[38] A. AK. Tahir, and S. Anghelus, "An accurate and fast method for eyelid detection" International Journal of Biometrics (IJBM), Vol. 12, No. 2, 2020, pp. 163-178, doi: 10.1504/IJBM.2020.107715.
[39] S. Brindha, "Finger-vein recognition", International Research Journal of Engineering and Technology (IRJET), Vol. 4, No. 4, 2017, pp. 1298-1300.
[40] A. A. Mustafa, and A. AK. Tahir, "Improving the Performance of Finger vein Recognition System Using a New Scheme of Modified Preprocessing Methods", Academic Journal of Nawroz University (AJNU), Vol. 9, No. 3, 2020, pp. 397-409, https://doi.org/10.25007/ajnu.v9n3a855.
[41] R. Bansal, P. Sehgal and P. Bedi "Minutiae Extraction from Fingerprint Images - a Review" IJCSI International Journal of Computer Science Issues, Vol. 8, Issue 5, No 3, 2011, pp. 74-85
[42] S. A. Mahmood and A. I. Melhum "An Authentication System Using Fingerprint Minutiae Extraction and Neural Network", Journal of Al-Nahrain University, Vol.13, No. 4, 2010, pp.216-220
[43] F. Y. Shih, S. Cheng and C. Chuang, "Extracting Faces and Facial Features from Color Images", International Journal of Pattern Recognition and Artificial Intelligence, Vol. 22, No. 3, 2008, pp. 515–534.
[44] A. AK. Tahir, S. S. Dawood and S. Anghelus, "An Iris Recognition System Based on A New Method of Iris Localization, International Journal of Open Information Technologies, Vol. 9, No. 7, 2021, pp. 67-76.
[45] W. Chen, K. Chih, S. Shih, and C. Hsieh, "Personal identification technique based on human iris recognition with wavelet transform", Proceedings of the IEEE International Conference on Acoustics, Speech, and Signal Processing, (ICASSP '05), 2005, pp.949–952.
[46] X. Liu, K. W. Bowyer, and P. J. Flynn, "Experiments with an improved iris segmentation algorithm", Proceedings of the Fourth IEEE Workshop on Automatic Identification Advanced Technologies, Buffalo, NY, USA, AutoID 2005, pp.118–123.
[47] Z. He, T. Tan, Z. Sun, and X. Qiu, "Robust eyelid, eyelash and shadow localization for iris recognition", Proceedings of the 15th IEEE International Conference on Image Processing, (ICIP), 2008, pp.265–268.
[48] T. Tan, Z. He, and Z. Sun, "Efficient and robust segmentation of noisy iris images for non-cooperative iris recognition", Image and Vision Computing, Vol. 28, No. 2, 2010, pp.223–230.
[49] H. Rai, and A. Yadav, "Iris recognition using combined support vector machine and hamming distance approach", Expert Systems with Applications, Vol. 41, No. 2, 2013, pp.588–593, Elsevier.
[50] F. He, Y. Liu, X. Zhu, C. Huang, Y. Han, and H. Dong, "Multiple local feature representations and their fusion based on an SVR model for iris recognition using optimized Gabor filters", EURASIP Journal on Advances in Signal Processing, 2014, doi: 10.1186/1687-6180-2014-95.
[51] A. M. Wagh, and S. R. Todmal, "Eyelids, eyelashes detection algorithm and Hough transform method for noise removal in iris recognition", International Journal of Computer Applications, Vol. 112, No. 3, 2015, pp.28–31.
[52] A. A. Mustafa and A. AK. Tahir, A new finger-vein recognition system using the complete local binary pattern and the phase only correlation, Int. J. Adv. Sig. Img. Sci., Vol. 7, No. 1, 2021, pp. 38-56, https://doi.org/10.29284/ijasis.7.1.2021.38-56.
