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A Concise Survey on Biometric Recognition Methods

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Abstract: In this modern era, user authentication has become vital regarding security and privacy in keeping their information and valuables safe. Password or pin-based authentication systems are insufficient to protect the security of individuals. People now anticipate more dependable and secure biometric authentication systems as a result of virtualization in both academics and industry. In this study, we discussed biometrics, various biometric authentication methods, and the work in each biometric system. We summarised and emphasised the significant contribution made by several researchers in this field. Our goal is to present a thorough analysis that may throw light on the important contributions and aid researchers looking to contribute their work to biometrics.

Keywords: Biometric, Feature Extraction, Recognition methods

1. Introduction

People live in a digitalized world where science and technology are advancing quickly. Mostly information was written down centuries ago, so individuals did not have to worry about digital theft or copying when storing it in a safe locker. Thanks to cloud networks and storage devices for this stage of development, information storage and transfer in the modern world have become easier to manage. However, this development has also created an easier way to steal information. Thus, the role of authentication systems acquired increasing focus. These innovations gave rise to unethical methods of information theft, such as password cracking.

In conventional authentication methods, users must remember long passwords and four or six-digit pins to prove their identity. Even though these passwords must meet specific requirements, such as being 6 or 8 characters long and including at least one uppercase, lowercase, number, and symbol there is no assured security from brute force assaults. According to a survey [1], users have trouble remembering these passwords. They use the same password for all of their accounts, endangering the security of the user. In order to tackle these problems, researchers came up with Biometric authentication systems. Biometrics is a field of study that deals with identifying and verifying users using biological data as input. Through feature vectors, biometrics uses a person's physiological or behavioral traits to identify the user. Any application that requires user authentication can make use of biometrics. Multiple biometrics, such as fingerprint, palm, iris, retina, gait, face, odor, voice, and keystroke, have been the subject of significant research to date. Figure 1 describes the biometric systems discussed in this paper.

While each system has advantages and disadvantages, the primary objective is meeting the user's needs. The system typically has four stages: comparison, feature extraction, collection, and recognition. Image data is collected and pre-processed at the collection stage to remove noise from the image. The suitable feature is obtained from the image data and compared to the database's information when extracting features. A decision is taken after analyzing the results of the comparison process. Flowchart 2 shows the general enrollment process and verification of a Biometric Authentication System.

We aim to compile a list of all significant and noteworthy works related to biometric authentication. We presented a visual representation in the form of flowcharts and tabulated the output of each contributor to simplify things. The paper is organized as follows: Section II covers each biometric authentication technology in detail. In Section III, the most recent methods for biometric identification and verification are discussed. Sections IV and V go into great length about the technological features of the various biometric technologies. In Section VI, the paper concludes with a few recommendations for further research.

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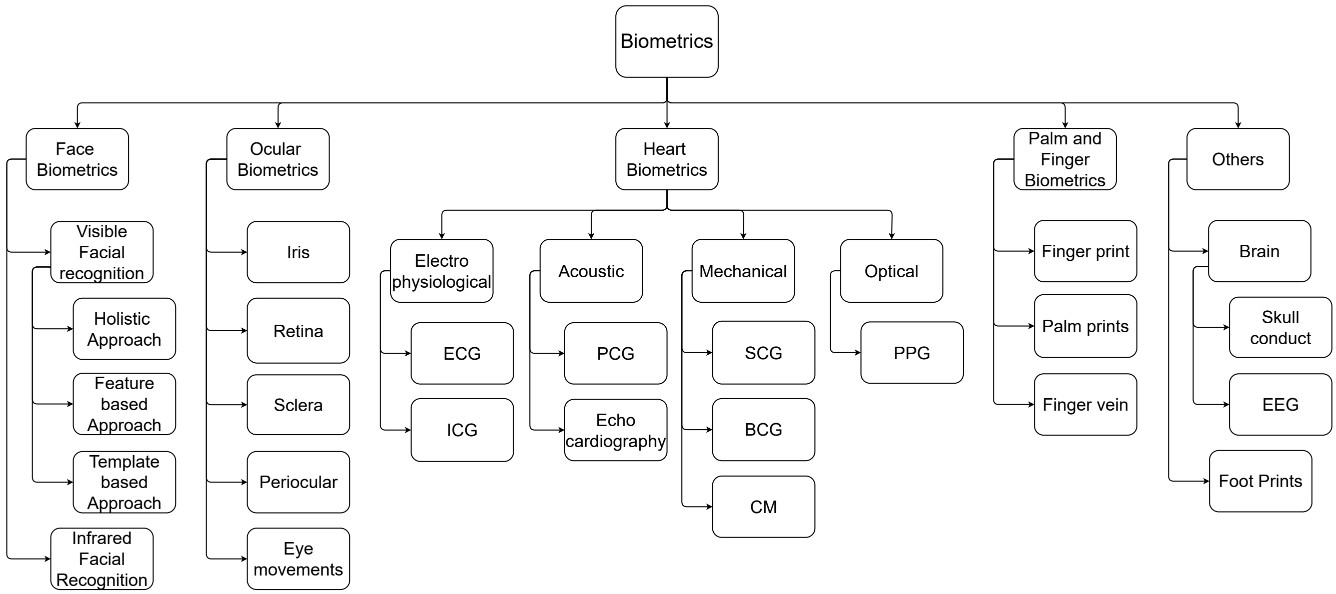

Figure 1. Biometrics

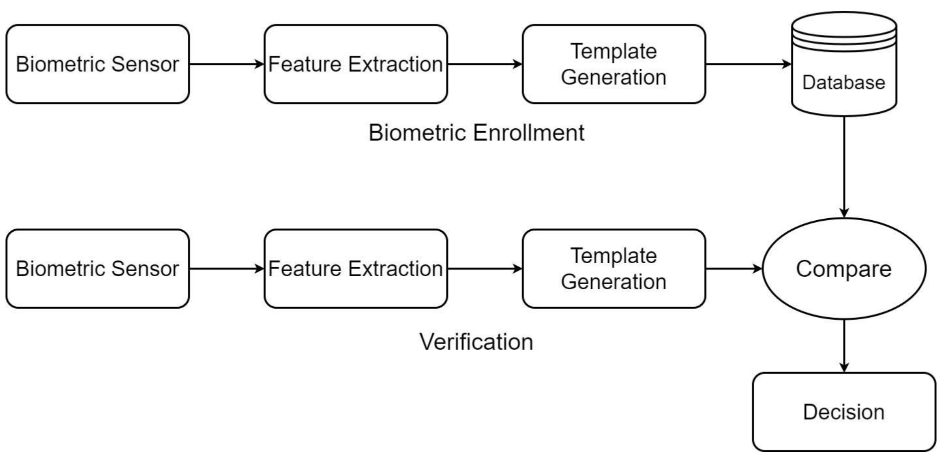

Figure 2. Process of enrolling and authenticating a biometric

2. Biometrics: Types and Techniques

A. *Fingerprint Biometrics and Palm Biometrics*

Fingerprint recognition [2], [3] is a method by identifying a person by correlating the supplied fingerprint data to the database's recorded fingerprint data. A fingerprint is an impression or pattern that appears on the fingertips of humans that can be analyzed. This pattern does not change over time (until any physical disorder like an accident or any disease occurs). Due to its numerous advantages, fingerprint authentication has grabbed the curiosity of numerous researchers in recent years, which led to the rise of state-of-the-art fingerprint recognition technologies. One of the most significant advantages is that the legal community widely accepts it. It is speedy and versatile, with good identification accuracy and a low error rate.

Fingerprint recognition is one of the most versatile and studied biometric systems. Fingerprints are unique for person to person, but they can be categorized based on their pattern similarity [4], [5], [6].

There are three main types of fingerprint patterns.

1) Arches

   Arches are a design in which the ridges go from one side to the other without rotating. Plain Arch, Ulnar Arch, and Radical Arch are some important Arch patterns.

2) Loops

   Loops are patterns consisting of ridges that go towards inside and return in line with the center. The different types of Loops are as follows. Plain loop, Lateral

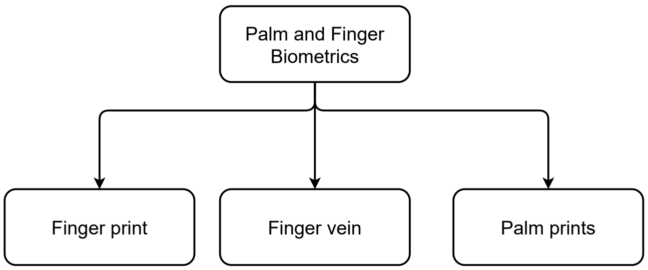

Figure 3. Various categories of Finger and Palm Biometrics

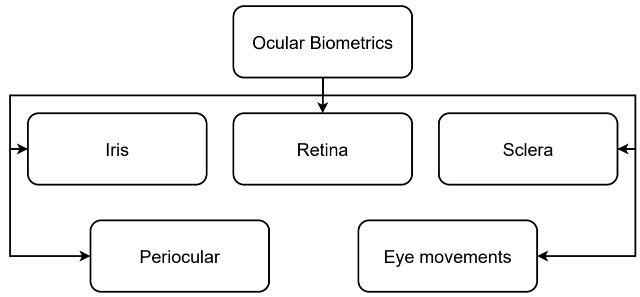

Figure 4. Various categories of Ocular Biometrics

Pocket loop, Twinned loop, and Central pocket loop.

3) Whorls

Whorls are patterns in which the ridges create a circular shape around a center point. Plain, Accidental, Central pocket loop, and Double pocket loop whorls are some of the important whorls.

Furthermore, Palm recognition [7] is more similar to fingerprint recognition. In Palm recognition, the line patterns of the palm, as well as wrinkles and ridges, are unique; Principle lines remain the same over a lifetime. Further, this data can be easily extracted even from low-resolution images [8].

A finger vein authentication system has many advantages. The finger vein recognition system takes FV's (Finger vein's) pattern into account for vein recognition [9] of veins present inside the finger are taken as an attribute in this technology. Because these patterns are different (even amongst identical twins), permanent, and secure because they are difficult to copy, it is user-friendly [10].

Figure 3 shows the Palm and Finger Biometrics we incorporated.

B. *Ocular Biometrics*

Ocular biometrics is a subcategory in biometrics that uses eye features for authentication. It is one of the practically implemented biometric authentication systems. Features such as the iris, retina, sclera, periocular, and eye movement are employed to identify a person. Figure 4 lists several kinds of ocular biometrics. Numerous studies on ocular biometrics have been conducted throughout history. A tremendous amount of study has been done on ocular biometrics. This study clearly grasped the method and uses of ocular biometrics. J Daugman [11] discussed new methods in iris recognition. Various biometric methods have been enhanced from time to time. In this context, iris biometrics comes to light as it provides robust biometric criteria.

