A Survey on Heart Biometrics

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In recent years, biometrics (e.g., fingerprint or face recognition) has replaced traditional passwords and PINs as a widely used method for user authentication, particularly in personal or mobile devices. Differing from state-of-the-art biometrics, heart biometrics offer the advantages of liveness detection, which provides strong tolerance to spoofing attacks. To date, several authentication methods primarily focusing on electrocardiogram (ECG) have demonstrated remarkable success; however, the degree of exploration with other cardiac signals is still limited. To this end, we discuss the challenges in various cardiac domains and propose future prospectives for developing effective heart biometrics systems in real-world applications.

CCS Concepts: • **Security and privacy** → **Biometrics**; • **Computing methodologies** → *Machine learning*; • **Hardware** → *Signal processing systems*;

Additional Key Words and Phrases: Cardiac signals, sensors, wearables, feature extraction, authentication

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1 INTRODUCTION

User authentication, referred to as human-by-machine validation, has become vital for secure transfer of credentials in various life domains, including access control, healthcare, monetary transactions, and many others. Traditional recognition that utilizes methods dependent on knowledge (e.g., PIN, password) and controlled assets (e.g., ID card, token) has become more vulnerable to attacks from malicious third parties and has spurred development of more secure authentication methods such as biometric recognition. Biometric recognition uses the inherent physiological and behavioral traits that are unique to the individual. However, existing state-of-the-art approaches are not ideal for commercial biometric products as shown in Table 1. Furthermore, there are many applications in the present literature that show the vulnerability of these modalities against circumvention, replay attack, and biometric obfuscation [74, 108].

To overcome issues with commercial viability and security, we investigate the promise of improved biometric recognition methods by determining the unique characteristics internal to the

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Table 1. Comparison among Biometric Techniques Based on Recent Advancements

	Modality	*Universality*	*Security*	*Acceptability*	*Performance*	*Measurability*	*Permanence*
Traditional	Iris	High	**Medium**	Low	High	Medium	High
	Fingerprint	High	**Low**	High	High	Medium	High
	EEG	Medium	**High**	Low	Medium	Low	Low
	Face	High	**Low**	High	Medium	High	Medium
Heart-based	ECG	High	**High**	High	Medium	Medium	Medium
	PCG	High	**High**	Medium	Low	Medium	Low

EEG, electroencephalogram.

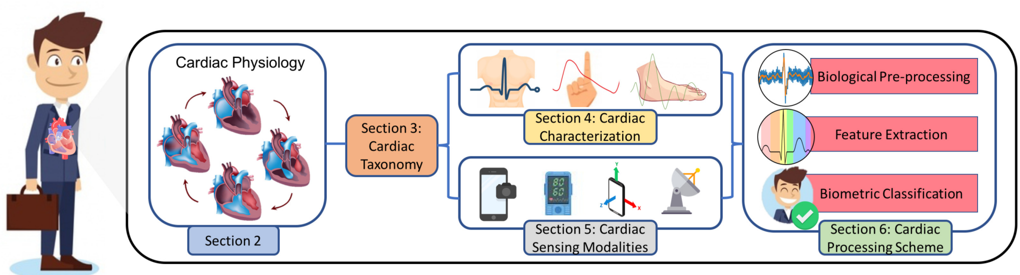

Fig. 1. Heart biometrics utilize the inter-individual variations in cardiac characteristics for user verification.

body, in particular, the inter-individual variability of the heart [48]. Heart biometrics, also referred as cardiac biometrics, rely on cardiac signals, i.e., electrocardiogram (ECG), photoplethysmogram (PPG), seismocardiogram (SCG), phonocardiogram (PCG), and others, which are universal and non-invasively measured through the surface of a human body. The heart waveform arises from multiple "sympathetic and parasympathetic factors" [7] of the human body and governing or morphing this physiological phenomenon is more challenging than traditional biological traits (e.g., fingerprint and face). The most critical advantages of heart biometrics are as follows: (1) intrinsic *liveness detection* ensuring that only a living subject can be recognized by the sensing modality, which further improves tolerance to malicious attacks. Other biometrics require additional processing to enable this feature, which comes at the price of computation cost and still does not provide sufficient security to the system. (2) Conventional biometrics such as fingerprints employ static biometric samples and can be spoofed as long as the sample, regardless of the time period, is leveraged by the adversary. Heart biometrics are preferable for *continuous authentication* due to their capability of providing a new biometric sample periodically.

The combination of these advances opens the door for new innovative research on reliable, robust, and secure cardiac biometric applications (refer to Figure 1) that are likely to revolutionize our everyday lives. However, there are three notable and upcoming challenges that need to be further addressed to make this vision a reality. First, the cardiac signals are prone to noise caused by human dynamics (e.g., breathing, body motion) and suffer from instantaneous variations due to a drastic change in the environment. These variables not only affect the accuracy of the system in recognizing the cardiac recordings but also endanger biometric security with increased risk of attack such as Denial-of-Service. Second, it is challenging to design a sensing application for cardiac biometrics that is capable of inexpensive and unobtrusive data acquisition and requires low time complexity during classification. Last, cardiac signals can destabilize with respect to the biometric template due to body's physiological and psychological conditions, evolving over time.

To highlight the important contributions of the existing literature in addressing the above challenges, our work is summarized as follows:

- We provide the first comprehensive characterization study (Section 4) on diverse cardiac sensing methodologies by describing the unique and prominent attributes of their biometric signals. We perform an extensive analysis (Section 5) of different sensing modalities by enlisting the comparison among their cardiac signal, setup, and working mode based on the proposed taxonomy.
- We thoroughly review the existing approaches for processing raw signals and generate valuable features to be further utilized in different biometric classifications. Moreover, we extend our study (Sections 6 and 7) by analyzing the different configurations of cardiac biometric models to identify existing challenges and propose future prospectives.
- We describe the various applications (Section 8) for cardiac biometrics to provide motivation for future research. We also explore the feasibility of malicious attacks (Section 9) with varying threat levels against all cardiac domains to highlight the open issues that require immediate attention.

Note that the existing surveys on heart biometrics primarily focus on ECG-based approaches and provide no information regarding other cardiac domains and related research [7, 121]. Other literature on individual methodologies, such as SCG and ballistocardiogram (BCG), specifies the theoretical implications but does not elaborate on the unique attributes that can aid in biometric applications [71]. Furthermore, other research does not highlight the vast sensing modalities that can be employed for cardiac identification. To the best of our knowledge, this is the first survey that highlights all prominent cardiac domains and their related challenges and open issues when applied to biometric applications. The goal of this article is to bring the novice or practitioner not working in this field quickly up to date with the advances in the cardiac biometrics domain.

To establish the relevant literature for this survey work, we have employed key publication databases and search engines, including IEEEXplore, ScienceDirect, ACM Digital Library, Google Scholar, and Dblp. A representative combination of keywords include "electrocardiogram" and "ECG," "seismocardiogram" and "SCG," "photoplethysmogram" and "PPG," "phonocardiogram" and "PCG," "ballistocardiogram" and "BCG," "echocardiography," "impedance cardiogram" and "ICG," "cardiac motion" together with "biometric"; "authentication," "identification," "sensor," "feature extraction," "preprocessing," "classification," "security," "application," and "attacks." In addition, other research regarding cardiac physiology is also utilized.

2 CARDIAC PHYSIOLOGY

2.1 Background

2.1.1 Anatomy. The heart is the most critical organ, providing replenished oxygen and nutrients to the entire body and aiding in expelling metabolic wastes. It is typically the "size of a fist, weighing between 250 and 350 g and beats approximately 100,000 times a day and 2.5 billion times during an average lifetime" [142]. It is located in the middle mediastinum on the left portion of the chest, in line with the thoracic vertebrae. The heart's structure is mentioned in Figure 2. Physiologically, it comprises four chambers: the upper two atrias for receiving venous blood and lower two ventricles for pumping oxygenated blood into lungs and arteries [142]. The two atrioventricular valves are the tricuspid valve and the mitral valve; these separate the atrium from the ventricle on the right side and the left side of the heart, respectively [75]. The two semilunar valves are the aortic valve and the pulmonary valve. The endocardium, myocardium, and epicardium layers constitute the wall around the heart, and the pericardium, a double-membraned sac, provides a further layer of protection.

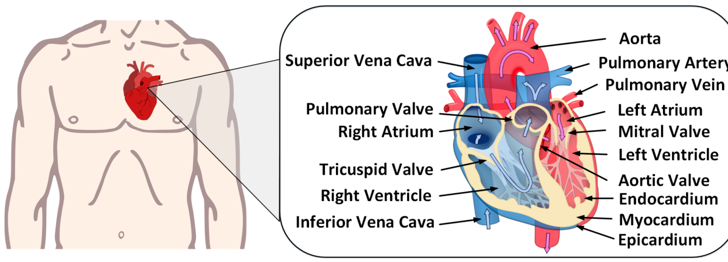

Fig. 2. Anatomy of a human heart.

2.1.2 Cardiac Cycle. In general, the array of events of contraction (systole) and relaxation (diastole) of ventricles with every heartbeat is referred to as cardiac cycle. The cardiac cycle begins with a diastole stage, where the the blood flowing via the open atrioventricular valves, thereby occupies the ventricles. The atria contract, forcing the blood further into the ventricles after which they begin to contract. The atrioventricular valves are forced shut due to an increase in pressure. An excessive pressure results in the opening of semilunar valves thereby allowing blood to traverse in left and right atrium via pulmonary veins and vena cavae, respectively. Last, the semilunar valves close due to the decreasing ventricular pressure with respect to the arteries [62]. This process completes a cardiac cycle.

2.1.3 Cardiac Conduction. Each time the heartbeats, the ventricular contraction is triggered by a wave of electricity, which arises spontaneously in a collection of specialized cells in the right atrium. These cells, namely the sinoatrial node, are the source of rapid electrical impulses through the left and right atria, which are further accumulated in the atrioventricular node. Specialized conducting fibers, i.e., the bundle of *His*, transmits the signal to ventricles along the bundle branches to trigger contraction [109]. Afterward, the Purkinje fibers convey the respective signal and transfer the electrical charge to the heart muscle.

2.2 Inter-individual Variation

Cardiac signals depict the diverse physiological characteristics of the cardiac muscle. Existing literature mentions that factors including "heart mass orientation, conductivity, and the activation order of the heart are sources of significant variability among individuals" [7]. These variations provide the primary challenges and advantages in biometric applications.

2.2.1 Static Cardiac Features. The contrast in geometrical relations of the heart with respect to its location and orientation, structure, and sensing position contributes to a significant variability [69, 83]. These factors are more pertinent depending on the body's habitus, gender, and age. Physiological variability includes "differences in the Purkinje system, the heart muscle fiber orientation, the electric conductivities of different parts of the heart and the activation order of the heart" [70]. Other geometrical factors constitute every prospect of volume conduction among the origin of heart activity and the associated sensing modality recording the cardiac signal.

2.2.2 Dynamic Cardiac Features. The electrical volume conduction within the thorax is impacted by the variations of the other organs. Furthermore, the timing of depolarization and repolarization is not consistent among individuals, which contributes to the inter-heart variability. Physical activities also influence the low-frequency components in signals [18], while the domain measures relative to heart rate variability are higher in active compared to sedentary individuals [97].

