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Leveraging ECG Biometrics for Enhanced Security and Health Monitoring

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Abstract:

Electrocardiogram (ECG) biometrics presents an innovative approach to identity verification and health monitoring, harnessing the unique electrical patterns of individual hearts as a means of authentication. This paper delves into the foundational principles of ECG biometrics, highlighting its distinct advantages over conventional biometric methods such as fingerprints and facial recognition, which can be susceptible to forgery and environmental factors. We provide a comprehensive exploration of the methodology involved in ECG feature extraction, discussing various signal processing techniques that allow for the isolation of key characteristics from ECG waveforms. This includes time-domain analysis, frequency-domain analysis, and advanced techniques such as wavelet transforms, all of which are essential for accurate feature identification. Furthermore, we examine a range of classification algorithms, from traditional machine learning models to cutting-edge deep learning approaches, that are employed to authenticate individuals based on their ECG profiles. The paper also addresses the practical challenges of implementing ECG biometrics in real-world scenarios, including issues related to data privacy, the variability of ECG signals due to factors such as physical condition and electrode placement, and the need for robust security measures to protect sensitive health data. Our findings suggest that ECG biometrics not only significantly enhances security systems by providing a highly reliable and user-friendly authentication method but also contributes to proactive health monitoring by offering insights into cardiovascular health.

Keywords: ECG Biometrics, Feature Extraction, Signal Processing, Machine Learning, Classification, Wearable Devices, Health Monitoring, Arrhythmia Detection, Deep Learning, Authentication.

1. Introduction

Biometrics has become essential in today's security landscape, offering a reliable and convenient means of identity verification [1]. With traditional methods like passwords and PINs increasingly vulnerable to fraud, biometric technologies such as fingerprints, facial recognition, etc. provide a unique and difficult-to-replicate alternative [2]. These systems enhance security by ensuring only genuine people can access to important and private information while streamlining authentication processes for users [3]. Additionally, biometrics facilitates improved health monitoring, enabling continuous tracking of vital signs and early detection of potential issues [4]. As the digital world

expands, the integration of biometric solutions will play a critical role in enhancing trust and safety across various sectors [5].
As biometric technologies continue to evolve, the requirement of more secure, reliable, and user-friendly identification techniques grows significantly. In an era where data breaches and identity theft are prevalent, organizations and individuals alike seek advanced solutions that not only provide robust security but also enhance the user experience. Traditional biometric modalities have been widely adopted; however, they come with inherent limitations that highlight the need for innovative alternatives [6].

Limitations of Traditional Biometrics

1. **Forgibility and Replication**: This is very important and major issue related to the traditional biometric systems [7]. Fingerprint recognition, for example, can be compromised through the use of artificial replicas created from gelatin or silicone. Similarly, anyone can misuse facial recognition systems with photographs or videos, particularly in poorly designed systems that do not incorporate liveness detection measures. This vulnerability raises questions about the reliability of these methods in high-security applications.
2. **Privacy Concerns**: Biometric data is unique to individuals and often considered sensitive information. The collection, storage, and application of such data can result in privacy violations and unauthorized access [8]. Users may be apprehensive about how their biometric information is handled, especially in light of increasing regulatory scrutiny surrounding data privacy. This concern is compounded by the potential for biometric data to be hacked or misused, creating a reluctance to adopt traditional biometric systems.
3. **Environmental Influences**: Environmental factors can significantly impact the performance of traditional biometric systems [9]. For instance, fingerprint readers may struggle to accurately capture prints in dirty or wet conditions, while facial recognition systems can be less effective in low-light scenarios or when the subject is wearing accessories like hats or glasses. Such limitations can hinder the usability and accuracy of these systems in real-world applications.

In this context, ECG biometrics emerges as a promising alternative, leveraging the unique electrical activity of the heart as a means of identification [10]. The heart's electrical signals, captured through an ECG, produce distinct patterns influenced by individual physiological traits. These patterns are not only stable over time but also resistant to external factors, making ECG an attractive option for biometric authentication. Additionally, ECG biometrics offers potential applications in health monitoring, providing insights into an individual's cardiovascular condition while ensuring secure access to sensitive information.
This research article primarily focuses on the methodology of ECG feature extraction, analysing various classification algorithms, and discuss the potential applications and challenges associated with ECG biometrics. This research study aims to present a detailed overview of this innovative field and its implications for future technology in security and healthcare.

2. Basic Biometric Systems

Figure 1 shows a basic biometric system. Various stages work together to accurately identify or verify an individual as per their unique physiological or behavioural characteristics [11].
First, the information acquisition step takes place, where a biometric sample (such as a fingerprint, face image, voice recording, or iris scan) is captured using a biometric sensor. This sample can be obtained through various devices such as cameras, fingerprint scanners, or microphones, as per the type of biometric system being used.
After the collection of biometric data, the following step is preprocessing. Preprocessing involves preparing the captured data for feature extraction by enhancing its quality and removing any noise or irrelevant information that may affect the accuracy of the system. This can include steps such as image normalization, noise reduction, and alignment to ensure that the data is in a standard form and is of sufficient quality for analysis.
After preprocessing, the system proceeds with feature extraction. In this stage, distinctive and relevant characteristics or features are identified and extracted from the biometric sample. These features represent the uncommon traits of the person's biometric data, like the ridges in a fingerprint, the unique patterns in an iris scan, or the frequency patterns in a voice. The goal is of converting the raw biometric data into a compact and informative representation which are then used for comparison and matching.
Next, a biometric template is created. This is a digital reference or signature of the extracted features that serves as a permanent record of the biometric data that is belonged to a particular individual. A secured database is used to store the biometric template, either locally or in a central server, and it serves as the reference point for future identification

or verification tasks. The template is designed to represent the unique characteristics of the individual, making it useful for distinguishing them from others.
In the final step, matching is performed. Here, a matching algorithm is used for comparing the newly captured biometric sample (from the individual attempting to authenticate) with the stored templates. The matching algorithm computes the similarity between the input sample and the stored templates to determine whether they match. In a verification scenario, this step checks if the individual is the real person or not by comparing their input data to a single stored template. In an identification scenario, the system compares the input data to multiple stored templates for correct matching.
If the system finds a match, it confirms the identity of the individual, otherwise, it may reject the sample. The precision and performance of the biometric system highly rely on the quality of the feature extraction, the strength of the matching algorithm, and the precision of the preprocessing steps.

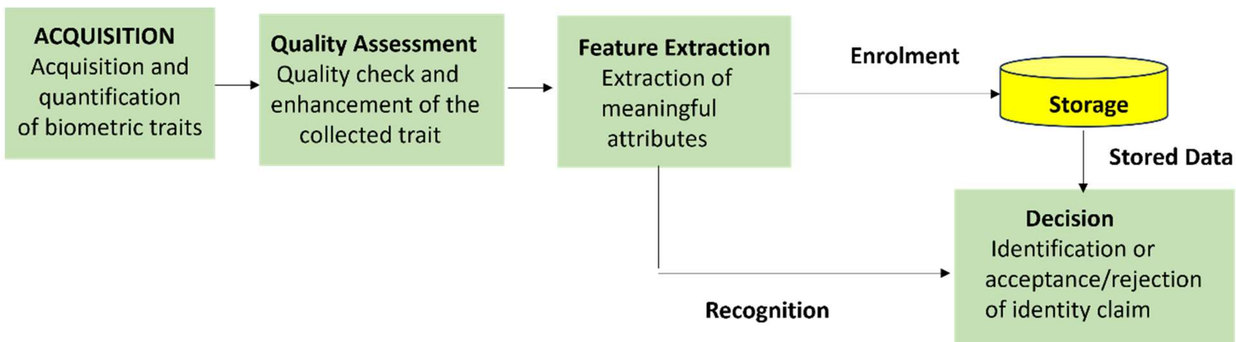

Figure 1: Block diagram for the Biometric system

Biometric authentication is classified into two modules which are enrolment and identification module. A sensor is used in the enrolment phase to scan the biometric characteristics for obtaining a digital characteristic. This data is then processed by a feature extractor to optimize the matching process and reduce storage requirements. Then, this processed data is sent a template database. Biometric authentication means verifying a specific person based on unique physiological or behavioural characteristics. As the demand for secure and convenient identification methods grows, various biometric modalities have been developed and deployed across diverse applications.

2.1 Behavioural and Physiological Biometrics

Biometrics means the unique physical and behavioural characteristics of a person. These unique features of a person are often used for identification or verification purposes in security systems. Biometrics can be of two main kinds: physiological and behavioural biometrics. Each type relies on different traits and offers distinct advantages and challenges.

