Биометрия на основе ЭКГ для распознавания с открытым множеством: особенности проектирования и вызовы

ECG Biometrics for Open-Set Recognition: Design Considerations and Challenges

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Аннотация
Биометрия на основе электрокардиограммы (ЭКГ) предлагает перспективное решение для безопасной и надежной аутентификации, используя уникальные и внутренние характеристики ЭКГ сигналов. В отличие от внешних признаков, таких как отпечатки пальцев или распознавание лиц, ЭКГ сигналы являются внутренними для тела, что делает их высокоустойчивыми к подделке и гарантирует, что только живые люди могут быть проверены и аутентифицированы. Хотя существующие исследования в основном сосредоточены на системах с закрытым множеством, которые работают в пределах заранее определенных наборов данных, реальные приложения требуют возможностей распознавания с открытым множеством. Распознавание с открытым множеством означает, что системы должны уметь распознавать зарегистрированных пользователей и одновременно отклонять неизвестных лиц, что приводит к следующим вызовам: вариабельность сигналов, ограниченная обобщаемость классификаторов и недостаток богатых наборов данных. В этом обзоре рассматриваются особенности проектирования, вызовы и решения для реализации биометрии на основе ЭКГ в условиях открытого множества. Обсуждаются передовые методы классификации, включая модели глубокого обучения, техники классификации и новые модели, ориентированные на открытые множества, такие как OpenMax и EVMs. Кроме того, анализируется роль извлечения признаков, увеличения данных и метрик оценки в повышении производительности систем. Решение этих задач может сделать биометрию на основе ЭКГ основой для безопасной аутентификации в здравоохранении, Интернете вещей (IoT) и финансовых системах. Эта статья направлена на то, чтобы направить будущие исследования на разработку надежных и масштабируемых биометрических систем на основе ЭКГ.
Ключевые слова: Биометрия на основе ЭКГ, распознавание с открытым множеством, распознавание с закрытым множеством, системы аутентификации, вариабельность сигналов, модели классификации, глубокое обучение, OpenMax, экстремальные машины значений (EVMs).

Abstract
Electrocardiogram (ECG)-based biometrics offer a promising solution for secure and reliable authentication, leveraging the unique and intrinsic characteristics of ECG signals. Unlike external traits such as fingerprints or facial recognition, ECG signals are internal to the body, making them highly resistant to spoofing and ensuring that only live persons can be verified and authenticated. While existing research has largely focused on closed-set recognition environments, where systems operate within predefined datasets, real-world applications demand open-set recognition capabilities. Open-set recognition means that the systems must recognize the enrolled users and at the same time reject the unknown individuals, which poses the following challenges: variability of signals, limited generalization of classifiers, and lack of rich datasets. This review examines the design considerations, challenges, and solutions for implementing ECG biometrics in open-set environments. Advanced classification methodologies that include deep learning models, classification techniques, and new open-set specific models including OpenMax and EVMs are discussed. Additionally, the role of feature extraction, data augmentation, and evaluation metrics in improving system performance is analyzed. By addressing these challenges, ECG biometrics can become the basis for secure authentication in health care, IoT and financial systems. This paper aims to guide future research toward developing robust and scalable ECG-based biometric systems.
Keywords: ECG Biometrics, Open-Set Recognition, Closed-Set Recognition, Authentication Systems, Signal Variability, Classification Models, Deep Learning, OpenMax, Extreme Value Machines (EVMs).