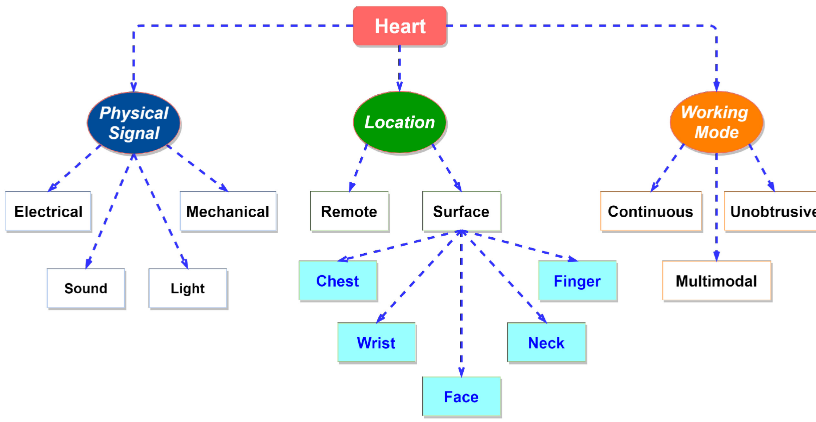

Fig. 3. A taxonomy for the cardiac sensing domain.

3 CARDIAC TAXONOMY

We employ the taxonomy, illustrated in Figure 3, to provide valuable insights into the categorization of cardiac sensing in different dimensions.

• **Physical Signal:** It conveys the information about the behavior and attributes of the heart and can be actively captured by a sensor. For instance, the ECG resemble the heart's electrical activity, the PCG recognizes acoustic signals, while the SCG can be used to evaluate the mechanical vibrations generated by heart movements. The characterization study of cardiac methodologies is grouped based on the physical signal in Section 4.

• **Sensing Location:** It describes the position at which the sensor is established. Generally, the placement of the sensor depends on the physical signal; however, a physical signal can be periodically measured from different positions (e.g., PPG from either face or finger). We categorize various sensing modalities based on their location in Section 5.

• **Working Mode:** Depending on the application, cardiac sensing can be performed continuously, such as electrodes for ECG or unobtrusively by using Doppler radar. To enhance security, there are many existing studies that focus on combining different biometrics, such as fingerprints and PPG, which are commonly referred to as multimodal biometrics. Different types of working modes are further elaborated on in Section 7.

The taxonomy presented in our work can be generalized to overall heart-based applications, since multiple sensors can be utilized to simultaneously perform diverse functions (e.g., the electrical signal from the heart is prominently used for diagnosis of cardiovascular diseases as well as biometrics).

4 CARDIAC CHARACTERIZATION STUDY

In this section, we comprehensively characterize the different methodologies that utilize body sensors to acquire cardiac signals, in addition to their unique attributes.

4.1 Electrophysiological-based Approach

4.1.1 Electrocardiography. ECG relies on the phenomenon of measuring the electrical activity of the heart. Conventionally, 12-lead electrodes are fixed on the upper body, where they recognize the variations from the electrophysiologic model of cardiac muscle due to repolarization and depolarization in the course of every heartbeat. The primary features of the ECG signal, i.e., the P wave, QRS complex, and the T wave, are illustrated in Figure 4. The P wave and QRS complex

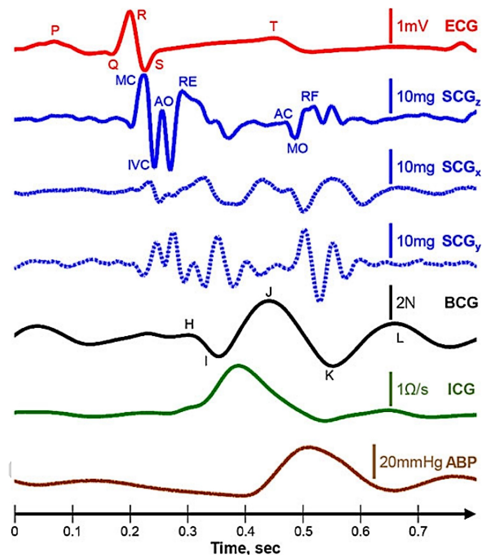

Fig. 4. Illustration of cardiac signals with fiducial features of a single individual whose arterial blood pressure (ABP) is recorded relative to the finger region [71].

depict the depolarization of atria and ventricle, respectively, while the T wave depicts the repolarization of the ventricles [63]. The ECG signal possesses a low-amplitude (100–300 uV) feature, i.e., the U wave, from the repolarization of inter-ventricular septum. However, it is frequently absent or obscured from power-line interference or baseline error.

The ECG demonstrates an immense potential for biometrics in terms of integrity by being dependent on the individual physiology and psychology. However, the system requires either physiological activity in the same fashion as in the enrollment stage [38] or periodical resampling of the training dataset.

4.1.2 Impedance Cardiography. The impedance cardiography (ICG) is a study of variations in the thorax impedance during the cardiac cycle. For the sensor placement, four electrodes are placed at the neck and the diaphragm level, eliminating the effect of skin-electrode impedance [115]. Depending on the system design, an excitation source is required, since the ICG signal is significantly weaker than the raw measured impedance recorded from the body [169]. The signal comprises components depicting contraction of the atrium (A wave), opening of the aortic and mitral valve (B and O wave), maximum systolic flow (C wave), and closing of the aortic and pulmonary valve (X and Y wave). Other than the previously described cardiodynamic parameters, these waves also provide insights into the ventricular ejection period.

Existing studies of ICG contrast with each other and have conflicting results due to their methodologies involving "devices of different generations, physical models, and equations" [95]. Moreover, any surgery affecting the thorax can significantly reduce the accuracy of the ICG system. Employment of ICG for biometric applications is severely underexplored and comprehensive investigations to address these challenges can result in valuable contributions to the research community.

4.2 Acoustic-based Approach

4.2.1 Phonocardiography. Human heart sounds are natural signals that are widely used in the medical domain for health monitoring. The stethoscope is a common instrument that converts the vibrations from the chest to acoustic signals that convey information about the individual's cardiovascular system. The PCG signal comprises two components, S1 (Lub) and S2 (Dub), produced from the traversal of blood through the valves in each cardiac cycle. S1 is low (around 40 Hz) and prolonged (about 150 ms) and generated from the closure of atrioventricular valves, while S2 is high pitched (around 50 Hz) and short (about 120 ms) and arises from the closure of semilunar valves [75]. Others, such as the third (S3) and fourth (S4) components, are also observed, although the possibility is low. S3 generates at the start of diastole, immediately after S2, when the left ventricle is obstinate [17], and is common among children and young adults.

For every individual, the details of time and frequency-domain waveforms in the PCG signal differ [119], thereby highlighting its potential as a biometric.

4.2.2 Echocardiography. Echocardiography constructs heart images utilizing the common multi-dimensional or Doppler ultrasound. It is often abbreviated as cardiac echo, i.e., a sonogram of the heart. An echocardiogram is primarily used in the medical domain to estimate cardiac output, diastolic function, ejection fraction, and hypertrophic cardiomyopathy. It can also provide a precise assessment of abnormality of blood flow through the heart. In a typical setup, the transducer is placed on the chest wall and transthoracic images of the heart are taken. An alternative method is to place the probe on the subject's esophagus to allow Doppler evaluation from the rear of the heart. A three-dimensional (3D) echocardiography can "reconstruct the heart chamber in all dimensions and aid in measuring left ventricular volume and ejection fraction accurately without any geometric assumptions" [113].

To employ the 3D echocardiography in biometric applications, an anatomical intelligence system would be required to distinguish between anatomies of the heart by learning from generic models.

4.3 Mechanical-based Approach

4.3.1 Seismocardiography. The SCG signal derives from the vibrations in the chest wall generated from the contraction of heart and discharge of blood into the cardiovascular system. Conventionally, a multi-axial accelerometer is placed near the heart on the sternum or apex where each axis portrays a specific pattern [100]. The majority of the literature in SCG domain focuses on the signal acquired from the dorso-ventral component, i.e., the Z-axis of accelerometer [168]. The Y-axis readings can be employed as a reference signal to reduce the noise from human dynamics (e.g., motion artifacts) [112], while the spatial distribution aids in identifying cardiovascular diseases [116]. An SCG signal possesses waves that depict the physiological activities of the heart: mitral valve closure (MC), isovolumetric contraction (IC), aortic valve opening (AO), rapid ejection (RE), mitral valve opening (MO), and rapid filling (RF).

The ability to non-invasively measure the heart activity increases the scope of application for SCG in the clinical and biometric domain. However, unlike the steady environment in clinical settings, SCG usually suffers from lower performance compared to ECG due to the exposure from environmental noise and motion artifacts during daily activities.

4.3.2 Ballistocardiography. During every cardiac cycle, an individual's center of mass varies with the acceleration of discharged blood into the vessels. BCG is the measure of recoil forces generated by the body to maintain overall momentum. It possesses distinct patterns in all three axis where the longitudinal and transverse BCG depicts the head-to-foot deflection and the dorso-ventral vibrations of human body, respectively [71]. The BCG waveform can be categorized into three groups: pre-systolic, systolic, and diastolic. The pre-systolic group (F and G wave) precedes the systolic and is rarely observed. The most prominent signal measured is the systolic group

(H, I, J, and K waves) while the diastolic components (L, N, and M waves) are smaller and less perceptible due to artifacts from device architecture or subject movement [120].

There are two important facts that need to be considered. First, there is much existing literature that uses the BCG and SCG terms interchangeably. However, these are two different cardiac sensing methodologies, having different characteristics and waveforms. Second, the ideal environment for BCG measurement is micro-gravity, since it is affected by any gravity force and contact with external objects [128]. Although a conventional sensing system employs the use of a bed, chair, and weighing scale, with recent advancement in this domain, wearables are increasingly explored to capture the real-time signal using on-board inertial sensors [52].

4.3.3 Full Cardiac Motion. The self-excitement of heart muscle leads to a “3D automatic heart deformation” [92] known as cardiac motion (CM). It is composed of atrial and ventricular contraction and relaxation that occurs amidst the cardiac cycle. Cardiac motion is a unique identifier for each person, as no two individuals have the same size, position, or anatomy of the heart. The signal can be categorized into the contraction of atrial muscles (AFP), maximum blood flow in ventricles (VFP), and atrial contraction/ventricular expansion (ASP).

A recent study [92] demonstrated the capability of CM as a biometric by employing a biomedical radar to measure the signal phase shift caused by the physiological motion. Furthermore, it is challenging to counterfeit and robust against replay attacks. However, the performance of biometric systems working on CM for people with cardiovascular diseases requires further investigation.

4.4 Optical-based Approach

4.4.1 Photoplethysmogram. PPG is a biometric signal obtained from the illumination (using a light emitting diode (LED)) of specific body parts such as fingertip or face and acquiring the reflected light by a photo-diode. It can assess the variations in the volumetric blood flow in the peripheral circulation [140]. A PPG waveform comprises alternating (AC) and static (DC) components, where the AC with frequency around 1 Hz presents valuable insights into the heartbeat of an individual [75]. The DC is coherence with the respiration system and is often used for measuring blood oxygen saturation because of the precise difference between “red and infrared absorption spectra of reduced and oxygenated hemoglobin” [158]. However, the PPG signal evolves with time, since there exist fluctuations in the amplitude of the signal from the autonomic nervous system [140].

The PPG offers an advantage of non-invasive and passive monitoring, since the sensor does not hinder the daily activities of an individual. Moreover, the sensors (e.g., pulse oximeters or camera in smartphone) are cost-effective and compact, unlike the other methods (i.e., ECG, BCG, and PCG) [22]. These attributes enhance its potential to be used in mobile biometrics applications.

5 CARDIAC SENSING MODALITIES

To perform effective cardiac sensing, the precise placement of sensors is critical, as they have a direct influence on sensing performance. Some of the sensors have the capability of providing continuous measurements, while others can be used for one-time authentication, similarly to traditional biometrics. Based on the sensing location illustrated in Figure 5, we further categorize the sensors in Table 2.