2.1.1 Physiological Biometrics

Physiological biometrics refers to physical attributes of an individual that are inherent and relatively stable over time. These characteristics are directly linked to the physical body and can often be captured using specialized sensors or imaging technologies.
Most widely used physiological biometrics include:

a. Fingerprint Recognition
This is the most commonly used type of recognition system. It has been used in numerous applications for the past many years. It works on the unique patterns of ridges and valleys on the surface of a person's fingers [12]. Each person's fingerprints are distinct, even among identical twins, and they remain stable till person is alive. This type of recognition system records the minutiae (points where ridges end or bifurcate) and use these features to match against stored templates [13]. Fingerprint scanners are very commonly used in mobile devices, law enforcement, and access control systems [14].

b. Facial Recognition
This recognition system makes the recognition of a person by using the unique features of an individual's face [15]. Key features analyzed include the gap between eyes, nose shape, jawline, and the overall structure of the face [16]. Modern facial recognition systems use deep learning algorithms to capture and match these features from images or videos [17]. Facial recognition is often used for surveillance, smartphone authentication, and identity verification in airports or public spaces [18].

c. Iris Recognition
The coloured part of a person eye is used in this system for recognition. Each person has unique patterns of the iris [19]. It captures high-resolution images of the iris to identify distinctive features such as texture, colour, and patterns [20]. The iris is stable over a person’s lifetime and is difficult to alter or forge, making it a reliable method of biometric identification. Iris recognition is commonly used in high-security areas like airports and government buildings [21].

d. Retina Scan
A retina scan analyzes the pattern of blood vessels in the retina [22]. This pattern is different in each person, even in twins. Retina scanning is highly accurate and can be used for high-security identification purposes [23]. However, it requires a specialized scanner and may be less convenient than other methods.

e. Hand Geometry
Hand geometry recognition captures the shape and size of a person's hand, including finger length, width, and the overall shape of the palm [24]. While hand geometry is not as unique as fingerprints or retina patterns, it offers a relatively easy and non-intrusive method of identification [25]. This method is often used in physical access control systems, such as in secure offices or buildings.

f. Voice Recognition (Physiological Aspect)
Voice recognition systems analyse the physical aspects of a person’s voice, including pitch, tone, cadence, and the shape of the vocal tract [26]. Although voice recognition is influenced by factors like emotion and health, certain traits remain stable enough to offer reliable identification. Voice-based authentication is often used in mobile devices and call centers [27].

2.1.2 Behavioural Biometrics

Behavioural biometrics refer to patterns in the way people act or interact with their environment. Unlike physiological biometrics, which rely on physical traits, behavioural biometrics are dynamic and can change over time depending on context, mood, or physical condition [28]. However, they can provide valuable data for continuous authentication in many applications. Some of the key types of behavioural biometrics include:

a. Keystroke Dynamics
In this type of biometric recognition system, the pattern in which a person uses a keyboard for typing is used for recognition [29]. This includes factors such as typing speed, rhythm, pressure on keys, and the time spent between keystrokes (dwell time) [30]. Each individual develops a unique typing pattern, which can be used to authenticate them or detect fraudulent activity. Keystroke dynamics can be integrated into systems as a passive form of authentication, particularly in banking or online security applications [31].

b. Gait Recognition
Gait recognition analyzes the way a person walks, including factors like stride length, speed, and the movement of arms and legs [32]. Each person has unique gait and hence it can be used for identification even from a distance or without direct contact. Gait analysis can be captured using video surveillance or specialized sensors and is increasingly used in areas like security monitoring and surveillance [33].

c. Signature Dynamics
Signature dynamics focuses on the way a person signs their name. This includes characteristics such as the speed, pressure, and movement patterns during the signature process [34]. Unlike a static image of a signature, dynamic

signature recognition focuses on how the person writes the signature, which remains unique and hard to replicate [35]. This method is often used in banking for check verification and document authentication.

d. Speech Recognition

While speech recognition also has a physiological component (voice), it has a significant behavioural aspect, as it involves how a person speaks rather than just what they say [36]. Speech patterns, including cadence, accent, pitch, and even the rhythm of speech, can be unique to an individual. Continuous speech recognition systems can be used for identifying or verifying individuals in phone systems, voice-controlled assistants, and security applications [37].

e. Mouse Dynamics

This recognition system uses the way a user interacts with a mouse or touchpad for recognition purpose [38]. This includes speed, movement patterns, pressure, and click habits. Similar to keystroke dynamics, mouse dynamics can serve as a behavioural biometric to authenticate users or track unusual behaviour patterns in applications like online banking, e-commerce, and user verification systems [39].

f. Eye-Tracking

Eye-tracking technology analyzes how an individual looks at objects or moves their eyes during a task [40]. It can capture the pattern of eye movements (such as saccades and fixations) and the way a person shifts their gaze. Eye-tracking is often used with various other forms of biometrics for continuous authentication, especially in mobile devices and online systems where users engage in repetitive tasks [41].

A detailed overview of Physiological and Behavioural Biometrics is given in below table.

Table 1: Comparison of Physiological and Behavioural Biometrics

Feature	Physiological Biometrics	Behavioural Biometrics
Stability	Highly stable over time (e.g., fingerprints, iris patterns)	Can change over time or in different conditions (e.g., gait, typing speed)
Uniqueness	Generally, more unique (e.g., DNA, fingerprint)	Unique but may be influenced by temporary factors (e.g., mood, stress)
User Acceptance	May require intrusive scanning (e.g., retina scan, fingerprint)	Often less intrusive (e.g., keystroke dynamics, gait recognition)
Use Case	Identification and verification in high-security environments	Continuous authentication, fraud detection, and behaviour analysis
Security	High accuracy, difficult to fake	Can be spoofed or imitated under certain circumstances (e.g., imitating signature or voice)

3. Introduction to ECG: Understanding the Basics

Electrocardiography (ECG) is used for assessing the electrical activity of the heart. By capturing the electrical impulses that trigger heartbeats, ECG provides crucial insights into heart function and health [42]. This section will explain how ECG works, outline its key components—the P wave, QRS complex, and T wave—and discuss how these components reflect individual physiological differences.

3.1 How ECG Works

An ECG measures the heart's electrical activity with the help of electrodes positioned on the body surface of the person. These electrodes capture the electrical signals produced by the heart as it contracts and relaxes. When the heart beats, it creates an electrical impulse that propagates through the heart muscle, leading to contractions that pump blood throughout the body【43】.

The ECG machine records this electrical activity as a series of waves on a graph, typically over a duration of 10 seconds or longer. The resulting waveform represents the heart’s electrical activity, which can be analysed for abnormalities that may indicate various cardiovascular conditions.

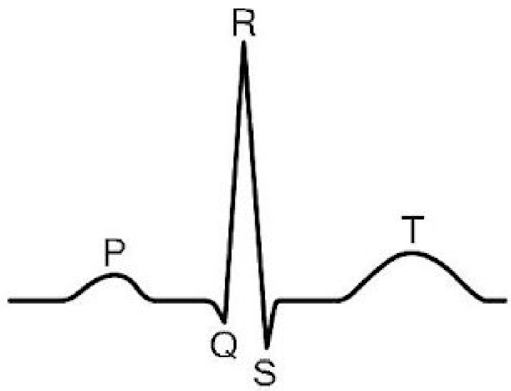

Figure 2: ECG peaks representation

3.2 Important Components of ECG

The ECG waveform consists of numerous distinct components (Figure 2), each representing different phases of the cardiac cycle [44]:

P Wave: The P wave represents the depolarization of the atria, the two upper chambers of the heart. It is the first wave in the ECG cycle and is typically small and rounded. The P wave indicates the electrical impulse originating from the sinoatrial (SA) node, the heart's natural pacemaker. The size and shape of the P wave can provide insights into atrial enlargement or other abnormalities.

QRS Complex: The QRS complex follows the P wave and represents the depolarization of the ventricles, the heart's lower chambers. This complex is typically sharp and tall, reflecting the rapid electrical activity that causes ventricular contraction. The QRS complex is critical for assessing ventricular function. Its duration and morphology can indicate various conditions, such as bundle branch blocks, ventricular hypertrophy, or myocardial infarction. A prolonged QRS duration, for example, may suggest conduction delays within the ventricles.

T Wave: It represents the repolarization of the ventricles, indicating the recovery phase after contraction. The T wave is generally broader and more rounded than the P wave. The T wave's shape and height can provide insights into electrolyte imbalances, ischemia, or other cardiac issues. Abnormalities in the T wave, such as inversion or flattening, can signal underlying conditions that require further investigation.