Introduction

The study of philological terms is a fascinating exploration into the intricate world of Biometric recognition systems are the basis of the modern identification and recognition that offer safer and more comfortable ways compared to traditional approaches like passwords and tokens [1]. They become a key form of user authentication such as smartphones, banks, websites and airports [2][3][4]. Among the diverse biometric modalities, electrocardiogram-based (ECG)-based biometrics stand out because of their unique physiological characteristics. ECG signals, which reflect the electrical activity of the heart, offer intrinsic advantages including individuality, universality, and resilience against forgery [5][6]. Unlike external traits, such as fingerprints or facial features, ECG signals are internal to the human body and can only be recorded from living individuals, enhancing their security and robustness [7][8]. Although ECG-based biometric systems have shown significant promise, much of the existing research and development has been limited to closed-set recognition. In closed-set scenarios, the system operates within a predefined set of known individuals, focusing solely on identifying or verifying the users from this set [9][10]. However, real-world applications often require open-set recognition, where the system encounters unknown subjects that are not included in training data. Open-set recognition systems must not only identify enrolled users, but also confidently reject imposters or unregistered individuals, which is a critical capability for enhancing robustness and reliability. Open-set recognition presents unique challenges for ECG biometrics. Variability in ECG signals owing to physiological differences, environmental factors, and hardware configurations complicates the task of distinguishing between known and unknown individuals [11]. Furthermore, the lack of diverse and standardized datasets tailored for open-set scenarios limits the ability to train and evaluate robust models [12]. Current methodologies, although effective in controlled settings, often fall short when applied to dynamic and unpredictable real-world environments. This review aims to provide a comprehensive investigation of ECG biometrics in open-set recognition environments by examining the design considerations, challenges, and solutions required to advance the field [13]. These are signal acquisition, preprocessing, feature extraction, and classifier design with special emphasis on the variability and uncertainty that are characteristic of open-set problems. By addressing these issues, this paper seeks to guide future research and development toward creating practical, scalable, and adaptive ECG biometric systems capable of meeting the demands of real-world applications.

Background

Biometric systems leverage unique physiological or behavioral traits to authenticate individuals, providing a secure alternative to conventional authentication methods [1]. Among the numerous biometric modalities, electrocardiogram (ECG)-based systems stand out due to the intrinsic link between an individual's cardiac activity and their identity [14]. ECG signals are not only unique to each individual but also challenging to replicate, making them a promising biometric modality for secure authentication systems. Interestingly, the ECG biometric modality as presented in Table 1, has shown to be the most promising than the other biometric modalities in terms of most of the characteristics used in describing biometric modality quality [15][16][17].

ECG Signals and Their Biometric Properties

The electrocardiogram (ECG) is a graphical representation of the heart's electrical activity over time, recorded using electrodes placed on the body [18]. An ECG signal is characterized by a repeating waveform that includes distinct components such as the P wave, QRS complex, and T wave as shown in Fig. 1. Each of these components reflects specific phases of the cardiac cycle: the P wave represents atrial depolarization, the QRS complex corresponds to ventricular depolarization, and the T wave indicates ventricular repolarization [19]. The morphology and temporal characteristics of these features vary significantly between individuals due to anatomical and physiological differences, making ECG signals uniquely identifiable.

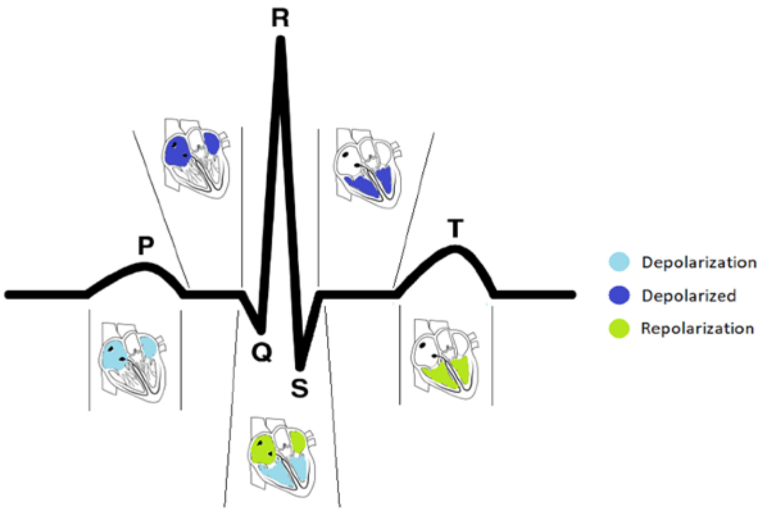

Fig. 1. The series of depolarization and repolarization in the heart, in relation to different waveforms in an ECG signal.

Table 1 - Pros and cons of the ECG when compared with the other biometric modalities.