5.1 Non-invasive Surface Sensing

5.1.1 Electrode. The electrodes are the primary sensor for measurement of ECG signals as they can transform the bio-electric activity inside the human body into measurable electrical current

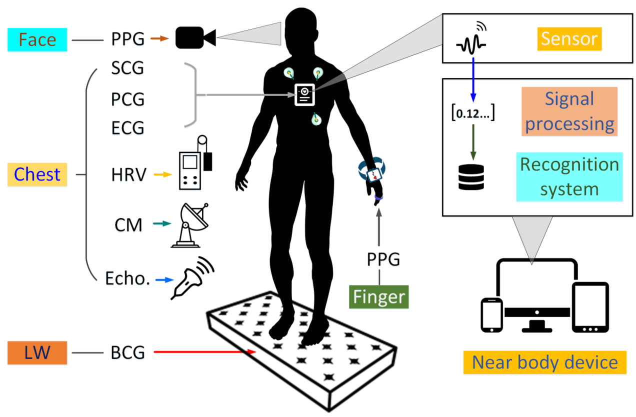

Fig. 5. Comparison between the location of cardiac signals with respect to the human body. The decision is allocated to different near body devices such as a smartphone.

Table 2. Characterization of Sensors Based on Proposed Taxonomy

	Sensors								
	Electrode	*Microphone*	*Stethoscope*	*Accel./Trans.*	*LDV*	*Radar*	*Camera*	*Probe*	*Oximeter*
Method	ECG/ICG	PCG	PCG	SCG/BCG	HRV	CM	PPG	Echo.	PPG
Signal	Electrical	Sound	Sound	Mechanical	Light	Radio	Light	Ultrasound	Light
Location	UP/Neck LW	UP	UP	Chest/LW	Chest/Neck	Chest	Finger/Face	Chest	Finger
Working Mode	Cont.	Unob.	Cont.	Cont.	Unob.	Unob.	Unob.	Cont.	Cont.
Cost	Low	Low	Medium	Low	High	Medium	Low	High	Low
Signal Quality	Medium	Low	Medium	Low	High	Medium	Low	High	Medium
Range	Contact	Contact	Contact	Contact	Long	Medium	Medium	Contact	Contact
Setup Size	Medium	Small	Medium	Small	Medium	Medium	Small	Large	Small
Mobility	Medium	High	Medium	High	Fixed	Fixed	High	Medium	High
Setup difficulty	Medium	Low	Low	Low	High	Medium	Low	High	Low

•Cont. = Continuous; Unob. = Unobtrusive; Accel. = Accelerometer; Trans. = Transducer.
•HRV = Heart-rate variability; LDV = Laser Doppler Vibrometer; UP = Upper Body; LW = Lower Body.

[10]. The electrode contact noise and motion artifacts directly affect the sensing performance, thereby highlighting the importance of selecting the proper type of electrode and its location.

Wet Electrodes: This conventional type is widely used for ECG measurement in the clinical domain. The wet Ag/AgCl electrodes are affixed to the surface skin, specifically on the chest, arms, or legs, using a conducting medium of electrolyte gel. The working principle relies on a half-cell potential, double layer capacitance coupled with parallel and series resistances [33]. While the wet electrodes provide satisfactory signal quality, they require additional care due to the possibility of skin irritation [103], which severely impacts the mobility of the user and could create cross-coupling between neighbouring electrodes [127].

Dry Electrodes: To eliminate the requirement of electrolyte gel, dry electrodes were proposed. Perspiration that gathers on the skin substitutes for the electrolyte medium. It also results in an increase of electrode surface area and enhances the conduction as a result of penetration of electrolyte into the stratum corneum [99]. The dry electrodes increase the long-term performance and cause low skin irritation. However, they have high impedance between the electrode and skin and are susceptible to motion artifacts [55].

Capacitive Electrodes: This type of electrodes provides non-contact ECG measurement, thereby having long-term convenience. A narrow insulator is positioned separating the body and metal-plate sensing electrode while the combination of electrode, skin, and insulator acts as a capacitance to deliver the cardiac information to the sensor [75]. This method results in no skin irritation and, more importantly, can be installed in different working environments (e.g., bed, chair, and clothing). However, the observed signal quality is inferior compared to wet electrodes while respective electrodes are highly sensitive to environmental noise.

The traditional setup for ECG placement requires 12 electrodes [19]. Based on the application, there are other configurations, such as five, three, or one lead placement, that are increasingly used to provide the performance close to the gold standard [67, 80, 163]. Furthermore, ECG shirts [21] and armbands [129] can be employed to enhance convenience for the user during ECG measurements and enable continuous monitoring of cardiac signal. There is a plethora of research that explores the use of mobile applications for ECG measurement for medical and biometric purposes [61, 143].

5.1.2 Stethoscope. A stethoscope is the most prominent device used by healthcare professionals for cardiac auscultation. To address the low sound level of conventional acoustic stethoscope, electronic stethoscopes were introduced, which amplify the heart and lung sounds using various filters and amplifiers [8]. The electronic stethoscope comprises a microphone and piezoelectric sensor with a frequency range between 0 and 2,000 Hz. Unlike the acoustic stethoscope, different transducers are employed for an electronic stethoscope, such as a piezoelectric crystal in Welch-Allyn's Meditron stethoscope, the capacitive transducer in Thinklabs One Digital, and a microphone in Cardionic E-scope 2 [89]. Some of these types also provide portability by connecting with handheld devices (e.g., smartphone) or transmitting the information to a remote location using Bluetooth.

5.1.3 Integrated Microphone. A cost-effective method to measure the PCG signal is by utilizing a microphone having good response characteristics for low-frequency sounds and tolerance to noise from motion or the environment [154]. Recently, a number of studies have focused on using highly sensitive microphones with wireless sensor networks (WSN) as an improvement over the developments focused on signal transmission via Bluetooth technology [135]. However, it is challenging to measure cardiac murmurs (between 20 Hz to 20 KHz) at a higher frequency using a WSN and thus requires a high-performance microprocessor [134].

5.1.4 Ultrasound Probe. The echocardiogram employs Doppler ultrasound to generate images of the heart for assessment of cardiac conditions. An ultrasound probe having a small footprint is positioned on the chest wall of the subject. It generates high-frequency sound waves while determining the characteristics of blood flow using the Doppler effect. Cardiac imaging requires intercostal acoustic windows, which can be addressed by ensuring the footprint of the transducer is as small as possible. Moreover, narrow beam width can lead to improvement in image resolution acquired by the probe [1]. Even though this sensor is highly deployed in the medical domain, its applicability to biometrics is challenging due to expensive instrument cost and setup difficulty.

5.1.5 Accelerometer. The dynamic vibrations are the foundation for both SCG and BCG signals that are recorded using an accelerometer or transducer. The majority of accelerometers rely on the piezoelectric effect; however, the use of a micro electromechanical system (MEMS) accelerometer is becoming increasingly prominent in biomedical applications [51]. The MEMS accelerometer is manufactured using a microelectronic fabrication technique offering great usability due to its small size and can measure frequencies close to 0 Hz [117]. Moreover, the measurement of SCG signal typically requires a 3-axial MEMS accelerometer, since the information, pertinent to biometric identification, is present in the dorso-ventral direction (Z-axis) while other axes (X and Y) can provide useful information about cardiac activity [71]. Other sensors, such as hydraulic testbed using transducers and optical sensors [136], including microbend fiber, fiber Bragg grating, piezoresistive fabric, electromechanical, and polyvinylidene fluoride film, can measure BCG signals.

5.1.6 Pulse Oximeter. A pulse oximeter is one of the conventional non-invasive sensors used for monitoring individual blood oxygenation (S_pO_2) and heart rate. It is primarily placed on a patient's fingertip, earlobe, or forehead to obtain the PPG signal. The sensor projects two wavelengths of light using a pair of LEDs to the photodetector via a specific body part. The phase shift in the wavelength due to absorption of light during variation in blood perfusion [11] is measured by the transmissive pulse oximeter. Another oximeter type (reflectance) can sense reflected light, allowing PPG to collaborate with other biometric, e.g., face, for multimodal biometrics [105]. Moreover, due to their compact size and superior usability, pulse oximeters are increasingly applied in wearables, such as Apple Watch, for smart health monitoring.

5.2 Non-contact and Remote Sensing

5.2.1 Doppler Radar. The use of Doppler radar has shown immense potential for unobtrusive heart rate monitoring. Unlike the laser Doppler vibrometer, which can only sense the motion at the body surface, Doppler radar can measure the motion of the heart [92]. The working principle relies on the Doppler effect, where the reflected radio-frequency (RF) wave undergoes a shift in frequency relative to the subject's velocity. Since the movement of the chest is limited, the transmitted and reflected waves are coupled to produce a low-frequency signal corresponding to the movement [174]. The *cardiac radar* has been explored for biometric applications due to its non-invasiveness and requires no subject cooperation or knowledge [133]. However, it is challenging to employ large antennas with high gain in systems where mobility is crucial, whereas smaller antennas [14] would require a higher-power signal source or RF amplifier during transmission and is worth exploring.

5.2.2 Laser Doppler Vibrometer. Besides Doppler radar, another method of long distance heart-rate measurement is through laser Doppler vibrometer (LDV). It is a non-contact technique that employs a low-power laser, projected toward the vibrating surface (e.g., chest or neck) and the reflected signal is measured to categorize the fluctuations induced by cardiovascular activities. Specifically, the LDV signal provides insight into the heart rate variability (HRV) [36] and information about heart-valve sounds [149] while offering comparable performance with ECG in correspondence with the carotid artery [37]. Moreover, the LDV signal is adequately textured to provide authentication among individuals using features that are preserved even during physical activities and mental stress [31]. Although LDV can be leveraged for unobtrusive and non-contact biometric applications, it suffers from inadequate training data and complicated probability and requires extensive setup compared to other cardiac sensing modalities.

5.2.3 Camera. A non-contact method for monitoring of PPG signals is desirable for biometrics and ubiquitous health tracking. The camera is explored as a feasible solution to monitor the minute variation in skin color caused from the inconsistent volume of blood in arteries and capillaries. Depending on the application, the camera can be either used for remote or surface sensing. However, the PPG signal acquired using a camera suffers from low signal strength, specifically for individuals with darker skin complexion, and motion artifacts due to body movement. Furthermore, the surrounding light conditions significantly impact the signal quality while several studies explore the use of ambient light for PPG imaging [160]. Therefore, the utilization of the camera requires the careful employment of techniques including a weighted average of signals across face regions [85], improved acquisition of light intensity, and precise feature tracking under motion.

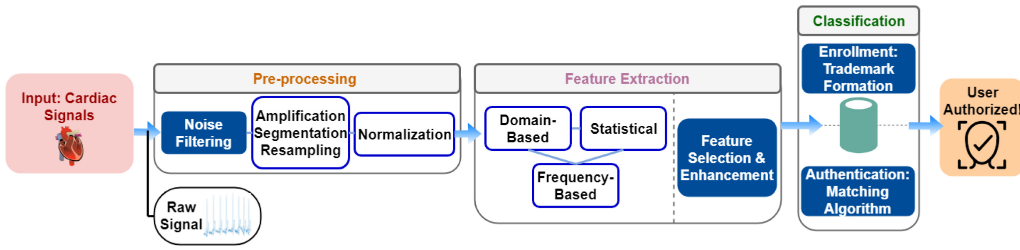

Fig. 6. Overview of heart-based biometric system.

5.3 Discussion

With the rise of sensors designed for unobtrusive monitoring, the future implications would rely on leveraging these sensors for robust cardiac biometric schemes with comparable or even greater performance than other biometrics (e.g., fingerprint, face). However, unlike the vast research performed on optimizing traditional modalities (e.g., electrodes in ECG or stethoscope in PCG), several problems as presented in this section still persist for upcoming sensor applications in the cardiac domain. To ensure that these low-cost or non-contact sensors can replace conventional methods, the constraints (refer to Table 2) related to their signal quality and setup difficulty needs to be addressed. Solutions may be explored from the modification of sensor hardware, integration of multiple sensor setups or a careful selection of processing techniques for acquired cardiac signal and underlying features that is further mentioned in the next section. The future resides in low-cost, robust and reliable products that can seamlessly monitor the cardiac signals to effectively meet the application requirements (e.g., continuous face PPG through video, privacy-oriented chest SCG through accelerometer or unobtrusive lower body BCG through a transducer) set by the user.