3.3 Reflection of Individual Physiological Differences

The components of an ECG not only provide information about heart activity but also reflect individual physiological differences. Several factors can influence the shape and duration of the ECG waves, including:

Age: Normal ECG patterns can vary significantly with age. For instance, older adults may show changes in wave morphology due to age-related cardiac remodelling.

Sex: There are inherent differences in ECG readings between males and females, often attributed to physiological variations in heart size and hormonal influences. For example, the QT interval tends to be longer in females.

Physical Condition: Athletes may exhibit specific ECG patterns indicative of enhanced cardiac efficiency, such as a lower heart rate or increased voltage in certain waveforms. Conversely, individuals with cardiovascular diseases may present with abnormal waveforms that signal underlying pathologies.

Genetic Factors: Genetic predispositions can influence heart structure and function, impacting ECG readings. For example, certain inherited conditions may lead to prolonged QT intervals or predispose individuals to arrhythmias, reflected in their ECG patterns.

4. ECG Signal Processing Techniques

ECG signals are crucial in order to monitor the electrical activity of the heart. However, noise and artifacts cause contamination in these signals, which can distort the accurate representation of heart activity. Some common sources of noise in ECG signals include electrical interference, motion artifacts (e.g., from patient movement), and baseline wander (e.g., due to respiration or improper electrode placement).

4.1 Filtering Process

Filtering is an essential pre-processing step to enhance the signal quality and improve the accuracy of feature extraction, which in turn enhances the performance of ECG-based diagnostic systems. To remove these unwanted noise components, several types of filters are used. Each filter type targets specific frequencies that correspond to particular types of noise or artifacts.

a. Low-Pass Filters

Low-pass filters are developed to filter out the signals above a set cutoff frequency [45]. These filters remove high-frequency noise, such as muscle artifacts or electrical interference from other devices. Muscle artifacts, often seen in the form of high-frequency oscillations, can obscure the true rhythm of the ECG signal. By applying a low-pass filter, this high-frequency noise can be suppressed, allowing for clearer identification of heartbeats and other important features in the ECG waveform. For instance, low-pass filters are typically set with a cutoff frequency of around 30–50 Hz, as per the specific features of the ECG data.

b. High-Pass Filters

In contrast to low-pass filters, high-pass filters are used to eliminate low-frequency noise, particularly baseline wander, which occurs due to movements in the patient, respiration, or improper electrode contact [46]. Baseline wander can cause slow shifts in the signal's baseline, making it challenging to detect the rapid, high-frequency changes associated with the heart's electrical activity. These filters are developed to permit high-frequency components—specifically the rapid fluctuations corresponding to the heart's electrical impulses to pass while attenuating slower, low-frequency signals. These filters typically have a cutoff frequency around 0.5–1 Hz, which is effective for removing unwanted baseline shifts without distorting the main components of the ECG signal.

c. Band-Pass Filters

Band-pass filters combine the functionality of both low-pass and high-pass filters. These filters allow only signals within a specified frequency range to pass, while attenuating frequencies outside this range [47]. For ECG signals, the frequency range of interest typically lies between 0.5 Hz and 100 Hz, as this range contains the primary characteristics of the heart's electrical activity. By using a band-pass filter, both high-frequency noise (like muscle artifacts) and low-frequency disturbances (such as baseline wander) can be effectively filtered out. The result is a cleaner ECG signal that retains the key information needed for accurate feature extraction and analysis. Band-pass filters are particularly valuable for isolating the relevant heart rate frequencies and ensuring that noise from surrounding environments is minimized.

4.2 Normalization

Normalization is an essential step in pre-processing ECG signals to standardize their amplitude and scale. Raw ECG signals can vary significantly across different individuals, devices, and recording conditions [48]. These variations can make it difficult to compare and analyze features across datasets or subjects. By applying normalization techniques, the amplitude and scale of the ECG signals are standardized, allowing for more consistent and accurate feature extraction, and ultimately improving the performance of downstream analysis or machine learning models. Two common methods of normalization used in ECG signal processing are Min-Max Normalization and Z-score Normalization.

a. Min-Max Normalization

Min-Max normalization rescales the values of the ECG signal to fit within a predefined range, typically between 0 and 1. This is done by transforming each signal value according to the following equation:

$$X_{norm} = \left(\frac{X - X_{\min}}{X_{\max} - X_{\min}} \right) \quad (1)$$

Where, X is the original signal value, $X_{\min}$ and $X_{\max}$ are the minimum and maximum values in the ECG signal, X_{norm} is the normalized value.

This method ensures that the relative characteristics of the ECG signal are maintained, but the entire signal is scaled to a consistent range. Min-Max normalization is particularly useful for preparing ECG signals for machine learning models that require input features to be within a fixed range, such as neural networks. By scaling the signals to a [0, 1] range, the model can more easily process and learn from the data, as it prevents one feature from dominating due to larger numerical values.

b. Z-score Normalization

Z-score normalization, also known as standardization, transforms the ECG signal so that it has a mean of 0 and a standard deviation of 1. This is done by subtracting the mean of the signal from each value and then dividing by the standard deviation:

$$X_{norm} = \left(\frac{X - \mu}{\sigma} \right) \quad (2)$$

where, X is the original signal value, μ is the mean of the signal, σ is the standard deviation of the signal.

This method is particularly effective when dealing with ECG signals that exhibit varying amplitude or when it is important to detect unusual patterns or outliers in the data. By centering the signal around zero and scaling it by the standard deviation, Z-score normalization standardizes the signal across different datasets, making it easier to compare data points regardless of their original scale. This method is commonly used when the goal is to perform statistical analysis, anomaly detection, or to feed the normalized data into machine learning algorithms that rely on standardized inputs.

4.3 Segmentation

It is a very important step in ECG signal processing that involves dividing the continuous ECG waveform into discrete intervals or segments, typically corresponding to individual heartbeats or cardiac cycles [49]. The heartbeats in an ECG signal are not static in time, and their durations and characteristics can vary between individuals or even across different cardiac conditions. By segmenting the ECG signal into manageable and meaningful parts, the signal can be analysed more effectively, enabling focused analysis of specific phases within the cardiac cycle. This is particularly important for tasks such as heart rate variability analysis, arrhythmia detection, and feature extraction for classification. The segmentation process generally involves identifying key markers within the ECG signal, such as the R peak, and extracting surrounding segments of the signal that represent individual heartbeats. These segments are then processed and analysed individually, providing more accurate results and insights into the heart's electrical activity.

a. R-Peak Detection

In ECG signals, the most prominent and easily identifiable feature is the QRS complex, which represents the depolarization of the ventricles. Within the QRS complex, the R wave stands out as the highest peak, making it the most critical marker for detecting the beginning of each cardiac cycle. Accurate R-peak detection is foundational for segmentation, as it marks the start of one heartbeat and provides a reliable reference point for extracting the rest of the cycle [50]. Several algorithms are used to identify R peaks within an ECG signal. Traditional approaches, like the Pan-Tompkins algorithm, employ a combination of filtering, differentiation, squaring, and moving window integration to detect the R peaks with high accuracy. More modern approaches, such as those based on machine learning, can provide even more precise detection by learning the characteristics of R peaks and adjusting to various signal qualities, such as noise and artifacts. Once R peaks are detected, the corresponding intervals surrounding each peak can be extracted to form individual heartbeats, providing a precise representation of each cardiac cycle. This step is crucial because the analysis of a single heartbeat or segment allows for more accurate feature extraction and classification in various diagnostic tasks.

b. Windowing Techniques

Once the R peaks are detected, windowing techniques are employed to extract the ECG signal segments corresponding to individual heartbeats. A "window" is defined around each R peak, typically including a specified number of samples before and after the peak [51]. The length of the window is chosen based on the duration of a typical heartbeat, which generally lasts between 600 ms and 1000 ms, but may vary depending on the heart rate or health conditions of the individual.

The windowed segment typically encompasses the P wave, QRS complex, and T wave, capturing the complete cycle of ventricular depolarization and repolarization. This ensures that all relevant features of the ECG, such as heart rate, rhythm, and abnormalities like arrhythmias, are retained within each segment. The number of samples before and after the R peak can be adjusted as per the requirement of the analysis. For instance, in some cases, a longer window may be required to capture more details, such as the full duration of the T wave, while a shorter window may suffice for basic heart rate analysis.

Once the segments are extracted, they can be processed individually, and relevant features can be extracted from each window. This segmented approach allows for more targeted analysis of the heart's electrical activity, and it is particularly useful for detecting abnormalities in specific phases of the cardiac cycle, such as premature ventricular contractions, atrial fibrillation, or other arrhythmic events.