Modality	Advantages	Disadvantages
ECG	Universality, uniqueness, permanence, and liveness assurance, hidden nature, simple acquisition	Requires contact, variability induced by human activity
Palmprint	High reliability, permanent over time, fast recognition even with low resolution scanners and cameras	Requires physical contact with the system
Fingerprint	Matching Process is fast, consumes less memory space, less expensive, reliable, high accuracy	Requires physical contact with the system, accuracy influences by obstacles such as cuts, scars, dust, dirt, twists
Voice	Easy implementation, Less expensive and convenient to use	Accuracy influenced by throat disease, low performance
Iris	High speed of processing, small sample size, requires no physical contact	Diseases may affect the accuracy, expensive equipment

Gait	Non-invasive, easy image capture, no distance problem, affordable equipment	Low accuracy, computationally expensive
Face	No physical contact involved, can be quantified, relatively simple measures, low-cost measuring instruments, quick time to recognize	Facial traits may change with time, age, accidental happenings; depends on face visibility and lighting
Retina	The trait cannot be faked; it is believed to be one hundred percent correct	Time consuming, may be physically uncomfortable requiring physical touch; diseases such as cataract, hypertension affect the efficiency

Open-Set vs. Closed-Set Recognition

Biometric recognition systems are generally categorized into two main paradigms according to classification task problems: closed-set recognition and open-set recognition [20]. Each paradigm addresses different operational requirements, with significant differences in their assumptions, capabilities, and real-world applicability.

Closed-Set Recognition

Overall, the materials and methods used in this study provide a comprehensive and nuanced understanding of the origin and formation of philological terms. By drawing on a diverse range of sources and methodologies, this study aims to contribute to the broader field of linguistics and philology by shedding light on the complex processes through which languages and their associated terms have evolved over time.

Open-Set Recognition

In contrast, open-set recognition reflects the reality of real-world systems where the system must account for the presence of unknown individuals. These systems must not only identify enrolled users but also accurately reject imposters or unknown subjects [24]. This additional capability introduces challenges that are absent in closed-set systems, such as (1) Signal Variability where variations in ECG signals due to physiological changes (e.g., heart rate variability, stress), environmental factors (e.g., noise, electrode placement), or hardware inconsistencies. (2) Generalization where the need for classifiers to handle unseen data without overfitting to the training set [25]. (3) Data Scarcity where the lack of diverse datasets that represent real-world scenarios, including variations in demographics, health conditions, and acquisition settings [26]. Based on Donald Rumsfeld's [27] "knowns and unknowns" concept, open-set recognition can be further expanded into four kinds of classes:

- Known Known Classes (KKCs): Labeled positive samples in the classes.
- Known Unknown Classes (KUCs): They have been labeled as negative samples that indicate potential outliers of the data set.
- Unknown Known Classes (UKCs): Classes with no specific samples for variants during the training process but other side information (e.g., semantic attributes).
- Unknown Unknown Classes (UUCs): Can Improve classes with no prior information or labeled samples.

Fig. 2 illustrates the relationships between these categories, showing how open-set recognition expands upon traditional classification by introducing mechanisms for handling UUCs and UKCs [28]. Table 2 presents a comparative analysis of these techniques, delineating their respective settings, training requirements, and objectives, while emphasizing the adaptability of open-set recognition for practical applications [26].

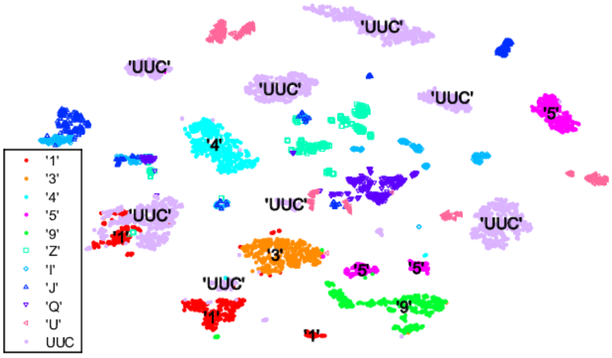

Fig. 2. An example of visualizing KKCs, KUCs and UUCs from the real data distribution using t-SNE.

Table 2. shows the distinction between open set recognition and the related tasks discussed above.