6 CARDIAC SIGNAL PROCESSING SCHEME

A heart-based biometric system is described in Figure 6, which comprises three primary modules: (1) Pre-processing, (2) Feature Extraction, and (3) Classification. Generally, the first step consists of acquiring the raw data from the sensor, at a particular sampling rate, while ensuring proper placement and the least environmental noise. Application of pre-processing techniques allows reduction of noise in the signal from which multiple features are extracted for matching. Last, the obtained features are leveraged to classify the input signal with the previously trained data to authenticate the individual.

6.1 Biosignal Pre-processing

To acquire a specific cardiac signal, different sensors are employed with varying hardware configurations, placement locations, sampling frequencies, and other technical constraints. The pre-processing module reduces the inevitable accumulated during measurement and ensure that sufficient features can be extracted from the processed signal. Specifically, the low-frequency noise arises from several factors such as baseline wander, surface contact, motion artifacts, and physiological state while high-frequency noise arises from power-line interference and digitization of analog potential [155]. The selection criteria for a pre-processing technique significantly relies on the application and overall domain and choosing the optimal technique is essential for achieving exceptional performance for the biometric system. A comprehensive analysis of pre-processing methods with future prospectives is elaborated in the supplementary materials.

Table 3. Summary of Domain, Statistical, and Frequency-based Features for Cardiac Biometric Applications

Signal	*Features*	*Feature Count*	*Subjects*	*Sensor/Database*	*Performance*
ECG	P,QRS,T wave-based	8 [34]	175	Neurosky CardioChip	EER = 1.87%
		15 [73]	29	—	Acc. = 97%
		19 [145]	50	PhysioNet QT	Acc. = 99%
		21 [162]	26	PTB Diagnostic MIT-BIH Normal Sinus	Acc. = 94.4% Acc. = 97.8%
		53 [38]	77	PhysioNet PTB HiMotion	Acc. = 99.8% Acc. = 99.5%
	DCT, Haar Wavelet	215 [122]	6	N/A	EER = 2.66%
	DCT, MFCC, QRS	153 [59]	30	PTB Diagnostic	Acc. = 97.3%
	STFT	2048 [106]	269	Biopac TEL-100	EER = 5.58%
PPG	Peak-to-peak interval/slope	4 [56]	17	—	Acc. = 94%
	Systolic Peak Diastolic peak Augmentation index Pulse width	40 [82]	30	DCM03 Reflective	Acc. = 94.4%
	NN Parameters	8 [118]	30	HTC S510e	BAR < 10%
	Statistical Features	11 [79]	12	TROIKA	Acc. = 96.1%
SCG	HRV spectrum AO peaks/intervals	– [151]	20	MMA8451Q Accelerometer	r > 0.98
	AO peaks	1 [167]	10	Shimmer 3 Kionix KXRBS-2042	Acc. = 98.7%
BCG	H-I-J-K-L	300 [58]	25	Custom Chair	Acc. = 96%
	PSD, R-I R-J, R-K interval	4 [78]	13	Analog Amplifier	—
PCG	CMS	– [119]	10	Wireless Electronic Stethoscope	Acc. = 96%
	WPCC	24 [5]	206	HSCT-11	Acc. = 91.05%
	Marginal Spectrum	100 [173]	40	Digital Stethoscope	Acc. = 94.4%

r, Linear Relationship; BAR, Bland-Altman Ratio; EER, Equal Error Rate; Acc., Accuracy.

6.2 Cardiac Feature Extraction

To perform a comparison of the cardiac signals of different individuals, features relative to a domain, time, or frequency dimension are extracted and further utilized for classification. Table 3 summarizes the feature representations with number of subjects, sensor/database used, and their performance in existing literature. While a comprehensive selection of multiple features can improve the accuracy of the biometric model, it may also lead to higher computational cost. To overcome this scenario, we further list the methods that can be leveraged to lower the feature dimension in this section.

6.2.1 Domain-based Features. These types of features rely on the overall knowledge of the cardiac domain and are often based on fiducial points of ECG, PPG, SCG, and other signals. For an ECG signal, the P, QRS complex, and T waves are among the dominant features from which other information relative to interval, amplitude, and angle can be acquired. The amount of fiducial features for ECG signal can vary from 8 [34], 15 [73], 19 [145], and 21 [162] to a feature space dimension of 53 in Reference [38]. Pan-Tompkins QRS detection [111] is one of the most widely used techniques for locating the QRS complexes centering around R-peaks in the ECG signal. Other studies [156] propose peak valley extraction and adaptive thresholding as a decision rule for effective peak detection. The features in PPG signal rely primarily on the time domain characteristics such as peak-to-peak interval and slope [56], systolic peak, diastolic peak, augmentation index and pulse width [82], and NN parameters [118]. As mentioned in Section 4.3.1, aortic valve open (AO) peaks are detected in SCG signal to specify cardiac intervals [167], while the H-I-J-K-L components [58] of BCG signals are shown to incorporate more information pertinent for human identification.

• **Intuitive:** These features have a physical meaning and can be effortlessly comprehended by even non-medical professionals.

• **Informative:** Besides the inter-person individuality, other characteristics such as heart rate variability, existing cardiovascular diseases, and susceptibility to heart attack can be revealed.

• **Sensitive to diseases:** The subject's physical state can induce error during biometric identification, thereby leading to low permanence.

• **High complexity:** These features require precise localization of fiducial points in the signal, which further raises the complexity of the algorithm.

6.2.2 Statistical-based Features. In the signal processing domain, statistical features are typically used as they can be extracted from all the signals, with no dependency on its domain. They represent the mean, median, standard deviation, maximum and minimum value of a segment, skewness, kurtosis, and many others [79] and are coherent with the time series of the signal. Compared to domain or frequency-based features, these are computationally inexpensive. However, for superior performance, the statistical features needs to be computed from a segment of satisfactory length.

• **Computationally efficient:** As mentioned, these features can be calculated quickly and directly after pre-processing the raw signals.

• **Less reliable:** For real-world applications, relevant features should be acquired from both the time and frequency domain prior to selection and transformation.

• **Prone to noise:** Variations in the ambient environment, sensor misplacement, and human artifacts can introduce errors in the raw signal, which are also reflected in statistical features.

6.2.3 Frequency-based Features. After applying the frequency normalization to maximize the resolution, frequency-based features are computed using fast Fourier transform (FFT) of the signal. They include spectral roll-off, spectrum energy, spectral centroid and flux [43], and other features depending on the power spectral density of peak-to-peak intervals in the cardiac signal. Coefficients of discrete cosine transform (DCT) from ensemble heartbeats and second-level decomposition with DWT using Haar wavelet transform can provide a selection of multiple frequency-based features [122]. Mel-frequency cepstrum coefficients (MFCC), while extensively applied in speech recognition, demonstrate strong potential for human authentication through ECG signals [59]. A Kubios software environment can also be applied for analysis of the HRV spectrum in SCG signals [151]. Techniques such as power spectral density and discrete Fourier transform (DFT) can serve in the identification of the posture-induced differences [78], which are vital for ensuring the reliability of BCG-based systems. In addition to FFT, a hamming window is primarily utilized for short-time Fourier transform (STFT), whose logarithmic value generates a spectrogram for modeling the time-frequency samples of each subject [106]. It is worth mentioning that the frequency-based features have shown immense potential for the PCG domain, with existing application of MFCC [13], CMS [119], wavelet packet cepstral coefficients (WPCC) [5], and marginal spectrum analysis [173]. Prior to acquiring these features, it is necessary to perform sufficient pre-processing to reduce incorrect matching results by the biometric model.

• **Robust:** In contrast to statistical and domain-based features, frequency-based attributes are more robust to cardiovascular conditions and intra-session variability.

• **Flexible:** There is no necessity to trace the accurate location of fiducial points or perform any restrictive segmentation process.

• **Less intuitive:** As a tradeoff to flexibility, these features have an inferior meaning to human perception and require machine learning models for classification.

• **High dimension:** A sufficient feature dimensional space is necessary to achieve superior performance in cardiac biometric systems.

6.2.4 Other Feature Extraction Techniques. Wavelet analysis provides valuable insight by decomposing the time-series cardiac signals into multi-level coefficients at different frequency subband. Besides the widely used DWT, other wavelet techniques such as cross wavelet transform [15], flexible analytical wavelet transform [84], and continuous wavelet [6] can additionally be explored for cardiac signals in individual authentication. Other studies describe the potential of Radon transform [65], AC/DCT [59, 124], Llyod-max quantisation [38], pulse active ratio [137], random projections [35], one-dimensional multi-resolution local binary patterns [96], bivariate empirical mode decomposition [49], fuzzy logic discriminator [94], ensemble empirical mode decomposition [104], and Baum-Welch algorithm [161] for cardiac sensing and biometric applications.

6.2.5 Feature Selection and Transformation. In past few years, the dimensionality of features, particularly in machine learning, has increased exponentially and is one of the primary concerns in cardiac analysis. To address the curse of dimensionality, feature selection is widely adopted, which selects a minimum subset of important features from the overall ones based on specific evaluation criteria. Similarly, feature transformation is also leveraged and relies on shifting the initial space in minor subspace. A careful selection of these techniques, based on the feature set and domain knowledge, is crucial for achieving better learning performance and model interpretability [153] for machine learning classification and minimized computational cost preferred for cardiac biometric systems. We further describe the widely adopted techniques to accomplish this goal.

Linear Discriminant Analysis (LDA): This technique focuses on determining the projection hyperplane that reduces the interclass variance and maximizes the ratio of inter and intra-class scatters of the training sample sets. In biometric problems, studies have used this technique for better class separation among spectral coefficients initially subjected to Mel-frequency filter bank [48] and to obtain LDA-feature representation from a linear projection of input heartbeat [162].

Independent Component Analysis (ICA): This relies on a statistical model where the multivariate data is assumed as nonlinear or linear combination of latent variables. While the use of ICA can enable classification of desired signal components from the associated noise, the elimination of noisy components can lead to loss of essential cardiac data. Therefore, it is critical to ensure that the cardiac signals are spatially stationary and independent, deficient of Gaussian distribution and preferably have components characterized by overlapping topography [30].

Principle Component Analysis (PCA): This is an unsupervised learning method, which provides an ideal representation of input features with lower dimensionality, in terms of least mean squares [162]. This is accomplished by solving an eigenvalue problem by finding the least reconstruction error from depicting the "variance of data matrix with a set of orthogonal directions" [66]. Generally, cardiac signals comprise a high degree of correlation between some of the fiducial features, thereby making the PCA technique optimal for de-correlating and reducing the dimension while keeping the morphology of the original signal. However, the PCA can only determine the linear subspace of initial data and is inadequate against nonlinear space configuration [30]. Furthermore, LDA is often applied after PCA [90], since the latter is able to preserve the majority of variance after the projection but does not ensure better discrimination representation of related coefficients. Although few studies report the comparison of system performance with/without data compression [26], it can demonstrate the usability of cardiac biometric system in real-world scenarios.

Other techniques involve shift invariant transformation [72], normalized relative compression [29], Walsh-Hadamard transform [148], Kanade-Lucas-Tomasi feature tracker [32], and correlation [93] that are primarily explored for ECG and PPG signals and can provide valuable insights for other cardiac signals.

6.2.6 Future Prospectives. Although the application of fiducial-based methods, primarily relying on time domain-based information, has shown excellent performance and remains the optimal choice for feature extraction, the attributes of non-fiducial methods are often superior in the presence of chaotic cardiac signals. Furthermore, an optimal feature extraction method is difficult to determine, since the existing datasets incorporate several subjects with irregular cardiac activities. Before designing the system, researchers need to carefully think about the problem domain, computational cost and data acquisition process when choosing the feature extraction technique. The feature selection and transformation can significantly aid in reducing the features' dimension, which is essential for reducing the computational cost, particularly when adding a lengthy classification approach.