[53] A. AK. Tahir and A. A. Mustafa, "Improving the Performance of Finger Vein Recognition Using the Local Histogram Concatenation of Image Descriptors", International Journal of Pattern Recognition and Artificial Intelligence (IJPRAI), Vol. 36, No. 14, 2022, pp. 2256020-1-2256020-22, doi: 10.1142/S0218001422560201.
[54] G.A. Bahgat, A.H. Khalil, N.S. Abdel Kader, S. Mashali, "Fast and accurate algorithm for core point detection in fingerprint images", Egyptian Informatics Journal, Volume 14, Issue 1, 2013, pp. 15-25, doi: https://doi.org/10.1016/j.eij.2013.01.002.
[55] E. N. Zois, D. Tsourounis, I. Theodorakopoulos, A. L. Kesidis, and G. Economou, "A Comprehensive Study of Sparse Representation Techniques for Offline Signature Verification", IEEE Transactions on Biometrics, Behavior, and Identity Science, Vol. 1, No. 1, 2019, pp. 68–81. https://doi.org/10.1109/TBIOM.2019.2897802
[56] R. P. Wildes, "Iris Recognition: An Emerging Biometric Technology", Proceedings of the IEEE, Vol. 85, No. 9, 1997, pp. 1348-1363.
[57] J. Daugman, "New Methods in Iris Recognition," IEEE Transactions on Systems, Man, And Cybernetics—Part B: Cybernetics, Vol. 37, No. 5, 2007, pp. 1167-1175.
[58] A. AK. Tahir and S. Anghelus, "Improving iris recognition accuracy using Gabor kernels with near-horizontal orientations", Int. J. Adv. Sig. Img. Sci., Vol. 8, No. 1, 2022, pp. 25–39, https://doi.org/10.29284/ijasis.8.1.2022.25-39.
[59] KR. Moses, P. Higgins, M. McCabe, S. Prabhakar, and S. Swann, "Automated Fingerprint Identification System (AFIS)", In: McRoberts A, editor. The Fingerprint Sourcebook. Washington, DC, USA: U.S. Department of Justice, National Institute of Justice; 2011. pp. 1–33.
[60] M. Iqtait, F. S. Mohamad, M. Mamat, "Feature extraction for face recognition via Active Shape Model (ASM) and Active Appearance Model (AAM)", IOP Conf. Series: Materials Science and Engineering Vol. 332: 012032, 2018, doi:10.1088/1757-899X/332/1/012032.
[61] S. Ahmed, M. Frikha, T. D. H. Hussein, and J. Rahebi, "Optimum Feature Selection with Particle Swarm Optimization to Face recognition System Using Gabor Wavelet Transform and Deep Learning", BioMed Research International, Vol. 2021, Article ID 6621540, 2021, pp. 1-13, https://doi.org/10.1155/2021/6621540.
[62] O. Tadmor, Y.Wexler, T. Rosenwein, S. Shalev-Shwartz, and A. Shashua, "Learning a metric embedding for face recognition using the multibatch method," arXiv preprint 2016, arXiv:1605.07270
[63] O. Mamyrbayev, N. Mekebayev, M. Turdalyuly, N. T. Oshanova, T. I. Medeni, and A. Yessentay, "Voice Identification Using Classification Algorithms", Intelligent System and Computing, Yang Yi Ed. IntechOpen,2020 doi:10.5772/intechopen.88239.
[64] M. Saleem and B. Kovari, "Online signature verification based on signer dependent sampling frequency and dynamic time warping," in Proceedings of the 2020 7th International Conference on Soft

Computing & Machine Intelligence (ISCMI), pp. 182–186, Stockholm, Sweden, November 2020.
[65] Y. Zhou, J. Zheng, H. Hu, and Y. Wang, “Handwritten signature verification method based on improved combined features”, Applied Sciences, Vol. 11, 5867, 2021, pp. 1-14, https://doi.org/ 10.3390/app11135867.
[66] M. Fayyaz, M. H. Saffar, M. Sabokrou, M. Hoseini, and M. Fathy, “Online signature verification based on feature representation”, Proceedings of the International Symposium on Artificial Intelligence and Signal Processing (AISP), 2015, pp. 211–216, Mashhad, Iran, March 2015.