In Ocular Biometrics, the iris and retina quickly became the topic of attention. In contrast to the iris and retina, other ocular biometrics require further research and development. Iris is a secured interior organ protected by an outer layer called the cornea. The iris was acknowledged for the first time as a method of identification in 1953 in F.H. Adler's book Physiology of the Eye [12]. The retina is a thin layer of cells located at the backside of the eyeball. Photoreceptors help convert light into nerve signals, and each eye has its solitary specimen of blood vessels. This uniqueness of the blood vessel pattern is the key for retina recognition. For personal identification, Retinal vessel images are used [13]. The general process of most ocular biometrics includes recognition, feature extraction, segmentation, normalization, encoding, and matching [14].

Ocular biometrics provide robust security, widely used in banks, commercial spaces, and even space agencies to provide a secure environment. Compared to other biometrics, Ocular biometrics has fewer chances of spoofing and works as secure biometrics. Iris, retina, and Sclera patterns differ from person to person, even between two eyes of the same person, making them Unique.

C. *Facial Recognition*

Facial Recognition is the most used and safer means of authentication, as it avoids the interaction with sensors and scanners. It is a well-known method of authenticating a person by matching their current visual data with those in a database that was enrolled before. Fundamentally, Holistic, Feature-based, and Template-Based are the three primary methods for accomplishing Visible Face Recognition. Figure 5 depicts the various facial recognition strategies discussed in this paper.

The complete face data is considered as input to identify a person in the holistic approach accurately. Face features, including the eyes, nose, and mouth, are used in feature-based techniques to identify individuals. This method involves initially training the collection of samples. In the Geometric Face Based Approach, the placement of characteristics in the image and an analysis of the distances and angles between these positions of facial features [15] are utilized to identify an individual using this training dataset.

The template-based technique is built on a collection of templates that are stored in the database. The majority of the undesirable facial area is ignored while making a template. As a result, registering a template uses less memory space.

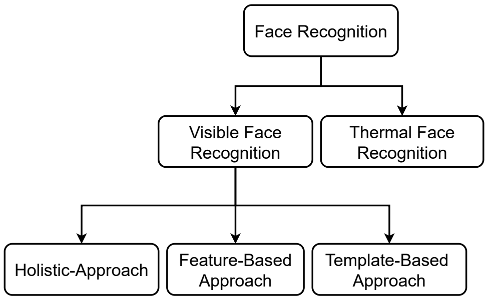

Figure 5. Various categories of Facial Biometrics

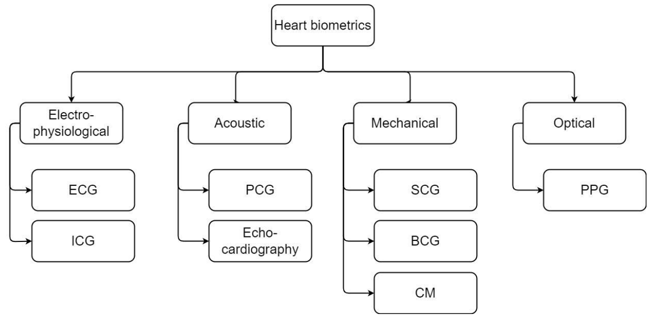

Figure 6. Various categories of Heart Biometrics

To improve performance matching with templates, extra curves are added to the curves generated using fundamental curve characteristics. A vision module can scan the face and make a template of it to determine the face's distinguishing characteristics. Once a template has been developed, it is evaluated to determine whether it matches any of the ones already in use. Template-based methods can tolerate picture distortions. This method can manage alignment changes (with in-plane facial rotation up to 55 degrees), and function under a variety of illumination settings [15]. 3-Dimensional face recognition can withstand and overcome the limitations of 2-Dimensional face recognition that are brought on by external factors like illumination, posture, and facial expressions. A 2-Dimensional intensity picture is combined and used to depict the contour of a face during recognition. These two-dimensional intensity pictures can be used to assess faces [16], [17].

Some well-known and essential techniques used in these approaches are SIFT, LBP (which is discussed in Sub Section 4-E), Gabor Wavelet Technic [18], PCA, and LDA (which is discussed in Sub Section 4-C).

D. Other important Biometrics

Biometrics based on brain (EEG) (which is discussed in Sub Section 5-D) and heart (ECG) signals have recently become popular. Everyone possesses unique heart features that differ by size, position, or anatomy. Heart biometrics, mainly rely on non-invasively monitored cardiac signals such as electrocardiograms (ECG), photoplethysmograms (PPG), seismocardiograms (SCG), and phonocardiograms (PCG) [19]. These are depicted in Figure 6. Heart biometrics are prone to a huge decline in performance due to improper sensor alignment.

The key features of heart biometrics are the ability to check the liveness of the subject and the security it provides. Inherent liveness detection assures that the sensing modality can only recognize a living individual, which increases resistance to hostile attacks. Even the liveness detection is available in other biometrics; Heart biometrics is one of the secure biometrics. Traditional biometrics, especially fingerprints, rely on fixed biometric data that can be forged as soon as the adversary has access to the sample. Hence, Cardiac sensors are chosen for constant validation because they can supply a new biometric sample frequently.

However, there are three significant issues in Heart biometrics:

1) Human dynamics (e.g., breathing, body movements) can produce noise in cardiac data and quick variations caused by a dramatic shift in the surroundings. It not only reduces the system's accuracy in detecting cardiovascular data but threatens biometric security by making assaults like Denial-of-Service or DoS attacks.

2) Developing cardiac biometric sensing applications that can collect data cheaply and invisibly while demanding minimal time complexity difficulty during categorization is tough.

3) Cardiac signals can deviate from the biometric template as the body's physiological and psychological condition changes over time.

Biometrics based on the brain are more secure and more rigid to spoof. For instance, plastic molds can be used to mimic fingerprints. When they come into contact with a surface, high-resolution cameras may acquire the biometrics, such as palm and iris prints [20]. These biometrics are simple to fabricate. Because one's fingerprints and iris do not change over time, they cannot be altered. Users will benefit from this in the event of theft. Brain biometrics are taken with the subject's permission and are revocable if required. These are gathered using several technologies and algorithms in different ways.

3. Existing Works

There are multiple evaluation criteria for evaluating the performance of a biometric system. Zhang et al. [21] surveyed biometric authentication methods and stated that the performance of biometric authentication systems is governed by accuracy, efficiency, usability, security, and privacy. Table I gives an overall analysis of the Biometrics reviewed in this survey.

"The accuracy of biometrics can be estimated using the measurement of False acceptance rate (FAR), False rejection rate (FRR), and equal error rate (EER), specified in [22]". False acceptance or False rejection rate is detected

TABLE I. Analysis metrics of the Biometrics reviewed in this paper

Biometric	Accuracy	Efficiency	Usability	Security	Privacy
Fingerprint	Medium	Medium	High	Medium	Medium
Palm	Medium	Medium	High	Medium	Medium
Fingervein	High	Medium	Low	High	High
Iris	High	High	Medium	High	Medium
Retina	High	Medium	Medium	High	Medium
Sclera	High	High	Low	High	Medium
Periocular	Medium	High	Low	Medium	Medium
Eye movements	Medium	Medium	Low	High	Medium
ECG/ICG	High	Medium	Medium	High	High
PCG	Medium	Medium	Low	High	Medium
SCG/BCG	Medium	Medium	Low	Medium	Low
PPG	Medium	High	Medium	Medium	Medium
Brain waves	High	Low	Medium	High	Medium
Foot prints	High	Medium	Medium	High	Medium
Facial (Thermal)	High	Medium	High	Medium	Low
Facial (Infrared)	Medium	Medium	High	Medium	Medium

when authentication issued by the system is false. A receiver operating characteristic curve is the culmination of the verification procedure in producing a biometric system (ROC). An EER is a number derived from the ROC curve where FRR is the same as FAR. Utilizing a "Cumulative Match Characteristic Curve (CMC)" performance in the identification process is determined. Factors like universality, uniqueness, permanence, and acceptability determine the usability of a biometric.

Moreover, a biometric's effectiveness is measured by the time needed for a system to complete a single authentication, which primarily includes the time spent on data collection, data processing, feature extraction, and authentication decision. Resistance of a biometric towards cyber-attacks and spoofing attacks determines its security. If the security of a biometric is low, it is more prone to cyber-attacks and thus to the leakage of private information. Many researchers made contributions in different ways. Some of them overcame the challenges and made discoveries. Table II provides a quick summary of the works mentioned. The leakage of private information is of two types: privacy disclosure in a suitable environment and a network environment. Table III describes the essential criteria for evaluation.

A. Palm and Finger Biometrics

1) Fingerprint

Different practices exist in fingerprint recognition, such as minutiae-based and non-minutiae-based approaches. Non-minutia-based approaches include Ridge-feature-based [26], image-based [25], and Level-3-based methods, including characteristics of intra-ridge information such as breadth, shape, curvature, edge contours, and even sweat pores. Minutia-based approaches [23], [26] include matching local minutia and global minutia. Hybrid approaches [24] use minutia and non-minutia-based approaches to achieve more accuracy and precision.

German et al. [23] suggested an indexing method in fingerprint recognition, by employing three minutiae points as an index, based on the following: lengths between three minutiae points that form a triangle, number of ridges between two minutiae points, and angles of the ridges between two points on the plane. This approach has several drawbacks, including the ridge count varying according to the picture quality. It also discovered that the picture quality affects ridges' angle and texture.

Lim et al. [24] proposed incorporating particular features from the image-based and minutiae-based approaches to improve the matching accuracy of fingerprints with low-quality photos of the fingerprints. For more accurate fingerprint matching, minutiae alignment is performed between the database-stored data and the one that was processed.

Yang et al. [25] developed an improved image-based approach employing tessellated invariant moment characteristics. The improved technique minimized multi-spectral noise by improving the reference point to obtain a more accurate picture. The picture was aligned appropriately when the orientation and location at the point of reference were calculated. They then extracted a collection of moment features (fixed-length) which are invariant to the affine transformation from tessellated cells in the area of interest.

Jain and Ross [26] explored the interoperability of sensors by gathering fingerprints from 160 people using optical and capacitive sensors. They observed a considerable downfall in the performance while evaluating the performance of several sensors in matching algorithms. In the matching fingerprints obtained using an optical sensor with those data gathered using a capacitive device, the inter-device EER was 23.13%.

MCC [67] is an advanced matching algorithm based on minutiae. This method utilizes a 3-Dimensional data structure called a cylinder, which is constructed from a distance between two points and their placement. Translation and rotation of the cylinder structure are invariant and have a constant coding length.