6.3 Biometric Classification

Upon receiving the optimized feature vector comprising the domain, statistical or frequency features, a matching algorithm is implemented to finalize a decision. In the biometric system, if the purpose is authentication, then the classification will result in either authorized user or an imposter. For identification, the classified values among all the classes will be returned. In a typical scenario, the cardiac biometric system is designed for authentication purpose rather than identification, since the latter requires a large scale setup to store training data for subjects that can be heavily taxing during tracking and maintenance. Moreover, the design of a scalable cardiac system is still an active topic of research in the biometric field.

The location of the feature extraction and classification model is essential for a secure biometric system. For instance, off-the-person ECG or PPG via smartphone typically embeds the classification software with the sensor modality. This ensures the low possibility of an attack across a communication channel. Other sensors, such as BSN for ECG, MEMS accelerometer for SCG, or microphone for PCG, require an exclusive communication channel to accumulate information from various sources and transmit to the software, often increasing the vulnerability of the biometric system. This becomes more pertinent for multimodal biometrics.

The matching algorithms employed for heart biometrics can be broadly categorized into signal matching and machine learning techniques with computational complexity described in Table 4.

6.3.1 Signal Matching. The techniques under this category involve a comparison between the signals obtained by the sensor through distance and correlation measures.

Distance Functions: The Euclidean distance is the typical distance function [20], and its normalized form among feature vectors, x_1 and x_2, can be computed as:

$$D_{\text{norm-euclidean}}(x_1, x_2) = \frac{\sqrt{(x_1 - x_2)^{\mathrm{T}}(x_1 - x_2)}}{V}, \tag{1}$$

where V is the feature vector dimension, i.e., the amount of DCT coefficients employed in various biometric problems [124, 162].

To compare the resemblance between wavelet coefficients, a wavelet distance can be computed using a Matlab function "Wavelet Dist" or through Equation (2). The shortest wavelet distance [2] can be used to find the template of cardiac data as:

$$WaveDIST_n = \sum_{p=1}^{P} \sum_{q=1}^{Q} \frac{\left|\gamma_a^{p,q} - \gamma_b^{p,q}\right|}{\max\left(\gamma_0^{p,q}, \tau\right)}, \tag{2}$$

where $\gamma_a{}^{p,q}$ and $\gamma_b{}^{p,q}$ are detail coefficients of DWT, q, at the pth level of decomposition, and τ is the threshold for minimum overemphasis of difference between two signals by the wavelet coefficients.

To perform a comparison among coarse-grained structures acquired from different individuals, a Euclidean distance is computed from each point (x_p) in first structure (X) to its nearest point (y_{Np}) in other structure (Y). Similarly, the opposite is applied from point (y_p) in Y to nearest point (x_{Np}) in X. The sum of individual means is known as mutual nearest point distance, a proven metric for QRS free detection in ECG signals [47] and can be explored for fiducial independent detection in other cardiac signals,

$$MutualDIST(X, Y) = \frac{\sum_{p=1}^{N_X} D_{\text{euclidean}}(x_p, y_{\text{Np}})}{N_X} + \frac{\sum_{p=1}^{N_Y} D_{\text{euclidean}}(y_p, x_{\text{Np}})}{N_Y}. \tag{3}$$

In the scenario when the assumption of Gaussian distribution holds, the Gaussian log likelihood can be employed as a distance function [124]. Given that prior probabilities are consistent for occurrences and variances of a specific subject i, the normalized Gaussian log likelihood is computed as:

$$NGLL_i(x) = -\frac{(x - \overline{x}_i)^T S^{-1} (x - \overline{x}_i)}{2C}, \tag{4}$$

where $\overline{x}_i$ represent sample mean vectors, S is the overall covariance matrix, and the factor C ensures modest comparisons. The higher the log likelihood value, the higher the possibility that the respective feature belongs to subject i. While some distance functions (e.g., Euclidean function) are computationally fast, they may employ additional constraints to the biometric model. Others, such as WaveDIST, can lead to more effective results but have superior cost and time complexity.

Correlation: It is a technique to identify a degree of coherence between two feature vectors (X and Y) by analyzing the dependency among the variables [65]. The Karl Pearson correlation coefficient is calculated using:

$$Correlation(X, Y) = \frac{\sum_{i=1}^{p} \sum_{j=1}^{q} (X - \overline{X})(Y - \overline{Y})}{\sqrt{\left[\sum_{i=1}^{p} \sum_{j=1}^{q} (X - \overline{X})^2\right]\left[\sum_{i=1}^{p} \sum_{j=1}^{q} (Y - \overline{Y})^2\right]}}, \tag{5}$$

where $\overline{X}$ and $\overline{Y}$ represents the respective means and the correlation value lies between −1 and 1. If the value is 1, then the features are fully related, 0 if they are independent, and −1 for the inverse relationship. A threshold is set on the correlation value for achieving the desired level of security, typically as 0.9 for an authentication model.

Dynamic Time Warping (DTW): The DTW determines the point-to-point relation among the time-series signals by satisfying the constraints relative to boundary, continuity, and windowing [159] and producing a minimum cost associated with the matching of data points. It utilizes dynamic programming to effectively determine the wrapping path. To further optimize the cost of DTW, a multilevel approach, namely FastDTW [139], was proposed that shrinks the time-series signal without significantly altering the morphology, determines the wrapping path at a lower resolution, and refines it further through local adjustments. However, the FastDTW is an approximate technique and may be unreliable for finding an optimal solution depending on the biometric problem. In such a case, Viterbi algorithm [50] can be used, which provides the most likely path through hidden Markov model (HMM) and has comparable performance with stochastic DTW.

Spectral Coherence: This technique identifies the frequency-based correlation between two signals where a coherence value of 0 depicts uncorrelated signals while a value of 1 indicates that frequency components are correlated. In the frequencies where the spectral coherence is high, additional information about the relative phase among correlated components can be computed through the cross spectrum phase.

6.3.2 Machine Learning and Other Classifiers. The selection criteria for the classification algorithm relies heavily on the biometric problem. For instance, if the goal is to design a traditional or hybrid system for biometric identification, then multi-class classifiers are the optimal choice, whereas the binary classification is pertinent to biometric verification, i.e., increasingly employed in wearables and handheld devices. Although some multi-class classifiers are capable of substituting binary classifiers, the reverse is infeasible. Specific to cardiac biometrics, the classifiers utilized in the existing studies are summarized in Table 5.

Artificial Neural Network (ANN): An ANN is a computational structure, inspired by the networks functioning of biological neurons within the human brain. A neural network is a powerful tool for modeling, specifically when the relationship among the underlying data is unknown [64]. To solve the classification problem of cardiac signals among individuals, ANN employs an activation function for non-linearly mapping of inputs and outputs. Although the statistical approaches are effective for linear biometric problems due to the assumption of linear time-series signal, ANN is preferred, since they can efficiently model the low frequencies of the cardiac signal, which are typically non-linear [76]. Furthermore, from the signal processing perspective, ANN possess two primary advantages: (1) adaptiveness to the variability in signal due periodically and (2) effective learning capability from the arbitrary noise in the cardiac signal following their removal. We further describe the various techniques using different types of ANN employed in current cardiac biometric studies.

• *Convolutional Neural Networks (CNN):* The CNN is a widely used neural networks in image processing and shows great promise for application in cardiac signal classification. CNNs are simple neural networks that utilize convolution instead of general matrix multiplication in the respective layers. The convolution improves the performance of the associated system through sparse interactions, parameter sharing, and equivariant representation and further provides a platform for input data of variable size [54]. Due to the noninvariance of convolution to transformation in input data, an activation function (e.g., sigmoid, softmax, tanh and rectified linear unit (ReLU)) is applied to restrict the output within a certain range while pooling modifies the output at a certain network location with the aggregate of nearby outputs. After several convolution and pooling layers, fully connected layers are leveraged for classification purposes.

A recent study [42] proposed a non-fiducial method for off-the-person ECG classification in a biometric model based on 1D CNN for raw heartbeat signal and 2D CNN for heartbeat spectrogram. The study provides the lowest equal error rate (EER) for the CYBHi and UofTBD databases compared to other state-of-the-art techniques. However, performance restricted from the fusion techniques employed by the study can be outperformed by other complex feature levels. Another study [171] employed a multiresolution 1D CNN for learning the multi-scale feature hierarchies of ECG data processed through wavelet transform. A careful selection of topology among CNN and wavelet assisted their system to reach an overall accuracy of 93.5% on eight ECG datasets. Nevertheless, the researchers raise the challenge of data availability compared to other widely used biometrics such as a fingerprint. To extract fine-grained features from the cardiac signal, a two-level 1D CNN and a dynamic feature, i.e., RR interval difference, of arrhythmia was employed for the MIT-BIH and INCART databases and shown to achieve an overall accuracy of 97.8% [165]. However, the evaluation against irregular data containing arbitrary noise is not comprehensive and requires further exploration. The performance of deep CNN was examined for three tasks, including "closed-set identification, identity verification and periodic re-authentication" [86], using real and binary templates and standard distance functions. For 52 subjects in the PTB Diagnostic ECG database, an accuracy of 100% was reported, although extensive analysis is required for the technique to be scalable to other databases, especially with subjects suffering from cardiovascular diseases. A three-stage CNN was proposed for 2D signal representation using a softmax function with an accuracy of 98.4% for single-arm ECG authentication [172]. Nevertheless, only 10 subjects were examined with the requirement of expensive computational resources.

Respective to other cardiac signals, BiometricNet [46] was proposed for user identification leveraging the wrist-worn PPG, involving two CNN in addition to two layers of long short-term memory (LTSM). Even though a satisfactory accuracy of 96% was observed for the TROIKA dataset, the total amount of subjects were low and the evaluation did not comprise robustness tests that are crucial before application in wearable devices. More importantly, the proposed algorithm utilizes a complex deep neural network further requiring efforts to reduce its computational cost and energy consumption. CNNs are also capable for automatic quality assessment [3] of echocardiogram by scoring the apical four-chamber view containing cross-longitudinal sections of the heart chambers. However, the application of the system is limited, since the framework does not acknowledge the entire cardiac cycle but only a single frame.

• *Multilayer Perceptron (MLP):* It is a feedforward ANN that is typically used for supervised learning problems. It comprises an input layer to obtain the cardiac signal, a number of hidden layers, and an output layer for prediction. During the training phase, the error corresponding to weights and bias are backpropagated through MLP. The main advantage of MLP is its capability to differentiate among non-linearly separable data. Its potential was examined against logistic regression and Bayesian network for face authentication inherent with PPG signals with the result showing the superior performance of MLP under low ambient light conditions and other physical factors [32]. However, no clear indication was provided regarding the most optimal algorithm for the associated biometric model. Another study [122] evaluated the performance of ECG classification on the steering wheel by comparison among MLP, support vector machines (SVM), K-nearest neighbor (KNN), and Gaussian mixture models (GMM). SVM outperforms MLP in the authentication model while comparable results were observed among SVM through DCT and MLP through Haar transform in the identification model.