5. ECG Feature Extraction

ECG feature extraction is a critical step in analyzing electrocardiographic (ECG) signals, particularly for applications such as biometric authentication, health monitoring, and diagnosing cardiovascular conditions [52]. The basic aim of feature extraction is to identify unique and meaningful characteristics from the raw ECG data that can be used to classify, recognize, or predict various heart-related conditions. This process typically involves a range of signal processing techniques designed to upgrade the quality of the ECG signal and extract relevant features for further analysis.

Below, we discuss the main methods used in ECG feature extraction:

5.1 Time-Domain Analysis

Time-domain analysis focuses on evaluating the ECG signal based on its characteristics in the time domain, such as the shape, duration, and amplitude of the waveform. It is one of the most straightforward and widely used methods in ECG analysis [53].

Key Features

- **PR Interval**: The PR interval is measured from the beginning of the P wave to the beginning of the QRS complex. This interval is important in assessing the electrical conduction from the atria to the ventricles and can be indicative of conditions like heart block.

- **QRS Duration**: This represents the duration of the QRS complex, which reflects the time it takes for the ventricles to depolarize. Prolonged QRS duration may be a sign of ventricular conduction delays or other heart abnormalities.

- **QT Interval**: The QT interval spans from the start of the Q wave to the end of the T wave. It represents the time taken for the ventricles to contract and relax. A prolonged QT interval can be associated with an increased risk of arrhythmias and other cardiac conditions.

Amplitudes

- The amplitude of the P wave, QRS complex, and T wave can be measured directly. These amplitudes provide valuable information about the atrial and ventricular function. For instance, an abnormally large or small QRS amplitude could indicate a condition like hypertrophy or ischemia, while changes in T wave amplitude could point to issues such as electrolyte imbalances.

5.2 Frequency-Domain Analysis

While time-domain analysis offers insights into the shape and timing of the ECG waveform, frequency-domain analysis provides a different perspective by transforming the ECG signal into the frequency domain [54]. This is typically achieved using techniques such as the Fast Fourier Transform (FFT), which decomposes the signal into its constituent frequency components.
Frequency-domain analysis can reveal important spectral features, including:

- **Dominant Frequencies**: The ECG signal contains several dominant frequencies that correspond to different phases of the cardiac cycle. For example, the frequency components related to the QRS complex are typically higher than those related to the P and T waves.

- **Spectral Characteristics**: These characteristics help identify abnormalities in the signal's frequency content, which may be indicative of conditions such as atrial fibrillation, heart failure, or other arrhythmias.

Frequency-domain features can be particularly useful for detecting subtle anomalies that might not be as evident in the time domain, offering a complementary layer of analysis that enhances the overall diagnostic capability.

5.3 Wavelet Transform

In addition to traditional time-domain and frequency-domain methods, wavelet transform is quite useful for ECG feature extraction. Unlike the Fourier transform, which only provides information about the frequencies present in a signal, wavelet transform gives both time and frequency information, making it highly effective for analyzing non-stationary signals like ECG [55].
Wavelet transforms break the signal into different frequency components at various scales, allowing for a more detailed analysis of transient events and rapid changes in the ECG. This can be particularly beneficial for detecting arrhythmias and other sudden heart conditions.

5.4 Nonlinear Dynamics

ECG signals, especially those associated with certain types of arrhythmias, often exhibit nonlinear dynamics. Methods like entropy-based features are used to quantify the irregularity or complexity of the signal [56]. High entropy values may indicate chaotic heart rhythms, while low entropy may reflect a more regular pattern, such as normal sinus rhythm. These nonlinear features are useful for detecting abnormal heart rhythms, where traditional linear methods might struggle.

a. Power Spectral Density (PSD)

PSD measures the power (or energy) distribution of the signal across different frequencies. By analyzing the PSD of an ECG signal, we can determine which frequency components contribute most to the signal's overall power [57]. This is particularly useful for identifying abnormalities related to heart rhythms and detecting potential issues like arrhythmias or ischemic events.
PSD can also be used to assess the overall health of the heart by identifying deviations from typical frequency patterns that are associated with certain heart conditions. For instance, changes in the low-frequency and high-frequency bands in the PSD may signal issues related to autonomic nervous system activity, heart rate variability, or myocardial ischemia.

b. Dominant Frequencies

Identifying dominant frequencies in the ECG signal helps reveal the most prominent components of the heart's electrical activity [58]. Each phase of the cardiac cycle—such as atrial depolarization, ventricular depolarization, and repolarization—has associated frequencies that are fundamental to understanding the heart's functioning. Abnormalities in these dominant frequencies may indicate arrhythmias, tachycardia, or bradycardia.

- Tachycardia (high heart rate) may cause higher frequency components in the ECG signal, while bradycardia (low heart rate) could result in a shift toward lower frequency ranges.
- Detecting shifts in these dominant frequencies can be crucial in diagnosing arrhythmias or irregular heartbeats.

c. Time-Frequency Analysis

Time-frequency analysis is a powerful technique that combines both time-domain and frequency-domain methods, making it particularly suitable for analyzing non-stationary signals such as ECG [59]. ECG signals are inherently dynamic, with the frequency characteristics changing over time due to various factors like heart rate variability, changes in rhythm, or the presence of arrhythmias.

Unlike traditional frequency-domain methods, which assume that the signal is stationary (i.e., its frequency content does not change over time), time-frequency analysis allows for capturing how the frequency components evolve as the signal progresses. This technique is valuable for detecting transient features and non-stationary phenomena in the ECG that may be missed by other methods. For instance, arrhythmic events like premature ventricular contractions (PVCs) or atrial fibrillation can be better identified with time-frequency methods**.**

d. Wavelet Transform

The Wavelet Transform is another sophisticated method used in ECG signal analysis. Unlike the Fourier transform, which only provides frequency information, the wavelet transform decomposes the signal into different frequency components while preserving time information [60]. This makes wavelet transforms particularly useful for detecting transient features or sudden changes in the ECG signal, which may not be evident in traditional frequency-domain analysis.

The wavelet transform allows for a multiresolution analysis, meaning it can capture both high-frequency and low-frequency components at different scales. This is useful for detecting both short-term events (e.g., PVCs or ectopic beats) and long-term patterns (e.g., changes in heart rate or rhythm) that might indicate broader cardiac issues [61].

In practice, wavelet transforms provide a more flexible and detailed analysis of the ECG signal, especially when dealing with complex patterns or transient events that occur over short periods.

e. Short-Time Fourier Transform (STFT)

The STFT is a technique that segments the ECG signal into smaller time windows and applies the Fourier Transform to each window separately [62]. The result is a two-dimensional representation of the signal, where one axis represents time, the other represents frequency, and the intensity (or magnitude) of the signal is indicated by colour or amplitude. STFT is particularly useful for observing how the frequency components of the ECG signal evolve over time. This is important for detecting time-varying features, such as changes in heart rhythm, the onset of arrhythmias, or the effect of different physiological conditions on the heart [63]. By visualizing the signal in the time-frequency domain, STFT provides a more detailed view of the ECG signal, highlighting variations that might otherwise be overlooked in a purely time-domain or frequency-domain analysis.

6. Classification Algorithms for ECG Biometrics

The ECG signals classification plays a pivotal role in leveraging their distinct characteristics for numerous applications, such as biometric authentication, health monitoring, and cardiac disease diagnosis [64]. The ECG signals contain vital information about the electrical activity of the heart, and by accurately classifying them, we can detect abnormalities, identify specific cardiac conditions, and even use them for personal identification. Generally, the decision-making stage for most of the ECG biometric algorithms use the classifiers. For these classifiers, original templates stored by the biometric system at the time of enrollment of subjects are necessary to let the algorithm to pay attention to the separation between the subjects. The classifier is intended to have its function to assist in the identification or verification function of the system when needed. In identification tasks, classifiers are used more frequently than features and some of the models are SVM's, Nearest Neighbour classifiers and ANNs. All of these methods help to enhance the reliability of the described biometric system.

6.1 Machine Learning (ML) Approaches

These techniques are used for classifying ECG signals after extracting meaningful features [65]. These approaches can be of two types: supervised learning or unsupervised learning methods. Both are very useful in improving the accuracy and efficiency of ECG classification.