Task	**Description**	**Goal**
Traditional Classification	Relies on the ability to classify through known classes using training and testing information sourced from the same set of known people.	Classifying known known classes
Classification with Reject Option	Includes a reject option to identify low-confidence samples but still only classifies within the known set.	Classifying known known classes & rejecting samples of low confidence
One-class Classification (Anomaly Detection)	Detects outliers by training on known classes and some near-boundary or unrelated samples from unknown classes.	Detecting outliers
One/Few-shot Learning	Learn to classify unknown classes using a limited number of examples for each new class.	Identifying unknown known classes
Generalized Few-shot Learning	Expands few-shot learning to both known and unknown classes, identifying and handling unknown classes effectively.	Identifying known known classes & unknown known classes
Zero-shot Learning	Uses semantic information or side data to classify unknown classes without any training examples for them.	Identifying unknown known classes
Generalized Zero-shot Learning	Combines semantic data and known examples to handle both known and unknown classes effectively.	Identifying known known classes & unknown known classes
Open Set Recognition	Identifies known classes while rejecting unknown samples, focusing on flexible decision-making for real-world applications.	Identifying known known classes & rejecting unknown unknown classes
Generalized Open Set Recognition	Handles both known and unknown classes, using semantic data to understand unknown classes beyond rejection.	Identifying known known classes & cognizing unknown unknown classes

Classification Techniques

Classification techniques play an important role in the execution of closed-set and open-set biometric systems since it involves the right classification of the extracted features by mapping them into certain classes or labelled as unknown by the system [29]. This section describes the development of classification techniques from previous methods to new strategies developed to suit new advances in the open-set recognition [30].

Traditional Classification Methods

Classification techniques form the backbone of biometric systems, enabling the identification or verification of individuals based on extracted features [31]. Traditional methods, such as k-Nearest Neighbors (k-NN), Support Vector Machines (SVMs), and Linear Discriminant Analysis (LDA), have been widely employed in closed-set recognition tasks due to their simplicity and effectiveness in controlled environments [32]. For instance, k-NN assigns class labels based on the majority vote of the nearest neighbors in the feature space, making it particularly effective for small-scale datasets. SVMs, on the other hand, separate classes by constructing hyperplanes in a high-dimensional space, which allows for robust generalization. LDA focuses on maximizing the separability between classes by finding a linear combination of features that best separates them. While these traditional methods have achieved substantial success in closed-set scenarios, their reliance on predefined decision boundaries limits their applicability to open-set recognition, where the system must handle unknown classes [33] [34]. Without the ability to reject inputs from unknown classes, these methods often misclassify such inputs into one of the known classes, reducing system reliability.

Emerging Classification Methods

To overcome the limitations of traditional classifiers, emerging techniques have been developed to address the unique requirements of open-set recognition [35]. Deep learning-based approaches, such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), have shown significant promise due to their ability to learn complex, high-dimensional representations of ECG signals [22]. Techniques like autoencoders and variational autoencoders (VAEs) further enhance feature extraction, utilizing reconstruction error to detect unknown classes [36] [37]. Similarly, one-shot and few-shot learning methods have been introduced to classify unknown classes based on limited training examples [38]. These approaches leverage models like Siamese Networks and Prototypical Networks, which measure similarity between samples to identify unknown inputs effectively. Advanced classifiers specifically designed for open-set recognition, such as OpenMax and Extreme Value Machines (EVMs), have also been introduced [39] [40]. The OpenMax classifier extends traditional softmax layers in deep learning models to recalibrate class probabilities, utilizing extreme value theory to model the tail distribution of activation values [41] [42]. This approach significantly improves the system’s ability to reject unknown inputs. EVMs take this further by reserving space for unknown classes in the feature space, effectively modeling the distribution of known classes while accounting for the possibility of encountering unseen data [43] [44] [45]. Hybrid approaches, which combine traditional and deep learning techniques, offer another promising solution by integrating handcrafted features with deep embeddings to enhance robustness and interpretability [46]. For example, fiducial points extracted from ECG signals can be used alongside deep-learned representations to create a more resilient classification system [47].

The conventional problem of OSR is intended to identify samples from given classes and at the same time exclude samples from other unknown classes. The open set classifier is capable of learning the decision planes for known classes and at the same time rejecting the unknown samples with labels other than the training set labels outside the decision regions of the known classes. As illustrated in Fig. 3, the unknown class samples will spread out in an area that is far from the decision regions known as open space.