• *Recurrent Neural Networks (RNN):* This is another class of ANN that is an upcoming area of interest for cardiac biometric systems. In contrast to traditional feedforward networks, RNN can be used for processing of sequential data (e.g., cardiac signal) due to their internal state of memory and connection between the nodes. Given the prior knowledge of adjustment between input and output, it can map various sequences with sequences [150]. However, it is challenging to apply RNN in scenarios where input and output sequences have a complex relationship, in addition to possessing different lengths. Long short-term memory (LSTM) is widely adopted in RNN, collectively known as LSTM networks, to address the problem of vanishing gradients [68]. Specific to cardiac biometrics, the LSTM networks have been explored for authentication purpose using ECG-ID and MIT-BIH databases to observe an EER of 3.5% for 15% of subjects utilized during training [138]. The model required no feature extraction through fiducial- or frequency-based techniques and achieved 100% accuracy during identification. While a comprehensive study is essential to assess the presented system's practicality and usability, it shows the potential of LSTM networks for further exploration in cardiac authentication and identification systems. RNN has also been applied with deep residual neural networks (ResNet) for automatic characterization of the cardiac cycle in echocardiograms [44]; however, its potential application toward biometrics requires further exploration.

Support Vector Machines (SVM): Existing studies have widely acknowledged the excellent performance of SVM due to its exceptional performance observing reduced generalization errors in detection and classification problems [66]. It is a statistical learning method that determines an optimal hyperplane to divide two classes by maximizing the margin between the closest points. The points lying on the boundary are referred to as support vectors. SVMs are primarily used for solving binary classification problems, i.e., authentication; however, they can be employed for multi-class classification (e.g., identification) using one-against-one technique [98] by fitting all binary subclassifiers.

In Reference [91], the Hermite polynomial expansion and SVM are proposed to model the inter-heart variability among individuals by utilizing linear kernel function. The results using SVM indicate an accuracy of 98.11% but from only analyzing 18 ECG recordings. A novel study [41] was performed using off-the-person ECG data collected several months apart to analyze the impact of permanence on the cardiac signal with result showing an EER of 9.1%. With the integration of kernel functions [93], this classifier can also be explored for individual identification during physical exercises by leveraging chaotic cardiac signals. However, the SVM is challenging to employ for unstable signals due to their sensitivity toward the morphology of the signal. Furthermore, factors such as data overfitting and bias are some of the primary concerns that adversely affect the performance of the SVM model.

K-nearest Neighbor (KNN): In the scenario when little to no prior knowledge is present for the distribution of cardiac data, KNN, being a fundamental classifier, is widely applied. It is referred to as a lazy algorithm, since it "memorizes" the features stored in the training dataset while the computations are deferred until classification. Upon obtaining the test data, KNN relies on computing the distance (e.g., Euclidean) between the specified training samples and the testing dataset, and the test samples are classified to the class that has nearest k neighbors. It is widely used in cardiac biometric systems for authentication with the value of $k = 1$ [144].

Apart from aforementioned, studies have explored different settings such as $k = 3$ [41, 59] and $k = 5$ [159] for QRS complex in ECG signals and $3 <= k <= 40$ [82] for systolic and diastolic peaks in PPG signals. For an extensive evaluation, it is ideal to first empirically evaluate the best settings for the KNN classifier. Furthermore, algorithms based on feature ranking can also be applied for boosting classification accuracy. However, a few drawbacks of KNN are that it is computationally expensive because of the usage of the entire set of training samples, heavily dependent on the training set, and no weight difference is present between the samples. To overcome this, k amount of samples can be chosen for each iteration and classification accuracy can be further calculated to record the highest accuracy during each time.

Gaussian Mixture Model (GMM): These are commonly used in biometric systems as a parametric probability distribution of cardiac signals and related features and characterizes the weighted sum of Gaussian components as a density function. The weights of each parameter are obtained from the Expectation-Maximization algorithm [102] and Maximum A Posteriori estimation [132] while the classification scheme involves calculating the likelihood that the input sample is associated with the respective class. One of the significant advantages of GMMs is that they generate smooth approximations to densities of randomized shape.

In Reference [91], researchers used GMM in combination with cepstral feature extraction for segmentation and normalization independent modeling of short-time attributes of ECG signals. An identification accuracy of 95.90% was achieved; however, the number of samples was highly limited. Multivariate Gaussian distribution [26] can also be applied to the model estimation to determine a statistical model capable of providing insightful score function in biometric verification using SCG signals. Moreover, GMM is one of the first choices for classifiers for PCG signals [119, 147], due to its effectiveness in modeling frequency-based features. Nevertheless, the application

Table 4. Comparison of Complexity between Classification Methods [20]

Distance	*Complexity*	*Algorithm*	*Learning Complexity*	*Query Complexity*
Euclidean	$O(n)$	ANN	$O(m^2 * r)$	$O(m^2)$
Wavelet	$O(p * q)$	SVM	$O(m * r^2)$	$O(m)$
Mutual Nearest Point	$O(n)$	KNN	$O(1)$	$O(r) * O(distance_{\text{function}})$
Correlation	$O(n)$	GMM	$O(m * r * g)$	$O(m * g)$
DTW	$O(n^2)$	HMM	$O(m * s^2)$	$O(m)$
FastDTW	$O(n)$	Bayesian Network	$O(m^2 * r)$	$O(m^2)$
Coherence	$O(n * m)$	Naive Bayes	$O(m * r)$	$O(m)$

n is the length of feature vector; m is the number of features; s is states in the HMM model.
p is the number of coefficients; q is level of decomposition.
r is the number of trained samples; g is number of gaussian distributions.

of GMM in cardiac biometric systems needs to be further explored, since the component densities have the chance to model the underlying hidden classes, which may be valuable for individual characterization.

Hidden Markov Model (HMM): An HMM is a method for predicting the probability distributions over a sequence of observations. It comprises three primary assumptions [53], including: (1) a process with state S_t generates an observation that is hidden; (2) state of the hidden process satisfies the Markov property; and (3) the discreteness of state variable, i.e., S_t can occupy N values. While the present use of HMM is more focused on speech recognition [131], it can also be utilized for cardiac signal classification.

An HMM-based approach was proposed for processing SCG signals by dividing the cardiac vibration into hidden states traversed sequentially [161]. Features such as heart rate, HRV indices, and cardiac intervals are estimated for 67 subjects with results validating the superior performance of HMM over the envelope and spectral-based methods. Moreover, the use of HMM for SCG signals demonstrates comparable accuracy against time and frequency domain methods [24] in BCG signals and optical sensor-based techniques utilized for BCG [23] and PPG signals [114]. However, it is crucial to consider that a fully-connected model can lead to overfitting. The HMM also requires a significant number of parameters and training data, which may be difficult to gather in cardiac signals such as echocardiography, BCG, CM, and ICG due to insufficient public databases.

Others: In addition to the aforementioned techniques, studies have explored the use of bayesian network [32, 143], naive bayes [143], logistic regression [32, 91], bag-of-words [35], Bagging [96], kernel classifier [60], quadratic discriminant classifier [141], random forest [152], and fuzzy logic discriminator [94] for cardiac-based biometric problems. The Bland Altman plot is widely used for comparison among different cardiac techniques, e.g., SCG and ECG monitoring systems [88, 166].

6.3.3 Future Prospectives. The conventional classification approaches, i.e., SVM and KNN, have shown excellent usability in several biometric problems. However, these are yet to be extensively explored for SCG, BCG, CM, and ICG signals as well as echocardiography, which are the potential domains for future cardiac authentication and identification systems. With the advancement of ANN, it is possible to overcome the constraints of conventional techniques; nevertheless, a careful pre-evaluation is necessary to ensure that the corresponding approach does not incorporate additional burdens to the system. As observed from Table 4, there is a tradeoff between the complexity of the classification method and the accuracy. It would be ideal if a system could overcome these constraints and concurrently meet the desired application requirements.

Table 5. Performance of Machine Learning Classifiers

Signal	*Subjects/Database/Sensor*	*Preprocessing/Feature Extraction*	*Classifier*	*Performance*
ECG	CYBHi (65 subjects) UofTBD (100 subjects)	Heartbeat segmentation Outlier removal	1D CNN on raw ECG 2D CNN on Spectrogram	EER = 1.33–14.27 [42]
	CEBSDB, WECG, Fantasia NSRDB, STDB, MITDB AFDB, VFDB (220 subjects)	Filtering, Scaling Blind segmentation Wavelet Transform	1D CNN	Acc. = 93.5 % [171]
	MITDB (47 subjects) INCART (75 subjects)	Heartbeat normalization RR interval difference	Two-level 1D CNN	Acc. = 97.8% [165]
	E-HOL (185 subjects) PTB (52 subjects)	Notch IIR filter, 3rd order high-pass, QRS vector	CNN	Acc. = 100% [86]
	10 subjects	2D Data representation	Three-stage CNN	Acc. = 98.4% [172]
	6 subjects	Heartbeat segmentation Outlier removal DCT, Haar transform	MLP	EER = 2.66% [122]
	ECG-ID (90 subjects) MITDB (47 subjects)	R-peak detection	LSTM, RNN	EER = 3.5% [138]
	NSRDB (18 subjects)	Hermite polynomial expansion, cepstral features	GMM, SVM, Logistic Regression	Acc. = 95.9–98.1% [91]
	63 subjects	Partially fiducial, Mean and median wave, Outlier removal	SVM	EER = 9.1% [41]
	26 subjects	Time/frequency/chaos features	SVM	Acc. = 81.7% [93]
	PTB (30 subjects)	AC/DCT, MFCC, QRS complex	KNN	Acc. = 97.31% [59]
	NSRDB (15 subjects)	Band-pass filter, Zero crossing DTW, Fisher's LDA	KNN	Acc. = 97% [159]
	NSRDB (21 subjects)	R-peak detection, QRS complex	Bayesian network Naive Bayes, MLP, KNN	Acc. = 98.3–99% [143]
	PTB (290 subjects) CYBHi (65 subjects)	DCT, DWT, Random projection	Bag-of-words	Acc. = 98% [35]
	UofTDB (1012 subjects) PTB (290 subjects)	1DMRLBP, Sequential sampling	Bagging	EER = 7.89% [96]
	NSRDB (18 subjects)	4th order Butterworth bandpass DCT coefficients	Nonlinear Kernel	Acc. = 94% [60]
	47 subjects	Noise filtering, Alignment using angular position, Sum-of-Gaussians	Quadratic Discriminant	Acc. = 97% [141]
	184 subjects	FFT, R-peak detection P-QRS-T complex delineation Fiducial/non-fiducial features	Random Forest	Acc. = 99.5% [152]
PPG	TROIKA (12 subjects)	–	DNN and LSTM	Acc. = 96% [46]
	18 subjects	ROI selection, Maximum cross correlation, Statistics of amplitude ratio	MLP, Bayesian network	EER = 5.98% [32]
	DCM03 sensor (30 subjects)	Systolic and Diastolic peaks Peak-to peak and pulse interval	KNN	Acc. = 87.2–94.4% [82]
	Firstbeat Bodygaurd sensor (10 subjects)	Beat-to-beat interval	HMM	Acc. = 99.5% [114]
	12 subjects	Wavelet filter Correlation detection	Fuzzy Logic Discriminator	RMSE = 5.15 [94]

(Continued)

Table 5. Continued

Signal	*Subjects/Database/Sensor*	*Preprocessing/Feature Extraction*	*Classifier*	*Performance*
SCG	20 subjects	Low-pass filter, Normalization Autocorrelation	GMM	Acc. = 98.8% [26]
	67 subjects	State-space model, Baum-Welch algorithm, HRV indices	HMM	MAE = 5 [ms] [161]
	MEMS accelerometer (30 subjects)	Cubic-spline interpolation, Savitsky-Golay filter, Sparse FFT, Peak-to-peak interval	Bland-Altman plot	RMSE = 3.41–8.41 [88]
	Shimmer 3 (10 subjects)	LPF, NLMS adaptive filter, Peak detection	Bland-Altman plot	Acc. = 98.7% [166]
BCG	EMFi sensor (8 subjects)	HRV indices, interval estimation	HMM	r > 0.9 [24]
CM	2.4GHz Doppler radar (78 subjects)	Butterworth bandpass filter, Extented differentiate and cross-multiply algorithm, Fiducial descriptors	SVM	EER = 4.42% [92]
PCG	128 subjects	STFDT, Filter-bank Dimension compression, CMS	GMM	Acc. = 99% [119]
	HSCT-11 (206 subjects)	S1/S2 detector, LFCC	GMM-UBM	EER = 13.66% [147]
Echo	VGH (6916 subjects)	–	CNN	MAE = 0.71 [3]
	1868 subjects	–	ResNet, LSTM	EER = 3.7% [44]

MAE, Mean Absolute Error; Acc., Accuracy; EER, Equal Error Rate; r, Correlation.