6.1.1 Supervised Learning Methods

In this type of method, the model is trained on labeled data, meaning each input is paired with a corresponding output label [66]. The model learns to map input features to the correct labels during training. In the context of ECG classification, the features extracted from the ECG signals are used as inputs, while the output could represent different cardiac conditions, such as normal sinus rhythm, arrhythmia, or other specific heart diseases.

a. Support Vector Machines (SVM)

SVM are one of the most powerful supervised learning algorithms used for classification tasks. SVM constructs an optimal hyperplane that best separates different classes in a high-dimensional feature space [67]. One of the key strengths of SVM is its ability to handle non-linearly separable data by using kernel functions, which map the input data into higher-dimensional spaces where a linear hyperplane can be used to separate the classes.
In ECG classification, SVM can be employed to classify various heart conditions or to identify specific patterns in the ECG signal for biometric authentication. The technique performs well even with small to medium-sized datasets and is capable of managing high-dimensional features extracted from ECG signals.

b. Neural Networks

These are ML models which are developed on the basis of the human brain's structure and functioning. These networks consist of layers of interconnected nodes (or neurons) that process and transform input data [68]. Neural networks are highly effective at modeling complex, non-linear relationships, making them suitable for tasks such as ECG classification.
Feedforward Neural Networks (FNN) [69], a basic type of neural network, can be used for ECG classification tasks by learning the relationship between extracted features and the output labels. More advanced neural network architectures, such as Recurrent Neural Networks (RNNs) [70], are particularly well-suited for time-series data like ECG signals. RNNs can capture temporal dependencies in the sequential nature of ECG data, which is essential for detecting abnormal heart rhythms and other dynamic cardiac events.

c. Decision Trees and Random Forests

These are supervised learning models that partition the input feature space into decision regions based on splitting rules, typically involving binary decisions at each node [71]. Each branch represents a decision outcome, and the leaf nodes contain the predicted class label. While decision trees can be prone to overfitting, they offer a transparent and interpretable approach to classification.
Random Forests, an ensemble method, improve upon decision trees by combining various decision trees to develop a robust classification model [72]. The ensemble approach helps reduce overfitting and enhances accuracy by averaging the results of many trees, each trained on a random subset of the data. In ECG classification, decision trees and random forests can classify different heart conditions based on the extracted features, while providing intuitive results that are easy to interpret.

6.1.2 Unsupervised Learning Methods

In unsupervised learning, the algorithm works with unlabelled data and aims to figure out the concealed patterns or groupings within the data [73]. These methods are useful for exploratory analysis, identifying inherent structures in ECG data, and preprocessing data for supervised learning.

a. Clustering Algorithms

Clustering is a key unsupervised learning method that groups similar data points together based on their feature similarities. Popular clustering algorithms, such as k-means and hierarchical clustering, can be used to identify natural groupings within ECG data, revealing patterns that may represent different physiological states or cardiac conditions [74]. For example, clustering may identify groups of ECG signals that correspond to normal heartbeats or those indicative of arrhythmic episodes.
Clustering helps uncover relationships in data, facilitating the discovery of previously unknown conditions or anomalies, which can then be further analyzed using supervised methods. It is often applied as a preprocessing step in ECG classification systems to organize the data and guide subsequent classification efforts.

b. Principal Component Analysis (PCA)

PCA is a dimensionality reduction technique that transforms the data into a new coordinate system, where the first few dimensions (principal components) capture the most variance in the data [75]. This technique is particularly useful for reducing the complexity of ECG data by eliminating redundant features while retaining the most important information.PCA can be used as a preprocessing step before applying classification algorithms. On decreasing the number of features in the ECG data, PCA enhances the computational efficiency of the classifier and helps improve its performance. It can also mitigate issues such as multicollinearity, which may arise when features are highly correlated. In ECG classification, PCA is helpful for simplifying the data, making it easier for machine learning models to learn from the features and perform accurate classifications.

6.2 Deep Learning Models

These models have gained prominence in recent years. This is due to the fact that these models can automatically extract features from raw data without the need for extensive preprocessing.

6.2.1 Convolutional Neural Networks (CNNs)

CNNs are specialized neural networks that excel in processing structured grid data, such as images and sequential data like electrocardiogram (ECG) signals. Unlike traditional neural networks, which treat inputs as flat vectors, CNNs are designed to capture the spatial relationships inherent in grid-like data [76]. At the core of CNNs are convolutional layers, which apply convolutional operations to the input data. These layers automatically learn to detect various features at different levels of abstraction. This hierarchical learning process allows CNNs to identify simple features in the initial layers, like edges or corners, and gradually build up to more complex structures, such as shapes or objects, in deeper layers [77]. The use of shared weights and local receptive fields in convolutional layers significantly reduces the number of parameters, making CNNs more efficient and effective at learning from large datasets. Additionally, pooling layers are often incorporated to down-sample the feature maps, further emphasizing the most relevant information while reducing computational load. CNNs are particularly effective in applications such as image recognition, where they can classify images, detect objects, and segment regions.In the case of sequential data like ECG signals, CNNs can learn temporal patterns and variations, aiding in the detection of anomalies or predicting health conditions. CNNs can be applied to classify ECG signals directly from raw waveform data or spectrograms generated through time-frequency analysis, achieving high accuracy in recognizing patterns associated with different cardiac conditions.

6.2.2 Long Short-Term Memory Networks (LSTMs)

LSTM networks are a kind of recurrent neural network (RNN) which are specially designed to effectively learn from sequences of data by retaining information over extended periods [78]. This capability is essential for processing time-dependent signals, such as electrocardiogram (ECG) readings, where understanding the temporal context is crucial for accurate interpretation.

LSTMs address the common challenges faced by traditional RNNs, particularly the issues of vanishing and exploding gradients. They achieve this through a unique architecture that includes memory cells and gates. The memory cells store information, while the gates—specifically the input, output, and forget gates—regulate the flow of information into, out of, and within the cell. This allows LSTMs to maintain relevant information over long sequences while discarding less important data [79].

In ECG signals, LSTMs can effectively model the temporal dynamics of the heart's electrical activity. They are capable of capturing complex patterns and anomalies that may occur over time, making them highly useful for tasks such as arrhythmia detection and predicting cardiovascular events. By leveraging their ability to learn from historical data, LSTMs enhance the performance of predictive models in healthcare applications.

Overall, LSTMs represent a significant advancement in the field of sequence modelling, enabling more accurate analysis and predictions for a wide range of time-dependent data.

LSTMs are effective for tasks such as arrhythmia detection or biometric authentication, as they can capture temporal dependencies and patterns within the ECG signal.

7. Evaluation Metrics

These metrices are used to evaluate the performance of ECG classification systems [80]:

Accuracy: Accuracy measures the proportion of correctly classified instances among the total instances. It is calculated as:

$$A = \frac{T^{+} + T^{-}}{T^{+} + F^{+} + T^{-} + F^{-}} \tag{3}$$

While accuracy is a useful measure, it can be misleading in cases of class imbalance, where one class significantly outnumbers the others.

Precision: Precision indicates the proportion of true positive predictions among all positive predictions.

$$P = \frac{T^{+}}{T^{+} + F^{+}} \tag{4}$$

Precision is particularly important in contexts where false positives carry significant consequences, such as in medical diagnoses.

Recall: Recall measures the proportion of true positives among all actual positive instances. It is calculated as**:**

$$R = \frac{T^{+}}{T^{+} + F^{-}} \tag{5}$$

High recall is critical in medical applications where failing to identify a condition can have serious implications.

F1-Score: The F1-score is the harmonic mean of precision and recall, providing a balance between the two. It is calculated as:

$$F = \frac{2PR}{P + R} \tag{6}$$

The F1-score is particularly useful in situations with class imbalance, offering a single metric that considers both false positives and false negatives.

8. Applications of ECG Biometrics

ECG biometrics plays a significant role across numerous domains including security systems and health monitoring. By leveraging the unique electrical patterns of the heart, ECG can enhance security protocols and improve health outcomes. This section explores two primary applications: security systems and health monitoring.

8.1 Security Systems

ECG biometrics offer a promising approach to enhancing security systems. This is done by with the inclusion of an additional layer of authentication based on an individual's unique heart rhythm. One significant application is in secure access control. By integrating ECG biometrics, access systems can authenticate users on the basis of their heart signals, which are unique to each person, thereby improving security beyond traditional methods such as passwords and fingerprints [81]. This approach has several benefits, including increased security since ECG patterns are intrinsically tied to the individual's physiology, making them much harder to spoof compared to fingerprints or facial recognition. Moreover, it enhances user convenience, as ECG biometrics allow for quick, non-intrusive authentication, typically through devices like smartwatches or other wearable technology, making the process seamless.