The National Institute of Standards and Technology (NIST) created Bozoroth3, a minutiae-based matching system. This algorithm is rotation and translation invariant. It only matches minutiae based on their positions and orientations.

From Neurotechnology, a matching algorithm based on minutiae points, VeriFinger [68], was proposed. It caught great attention, and it is a popular matching algorithm. Likewise, it is based on minutiae and employs minutiae in conjunction with other features.

2) Palm

Many palmprint recognition studies have been proposed, with investigations focused on three primary methodologies: "line-based", "subspace-based", "statistically-based", and "coding-based approaches".

A technique for extracting line characteristics from palm

TABLE II. Quick Summary of Some Notable works

	Researchers	Work
Hand Biometrics	Borra et al. [2]	Borra et al. in their survey they categorised fingerprint patterns, discussed several crucial techniques for identifying fingerprint patterns, and suggested a number of techniques for enhancing the pattern.
	Harb et al. [7]	Harb et al. proposed a study for recognition is based on the principal lines of the palm print over CASIA and PolyU database using Modified Finite Radon Transform (MFRaT) which gained a good accuracy
	German et al. [23]	German et al. worked on minutiae points and suggested a approach recognition approach, but their approach has many challenges which degraded the performance.
	Lim et al. [24]	Lim et al. used both image based and minutia based approaches for getting better results. They also employed minutia alignment
	Yang et al. [25]	For the purpose of recognising fingerprints, Yang et al. derived a set of fixed length invariant moment features from tessellated invariant properties. Their approach reduced multi-spectral noise
	Ross et al. [26]	Ross et al. suggested a template selection method for fingerprint recognition. They recommended the two methods DEND and MDIST for autonomously selecting a prototype fingerprint template for a finger from a group of fingerprints.
	Pavešić et al. [27]	In order to obtain 0.002% EER, Pavešić et al. employed a Karhunen-Loeve transform-based technique and information fusion. On the basis of thermal photographs of the hand dorsa, they also included an aliveness detecting module.
	Yang et al. [28]	Yang et al. proposed a finger vein recognition method using personalized best bitmap (PBBM)
	Peng et al. [29]	Peng et al. suggested an unique method for identifying finger vein patterns with an EER of 0.46%. They chose parameters with eight orientations using the Gabor filter, and utilised SIFT to correct for rotation and shift throughout the verification process.
	Lee et al. [30]	In their novel finger biometric approach, Lee et al., they achieved an EER of 0.13% by using a modified Gaussian high-pass filter for feature extraction using binarization, LBP, and LDP methods
Eye Biometrics	Seto [13]	Yoichi Seto mainly emphasized the process of enrollment and verification in a retinal scanning system i.e., Acquisition and preprocessing, Feature extracting, format data creation and matching techniques.D
	Verma et al. [14]	Verma et al. performed iris recognition using iris images from CASIA database with help of various Daughman's algorithm methods for segmentation, normalization and then convolved the normalized iris region using 1D log gabor filter.
	Nazmdeh et al. [22]	Nazmdeh et al. provided an overview of iris recognition system iris and also provided comparison between prior works and suggested improvements in various methodologies
	Alam et al. [31]	Alam et al used Daugman Algorithm with CASIA dataset for iris recognition in combination with face recognition and proposed an efficient multimodal biometric system technique
	Das et al. [32]	Different steps in sclera biometric recognition like sclera segmentation, vessel enhancement and image registration, feature extraction and classification are clearly discussed along with datasets available for the performance of sclera biometric recognition
	Khosravi et al. [33]	Drawbacks of Time-adaptive self-organizing map (TASOM) based active contour model algorithm for identifying the boundaries of human eye sclera are investigated and a new method is introduced to overcome these drawbacks.
	Vitek et al. [34]	Vitek et al. introduced a novel dataset called "Sclera Blood Vessels, Periocular and Iris (SBVPI)" to encourage research into sclera biometrics. The unique characteristics of this dataset and extensive investigation into sclera biometric are discussed across the paper.
	Ross et al. [35]	Arun Ross et al. explored how the small regions around the eye can be used as an additional biometric. To make Periocular biometric work they used global and local descriptors for feature extraction and matching.
	Bednarik et al. [36]	Roman Bednarik et al. presented a first step towards using eye-movements as a biometric. They considered the factors like distance between the eyes and potential of eye tracking signal with the help of eye tracking devices.

	Researchers	Work
Facial Biometrics	Bhattacharyya et al. [37]	Bhattacharyya et al. clearly explained how Linear discriminant analysis can be used to identify a face comparing between-class scattered matrix and within-class scattered matrix of an Image.
	Annalakshmi et al. [38]	Annalakshmi et al. developed a method to classify an individual's gender using a SVM classifier. They employed specially enhanced SLBP and HOG as part of their hybrid feature selection and local feature representation approach to enhance the recognition rate.
	Zahraddeen et al. [39]	Sufyana Zahraddeen et al. proposed a new framework namely "ASDCT" which uses anisotropic diffusion illumination normalization technique and DCT in order to tolerate poor illumination of the images
	Huang et al. [40]	Zheng-Hai Huang et al. proposed a method for facial recognition using 2D-DWT and a new patch strategy, which is used to represent the structural features of a face. These patches are further used to compare the testing and trained images.
	Payil et al. [18]	P. R. Police Patil et al. described the various methods to extract facial features and attributes. These extracted features have different kinds of applications
	Archana et al. [15]	T.Archana et al. proposed a template-based approach for face recognition. They compared their approach with the holistic approach and got better results. Moreover, they described that their model can tolerate various factors such as pose and in-plane rotation.
	Lam & Yam [41]	Kin-Man Lam and Hong Yan made a model in which if similar faces are detected, then the face attributes are considered for evaluation at the next stage.
	Bowyer et al. [16]	Kevin W. Bowyer et al. described the various methods which are mainly based on 3D shapes and problems while capturing 3D face images such as spikes and holes in the captured images, effects of projecting coherent light, and accuracy of 3D points
	Zhao et al. [42]	J. Zhao, S. Yan, and J. Feng proposed CAFR dataset which consists of a large number of images considering various factors of a set of individuals. They even built an Age Invariant model which not only overcame the aging factor but also was able to tolerate various conditions.
	Yachen He et al. [43]	Yachen He et al. proposed an approach to authenticate a face using fuzzy commitment system, Honey Pot technology, and cipher encryption algorithms.
	Park et al. [44]	U. Park et al. analyzed the face shape and face appearance separately on a collection of facemodels at different ages by space pattern shape and Texture pattern space.
Other Biometrics	Agrafioti et al. [19]	Agrafioti et al. developed numerous approaches based on techniques, such as autocorrelation and LDA, to deal with the challenges of integrating ECG into biometrics which are resilient to HRV.
	Karimian et al. [20]	Karimian et al. examined the ECG biometric's vulnerability using a methodological mapping function that converts the ECG signal of an attacker to that of a victim.
	Rathore et al. [45]	In their survey, Rathore et al. emphasized all major cardiac domains, as well as the existing relevant challenges and unresolved issues associated with biometric applications.
	Yazdanian et al. [46]	Yazdanian et al. developed a promising system that measures stroke volume
	Guennoun et al. [47]	Guennoun et al. proposed a novel prototype for identifying users with the extracted ECG signals for continuous authentication using the Alivecor sensor and feature extraction module.
	Labati et al. [48]	Labati et al. proposed a model considering different electrodes for the QRS complex of ECG signals using correlation and score fusion techniques for continuous authentication.
	Camara et al. [49]	Camara et al. investigated data stream mining in real-world applications for ECG signals, including a variety of sensors.
	Louis et al. [50]	Louis et al. developed sequential collection with "Local Binary Patterns (LBP)" for dynamic heart signals.

	Researchers	Work
Other Biometrics	Pinto et al. [51]	Pinto et al. demonstrated continuous authentication by identifying the driver using ECG signals at 5-second intervals and by implementing a grading algorithm to eliminate deviations in the most recent result based on previous values.
	Wahlstrom et al. [52]	Wahlstrom et al. developed an HMM-based technique using Baum-Welch and Viterbi algorithms for SCG signal processing by separating heart vibrations into hidden states.
	Sadek et al. [53]	Sadek et al. proposed a discreet and non-invasive system for measuring heart rate which makes use of BCG signals generated by a Microbend Fiber Optic Sensor. Data transmission to a PC was done via Wi-Fi or Bluetooth.
	He et al. [54]	He at al. examined the viability of using BCG signals for continuous vital sign monitoring via wireless access among servers and the BCG and ECG signal reliability test with the help of cross-correlation
	Lin et al. [55]	Lin et al. developed a unique continuous authentication system using the non-volatile and the geometric properties of full cardiac motion recovered from radar signal demodulation.
	Sancho et al. [56]	In this paper, Sancho et al. tested the reliability of PPG signal as a biometric authentication method by high-pass filtering 4 PPG databases.
	Bonissi et al. [57]	Bonissi et al. analyzed PPG signals from a pulse oximeter for continuous authentication and proposed a model using a high-pass Butterworth filter and a simple correlation technique.
	Eberz et al. [58]	Eberz et al. developed a systematic attack on the Nymi band to illustrate the efficacy of ECG biometrics using 2 AWGs and audio playback of ECG signals.
	Zhou et al. [59]	Zhou et al. investigated the possibility of determining the number of cardiac subjects in a defined range using an antenna or doppler radar by high-pass filtering continuous wave radar system.
	Yongjin et al. [60]	Yongjin et at. implemented the band-pass Butterworth filter for noise removal, PAW as a signal processing technique, SVM, and k-NN classifiersfor ECG biometric authentication.
	Fatemian et al. [61]	A multi-modal biometric system was reviewed using the individual actions taken by the ECG and the PCG classifier. Fatemian et al. proposed a wavelet-based recognition method that tries to overcome difficulties like noise and HRV.
	Chawla et al. [62]	Chawla et al. examined the benefits and drawbacks of PCA and various models of ICA like sICA, fICA, and tICA for separating artifacts and noise from multi-channeled ECG data.
	Zhong et al. [63]	Zhong et al. suggested a novel approach built on HMM to identify heart murmurs using wavelet theory and envelope extraction techniques.
	Silva et al. [64]	Silva et al. employed the k-NN decision rule and Euclidean neighborhood matrix to analyze lead V2 ECG biometrics. For further improvement in the accuracy of human identification they used a 1-NN sequential classifier.
	Li & Narayanan [65]	Li & Narayanan proposed a novel biometric algorithm that combines linear kernel, HPE, and SVM with GMMs and cepstral feature extraction to monitor ECG features.
	Todd K. Moon. [66]	This paper gives the reader a detailed idea of when and how to use the Expectation-maximization algorithm.

photos has been put forth by certain researchers, including Han et al. [69], and is Built on morphological procedures using a "Sobel Edge Detector". By calculating the pam line magnitude and aligning them along the x and y axes, Wu et al. [70] used the "Sobel Mask" for creating histograms. Although the line-based techniques operate satisfactorily, their fundamental drawback is that they demand a high-resolution palmprint, which could be more budget-friendly.