[67] A. Beresneva, A. Epishkina, and D. Shingalova, “Handwritten signature attributes for its verification,” in Proceedings of the 2018 IEEE Conference of Russian Young Researchers in Electrical and Electronic Engineering (EIConRus), pp. 1477–1480, Petersburg, Russia, January 2018.
[68] Z. Hashim, H. M. Ahmed, and A. H. Alkhayyat, “A Comparative Study among Handwritten Signature Verification Methods Using Machine Learning Techniques”, Scientific Programming Volume 2022, Article ID 8170424, 2022, pp. 1-17, https://doi.org/10.1155/2022/8170424.
[69] M. B. Ashwini, I. Mohammad and A. Fawaz, “Evaluation of Iris Recognition System on Multiple Feature Extraction Algorithms and its Combinations”, International Journal of Computer Applications Technology and Research, Vol. 4, No. 8, 2015, pp. 592 – 598.
[70] S. Salve, “Iris Recognition Using Wavelet Transform and SVM Based Approach”, Asian Journal of Convergence in Technology, Vol. V, No. I, 2019, pp. 1-9.
[71] A. Pokhriyal, and S. Lehri, “A NewMethod of Fingerprint Authentication Using2D Wavelets”, Journal of Theoretical and Applied Information Technology, Vol.13, No.2, 2010, pp.131-138
[72] K. Daqrouq, H. Sweidan, A. Balamesh, and M. Ajour, “Off-Line Handwritten Signature Recognition by Wavelet Entropy and Neural Network”, Vol. 19, No. 6, 2017, pp. 1-20, doi: 10.3390/e19060252.
[73] M. R. Nilchiyan, and R. B. Yusof, “Improved Wavelet-Based Online Signature Verification Scheme Considering Pen Scenario Information”, In 2013 1st International Conference on Artificial Intelligence, Modelling and Simulation, 2013, pp. 8-13, Ieee.
[74] M. Tahir, and M. U. Akram, “Online Signature Verification Using Hybrid Features”. In 2015 Second International Conference on Information Security and Cyber Forensics (Infosec), 2015, pp. 11-16, Ieee.
[75] M. R. Pourshahabi, M. H. Sigari, and H.R. Pourreza, “Offline Handwritten Signature Identification and Verification Using Contourlet Transform”, In 2009 International Conference of Soft Computing and Pattern Recognition, 2009, pp. 670-673, Ieee.
[76] S. Y. Ooi, A. B. J. Teoh, Y. H. Pang, and B. Y. Hiew, “Image-Based Handwritten Signature Verification Using Hybrid Methods of Discrete Radon Transform, Principal Component Analysis and Probabilistic Neural Network”, Applied Soft Computing, Vol. 40, 2016, pp. 274-282, https://doi.org/10.1016/j.asoc.2015.11.039.
[77] A. A. Abdelrahaman, and M. A. Abdallah, “K-Nearest Neighbor Classifier for Signature Verification System”, In 2013 International Conference on Computing, Electrical and Electronic Engineering (ICCEEE), 2013, pp. 58-62, Ieee.
[78] A. I. Mohammed and A. AK. Tahir, A new image classification system using deep convolution neural network and modified AMSGrad optimizer, J. Univ. Duhok Vol. 22, No. 2, 2019 pp. 89–101, https://doi.org/10.26682/sjuod.2019.22.2.10.
[79] A. I. Mohammed and A. AK. Tahir, A new optimizer for image classification using Wide ResNet (WRN), Academic. J. Nawroz University (AJNU), Vol. 9, No. 4, 2020, 1–13, https://doi.org/10.25007/ajnu.v9n4a858.