In the context of financial transactions, ECG biometrics can further strengthen security by adding an extra verification layer during digital payments. This added protection can help prevent fraud by confirming a user's identity through their unique heart signals, significantly reducing the risk of unauthorized access. The integration of ECG in financial transactions also bolsters user trust, as individuals feel more secure knowing that their sensitive financial data is being protected by advanced biometric verification, encouraging broader adoption of digital payment platforms [82].

User authentication is another area where ECG biometrics can provide robust security. As an authentication method, ECG can serve as a multifactor authentication system, complementing traditional methods like passwords or PINs, thus enhancing overall security without compromising user experience. Additionally, it enables remote access for users, allowing them to authenticate their identity through wearable devices. This method provides secure access to sensitive systems and information without the need for physical tokens or passwords, making it especially convenient for those on the go.

8.2 Health Monitoring

In the realm of health monitoring, ECG biometrics can be seamlessly integrated into wearable devices such as smartwatches and fitness trackers to offer continuous, real-time health insights [83]. These devices enable users to monitor their heart activity regularly, which can lead to early detection of abnormalities and ultimately improve cardiovascular health. Furthermore, they can provide personalized health insights, analyzing ECG data to generate recommendations for exercise, stress management, and lifestyle adjustments, tailored to the individual's needs.

ECG biometrics are also crucial in anomaly detection, where they can identify irregular heart rhythms such as arrhythmias [84]. This capability is beneficial for timely intervention, as abnormal heart rhythms can be detected early, allowing for prompt medical action to prevent serious cardiovascular events. Additionally, ECG-based remote monitoring makes it possible for the specialist to monitor the patients' heart health from a distance, facilitating proactive care management and reducing the need for frequent in-person visits.

Finally, real-time alerts for cardiovascular events are another significant advantage of ECG biometrics [85]. Advanced algorithms can analyse ECG data in real time to detect critical conditions like atrial fibrillation or even heart attacks. Such alerts can trigger immediate notification to users or their caregivers, ensuring emergency response is prompt, which is critical in life-threatening situations. These systems also foster enhanced patient engagement.

9. Challenges and Future Directions in ECG Biometrics

ECG biometrics holds great potential for revolutionizing both security systems and health monitoring applications, but several challenges remain that hinder its widespread adoption and effectiveness. One of the primary challenges is signal quality and noise contamination. ECG signals are inherently prone to various types of noise and interference, such as motion artifacts, electrical noise, and baseline wander. These distortions can significantly degrade the accuracy of feature extraction and classification, leading to incorrect or inconsistent biometric results. In real-world applications, where individuals may be on the move or in noisy environments, ensuring high-quality, noise-free ECG data is a significant hurdle. Advances in signal processing techniques, such as adaptive filtering and noise reduction algorithms, are necessary to overcome this challenge and improve the robustness of ECG biometrics.

9.1 Inter-individual Variability in ECG Signals

Another significant challenge is inter-individual variability. Although ECG signals are unique to each individual, the features derived from these signals can vary considerably across different people, even for the same person under different conditions. Components like age, gender, health conditions, and environmental influences can all lead to variations in heart rhythms. This variability makes it difficult to develop generalized models that perform consistently across diverse populations. In addition, the complexity of the ECG signal itself, with its various waves, intervals, and morphologies, requires highly sophisticated feature extraction and classification techniques to capture the subtle differences that distinguish one individual from another. To address these issues, researchers are focusing on improving personalized models that adapt to individual differences, as well as multi-modal biometrics, which combine ECG with other biometric traits to increase accuracy and reliability.

9.2 Real-Time Processing Challenges

Real-time processing is another critical challenge in ECG biometrics, especially in health monitoring applications. The need for continuous, real-time analysis of ECG data, particularly in wearable devices like smartwatches and fitness trackers, requires efficient and fast algorithms that can process large amounts of data with minimal latency. This places high demands on both the computational resources and the energy efficiency of the devices used. As ECG-based systems become more integrated into daily life, the ability to monitor heart health and perform biometric authentication on the go will depend on the development of lightweight, energy-efficient algorithms that can deliver real-time results without draining battery life or overloading the device's processing capacity.

9.3 Integration with Existing Security and Healthcare Systems

Furthermore, the integration of ECG biometrics with existing security and healthcare infrastructures remains a challenge. While many organizations and healthcare providers are keen to adopt ECG biometrics, the integration of these systems with existing databases, networks, and authentication protocols can be complex. The development of standardized, interoperable systems that allow for seamless integration of ECG-based authentication with other forms of identity verification (like passwords, fingerprint scanners, or facial recognition) is essential for broader adoption. Additionally, healthcare providers must assure that ECG data is securely stored, shared, and transmitted, adhering to standard privacy regulations.

9.4 Future Directions in ECG Biometrics

In terms of future directions, researchers are exploring the potential of deep learning techniques for ECG biometric analysis. Conventional ML techniques often rely on manual feature extraction, but deep learning models, particularly CNNs and RNNs, have the potential to automatically learn relevant features from raw ECG signals. These models could help improve accuracy and reduce the reliance on handcrafted features, making ECG biometrics more scalable and adaptable to a wider range of users and use cases. Furthermore, advances in edge computing could allow for real-time ECG analysis to be performed directly on wearable devices, minimizing latency and mitigating the requirement of transmitting sensitive biometric data to central servers.

a. Multi-modal Biometric Systems

The integration of ECG biometrics with multi-modal systems is another promising future direction. By combining ECG with other biometric modalities systems can achieve higher levels of accuracy and security. Multi-modal systems could leverage the complementary strengths of different biometrics to mitigate the limitations of individual modalities, such as the variability of ECG signals or the susceptibility of face recognition to lighting conditions.

b. Personalized and Context-Aware Systems

Finally, as more data is collected through wearable devices and other personal health technologies, there is an opportunity to develop personalized, context-aware ECG biometric systems. These systems could account for factors such as an individual's health status, physical activity level, or emotional state, tailoring the biometric authentication process to be more accurate and adaptable. For example, ECG patterns might change during exercise, stress, or illness, and incorporating such context into biometric models could improve their robustness in dynamic, real-world environments.

10. Conclusion

This research article presented a comprehensive exploration of ECG-based biometric systems, focusing on their potential for secure authentication and health monitoring. By leveraging advanced signal processing techniques such as filtering, normalization, and segmentation, along with feature extraction methods like time-domain, frequency-domain, and wavelet analysis, we demonstrated how ECG signals can be effectively utilized for both individual identification and health condition monitoring. The integration of ML algorithms, particularly deep learning models like Bi-LSTM, further enhances the accuracy and robustness of ECG classification systems. The research highlights the growing potential of ECG biometrics in practical applications, including secure access control, financial transactions, and continuous health monitoring through wearable devices. Despite the promising results, challenges such as signal noise, inter-individual variability, and the need for real-time processing remain. It is quite important to deal with these issues to have a broad adoption of ECG-based biometrics in diverse real-world applications. Future research should explore further optimization techniques, multi-modal systems, and the development of context-aware algorithms to enhance the efficiency and versatility of ECG biometrics. With continued advancements, ECG biometrics holds the potential to redefine personal security and health management, offering a reliable and non-intrusive solution for both authentication and health monitoring.