Many statistics, such as mean, standard deviation, Zernike moments, hu moments, and other transformations, are employed using statistical methodologies. A unique statistical-based technique for palmprint identification utilizing a quaternion matrix was suggested by Xingpeng et al. [71]; textural characteristics from the quaternion matrix are extracted using the Discrete Wavelet Transform (DWT) and Principal Component Analysis (PCA). After that, the recognition decision is made using two distances between features. These statistically based techniques have a significant flaw in that they are not noise-resistant and highly susceptible to light variations.

A unique classification framework built on the unsupervised optimum feature selection (UOFS) model has been proposed by Wen et al. [72]. In order to identify a palmprint from contactless palm pictures, Fei et al. [73] introduced the

TABLE III. Criteria in evaluating the performance of a Biometric authentication system

Criteria	Description
Accuracy	The False Rejection Rate (FRR) is the proportion of times a biometric authentication system fails to allow access to a legitimate user.
	The False Acceptance Rate (FAR) refers to the proportion of times a system permits illegal access to an imposter.
	The rate at which the proportion of false acceptance equals the proportion of false rejection is referred to as Equal Error Rate (EER). A low EER suggests superior performance.
Efficiency	Time duration needed for a system to conduct single authentication primarily comprising data gathering and pre-processing, feature extraction and judgment, is referred to as Efficiency.
Usability	Universality refers to the suggested biometric authentication system being acceptable to all users.
	Uniqueness refers to the fact that the suggested biometric authentication system is based on the biological traits of two persons which are completely distinct.
	Permanence refers to the fact that the proposed biometric authentication system should not alter over time.
	Acceptability refers to the user's willingness to accept the proposed biometric authentication system as intended, including the method of data acquisition too.
	Extra Equipment indicates whether or not additional equipment is required to acquire biometric signals.
Security	Security implies that the system be able to withstand cyber-attacks, implying that the suggested biometric authentication method be difficult to cheat and fool.
Privacy	The capability of effectively opposing assaults and safeguarding the privacy of biometric data is referred to as the Mission Success Rate (MSR).
	Noninvertibility refers to the algorithm's capacity to alter biometric data in such a way that it cannot be readily reversed. Noninvertibility is exemplified via hashing.
	To maintain optimum privacy for the user, revocability refers to the ability to remove previously submitted biometric data and re-register new data.
	The ability of a technology to make the original biometric information unlinkable to the outside world is referred to as unlinkability.

(LRRIPLD) approach, which integrates the "LRR" with a flexible central line distance. For robust subspace learning and selection, the authors added a "projection matrix with L2, 1-norm regularization" to the model.

Pavešić et al. [27] proposed a palm-based system that relies on multimodal biometric verification. The system incorporates a module for detecting aliveness based on thermal pictures of the hand dorsa. A user must extend their hands into the device's window so that a camera below will take a picture of their palm prints and an above-mounted thermal camera will take a picture of their body heat to determine whether they are still alive. The experiment used a database with 29 actual thermal photos and 56 fictitious thermal images. This system requires a specific hardware device to support it, which most mobile devices cannot provide. This method does not explore how to secure palm prints, even though they can be sensitive private information. As a result, this approach has a high accuracy and a medium level of usability but no privacy concerns.

Setiawan et al. [74] developed a palm vein-based biometric system that uses phase symmetric features extraction of palm vein images. They used Learning Vector Quantization (LVQ) to train the model with the image sample by choosing the optimal LVQ features. The two-stage LVQ classification method is done with 470 sample images in the identification stage, with 70% of samples in the first and 30% in the second stage.

3) Finger vein

Pre-processing has a crucial role in Fingervein's (FV's) biometrics. During pre-processing, Region of image segmentation (ROI), scaling, alignment, and image enhancement are conducted. Finger positioning fluctuation, wrong finger placement, and improper lighting are the primary reasons for performance degradation in finger vein identification. These vulnerabilities should be rectified during pre-processing.

Peng et al. [29] study combined optimum parameters to develop a Gabor filter in 8 ways. They merged the output images of the Gabor filter with the input FV images to get more accurate results. Furthermore, they assessed performance using Scalar-Invariant Feature Transform (SIFT) matching, which is resistant to rotation and shift and was used to assess performance. Similarly, Shin et al. [75] used a fuzzy-based fusion to merge a Gabor-filtered (4-way) picture and Retinex to improve image quality.

An enhanced picture is created by applying a modified Gaussian high-pass filter, followed by an extraction of binary code. Lee et al. [30] employed Local Binary Patterns (LBP) and Local Directional Pattern (LDP) descriptors. Using Local Binary Patterns and Local Directional Patterns, they measured brightness differences among the pixels in each picture and the surrounding pixels. They calculated the irregularity in Hamming distance between retrieved characteristics and binary codes enrolled with those characteristics. As a result, they have the advantages of being resistant to variations in image brightness and having a quick processing time.

Resolving the problems in the study of Lee et al. [30]; Yang et al. [28] developed a Personalized Best Bitmap (PBBM) approach that employed consistent bits. The following procedure forms a PBBM where FV samples are recorded per person. To match Local Binary Pattern codes, consistent bits of these codes are retrieved and saved from the exact position of the same finger-vein image. Only these consistent bits are considered for further analysis in recognition when using the PBBM. As a result, it decreases the effect of noise bits by achieving more excellent performance in less processing time than conventional LBP approaches.

B. Ocular Biometrics

1) Iris

Various iris biometric methods have been enhanced and used to authenticate a person. The false validation rate of iris biometrics stands second just after DNA biometrics due to its uniqueness, quick speed, robust acquisition, and non-interruption factors.

Different parts of the standard ocular authentication framework include image acquisition, preprocessing, feature extraction, and matching. Image acquisition and preprocessing involve getting the image set for computerized handling by improving the information procurement of the image, and extraction of the feature vector is done after image preprocessing. The feature vector enables the extraction of unique traits of iris or retina tissue and will encode only the vital information on the tissue. Nazmdeh et al. [22] described about the improved methodology related to iris localization, segmentation, classification, and encryption of iris images. Matching various iris codes requires databases which leads to the introduction of distinct standard iris databases.

Various standard iris databases include CASIA and UBIRIS. The automation institution developed the CASIA database at the Chinese academy of sciences. The database contains information on captured iris images of 108 eyes [31]. The University of Beira Interior introduced a UBIRIS database with the end goal of iris acknowledgment calculation. Later, the second form of UBIRIS, UBIRIS v2, was introduced, consisting of 11,000 eye pictures [22].

2) Retina

Yoichi et al. [13] explained retinal recognition based on Geometrical and Gabor features. The basic process of retina recognition involves preprocessing the captured image of the eye and extracting the retina feature from the preprocessed image. Preprocessing involves Color transformation, and Feature extraction involves the Extraction of Geometrical features, Texture features from the Gabor Wavelet transform. In the Extraction of Geometrical features, vessel bifurcation points and cross points of vessel interaction are used to extract information. With the help of the Region of interest (ROI) and feature vector extracted, the system determines the authentication of an individual.

3) Sclera

Abhijit et al. [32] discussed the anatomy of the sclera and various steps involved in typical sclera biometrics like segmentation, sclera-vessel-enhancement, image registration, and classification. The sclera is the white region of connective tissue with blood vessels of different orientations and layers surrounding the iris. The vessel pattern in the sclera is highly secured and possesses great randomness, making sclera biometrics challenging to spoof. Time-adapting contour-based theory discusses the first-ever sclera segmentation in [33]. In a collection of photographs, the borders and motions of the sclera are detected using a technique called time adaptive self-organizing map (TASOM). TASOM is investigated based on active contour-based methods (ACM) [33]. Various databases used for sclera biometrics are discussed and compared in Vitek et al. [34] study, which also introduced a new novel dataset called SBVPI to overcome the need for efficiency. These datasets are introduced based on the parameters like gender, age, gaze direction, and image resolution.

4) Periocular and eye movements

We can consider the small area around the eye as an additional biometric, a Periocular biometric. Mainly, this biometric can be used by integrating it with iris recognition. There are two types while matching images - 1—Global and 2—local matches. The main difference between these two depends on the region (the entire region is considered or the region of interest is considered) [35]. Color and Shape come under Global matcher. However, local features show better performance than global ones. These periocular images also contain standard components like the iris, sclera, and eyelids. When a set of factors is considered, these factors are employed in picture comparison. For improved results, feature extraction and matching are performed globally and locally. Periocular biometrics should be used as a secondary biometric or as an alternative. Since, the periocular region involves 80% of facial information, which is essential in Facial recognition [35].

Bednarik et al. [36] explained that Eye movements can be used as additional biometrics by integrating with other biometrics. However, the potential of eye-tracking is yet to be discovered. Eye-tracker is a device used to track eye movements. The pupil diameter in the eye is never constant. Biometric systems use this property, so integrating these biometrics helps in projecting better outcomes. Eye trackers can directly provide pupil measurements, so the distance between eyes will be the most discriminating and firm measurement [36]. This biometric is further enhanced by integration with a video-based system.

C. Facial Biometrics

A two-step analytical approach for assessing faces was created in 1998 by Kin-Man et al. [41]. The initial step's comparable faces are passed on to the following stage when the correlation of the features of the mouth, nose, and eyebrows is computed. The design of this study allows it to accommodate face rotation. This analysis backs up the idea that integrating feature-based and holistic techniques may raise the identification rate.

The VGG-Face network was created by Parkhi et al. [76] by training the VGG-16 network using a custom-built large-scale database. A lightweight CNN has been introduced by Wu et al. [77], which has ten times less number of parameters than the VGG-Face network. de Freitas Pereira et al. [78] and Schroff et al. [79] mainly used the interception network architecture to develop heterogeneous face recognition networks and build the FaceNet network, respectively. Sandberg implemented FaceNet again as an open-source system [80]. DeepFace, a 9-layered CNN was proposed by Taigman et al. [81] improves the facial alignment phase using explicit 3D face modeling and derives the face representation using CNN. In contrast to previous methods that used discriminative classifiers, DR-GAN, a generative classifier suggested by Tran et al. [82], learns a disentangled representation.

One of the big problems with facial recognition is Facial aging. Aging mainly shows the impact of changes in a face's shape and appearance. In lower age groups less than 18 years old, the facial aging process is represented by changes in the shape of a face. Whereas for the later age groups older than 18 years old, it is primarily represented by the change in appearance than the change in shape. The main factor in the aging of facial boundaries is cardioid strain. As a result of facial aging, the accuracy of face recognition decreases [83].