[80] A.S. Al-Waisy R. Qahwaji S. Ipson, et al., “A multi biometric iris recognition system based on a deep learning approach,” Pattern Analysis and Applications, Vol. 21, Issue. 3, 2017, pp. 783–802, https://doi.org/10.1007/s10044-017-0656-1
[81] Y. W. Lee, K. W. Kim, T. M. Hoang, et al., “Deep Residual CNN-Based Ocular Recognition Based on Rough Pupil Detection in the Images by NIR Camera Senso,” Sensors, Vol. 19, No. 4, 842, 2019, pp. 1-30, https://doi.org/10.3390/s19040842.
[82] H. G. Hong, M. B. Lee and K. R. Park, “Convolutional Neural Network-based finger vein recognition using NIR image”, Sensors Vol. 17, No. 6, 2017, doi: org/10.3390/s17061297.
[83] S. Tang, S. Zhou, W. Kang, Q. Wu, and F. Deng, “Finger vein verification using a Siamese convolutional neural network, IET Biometrics, Vol. 8 Issue. 5, 2019, pp. 306-315, doi: 10.1049/iet-bmt.2018.5245.
[84] R. Das, E.Piciucco, E.Maiorana, and P.Campisi, “Convolutional neural network for finger vein based biometric identification”, in IEEE Trans. Inform. Forensics Sec. Vol. 14, No. 2, 2019, pp. 360–373.
[85] V. Pawar and M. Zaveri, "Graph based K-nearest neighbor minutiae clustering for fingerprint recognition," 2014 10th International Conference on Natural Computation (ICNC), Xiamen, China, 2014, pp. 675-680, doi: 10.1109/ICNC.2014.6975917.
[86] N. Kanjan, K. Patil, S. Ranaware, and P. Sarokte, “A Comparative Study of Fingerprint Matching Algorithms”, International Research Journal of Engineering and Technology (IRJET), Vol. 4, Issue 11, 2017, pp. 1892-1896.
[87] T. H. Fuad, A. A. Fime, D. Sikder, A. R. Iftee, J. Rabbi, M. S. Al-Rakhami, A. Gumaei, O. Sen, M. Fuad, And N. Islam, “Recent Advances in Deep Learning Techniques for Face Recognition”, IEEE Access, Vol.9, 2021, pp. 99112-99142, https://doi.org/10.1109/ACCESS.2021.3096136.
[88] M. Kirby and L. Sirovish, "Application of the Karhunen-Love procedure for the characterization of human faces", IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 12, No. 1, 1990, pp 103-108.
[89] M. Turk and A.P. Pentland, "Eigenfaces for recognition", Journal of Cognitive Neuroscience, Vol. 3, No. 1, 1991, pp 71-86, https://doi.org/10.1162/jocn.1991.3.1.71.
[90] L. Muda, M. Begam, and I. Elamvazuthi, “Voice recognition algorithms using Mel frequency cepstral coefficient (MFCC) and dynamic time warping (DTW) techniques”, ArXiv preprint, 2010, arXiv:1003.4083.
[91] S. Yella, N. Gupta, and M. Dougherty, “Comparison of pattern recognition techniques for the classification of impact acoustic emissions”, Transportation Research Part C: Emerging Technologies, Vol. 15, No. 6, 2007, pp. 345-360.
[92] S. Hazmoune, F. Bougamouza, S. Mazouzi, “A new hybrid framework based on hidden Markov models and K-nearest neighbors for speech recognition”, International Journal of Speech Technology, Vol. 21, No. 3, 2018, pp. 689-704, https://doi.org/10.1007/s10772-018-9535-4.
[93] J. Fierrez, J. Ortega-Garcia, D. Ramos, and J. Gonzalez-Rodriguez,Hmm- “Based On-Line Signature Verification: Feature Extraction and Signature Modeling”, Pattern Recognition Letters, Vol. 28, No. 16, 2007, pp. 2325-2334.
[94] S. Sanda, and S. Amirisetti, “Online Handwritten Signature Verification System: Using Gaussian Mixture Model and Longest Common Sub-Sequences”, Master Thesis, Electrical Engineering, 2017, Pages (40).

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