7 CARDIAC IDENTIFICATION WORKING MODE

With the advent of cardiac sensors possessing different attributes such as off-the-person, non-contact and wearable, the biometric system can be designed to meet various application requirements demanded in important domains. In this section, we categorize three primary working modes, based on the taxonomy illustrated in Figure 3, that are increasingly used in biometric applications.

7.1 Continuous Authentication

User authentication is highly essential for ensuring the security of computer, network, and cyber-physical systems. Presently, the existing systems relying on fingerprint or voice authentication require the user to login at the initial session and does not reauthenticate until the user terminates the activity or there is a substantial time interval among the activities, as shown in Figure 7. The associated individual is denoted as a trusted party and can access the underlying information present in the system with no obstruction. These induce several security flaws as an adversary can access the resources by masquerading or replaying the stolen biometric feature of the authorized user. Continuous authentication relies on continuously monitoring and verifying the user throughout the entire span of activity. Due to the long time periods of the cardiac signals during data acquisition, they can be ideally employed for authentication, provided that the data can be acquired seamlessly.

To begin the research initiative of employing cardiac signals for continuous authentication, further elaborated in Table 6, a novel framework based on the Mahalanobis distance was proposed to identify the individuals using ECG signals [57]. Following this, studies explored the use of correlation and score fusion techniques for 24-hour authentication [87], data stream mining for ECG streams in real-time applications [28], and sequential sampling with local binary patterns in cardiac

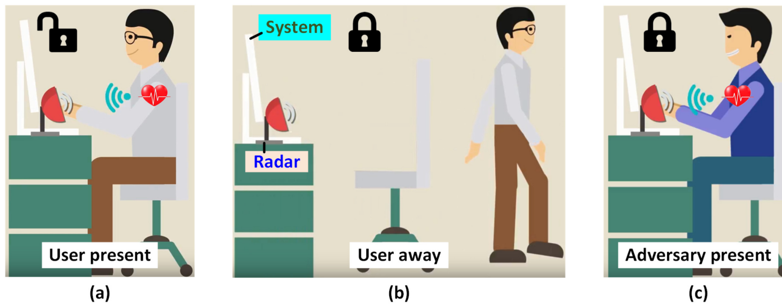

Fig. 7. Three events: (a) The system remains unlocked during access by the legitimate user; (b) the system locks when the legitimate user is away; and (c) the system remains locked when accessed by the adversary. Radar is used as an example to measure the biometric signals.

Table 6. Summary of Continuous Authentication Techniques Proposed for Cardiac Biometrics

	Signal	*Off-the-person*	*Sensor*	*Subjects*	*Threshold*	*Performance*
Guennoun et al. [57]	ECG	Yes	AliveCor	16	Predefined	Acc. 83.3%
Labati et al. [87]	ECG	No	Electrodes	185	Predefined	EER 5.36%
Camara et al. [28]	ECG	—	Various	10	Predefined	Acc. 96%
Louis et al. [96]	ECG	No	Electrodes	1020	Dynamic	EER 7.89%
Pinto et al. [122]	ECG	Yes	—	6	Dynamic	EER 2.66%
Bonissi et al. [22]	PPG	No	Oximeter	44	Predefined	EER 9%
Sadek et al. [136]	BCG	Yes	MFO	50	Predefined	MAE 7.31%
Lin et al. [92]	CM	Yes	Radar	78	Various	EER 4.42%

MAE, Mean Absolute Error; Acc., Accuracy; MFO, Microbend Fiber Optic.

signals for dynamic allocation of decision thresholds [96]. The application of continuous authentication was also shown in driving environments by recognizing the driver during each 5-second interval through ECG signals and applying a weighting function for minimizing the outliers in the recent score using past scores [122]. With respect to other cardiac signals, a preliminary study [22] was performed to investigate the PPG signals for continuous authentication based on correlation analysis; however, the features suffer from low durability, thereby leading to high EER and requiring further investigation. Despite focusing on user authentication, researchers have instead explored the feasibility of BCG signals for continuous vital signs monitoring through a remote connection between servers and the sensor [136], and correlation analysis between BCG and ECG signals [40]. However, the remote monitoring relied on an unreliable setup environment while strains due to hemodynamic responses were prominent, respectively. Last, a novel continuous authentication scheme [92] was designed with the non-volitional and geometric features of CM that are extracted from radar signal demodulation.

Presently, the cardiac continuous authentication suffers from two primary challenges. First, the frequent or continuous streaming of cardiac signals by the sensor raises the computational cost and energy consumption of the hardware. While short cardiac segments can be analyzed, rather than a seamless sequence, the accuracy of the system suffers from inadequate information. Second, a unique challenge arises from the errors accumulated over the runtime of the system. However, the implementation of continuous authentication using cardiac signals is still in infancy and requires further efforts to address the mentioned constraints.

7.2 Unobtrusive Monitoring

Conventional cardiac sensing modalities such as electrodes and stethoscope can provide adequate signal quality but arrive at the cost of user comfort. To ensure acceptability and comfort to the user during data acquisition, unobtrusive monitoring is becoming the ideal choice in existing applications and literature. Sensors such as a camera or radar can enable the respective measurements of PPG and CM signals without influencing the user's activities. Sensors, including microbend fiber optic for BCG [136], serve the purpose of both continuous and unobtrusive measurement of vital signs; however, limited studies have been performed for their application in user authentication. The domain of ICG still primarily relies on the use of electrodes due to the difficulty of designing an unobtrusive sensor for the required acquisition of signals through the thorax region. Nevertheless, unobtrusive monitoring has successfully closed the gap between methodologies and commercial applications with the development of wearable technologies, e.g., Nymi Band and Fitbit.

For the advancement of unobtrusive monitoring in various cardiac domains, several limitations need to be addressed. As mentioned previously, there is a tradeoff between the signal quality and the processing difficulty. Low-quality signals suffering from motion artifacts, power-line interference, and baseline wander are evident in cost-effective, non-invasive sensors such as microphones and accelerometers, which further increases the challenge of effective denoising and feature extraction. In addition, the majority of unobtrusive sensors (e.g., accelerometer for chest SCG) require the user to hold them at a fixed location without influencing the sensing process. This may still obstruct the user during physical activities while losing its effectiveness due to gradual misplacement from user's lack of attention. Based on the application, the user might be required to wear the sensor for a long time and provide extended signals in a frequent interval, which would reduce the acceptability of the overall system. These concerns must be solved to reach the ideal scenario of obtaining a viable cardiac sensing modality satisfying all application requirements.

7.3 Multimodal Biometrics

Unimodal biometric systems rely on knowledge of a single source, in our case the cardiac signal, for user authentication. However, these systems rarely demonstrate exceptional performance due to the influence of noise, inter-class variations (i.e., based on user's interaction with sensor), intra-class similarities (i.e., overlap of feature space), incomplete training, non-ideal learning algorithms, or spoof attacks employed specifically for the particular cardiac signal domain. Furthermore, some portion of the population may not be able to provide the data due to health problems or disabilities. To overcome these limitations, multimodal cardiac biometric systems rely on concurrently acquiring different cardiac signals and fusing them during the authentication process. The fusion can be employed at various locations in the biometric model depending on the application requirements.

Feature-level fusion combines the independent feature vector of different biometric signals as a single feature vector for the matching process. To enhance security, voice and ECG features were combined for non-invasive user identification [25]. An implementation of binaural brain entrainment [110] was proposed to minimize the inter-session uncertainty between the respective features of ECG and EEG and increase the classification performance. Score-level fusion based on the weighted sum rule is a widely adopted technique for merging the outputs of matching algorithm and has been proposed for ECG and fingerprint biometrics [9, 126] and shows exceptional performance utilizing ECG, face, and fingerprint information [146]. Decision-level fusion relies on combining the decisions from the individual matching algorithms and is optimal in scenarios when the training data have partial information about the user. It has shown significant capability for ECG with fingerprint [12] and ECG with PCG [48] multimodal biometric systems.

Table 7. Summary of Multimodal Techniques Proposed for Cardiac Biometrics

	Signals	*Fusion*	*Cardiac Database*	*Subjects*	*Performance*
Alajlan et al. [9]	ECG + Fingerprint	Score	Private	78	EER 4.28%
Singh et al. [146]	ECG + Fingerprint + Face	Score	European ST-T, MIT-BIH, PhysioBank	78	EER 0.98%
Bugdol et al. [25]	ECG + Voice	Feature	Private	30	Acc. 92%
Palaniappan et al. [110]	ECG + EEG	Feature	Private	5	Acc. 98.6%
Pouryayevali et al. [126]	ECG + Fingerprint	Score	Private	45	EER 0.084%
Arteaga et al. [12]	ECG + Fingerprint	Decision	European ST-T, QT, MIT-BIH, PhysioBank	73	EER 0.46%
Fatemian et al. [48]	ECG + PPG	Decision	Private	21	Acc. 97%

Acc., Accuracy.

Due to the characteristic of liveness detection, cardiac signals are increasingly explored as a supplement to state-of-the-art methods to further enhance the security of the biometric model and improve classification accuracy. However, the existing research on cardiac multimodal biometrics solely focuses on utilizing ECG with other biometrics as mentioned in Table 7. It would be valuable if other cardiac signals (e.g., SCG, BCG, ICG, CM, or echocardiography) are leveraged in a multimodal setup to gain insights into the optimization of fusion layers. Nevertheless, for the advancement of the above criteria, it is essential to ensure the growth in the cardiac dataset that is lacking in comparison to fingerprint or face datasets. Careful selection criteria would be required to obtain the benefits of the multimodal system and avoid overhead due to increased computational cost, delay, or energy consumption from the processing of different cardiac signals. Moreover, researchers should provide further effort into the development of a secure, robust, and non-invasive cardiac multimodal system that can concurrently utilize various cardiac signals from different regions of the body for user authentication.

8 APPLICATION SCENARIOS

Cardiac sensing has excellent performance and measurability with much potential beyond its current use for adoption in many biometric applications. The ECG, PPG, and PCG signals are heavily leveraged for biometrics [4, 107, 140]; however, we argue the potential of other methodologies in specific scenarios.

8.1 Access Control

The logic of access control refers to obtaining entry into the location, network, or application from either the place of the access point or a remote location. The use of biometrics (e.g., fingerprint and face recognition) for this application is well explored; however, they can be easily spoofed as the biometric sample of the legitimate user can be obtained secretly and fed to the system to generate a false positive result [146]. The heart-based methods involve liveness detection, which requires the physical presence of the respective user for authentication. The applications of cardiac biometrics in access control can be pertinent to two categories:

8.1.1 Physical Domain. In a general scenario, valuable documents, commodities, or monetary funds are stored inside a secure location. The level of security differs, from employing keys, badges, or identification cards to biometric authentication. Similarly, in numerous institutions or corporations, the employees or attendees are required to sign in when starting the event and sign out when exiting using key cards, but there is a shift toward using biometrics for maintaining the ***time and attendance*** records [130]. Smart ECG cards with statistical algorithms were proposed as a secure solution [157, 170]; however, they are constrained by the requirement that they must be carried, and therefore there is a risk of theft. Cardiac signals, including ECG, PPG, and PCG, are commonly used for human identification; however, not every cardiac methodology can be adapted for physical access control. For instance, consider a scenario where the authentication system is placed on the wall at a stationary location. Assuming the system is based on cardiac sensing, the ECG signal can be recorded off-the-person through fingers [42] while the camera can be used to record the PPG signal from a user's fingertip video [32]. However, the PCG signal will not have considerable usage or performance due to the requirement of the proximity of the microphone. The SCG and BCG will require using accelerometers, while electrodes need to be placed on the neck for the ICG signal, both of which are uncomfortable for the user and can be tampered with because of detached sensors. A similar situation would be observed for echocardiography measurement. The employment of radar can also enable CM to be leveraged in the authentication system [92]; however, its specific application in this domain has yet to be explored.