References

1. Jain, Anil K., Karthik Nandakumar, and Arun Ross. "50 years of biometric research: Accomplishments, challenges, and opportunities." *Pattern recognition letters* 79 (2016): 80-105.
2. Maltoni, Davide, Dario Maio, Anil K. Jain, and Salil Prabhakar. *Handbook of fingerprint recognition*. Vol. 2. London: springer, 2009.
3. Bodepudi, Anusha, and Manjunath Reddy. "Cloud-Based Biometric Authentication Techniques for Secure Financial Transactions: A Review." *International Journal of Information and Cybersecurity* 4, no. 1 (2020): 1-18.
4. Millett, Lynette I., and Joseph N. Pato, eds. "Biometric recognition: Challenges and opportunities." (2010).
5. Rao, P. Muralidhara, and Bakkiam David Deebak. "Security and privacy issues in smart cities/industries: technologies, applications, and challenges." *Journal of Ambient Intelligence and Humanized Computing* 14, no. 8 (2023): 10517-10553.
6. de Luis-García, Rodrigo, Carlos Alberola-Lopez, Otman Aghzout, and Juan Ruiz-Alzola. "Biometric identification systems." *Signal processing* 83, no. 12 (2003): 2539-2557.
7. Sarkar, Arpita, and Binod K. Singh. "A review on performance, security and various biometric template protection schemes for biometric authentication systems." *Multimedia Tools and Applications* 79, no. 37 (2020): 27721-27776.
8. Kindt, Els J. "Privacy and data protection issues of biometric applications." In *A Comparative Legal Analysis*, vol. 12. Springer, 2013.
9. Bolme, David S., Ryan A. Tokola, Chris B. Boehnen, Tiffany B. Saul, Kelly A. Sauerwein, and Dawnie Wolfe Steadman. "Impact of environmental factors on biometric matching during human decomposition." In *2016 IEEE 8th International Conference on Biometrics Theory, Applications and Systems (BTAS)*, pp. 1-8. IEEE, 2016.
10. Uwaechia, Anthony Ngozichukwuka, and Dzati Athiar Ramli. "A comprehensive survey on ECG signals as new biometric modality for human authentication: Recent advances and future challenges." *IEEE Access* 9 (2021): 97760-97802.
11. Palma, David, and Pier Luca Montessoro. "Biometric-based human recognition systems: an overview." *Recent Advances in Biometrics* 27 (2022): 1-21.
12. Dargan, Shaveta, and Munish Kumar. "A comprehensive survey on the biometric recognition systems based on physiological and behavioral modalities." *Expert Systems with Applications* 143 (2020): 113114.
13. Socheat, Sek, and Tianjiang Wang. "Fingerprint enhancement, minutiae extraction and matching techniques." *Journal of Computer and Communications* 8, no. 05 (2020): 55.
14. Shebaro, Bilal, Oyindamola Oluwatimi, and Elisa Bertino. "Context-based access control systems for mobile devices." *IEEE Transactions on Dependable and Secure Computing* 12, no. 2 (2014): 150-163.
15. Bruce, Vicki, and Andy Young. "Understanding face recognition." *British journal of psychology* 77, no. 3 (1986): 305-327.
16. Gates, Kelly A. *Our biometric future: Facial recognition technology and the culture of surveillance*. Vol. 2. NYU Press, 2011.

17. Kortli, Yassin, Maher Jridi, Ayman Al Falou, and Mohamed Atri. "Face recognition systems: A survey." *Sensors* 20, no. 2 (2020): 342.
18. Gates, Kelly A. *Our biometric future: Facial recognition technology and the culture of surveillance*. Vol. 2. NYU Press, 2011.
19. Bowyer, Kevin W., and Mark J. Burge, eds. *Handbook of iris recognition*. Springer London, 2016.
20. Lee, Young Won, and Kang Ryoung Park. "Recent iris and ocular recognition methods in high-and low-resolution images: A survey." *Mathematics* 10, no. 12 (2022): 2063.
21. Bharathi, B., and P. Bindhu Shamily. "A review on iris recognition system for person identification." *International Journal of Computational Biology and Drug Design* 13, no. 3 (2020): 316-331.
22. Abràmoff, Michael D., Mona K. Garvin, and Milan Sonka. "Retinal imaging and image analysis." *IEEE reviews in biomedical engineering* 3 (2010): 169-208.
23. Hill, Robert "Buzz. "Retina identification." *Biometrics: Personal identification in networked society* (1996): 123-141.
24. Ahmad, Irfan, and Manzoor Khan. *Hand recognition using palm and hand geometry features*. LAP LAMBERT Academic Publishing, 2017.
25. Jaswal, Gaurav, Amit Kaul, and Ravinder Nath. "Multimodal biometric authentication system using hand shape, palm print, and hand geometry." In *Computational Intelligence: Theories, Applications and Future Directions-Volume II: ICCI-2017*, pp. 557-570. Singapore: Springer Singapore, 2018.
26. Li, Xiaochang, and Mara Mills. "Vocal features: from voice identification to speech recognition by machine." *Technology and culture* 60, no. 2 (2019): S129-S160.
27. Wang, Chen, Yan Wang, Yingying Chen, Hongbo Liu, and Jian Liu. "User authentication on mobile devices: Approaches, threats and trends." *Computer Networks* 170 (2020): 107118.
28. Fairhurst, Michael, Cheng Li, and Márjory Da Costa-Abreu. "Predictive biometrics: a review and analysis of predicting personal characteristics from biometric data." *IET Biometrics* 6, no. 6 (2017): 369-378.
29. Crawford, Heather. "Keystroke dynamics: Characteristics and opportunities." In *2010 Eighth International Conference on Privacy, Security and Trust*, pp. 205-212. IEEE, 2010.
30. Bergadano, Francesco, Daniele Gunetti, and Claudia Picardi. "User authentication through keystroke dynamics." *ACM Transactions on Information and System Security (TISSEC)* 5, no. 4 (2002): 367-397.
31. Porwik, Piotr, Rafal Doroz, and Tomasz Emanuel Wesolowski. "Dynamic keystroke pattern analysis and classifiers with competence for user recognition." *Applied Soft Computing* 99 (2021): 106902.
32. Wan, Changsheng, Li Wang, and Vir V. Phoha, eds. "A survey on gait recognition." *ACM Computing Surveys (CSUR)* 51, no. 5 (2018): 1-35.
33. Tao, Weijun, Tao Liu, Rencheng Zheng, and Hutian Feng. "Gait analysis using wearable sensors." *Sensors* 12, no. 2 (2012): 2255-2283.
34. Linden, Jacques, Raymond Marquis, Silvia Bozza, and Franco Taroni. "Dynamic signatures: A review of dynamic feature variation and forensic methodology." *Forensic science international* 291 (2018): 216-229.
35. Fischer, Andreas, and Réjean Plamondon. "Signature verification based on the kinematic theory of rapid human movements." *IEEE Transactions on Human-Machine Systems* 47, no. 2 (2016): 169-180.
36. Gaikwad, Santosh K., Bharti W. Gawali, and Pravin Yannawar. "A review on speech recognition technique." *International Journal of Computer Applications* 10, no. 3 (2010): 16-24.
37. Isyanto, Haris, Ajib Setyo Arifin, and Muhammad Suryanegara. "Performance of smart personal assistant applications based on speech recognition technology using IoT-based voice commands." In *2020 International conference on information and communication technology convergence (ICTC)*, pp. 640-645. IEEE, 2020.
38. Shen, Chao, Zhongmin Cai, Xiaohong Guan, Youtian Du, and Roy A. Maxion. "User authentication through mouse dynamics." *IEEE Transactions on Information Forensics and Security* 8, no. 1 (2012): 16-30.
39. Khan, Simon, Charles Devlen, Michael Manno, and Daqing Hou. "Mouse dynamics behavioral biometrics: A survey." *ACM Computing Surveys* 56, no. 6 (2024): 1-33.
40. Zagermann, Johannes, Ulrike Pfeil, and Harald Reiterer. "Measuring cognitive load using eye tracking technology in visual computing." In *Proceedings of the sixth workshop on beyond time and errors on novel evaluation methods for visualization*, pp. 78-85. 2016.
41. Punde, Pramodini A., Mukti E. Jadhav, and Ramesh R. Manza. "A study of eye tracking technology and its applications." In *2017 1st International Conference on Intelligent Systems and Information Management (ICISIM)*, pp. 86-90. IEEE, 2017.