Park et al. [44] described the aging pattern as a collection of face models from one individual arranged by age. They modeled the face's shape and appearance separately at non-identical ages. They hypothesized that the weighted average of the aging pattern could be used to estimate any aging patterns. Shape (aging) pattern space and texture (aging) pattern space are used to accomplish this modeling task.

The Cross-Age Face Recognition (CAFR) dataset proposed by Jian Zhao et al. [42] encourages those who desperately work on age-invariant face recognition. CAFR is more extensive, diversified, and has essential properties compared to the datasets proposed before. It comprises 1,446,500 images taken from 25,000 individuals concerning age, personality, gender, race, and other factors. The images of CAFR are gathered from actual situations, containing the subjects with different conditions, emotions, positions, and other essential factors. The image's background in CAFR is more distinct and complicated than in other datasets proposed earlier.

Age Invariant model (AIM), a deep neural network, has been developed by Jian Zhao et al. [42] recently to solve this aging problem. AIM cooperatively learns the identity representations that are not complicated and invariant to age and synthesis of cross-age face images, which can focus on essential representations that appear to be hidden among the disentangled (representations that are not complicated). As a result, they work together to accomplish Age Invariant Face Recognition. AIM has learned to achieve resistance to variance in the pose, expressions, illumination, and skin color.

Yachen He et al. [43] introduced a new authentication method of authenticating a face in which they initially encrypted the face feature template, sent the template into the fuzzy commitment system, and finally made use of honeypot technology to enhance the protection level of the authenticating system. Some cipher encryption techniques save the face template of the user on the server. This encryption reduces the risk of attackers stealing or altering face characteristics. Furthermore, this method employs random projection [84] to facilitate the system's ability to reject a template and detect the leaking of a template, respectively. The revealed template can be deleted and a new template established if the trained template is breached. The user can reach the following level if their identity has been correctly verified.

One of the major problems faced in Facial Recognition is capturing images during the case of low illumination. Since it is illumination dependent, it decreases the efficiency of the Visible Face Recognition system. One of the solutions to overcome this issue is the usage of Infrared facial images. The fact that infrared imaging doesn't measure reflected radiation, hence it has drawn interest from all across the world.

A Thermal image of a face can be acquired in complete darkness as Illumination independent. Thermal Infrared Images, also known as thermograms, are so unique that they even recognize anatomical information of the fact, which makes them capable of detecting a person's disguise [85]. Recently night vision devices such as FLIR 7 were being used for Surveillance. Infrared cameras has increased potential these days as they determine the amount of heat generated from the object whose wavelengths range from 3 μm to 14 μm. The IR region is divided into four bandwidths. They are:

1) Near-Infrared Region (NIR)
2) Short wave Infrared Region (SWIR)
3) Medium wave Infrared Region (SWIR)
4) Longwave Infrared Region (LWIR)

Processing the acquired thermal image is necessary for extracting features to improve detection accuracy. They crop the acquired thermal picture after identifying the face so that it only contains the face. The Difference of Gaussian (DoG) filtering method is applied to the picture. "The Low-pass filtering technique helps remove unwanted noise like illumination variations [86]". "Basically, Infrared Thermal Face Recognition-based method is evolved from LDA and PCA which is discussed in Sub Section 4-C)".

D. Other important Biometrics

1) Heart

Heart-based biometric systems involve these steps: extracting cardiac signals, pre-processing, feature extraction, and classification.

For user verification, heart biometrics [45] exploit Inter-Individual Variations (IIV) in cardiac parameters. Foteini Agrafioti et al. [60] gave a detailed note on IVVs. Heart signals represent the cardiac muscle's various physiological features. Heart mass orientation, activation order, and conductivity are causes of significant variability across individuals. These distinctions are the main roadblocks and benefits of using biometrics.

Various approaches exist for cardiac characterization. They may be divided into four categories: electrophysiological, acoustic, mechanical, and optical-based methods. These approaches collect cardiac impulses and their distinctive characteristics using body sensors.

Electrophysiological-based approaches include Electrocardiography ECG) and Impedance Cardiography (ICG) [46], which mainly focus on measuring the heart's electrical activity; studying variations in electrodes was used to measure the thorax impedance during the cardiac cycle.

Guennoun et al. [47] established a unique paradigm for identifying persons using ECG signals based on Mahalanobis distance. They achieved this with an Alivecor sensor, and the results were 83.3% accurate with 16 individuals. Later, based on Guennoun's research, Labati et al. [48] used electrodes with 185 patients to investigate the application of correlation and won synthesis approaches for 24-hour authentication, yielding an EER of 5.36%.

Camara et al. [49] investigated data stream mining for ECG streams, including a variety of sensors in real-time. With ten individuals, the results showed a 96% accuracy. Louis et al. [50] presented sequential sampling with local binary patterns (LBP) for dynamic cardiac signals. Decision-making thresholds are assigned. In operating settings, continuous authentication was demonstrated by recognizing the driver using ECG signals during each 5-second interval and implementing a grading algorithm to eliminate deviations in the latest result using past values [51].

Phonocardiography (PCG) and Echocardiography are acoustic-based techniques that focus on translating vibrations into acoustic data and creating heart pictures using multidimensional or Doppler Ultrasonography. Cardiovascular pictures are obtained by placing the transducer on the sternum. However, it is a large study, and data extraction is harrowing. The medical domain typically uses a stethoscope for PCG and an echocardiogram for echocardiography to evaluate the output. It also offers an accurate evaluation of abnormalities in heart blood flow.

Seismocardiography (SCG), Ballistocardiography (BCG), and complete cardiac motion(CM) are some mechanical-based approaches. A gyroscope or sensor collects the dynamic vibrations of both SCG and BCG signals. Feng Lin et al. [55] developed a unique continuous authentication system using CM's non-volitional and geometric properties recovered from the demodulation of radar signals.

Leonard E. Baum et al. [87] proposed a Hidden Markov Model (HMM). By separating the heart vibration into hidden states that can be traversed consecutively, an HMM-based technique for processing SCG signals has been developed [52]. The data show that HMM outperforms envelope and spectral-based techniques in computing HRV indices, heart rate, and cardiac intervals among 67 patients. Furthermore, HMM has accuracy equivalent to frequency and time field techniques. It is important to realise, that a networked model might result in inaccuracies. The HMM also contains numerous elements and training data that are hard due to lack of publicly available datasets.

Instead of concentrating on the authentication process, investigators examined the viability of using BCG signals for continuous vital sign monitoring via wireless access among servers and the BCG and ECG signal reliability test [54]. Sadek et al. [53] used a Micro bend Fiber Optic sensor to monitor BCG signals, giving an MAE of 7.31%. On the other hand, remote monitoring was based on a poor atmosphere, and hemodynamic responses put a significant load on the system.

Photoplethysmogram (PPG) is an optically based method for assessing fluctuations in fractional blood circulation in the vasculature [56]. Bonissi et al. [57] conducted a preliminary study using correlation analysis to analyze the PPG signals for realtime-continuous authentication; Yet, the characteristics have a short expectency, leading in a high EER and necessitating more inquiry. The PPG has the benefit of being non-intrusive and passive monitoring because the detector does not interfere with a person's daily activities. "In contrast to the sensors used in previous technologies, i.e., ECG, BCG, and PCG, the sensors such as smartphone cameras or pulse oximeters are inexpensive and portable [57]". The above characteristics enhance its suitability for smartphone sensing operations.

2) Brain

"The skull conduct system provides secure user authentication by utilizing bone conduction of the sound in the person's skull on eyewear monitors [88]". Generally,

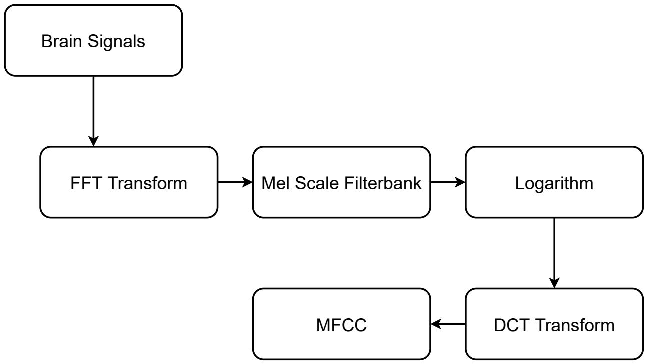

Figure 7. Flowchart of Skull Conduct

eyewear computers are used as personal devices which have sensitive information of the user, protecting it from hackers, eyewear computers are authenticated by skull conduct. Flowchart 7 shows about Skull Conduct.

Every individual has a unique alignment of skull, cartilage, nerves, and tissue [89]. Hence, the transmitted sound waves are unique for every user, which helps us in the authentication process. Skull conduct analyses the frequency response after it passes through the individual's skull using a microphone widely accessible on eyewear computers [90]. The frequency of transmitted sound waves alters the features of the skull. We compute the Power Spectral Density (PSD), which indicates the strength of stimulus passing through the skull that spreads over a frequency band. Specific differences are noticed towards the low frequencies, and the user's skull is more influenced between 2KHz to 4KHz.

Brain electrical activity can be captured from the scalp using Electroencephalogram (EEG) provides information only when the user is alive and in a conscious state. The brain's electrical activity is measured in voltage which uses huge current sensors, and hence it is impossible to have EEG without a person's consent. Due to any attempt of demand/threat, if the user feels stress, that would invalidate the inputs. Anyhow, more research is required to enhance the collectability, and acceptability [91].

As an input, EEG collects brain signals when the user performs different tasks, such as visualization and passing thoughts. Then the collected data is sent for digitalization. After digitalization, the data is transferred to enhance signal quality as input data has many noises [92]. As data is dimensionally large, feature extraction and dimensionality reduction approaches are endorsed to decrease dimensionality. Now that the data is set for authentication, it can be authenticated using machine learning or deep learning techniques. The outcome of the system's authentication will be a binary approval or denial. The outcome of the system's identification is the user's identity label.

As the user is engaged in different protocols which will impact the data recording. So, it is necessary to specify the protocol in all biometrics. Protocols are of two kinds Resting states and Cognitive tasks. In Resting states, data is collected continuously when the user is at rest and is easy to collect. The cognitive state performs different tasks like closing or opening eyes, thinking of mathematical calculations, reading or memorizing a paragraph, visualization of a picture, and having deep breaths.

3) Foot

Nakajima et al. [93] stated that Image matching was used to verify a 30.45% match between the input footprint and the raw inputs. The geometric information for the data normalization accuracy found using Euclidean distance is 85.00%. It is challenging to authenticate when a person has a lot of different walks with various speeds and patterns. Jung et al. [94] stated that Walking records from a mat-type pressure sensor are beneficial for obtaining user input data.