8.1.2 Digital Domain. To obtain the access into the network or application, conventional methods such as passwords are commonly used in present computing systems. Besides the active employment of ECG, PPG, and PCG signals for user verification, the deployment of SCG signals as a biometric in smartphones is still at a preliminary phase [26] and needs comprehensive investigation. The BCG signal possesses the inter-individual variability based on physiological factors and can be measured through modern systems requiring the user to sit in a chair in a fixed position. However, specialized sensor placements and the stationary individual state would be a necessity, which is not feasible in many real-world application scenarios [58]. A biometric modality for digital access control comprising either ICG or echo would incorporate the use of electrodes and probes, which are not possessed by the majority of people and are often uncomfortable while measuring. The CM requires a high learning curve due to radar technology. Moreover, the acquisition of training data for a mass population in larger applications would be difficult due to a limited cardiac database.

The exploration of secure ***data transmission*** using biometrics also falls under the domain of digital access control. Conventionally, symmetric and anti-symmetric key generation methods are used to ensure privacy and security during data transmission [77] but require complex and computationally expensive key generating techniques. The ECG was leveraged as a biometric feature for securing the physiological information processing in body sensor networks (BSN) by using the ratio between the standard deviation between two R-R peaks and root mean square of the successive differences [123] for generating the authentication key. Another study explored the interpulse interval for securing BSN via leveraging the ECG and PPG signals [125]. However, there is an existing research opportunity to explore other cardiac sensing methodologies to utilize for secure data transmission. Moreover, it has been observed that biometric data visualization can affect the interactions among viewer and the proprietor [39], serving as a motivation for implementing a secure solution to manage the biometric information for the online medium.

8.2 Law Enforcement and Forensic Investigation

A prominent limitation of cardiac sensing modalities is that they cannot be acquired from the forensic scenes posterior to the crime, in contrast to fingerprints. In addition, they are infeasible for surveillance due to the proximity of sensors required for measuring cardiac signals. Nevertheless, the different types of cardiac signals can be used for lie detection for precise heart rate and cardiac output measurement to identify any abnormal changes in the cardiac activity or blood flow. Furthermore, remote sensing of CM from radar, PPG signals from cameras, and HRV from laser Doppler vibrometry without the need of surface contact can lead to monitoring of a suspect's

Table 8. Examination of Attack Potential against Each Cardiac Methodology with Decreasing Order of Difficulty

	*Imitation**	*Replay**	*Morphing*	*Denial-of-Service*	*Comm. Channel*	*System Mod.*
ECG	✗	✗	√	☆	✗	√
PPG	✗	✗	✗	✗	✗	☆
SCG	✗	✗	☆	☆	☆	☆
BCG	✗	✗	✗	☆	☆	✗
PCG	✗	✗	✗	☆	☆	☆
Echo.	✗	✗	✗	✗	☆	✗
CM	✗	✗	☆	☆	✗	✗
ICG	✗	✗	☆	☆	✗	☆

Left to Right.
•☆= Requires exploration; ✗= Low possibility; √= Already adapted;
•Mod. = Modification; Comm. = Communication.
* Performed without significantly altering the original cardiac signal.

heart conditions without their knowledge. This has the potential to be effective in various forensic investigations and requires further investigation to be deployed in real-world scenarios.

9 OPEN ISSUES IN PRIVACY AND SECURITY METRICS

Due to the drastic shift of cardiac sensing applications toward the biometric domain, it is critical to ensure the security of the underlying system against varying threat levels. An adversary can exploit various channels in the cardiac biometric system to perform the attacks described in Table 8. At present, few studies have explored attacks on cardiac modalities to examine their vulnerabilities. To this end, we further elaborate on the potential of specific attacks in the presence of each cardiac methodology. These opportunities require in-depth exploration and are still the open issues to address for strengthening the security of cardiac biometric systems, thus aiding their deployment in real-world scenarios.

9.1 Imitation and Replay Attack

In the preliminary phase, the user's cardiac sample is either registered (if first time) or measured by the sensor for authentication. An adversary can compromise the system's security by using a fake biosignal sample by imitating the authorized user or from replaying the trusted sample to the sensor. Examples from other recognition techniques include recording the voice of the proprietor and replaying it to bypass the security of a voice recognition system [164], gelatin fingers for fingerprint recognition modalities [16], or imitating gait movements [101]. However, the characteristic of cardiac signals to provide liveness detection demonstrates great potential for security enhancement. The static and dynamic features of the heart (refer to Section 2.2) results in a highly complex and inter-person variable cardiac signal, thus leading to a low possibility of imitation attack through brute force methods for any cardiac methodology. Furthermore, due to the attribute of liveness detection, replay attacks are infeasible unless the authorized user him- or herself feeds the cardiac signal to the sensor. Presently, several studies leverage this attribute by integrating their system initially based on behavioral biometrics with cardiac sensing. Although this might enhance the security, it would increase the overhead of the system due to additional processing required for the cardiac signal, similarly to the case of multimodal biometrics. For future advancement, it would be vital to exclusively employ cardiac signals acquired from different regions of the body to improve the system's security. For instance, to mitigate video-based and photo-based forgery attacks against a face verification system, PPG signals from face and fingertip were employed concurrently for mobile device authentication [32]. The related research is just beginning, and we can imagine considerable development in this area over the next few years.

9.2 Morphing Attack

The belief of cardiac signal being unclonable has been challenged recently by spoofing the system through signal injection attacks. A subset of these attacks, i.e., morphing, has been explored that relies on mapping the biosignal of the adversary to that of the authorized user by training the model with the small templates of victim's cardiac signals. An online and offline morphing attack [81] using a single ECG beat as a template has been proposed with results showing a 90% accuracy for the online scenario with limited resources. However, to achieve high accuracy, the heart rate and HRV are required to be similar between the authorized user and the adversary. To the best of our knowledge, Reference [45] is the only study that has successfully shown the vulnerability of a commercial product, i.e., Nymi Band, through a systematic attack using a mapping function for impersonating the authorized user by presenting ECG signals acquired from different devices. While significant results were observed, the proposed attack can be mitigated by using liveness detection. Furthermore, the morphological alterations can also be detected by comparing the cardiac signals acquired from various parts of the human body, since they possess comparable inherent characteristics, and alterations of one signal would not affect the others. Moreover, other correlated physiological signals (e.g., ABP) [27] can aid in the detection of morphing attacks when analyzed in addition to cardiac signals. Considering cardiac signals other than ECG, it is essential to analyze their vulnerabilities to morphing attacks. Due to the influence of gravity in the recording and high variability in signals due to noise arising from environmental factors, the possibility of morphing BCG and PCG signals, respectively, is low. Echocardiography utilizes imaging of the heart, which is distinct for each individual and resistant to these types of attacks. While it is possible to explore the mapping function for PPG signal for morphing attack on oximeters, the potential of the same attack on measurements through the camera is low due to the variability in reading added by the ambient light and other dynamical factors in the adversary and victim's environment. The domain of SCG, CM, and ICG is upcoming and requires in-depth exploration to verify the security of related biometrics systems.

9.3 System Attack

In the scenarios when the adversary has access to the biometric system or related components, the potential attacks can be categorized into three types: (1) System Modification, (2) Communication Channel, and (3) Denial-of-Service. The system modification attack is pertinent in physical access control devices where the adversary can directly modify the intermediate components to sabotage the cardiac biometric system. As mentioned, even though the study [45] employing mapping function was categorized into a morphing attack, it performed system modifications to the original Nymi Band to carry out the attack. Due to the increasing employment of unobtrusive monitoring, the majority of cardiac sensing modalities (mentioned in Section 5) are separate from the processing system, thereby increasing the threat of exploitation of the communication channel by the attacker. Finally, Denial-of-Service attacks are one of most severe forms of threat to biometric systems that results in denial of access to the legitimate users. These are often achieved by flooding the resource with superfluous requests, such as enrollment of noise samples, to degrade the performance of cardiac biometrics. Table 8 highlights the potential of these attacks in each cardiac domain with certain low possibilities due to upcoming off-the-person systems with integrated sensor and processing schemes, intricate configurations of the sensor, or intrinsic characteristics of the respective biosignal. Given the emerging significance of cardiac security, researchers should investigate and reduce the vulnerabilities of the corresponding system to enable future research and advancement.

10 CONCLUSION

In this survey, we have detailed the existing cardiac domains and associated sensing modality based on the proposed three-dimensional taxonomy. We also reviewed the state of the art for cardiac biometrics by extensively characterizing the general model for individual classification into sensors, signal processing units, and the matching algorithms. Cardiac biometrics have gained immense attention due to intrinsic feature representation and liveness detection providing superior security compared to other behavioral biometrics. To aid future research, we described various application scenarios and existing challenges toward security and privacy of underlying systems. Although the research of heart-based methods in biometrics is still nascent, the following aspects can be explored for gaining further insights:

- **Fusion of cardiac signals:** The majority of the existing work in cardiac biometrics is focused on ECG or PPG. The optimizations related to signal processing, application security, and real-world deployment that were previously performed for these domains have yet to be explored for other cardiac methodologies (e.g., SCG, CM, ICG, and others) that can be combined for multi-biometric applications. For instance, when a user positions his or her finger on the smartphone camera, PPG and BCG can be simultaneously analyzed from the optical variations in the recorded images. Electrical signals, i.e., ICG and ECG, can be examined by developing a necklace-type interface with off-the-person sensors at neck and upper-chest locations.
- **Large-scale evaluation:** The lack of biometric samples in the cardiac database, compared to fingerprint, poses challenges in effectively comparing the performance of the two underlying systems. Moreover, a large-scale evaluation is highly necessary before deploying a cardiac approach into a commercial product, specifically the ones that require high computational resources. In scenarios where data acquisition is expensive, researchers should utilize existing publicly available databases such as UofTBD (with 1,020 subjects), MGH/MF (with 250 subjects), and PPG-BP (with 219 subjects) to ensure the scalability of their proposed systems.
- **Biometric signal quality:** With the increasing employment of off-the-person, unobtrusive, or wearable data acquisition modalities, the impact of noise on the cardiac signal is significant enough to render the processing scheme infeasible. Denoising-aware methods, including level-dependent wavelets, multi-band spectral subtraction, and robust neural networks, should be actively explored for cardiac biometrics. Furthermore, the signal quality after the preprocessing stage should be verified for raw signals collected in different working environments.
- **Permanence:** One of the primary challenges that limits the growth of cardiac biometrics is the aging of corresponding signals. Future applications should consider this factor during system design and explore the employment of generative approaches that can model a relationship between periodical samples of an individual. Other countermeasures include improving the analog-to-digital conversion rate and sampling frequency on the hardware level, incorporating spectral features on the software level and training the model on data collected across extended time-frame (greater than one month).
- **Biometric security:** The evaluation of tolerance to malicious attacks of varying threat levels is as crucial as achieving high accuracy for any biometric system. Researchers should further explore novel techniques (e.g., cancelability, just-in-time privacy, and secure

sensing) for eliminating any false sense of security of existing or new cardiac applications. Given that the cardiac signals originate due to heart activity, it is worthwhile to explore attack scenarios where an adversary morphs difficult-to-acquire signals (e.g., ECG) from easy-to-acquire signals (e.g., PPG) to breach the biometric security.

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