42. Gacek, Adam. "An introduction to ECG signal processing and analysis." In *ECG Signal Processing, Classification and Interpretation: A Comprehensive Framework of Computational Intelligence*, pp. 21-46. London: Springer London, 2011.
43. Gacek, Adam, and Witold Pedrycz, eds. *ECG signal processing, classification and interpretation: a comprehensive framework of computational intelligence*. Springer Science & Business Media, 2011.
44. Halhuber, Max J., Robert Günther, and Max Ciresa. *ECG: An introductory course a practical introduction to clinical electrocardiography*. Springer Science & Business Media, 2012.
45. Christov, Ivaylo, Tatyana Neycheva, and Ramun Schmid. "Fine tuning of the dynamic low-pass filter for electromyographic noise suppression in electrocardiograms." In *2017 Computing in Cardiology (CinC)*, pp. 1-4. IEEE, 2017.
46. Censi, Federica, Giovanni Calcagnini, Michele Triventi, Eugenio Mattei, Pietro Bartolini, Ivan Corazza, and Giuseppe Boriani. "Effect of high-pass filtering on ECG signal on the analysis of patients prone to atrial fibrillation." *Annali dell'Istituto superiore di sanita* 45 (2009): 427-431.
47. Nobunaga, T., H. Tanaka, I. Tanahashi, T. Watanabe, and Y. Hattori. "Optimised band-pass filter to ensure accurate ECG-based identification of exercising human subjects." *Electronics Letters* 53, no. 4 (2017): 222-224.
48. Sun, P., Q. H. Wu, A. M. Weindling, A. Finkelstein, and K. Ibrahim. "An improved morphological approach to background normalization of ECG signals." *IEEE Transactions on biomedical engineering* 50, no. 1 (2003): 117-121.
49. Beraza, Idoia, and Iñaki Romero. "Comparative study of algorithms for ECG segmentation." *Biomedical Signal Processing and Control* 34 (2017): 166-173.
50. Qin, Qin, Jianqing Li, Yinggao Yue, and Chengyu Liu. "An Adaptive and Time-Efficient ECG R-Peak Detection Algorithm." *Journal of healthcare engineering* 2017, no. 1 (2017): 5980541.
51. Kumar, K. Sravan, Babak Yazdanpanah, and G. S. N. Raju. "Performance comparison of windowing techniques for ECG signal enhancement." *International Journal of Engineering Research* 3, no. 12 (2014): 753-756.
52. Karpagachelvi, S., Muthusamy Arthanari, and M. Sivakumar. "ECG feature extraction techniques-a survey approach." *arXiv preprint arXiv:1005.0957* (2010).
53. Khan, Tasnova Tanzil, Nadia Sultana, Rezwana Binte Reza, and Raqibul Mostafa. "ECG feature extraction in temporal domain and detection of various heart conditions." In *2015 International Conference on Electrical Engineering and Information Communication Technology (ICEEICT)*, pp. 1-6. IEEE, 2015.
54. Lin, Chia-Hung. "Frequency-domain features for ECG beat discrimination using grey relational analysis-based classifier." *Computers & Mathematics with Applications* 55, no. 4 (2008): 680-690.
55. Seena, V., and Jerrin Yomas. "A review on feature extraction and denoising of ECG signal using wavelet transform." In *2014 2nd international conference on devices, circuits and systems (ICDCS)*, pp. 1-6. IEEE, 2014.
56. Udhayakumar, Radhagayathri Krishnavilas. "Analysing Irregularity and Complexity in Short-length Heart Rate Variability Signals." PhD diss., The University of Melbourne, 2019.
57. Khazaee, Ali, and Ataollah Ebrahimzadeh. "Classification of electrocardiogram signals with support vector machines and genetic algorithms using power spectral features." *Biomedical Signal Processing and Control* 5, no. 4 (2010): 252-263.
58. Singh, Anupreet Kaur, and Sridhar Krishnan. "ECG signal feature extraction trends in methods and applications." *BioMedical Engineering OnLine* 22, no. 1 (2023): 22.
59. Al-Fahoum, Amjed S., and Ausilah A. Al-Fraihat. "Methods of EEG Signal Features Extraction Using Linear Analysis in Frequency and Time-Frequency Domains." *International Scholarly Research Notices* 2014, no. 1 (2014): 730218.
60. Bajaj, Nikesh. "Wavelets for EEG analysis." *Wavelet theory* (2020): 1-16.
61. Islam, Md Rabiul, and Mohiuddin Ahmad. "Wavelet analysis based classification of emotion from EEG signal." In *2019 international conference on electrical, computer and communication engineering (ECCE)*, pp. 1-6. IEEE, 2019.
62. Huang, Jingshan, Binqiang Chen, Bin Yao, and Wangpeng He. "ECG arrhythmia classification using STFT-based spectrogram and convolutional neural network." *IEEE access* 7 (2019): 92871-92880.
63. Cao, Minh, Tianqi Zhao, Yanxun Li, Wenhao Zhang, Peyman Benharash, and Ramin Ramezani. "ECG Heartbeat classification using deep transfer learning with Convolutional Neural Network and STFT technique." In *Journal of Physics: Conference Series*, vol. 2547, no. 1, p. 012031. IOP Publishing, 2023.

64. Houssein, Essam H., Moataz Kilany, and Aboul Ella Hassanien. "ECG signals classification: a review." *International Journal of Intelligent Engineering Informatics* 5, no. 4 (2017): 376-396.
65. Sahoo, S., M. Dash, S. Behera, and S. Sabut. "Machine learning approach to detect cardiac arrhythmias in ECG signals: A survey." *Irbm* 41, no. 4 (2020): 185-194.
66. Sarkar, Pritam, and Ali Etemad. "Self-supervised learning for ecg-based emotion recognition." In *ICASSP 2020-2020 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pp. 3217-3221. IEEE, 2020.
67. Karpagachelvi, S., M. Arthanari, and M. Sivakumar. "Classification of electrocardiogram signals with support vector machines and extreme learning machine." *Neural Computing and Applications* 21 (2012): 1331-1339.
68. Sánchez, FA Rivera, and JA González Cervera. "ECG classification using artificial neural networks." In *Journal of Physics: Conference Series*, vol. 1221, no. 1, p. 012062. IOP Publishing, 2019.
69. Hosseini, H. Gholam, Dehan Luo, and Karen Jane Reynolds. "The comparison of different feed forward neural network architectures for ECG signal diagnosis." *Medical engineering & physics* 28, no. 4 (2006): 372-378.
70. Salloum, Ronald, and C-C. Jay Kuo. "ECG-based biometrics using recurrent neural networks." In *2017 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pp. 2062-2066. IEEE, 2017.
71. Mert, Ahmet, Niyazi Kilic, and Aydın Akan. "ECG signal classification using ensemble decision tree." *J Trends Dev Mach Assoc Technol* 16, no. 1 (2012): 179-182.
72. Li, Taiyong, and Min Zhou. "ECG classification using wavelet packet entropy and random forests." *Entropy* 18, no. 8 (2016): 285.
73. Nezamabadi, Kasra, Neda Sardaripour, Benyamin Haghi, and Mohamad Forouzanfar. "Unsupervised ECG analysis: A review." *IEEE Reviews in Biomedical Engineering* 16 (2022): 208-224.
74. Lin, Zetao, Yaozheng Ge, and Guoliang Tao. "Algorithm for clustering analysis of ECG data." In *2005 IEEE Engineering in Medicine and Biology 27th Annual Conference*, pp. 3857-3860. IEEE, 2006.
75. Sharma, L. N., Samarendra Dandapat, and Anil Mahanta. "Multichannel ECG data compression based on multiscale principal component analysis." *IEEE Transactions on Information technology in Biomedicine* 16, no. 4 (2012): 730-736.
76. Labati, Ruggero Donida, Enrique Muñoz, Vincenzo Piuri, Roberto Sassi, and Fabio Scotti. "Deep-ECG: Convolutional neural networks for ECG biometric recognition." *Pattern Recognition Letters* 126 (2019): 78-85.
77. Kiranyaz, Serkan, Turker Ince, and Moncef Gabbouj. "Real-time patient-specific ECG classification by 1-D convolutional neural networks." *IEEE transactions on biomedical engineering* 63, no. 3 (2015): 664-675.
78. Chauhan, Sucheta, and Lovekesh Vig. "Anomaly detection in ECG time signals via deep long short-term memory networks." In *2015 IEEE international conference on data science and advanced analytics (DSAA)*, pp. 1-7. IEEE, 2015.
79. Lu, Peng, Saidi Guo, Yingying Wang, Lianxin Qi, Xinzhe Han, and Yuchen Wang. "Ecg classification based on long short-term memory networks." In *Proceedings of the 2nd International Conference on Healthcare Science and Engineering 2nd*, pp. 129-140. Springer Singapore, 2019.
80. Rathakrishnan, Kalaivani, Seung-Nam Min, and Se Jin Park. "Evaluation of ECG features for the classification of post-stroke survivors with a diagnostic approach." *Applied Sciences* 11, no. 1 (2020): 192.
81. Wu, Shun-Chi, Pei-Lun Hung, and A. Lee Swindlehurst. "ECG biometric recognition: unlinkability, irreversibility, and security." *IEEE Internet of Things Journal* 8, no. 1 (2020): 487-500.
82. Khaldi, Amine, Med Redouane Kafi, and Billel Meghni. "Electrocardiogram signal security by digital watermarking." *Journal of Ambient Intelligence and Humanized Computing* 14, no. 10 (2023): 13901-13913.
83. Arquilla, Katya, Andrea K. Webb, and Allison P. Anderson. "Textile electrocardiogram (ECG) electrodes for wearable health monitoring." *Sensors* 20, no. 4 (2020): 1013.
84. Serhani, Mohamed Adel, Hadeel T. El Kassabi, Heba Ismail, and Alramzana Nujum Navaz. "ECG monitoring systems: Review, architecture, processes, and key challenges." *Sensors* 20, no. 6 (2020): 1796.
85. Wang, Peng, Zihuai Lin, Xucun Yan, Zijiao Chen, Ming Ding, Yang Song, and Lu Meng. "A wearable ECG monitor for deep learning based real-time cardiovascular disease detection." *arXiv preprint arXiv:2201.10083* (2022).