"Single-sensor hand and footprint-based multimodal recognition by Nagwanshi et al. [95]". A pressure sensor mat and a charge-coupled device (CCD) capture footprints. Data noise is reduced using median filters. The picture is binarized since edge detection of fingerprints is necessary for authentication. The image is divided into sections since the threshold value is inadequate to binarize the full image.

4. Technologies Utilized

A. Neural Network

A neural network [96], [97] is a network of neurons with a set of algorithms that tries to detect the relationship of the data. It is analogous to the functioning of the human brain with connected nodes. A neuron in the neural network follows mathematical rules and functions that collect data based on a specific architecture [97]. The unique layout of the information handling system is the model's most distinguishing feature. It comprises many exceptionally well-connected processing nodes (neurons) collaborating to solve problems.

The two primary parts are an input layer, which may be weighted depending on several factors, and a processing layer (hidden layer), in which nodes and connections are concealed. Hidden connections entail calculations, and the word hidden implies they are not visible to a third party. This neural network's behavior is determined by the parameters chosen by the hidden layer nodes. The output layer is responsible for displaying the final result. Neural networks have got tremendous success rate in many domains. Different neural networks are being used to improve the accuracy and performance of many biometric authentication systems of massive databases. There are many neural networks; some of them are listed below.

Convolutional neural networks (CNN) are mainstream networks used for image processing. Advancements in deep learning indicate that complex image characteristics can be represented using CNN. CNN has a substandard anti-noise range and is stimulated by minor disruptions, which led to the introduction of the capsule network architecture. It was first introduced by Sabour et al. in 2006 [98]. It also solves the other drawbacks of CNN, like reducing the number of samples needed for training [99]. U-net is a CNN designed for precise image segmentation. Further, the developments in convolutional neural networks slowly enhanced the capability of Face Recognition systems. The majority of the modern FR systems [79] employ a network architecture like Visual Geometry Group (VGG) network architecture [100], interception network architecture [101], which performed very well in the ImageNet Challenge [102]. Improved Iris segmentation using evolved U-net is described by Zhang et al. in [103]. Nguyen et al. [104] described iris recognition as approached through deep learning and CNN features.

In some studies, the authors utilized a "Convolutional Neural Network(CNN), a deep learning technique for thermal IR face identification [105]". The thermal pictures are taken from a database and used on the CNN network. Compared to other cutting-edge approaches such as Local Binary Patterns (discussed in Sub Section 4-E) and Histogram of Oriented Gradients, this methodology exhibited higher identification rates. They tested their strategy using images from the RGB-D-T face database, which synchronizes the collection of the same item by RGB, Kinect, and thermal imaging cameras. Their approach recognized head rotation at 98%, expression fluctuations at 99.4%, and lighting variations at 99.97%. Because of the significant modality difference, thermal-to-visual face identification is difficult.

Deep neural network (DNN) architectures have recently received much interest since they quickly tackle challenging learning tasks. Image classification [76], recognition [77], and other areas have exhibited state-of-the-art performance. In Facial recognition systems, The modality in mapping visible face characteristics and thermal IR features is learned using a Deep Neural Network. Deep architectures are employed to resolve the modality gap in cross-modal face recognition. Deep learning uses a non-linear network topology with strong learning capabilities to approximate complicated functions. Unlike other traditional algorithms, deep learning integrates "Feature selection", "Extraction", and "Classification" into a single phase and may survey features to minimize the burden of the standard design process.

Deep Perceptual Mapping (DPM) [105] is a method for capturing the non-linear connections between various models that use DNN. The visible image-mapped descriptors are combined to create a long feature-vector. The normalized values and the thermal image vector are then compared. The University of Notre Dame's collection employed the technique mentioned above. Subjects were evenly distributed throughout the visual and thermal domains.

KNN [64], as a fundamental classifier, is often used when there is little to no prior information on the distribution of cardiac data. It is called a lazy algorithm because it memorizes characteristics in a modeling database by deferring until categorization and estimates. KNN depends on determining the distance between a particular training sample after acquiring the data from the dataset. The test samples are categorized into the class with the closest k-neighbors. The value of k = 1 is extensively utilized in heart biometrics for identification and authentication.

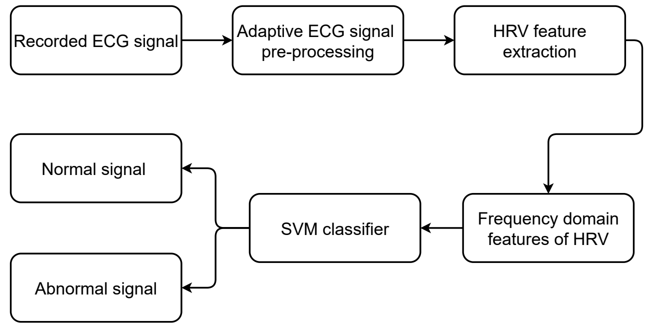

Figure 8. Using SVM Classifier in ECG signal

Figure 8 explains the SVM classifier that can be used in preprocessing ECG signals. It is a statistical-learning method for determining the best hyperplane to seperate classes by maximising distance. The support vectors are the points that lie on the boundary. SVM is typically used to solve binary classification issues, such as authentication; they are utilized for multi-class categorization by fitting all binary sub-classifiers using the one-against-one technique [62].

B. *Honeypot technology*

Yang et al. [106] introduced the basic idea of a honeypot template and adopted a biometric system based on honeypot technology. Honeypot technology is a face template securing technology that can tolerate fraudulent attempts and can detect if there is a leakage in a biometric template.

During registration, a Sugar Template and certain Honey Templates are created. Sugar Templates are made based on the user's original biometrics, but Honey Templates are some false templates. All of these templates are stored at random in the database. While storing the templates, the index of the original template (sugar template) is saved in the token. During authentication, a new template is produced using the user's biometric, and it is then compared to the templates currently stored in the database. If a template in the database matches the template being used, the application server receives the index number of the template. If both match, the biometric is successfully confirmed; if not, it means that someone is accessing the system using the corresponding Honey Template. This index is then compared with the index number of the Sugar Template that is in the token [43].

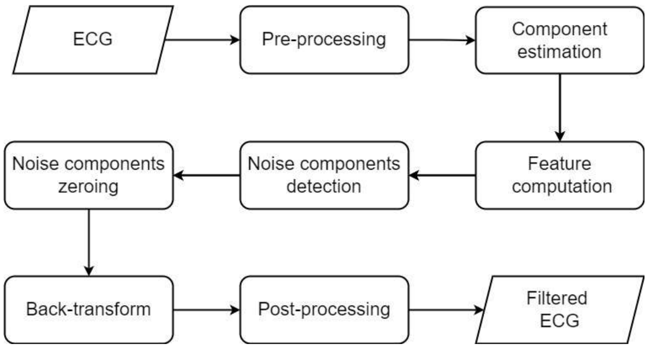

Figure 9. Preprocessing of ECG signal using ICA

C. Holistic Approach

Holistic approach features represent the finest variations of pixel data by considering complete information from the given set of images, which is used to identify a person distinctly. This approach's main task is to convert each image's pixel representation to feature vectors that are reduced to low dimensional space. There are various methods of achieving holistic approaches.

1) Principal Component Analysis

Principal Component Analysis (PCA) is an uncontrolled method of learning that uses least-mean squares to produce a reduced-dimensional optimal picturization of data inputs [60]. It is accomplished by determining the least reconstruction error by solving an eigenvalue problem that displays the variance of a data matrix with a selection of orthogonal orientations [107]. The PCA methodology is suitable for lowering the dimension simultaneously, unchanging the original signal.

In Facial recognition, PCA is widely used for dimensionality reduction and the creation of eigenfaces for evaluation. Eigenfaces, also known as the principal components, are the feature vectors that have maximum variance in the data, which is projected after the dimensionality reduction of the original data of the face. These feature vectors are used to compute the variation among numerous faces [108]. Illumination normalization techniques are very much required for generating eigenfaces [108]. Dimensionality reduction is made by considering eigenvalues and eigenvectors of the covariance matrix by picking the dimensions to reduce based on eigenvectors with corresponding eigenvalues, which have the highest magnitude. These reduced dimensions are the best way to represent the data with high variation. PCA finds the linear subspace of initial data; it is ineffective while dealing with nonlinear space configurations.

A new technique has been introduced in recent studies, mainly focusing on Multilinear Principal Component Analysis (MPCA) and Locality Preserving Projection (LPP). MPCA is used for facial image preprocessing, and LPP is used to extract facial features [108]. Results of some experiments show that these techniques can achieve a good amount of accuracy in facial recognition.

2) Linear Discriminant Analysis

Linear Discriminant Analysis (LDA) mainly concentrates on the linear projection of an image into a low-dimensional subspace. This technique aims to locate the projection hyperplane in the training dataset that lowers interclass variance while optimizing the ratio of intra and inter-scatters [37]. This technique has been used in cardiac biometric studies to generate classifier description [60] from a straight projection of raw heartbeats and to improve class separation among spectral coefficients that have been treated with the Mel-frequency filter bank [61].

The subspace found by Linear Discriminant Analysis is such that it can identify a maximum number of differences between different images and minimize the difference in exposure of identical images under different conditions by linear discriminant criterion. This approach can be used to fix PCA's issues.

3) Independent Component Analysis

Independent Component Analysis (ICA) filters an ECG signal by zeroing the noise components. Flowchart 9 depicts the preprocessing of ECG signal using ICA. The multivariate data is supposed to be a curve or straight patterns of latent variables in this statistical model. While the application of ICA can help distinguish useful signal components from background noise, removing noisy components can result in the loss of vital cardiac data. "As a result, it is crucial to guarantee that cardiac impulses are structurally steady and independent, free from Gaussian distribution, and have topographical features that overlap [62]".

D. Gabor Filter

Gabor filters [109], [110] are linear filters used for texture analysis, edge detection, feature extraction, and other image-processing tasks. Flowchart 10 shows the working of the Gabor Filter. A Gaussian wave modifies a sinusoidal signal with a specific frequency and direction. Gaussian function with multiplied harmonic function gives Gabor filter response. Demodulation of every pattern is done to obtain phase information through quadrature 2D Gabor wavelets. 2D Gabor filter is used in the Extraction of iris features [111], [112]. To eliminate the DC components induced by bright backgrounds, the log gabor filter is Gaussian on a logarithmic scale and features a stringent bandpass filter that permits a certain band of frequencies while rejecting the rest. [113]. Such filters can model the particular cell of the visual cortex in some mammals. These filters have strong spatial and frequency localization capabilities, making them perfect for texture segmentation. These filters are remarkably known for texture analysis. Thus, Gabor filters are extensively used in biometrics to identify the texture of the image given as input

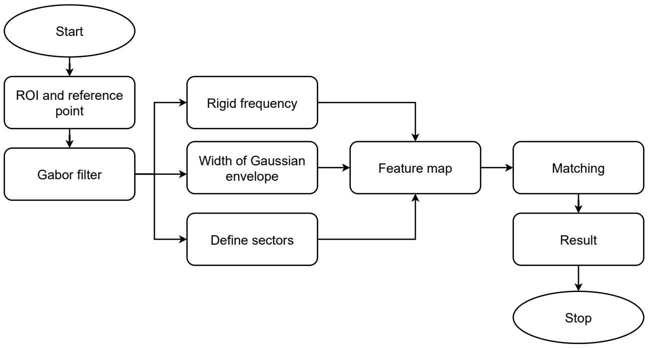

Figure 10. Flowchart of the Gabor Filter

E. Local Binary Pattern

Local Binary Pattern (LBP) is a basic yet powerful pattern algorithm that marks pixels in an image by quantizing the pixels in the immediate surroundings by 33% and treating the output like a binary number. LBP operator has been a well-known method in different domains due to its distinction accuracy and operational simplicity. This operator is viewed as a uniting approach to textural research-which typically involves disparate structures and statistic models. Local Binary Patterns (LBP) are used to identify an image's local grey-level structure [114]. "Ahonen et al. [115] used LBP for facial recognition". As Local Binary Patterns are invariant to grey-level transformations, they are characteristics for categorization that are highly discriminatory [116]. The Operator was later refined to deal with the textures of various scales by incorporating neighborhoods of different sizes [117], [118].

In real-world applications, the LBP operator's most essential quality is its resistance to grayscale, which is a monotone shift caused by lighting changes. Another advantage is that it can analyze the image in challenging situations in real life.

F. Daugman's Algorithm

Daugman's Algorithm [119] is primarily used to authenticate an individual using an iris. Iris biometrics evolved after Daugman introduced his first-ever algorithm related to recognition, feature extraction, and normalization. Flowchart 11 shows the Daugman Algorithm. It is considered a milestone in the chapter on biometrics. Phase structure generates an iris code for quick and efficient authentication. Daugman's calculation is significant among all the available methods as it contributes to almost every iris acknowledgment technique [119]. Attributes of Daugman's algorithm are discussed in detail in [22]. Daugman used a differential on the initial-level administrator for iris recognition and segregation.

1) Rubber sheet Model

Normalizing the iris is essential to standard iris authentication, where the iris region is mapped to a pseudo-polar coordinate system. This process obtains the rectangular structure, which can be used to reimburse for changes caused by pupil size. The Normalization process uses a rubber sheet model. The rubber sheet model cannot compensate for rotation variance [112].

2) Hamming Distance

Hamming distance is a fraction of unlikeness between two binary templates [119], [112]. As the templates are in binary code, Hamming distance has an efficient matching speed, easily comparable with millions of templates [111]. If two binary templates are entirely dissimilar, Hamming distance will be 0.5 [111].

3) Integro differential Operator

In Iris localization, the integral differential operator is most frequently utilized. Because it searches over a group of images for the global maximum, it produces accurate findings. Due to the effective utilization of partial derivatives and data from the first derivative in the computing process, accurate findings were produced. The integrodifferential operators' methodology and technology are explored in [111], [119], [112].

4) Wavelet

The Iris region is dissolved into parts of different resolutions by wavelet transform [120]. Many filters of wavelets are used on the iris region of interest (ROI) corresponding to resolution after normalization. Various wavelets used include Daubechies, Biorthogonal, Haar, and Mexican hat wavelets [121], [122].

G. Hough Transform

The Hough transform is a method used to extract features of an image using computer vision and digital image processing. Flowchart 12 shows about Hough Transform. The method's intention concentrates on finding objects' imperfections within a specific group of figures through a voting process. Hough transform helps in iris localization [123]. "Okokpuje et al. [124] introduced an algorithm for segmentation by using integrodifferential operators with the Hough transform". "To reduce the time during segmentation and improve accuracy, Umer et al. [125] suggested a limited hough transform method with a smaller parameter search field than the standard hough transform technique".

H. Scanning Window Analysis

Scanning Window Analysis (SWA) [126] is mainly used to draw the characteristics and is done at the pre-processing stage. The thinned picture is scanned such that lines are blended into one pixel with a window. If the color of the center pixel is black, it decides if there is any presence of ridges or bifurcation. When lines contain only three pixels, they can be considered continuous lines. If the number of pixels is greater than three, it can be considered a bifurcation. As the bifurcation points are found near the focal point, this SWA method helps locate points in images, even for complex disorder patterns.

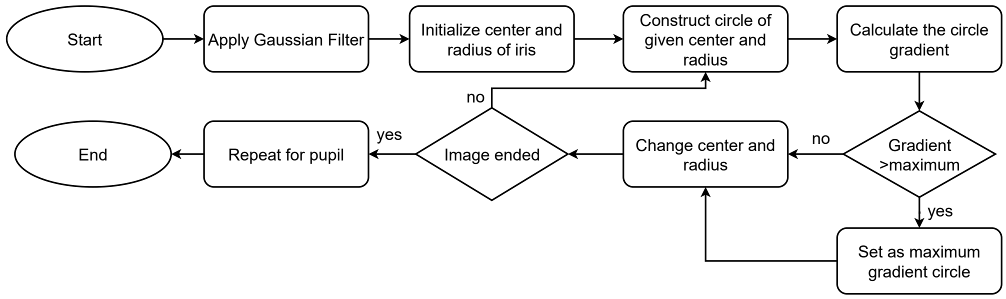

Figure 11. Flowchart of Daughman Algorithm

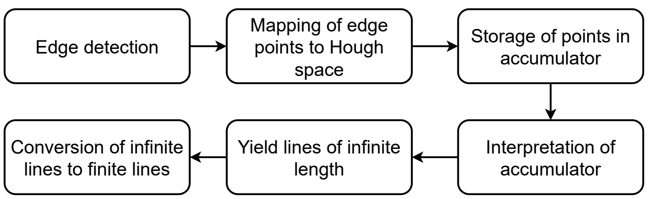

Figure 12. Flowchart of Hough Transform

I. *Optical Coherence Tomography*

Optical Coherence Tomography (OCT) technology [127] is mainly used in retina recognition. It works under the principle of Laser reflectance of a surface to locate blood vessels through various divided regions of the eye to avoid using intravascular dyes. The Optical Coherence Tomography scan of an individual's retina comprises A-scans and B-scans. When these scans are combined, it results in Cross-sectional structural information. During a scan, the same tissue area is frequently pictured. The differences are examined between scans, which helps in identifying the higher flow rate zone. Other zones, like slow or no flow, are similar compared to other scans.

J. *Retinal Birefringence Scanning*

Retinal Birefringence Scanning (RBS) [128] is mainly used to detect central fixation in the eye. With the help of the human eye's birefringent properties, RBS identifies the location of the fovea. When polarized light incidents on the fovea, the Henle fibers layer creates a unique pattern, along with the orientation of the bright parts, depending upon the polarity of light that falls on the retina.

K. *Canny edge detection*

Canny edge detection is used for locating the Optic disc in retinal images. The optic disc is a ring-shaped area at the center of the circle. Hough transform, which is discussed in [123] (which is discussed in Sub Section 4-G), is used in Canny edge detection to find the optic disc region and many straight lines. Flowchart 13 gives a pictorial representation of Canny edge technology. In this technology, locating the optic disc position is highly efficient. This edge detection is one of the best techniques because it first removes noise from the image by smoothening, reducing the amount of data to be processed.

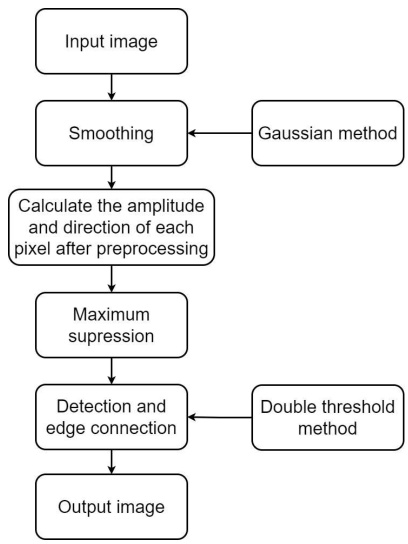

Figure 13. Flowchart of Canny edge detection

L. *Gaussian Mixture Model*

Gaussian Mixture Model (GMM) is defined as "the parametric probability distribution of variables in which the weighted sum of Gaussian components as a density function [65]". GMM is extensively used in biometric systems. Flowchart 14 represents working of Gaussian Mixture Model. GMMs have the benefit of producing smooth approximations to randomized form densities. The Expectation-Maximization [66] technique and Maximum A Posteriori estimation are used to calculate the weights of each parameter, whereas the classification scheme entails estimating the likelihood that the raw data belongs to the appropriate section.

M. *Hidden Markov Model*

Hidden Markov Models (HMM) are the most widely utilized categorization systems [63]. For developing PRSs, HMM is employed to record the sequential information available in feature vectors. HMM is Markov sources or probabilistic functions of Markov chains and is the stochastic signal model. This model variation on the Markov model considers the circumstance in which the analysis is a probabilistic function of the state. HMM is a discrete set

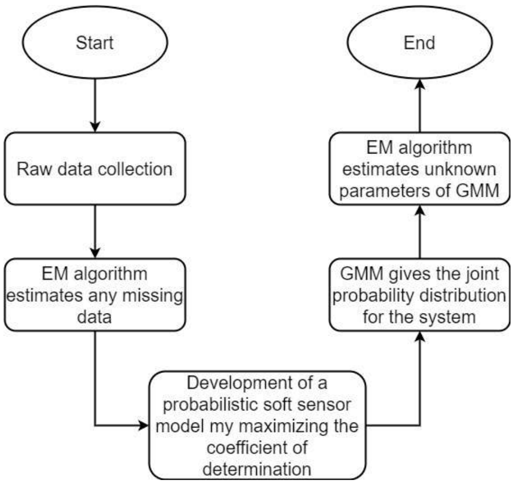

Figure 14. Flowchart of Gaussian Mixture Model

of states; each correlated with a probabilistic distribution. Transition probabilities generate transitions between states. A result or report can be generated in a particular state based on the corresponding probability distribution.

N. ART2

The ART2 algorithm is an unsupervised learning neural network that improves the stability of classic competitive learning algorithms, which has been identified as a flaw [129]. Flowchart 15 shows the working of the ART2 algorithm. Because the ART2 algorithm creates clusters dynamically, the conceptual framework can be finished at actual speed, irrespective of the volume of rapidly created data. The ART2 algorithm seamlessly blends new learning results into old ones to preserve past learning outcomes.

O. Trace Transform

A generalization of the Radon transform is the Trace transform [130]. The Trace transform's attributes are used to determine the rotation and translation parameters between two pictures. Its utility was proven in several applications, including invariant feature development, picture registration, and change detection.

P. Smoothing Algorithm

"Smoothing algorithm is described as the method that modifies a signal's data points such that individual points higher (due to noise) than the neighboring points are lowered and points lower than the neighboring points are elevated, resulting in a finer signal or curve. [131]". The linked operator is given an increasing property to avoid unnatural edges in the filtered picture. Finally, the linked areas of the footprint pictures, their relationships, cross structural adaptable restoration filters utilize tree data structure which is briefly described. Many tests show that this method can reduce noise from different-scale footprint photos and retain the contours of the footprint image. It is an excellent method to make a footprint image look more natural.

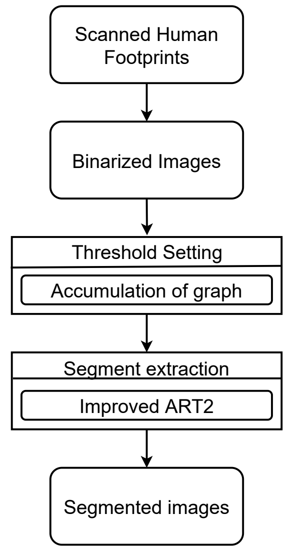

Figure 15. Flowchart of ART2 Algorithm

5. Hardware and sensors

A biometric recognition method's effectiveness, efficiency, and accessibility are all dependent on its hardware. Hardware modules with distinct principles ease biometric authentication.

A. Embedded systems

Any biometric system contains two parts called enrollment and test. Enrollment involves storing the obtained subject in the database, and the subject is compared within the database during the test to establish the subject's identity. Biometric architecture can be implemented using embedded systems. Other technical solutions for biometrics are discussed in [132], [133]

Different technological solutions that can be considered include the application-specific integrated component (ASIC), general-purpose processor (GPP), digital signal processor (DSP), and field-programmable gate array (FPGA). The impact of hardware implementation on recognition systems is discussed in [134]. Methods of interfacing accelerators using the ALTERA platform are detailed in [134]. TMS320DM642 DSP followed by EPIC12Q240 FPGA board is used in [135] to implement the matching phase through hamming distance.

B. Sensors

Sensors play an essential role in detecting the attributes. Sensors and lenses are used to prepare a database of images for training the models and evaluating input images. Data is collected using a variety of sensors like RGB sensors, depth sensors, EEG, thermal, and so on.

Facial recognition systems rely on these sensors to recognize face pictures in both static images and video sequences. These sensors are mainly used in filtering background noise and capturing data over a particular region.

When there is insufficient light, most optical sensors fail to capture high-quality images. In such situations, Thermal sensors make the job done with ease. It works on the principle of infrared imaging using infrared rays.

Considering finger-vein recognition, Thermal infrared pictures represent the heat patterns released by an item [136]. Infrared pictures are unique because each vein and tissue structure is distinct. Ambient lighting does not affect thermal IR imaging because the human face and body radiate thermal energy. The passive nature of thermal infrared systems reduces complexity while increasing dependability. Correctional facilities can also utilize thermograms to process suspects and convicts, assuring precise identification. Thermal sensors or scanners also help in aliveness detection algorithms. In terms of face recognition, A sensor is considered the best for getting high accuracy; it expects a person to be constant at a fixed distance away from the sensor.[16].

The major drawback with the Thermal sensor is that as it uses infrared technology, it cannot capture data behind glass as glass is opaque in infrared; it gets reflected when it hits a material made of glass [137]. Also, the hair present on the face (mainly facial hair like beard or mustache) blocks infrared radiation. It may cause an issue in facial recognition.

Ocular biometrics uses pattern recognition techniques using high-resolution images of the iris, retina, sclera, periocular, and eye movements. An Iris scan uses a snapshot sensor that does not require close contact with the camera, making it user-friendly.

There are many sensors for capturing finger patterns. Some of them are ultrasonic and optical sensors. The reflection of a propagating sound wave reflected on the fingertip creates an image in ultrasonic sensors. In optical sensors, the light gets reflected from valleys and absorbed at the ridges; when the finger is put on the clear prism surface, the ridges and valleys look dark and light, respectively.

Capacitive sensors are more complicated and expensive, but they are secure. They are made of tiny capacitive array circuits placed beneath the sensor, where air acts as a dielectric medium. The distance between valleys and ridges and the plates determines the intensity of the electric field [138]. This method is far more difficult to circumvent since an image cannot travel through the capacitive fingerprint sensor.

A Pressure Mat Sensor is an electronic device that detects the forces between two things. Multiple sensing devices are often placed on or within a flexible cushion in the Pressure mat sensor. These mats are used in real-time technologies to map forces between contacting surfaces [139]. When the user walks on this device, we obtain a normalized COP (Center of Pressure) trajectory. The HMM generates probabilistic methods of each person's foot, software records, and analyses sensor data. It also turns complex data into graphics that are simple to understand.

3-Dimensional Face recognition sensors need to be advanced to have more ability to cope with minor variations in a face (including spectacles and ornaments). These algorithms should decrease the computational efforts as far as possible [16].

C. Nymi

Nymi [58] is a wearable computing gadget that eliminates the need to memorize passwords. Nymi uses a person's heartbeat to create a key that can access any device. The Nymi bracelet has a sensor that measures the electrocardiogram (ECG) of the person wearing it and logs on to computers and other security devices using the user's unique heartbeat signature. To identify with Nymi, the user keeps on the wristband and presses an onshore sensor creating an electrical loop with the bottom-side sensor touching their wrist. Because it is a wearable device, the technology retains authenticity as hard as the user puts wristbands on.

D. Electroencephalogram

An Electroencephalogram (EEG) is a device that measures the electrical activity of the brain. Electrodes can be applied to a subject's scalp to measure brain activity. The EEG electrodes capture the electrical activity generated by neurons. The variety of electrodes used by EEG devices is because various brain regions produce distinct signals. The voltage of EEG signals is typically shallow, at ten microvolts or less. The electrode signals are sent to an amplifier device, which amplifies and stabilizes them to a level that can be precisely measured using standard electrical components, which then convert them to digital data. The electrodes capture brain wave patterns, which the EEG equipment subsequently sends to a computer or to cloud server.

E. Ultrasound probe

Using Doppler ultrasonography, an echocardiogram creates pictures of the heart that can be used to detect cardiac problems. The subject's chest wall is examined with an ultrasonic probe with a small footprint. High-pitched sound waves are produced to measure blood flow characteristics using the Doppler effect. Intercostal acoustic windows are needed for cardiac imaging. Making the transducer footprint as little as possible helps to avoid them. Additionally, the optical resolution of the probe can be enhanced by a narrow beam width. Despite the detector's widespread usage in medicine, difficulties with setup and the instrument's high cost make it difficult to employ in biometrics [141].

F. Doppler radar

The potential for non-intrusive heart rate monitoring using Doppler radar has been well established. The movement of the heart may be measured using Doppler radar. The Laser Doppler Vibrometer alternatively detects motion near the surface of the body. "The Doppler effect governs

TABLE IV. Summary of biometric systems

System	Characteristic	Strength	Weakness	Security	Cost
Fingerprint [2]	Highly comfortable and universal	Easy to extract	Can Fake the sensor	Normal	Low
Palm [7]	Highly comfortable and universal	Easy to extract	Not completely portable	High	Low
Finger vein [9]	Highly Secure and accurate	Highly unique and user-friendly	Susceptible to noise and proper alignment is needed	Excellent	Medium
Iris [22]	Highly accurate	Highly unique and user-friendly	It relays mostly in IR source	High	Medium
Retina [13]	Highly Secure and accurate	Highly unique	Not so easy to extract	High	Medium
Sclera [32]	Highly efficient	Highly unique	Unsatisfactory segmentation	Medium	Medium
Periocular [35]	Highly Secure and efficient	Easy to extract	Almost cannot be used independently	Medium	Medium
Eye movements [36]	Highly accurate	Highly Unique	Almost cannot be used independently	High	Medium
Brain [140]	Highly accurate	Cancellability	Hard to extract	High	High
Footprint [93]	Highly Secure	Easy to extract	Can be forged easily	Medium	Low
Heart [45]	Highly universal	Easy to revoke	Not completely developed	High	Medium
Face (Visible) [42]	Highly comfortable	Easy to extract and user-friendly	Can spoof easily	Medium	Medium
Face (Infrared) [85]	Highly accurate	Easy to extract	Can be varied by influence of other factors	High	Medium

how the reflecting radio-frequency (RF) waves changes frequency in response to the subject's movement.[59]". The transmitted and reflected waves create a low-frequency signal which correlates to the chest's restricted movement. Cardiac radar is studied for biometric applications because it is non-invasive and does not require patient consent or awareness.

G. Laser Doppler Vibrometer

In addition to Doppler radar which is discussed in 5-F, the Laser Doppler Vibrometer (LDV) is a method of measuring Long-Distance heart rate. It's a non-contact approach in which a minimal laser is focused on a vibrating body (such as the neck or heart). The resulting image is examined to classify the oscillations produced by the cardiovascular activity. Regarding the carotid artery, the LDV signal mainly details Heart Rate Variability and heartbeats, whereas functioning is similar to an ECG. Furthermore, the LDV pulse is sufficiently structured to identify subjects using qualities that are also maintained during physiological exercises and mental strain. Despite other cardiac monitoring systems, LDV lacks learning algorithms, a complicated probability, and a lengthy setup process. However, it is ideal for sensitive and non-contact biometric applications [142].

6. Conclusion

In this study, we have investigated biometrics and assessed the work done on biometric authentication systems. Our findings, which include characteristics, strengths, weaknesses, security, and implementation costs, are summarised in Table IV based on the study we conducted. We highlighted recent literature and provided a short review. With this, we intend to infer that the growing population demands the development of technologies and safe authentication methods. Biometric systems ensure the security of confidential data. Some systems also offer higher accuracy rates. It is beneficial to authenticate users using physical characteristics. Some biometrics, such as fingerprints, iris, and retina, are well-developed, while others, such as sclera, brain, and PCG, require further investigation. We propose that future research should prioritize the development of novel or multimodel biometric authentication systems with security and privacy concerns.

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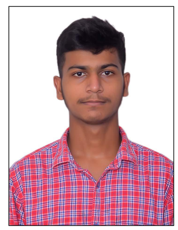

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