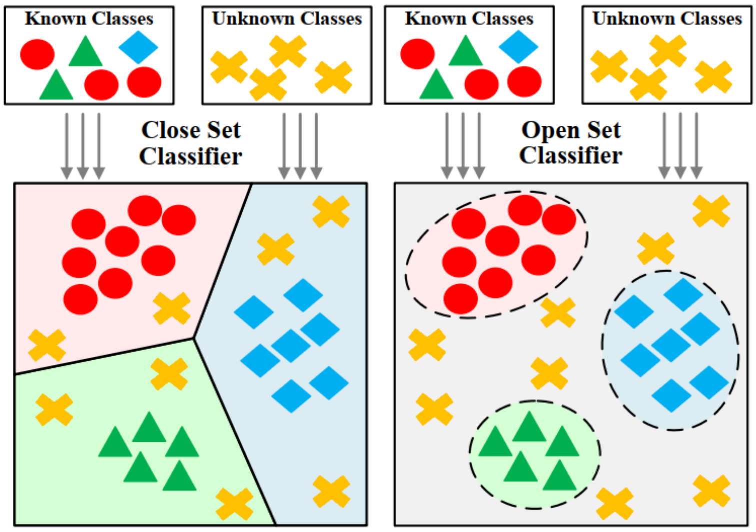

Fig. 3. The practical performance of closed/open set identification

Method

The present systematic review has been conducted according to Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines [48]. The literature research of the current paper was carried out in Scopus and the IEEE Xplore databases. An overview of literature search for this literature review is depicted in Fig. 4 and the process of literature search for this literature review is a three staged process of identification, screening and inclusion.

Identification

During the identification stage of this review, the general search terms were developed and used to search for related documents within Scopus, PubMed, and IEEE Xplore search engines that function on the title, abstract, and/or keywords. The search terms included combinations of keywords such as:

("biometric" OR "biometry") AND ("ECG" OR "Electrocardiogram" OR "Electrocardiography" OR "Heart") AND ("Authentication" OR "Identification" OR "Verification" OR "Recognition") AND ("Open-Set" OR "Closed-Set" OR "Classification" OR "Feature Extraction") AND ("Signal Acquisition" OR "Data Collection" OR "Biosensor*" OR "Electrode*" OR "Database*").*

Boolean operators AND and OR were used to ensure comprehensive coverage of relevant studies. The initial search identified 312 papers. After removing 20 duplicate records, a total of 292 unique papers were identified for further processing.

Identification

To refine the selection of studies, a two-phase screening process was implemented, combining automated filtering and manual evaluation to ensure relevance and quality. In the first phase, predefined exclusion criteria were applied to narrow down the studies. Only studies published between 2015 and 2024 were considered, which led to the exclusion of 62 papers. Relevant subject areas were defined as computer science, engineering, healthcare, and decision sciences, resulting in the exclusion of 48 papers from unrelated domains. To maintain a focus on high-quality research, only peer-reviewed journal articles, conference papers, and systematic reviews were included, excluding 15 studies such as editorials and non-peer-reviewed publications. Additionally, only papers published in English were considered, which excluded a further 7 studies written in other languages. After this automated filtering process, a total of 160 studies were excluded, leaving 132 papers for further analysis.

In the second phase, a manual screening process was conducted to ensure alignment with the review’s objectives. Each study was carefully evaluated based on its title, abstract, methodology, and findings sections. Studies were excluded if they did not focus on ECG-based biometrics, which accounted for 25 exclusions, or if they exclusively addressed closed-set recognition without discussing open-set scenarios, leading to the exclusion of 18 studies. A further 10 studies were excluded as they focused on non-biometric applications of ECG, such as medical diagnostics, while 9 studies were excluded for combining ECG with other biometric modalities without emphasizing ECG-specific contributions. After this thorough manual screening process, 70 studies were retained for the inclusion phase.

Inclusion

In the final stage, 70 studies were included after the screening process. To enhance the review, an additional 20 studies were added through backward citation searches, bringing the total number of included studies to 90 papers, Fig. 5 shows the distributions of included papers over years. These studies represent key contributions in signal acquisition, pre-processing, feature extraction, and classification methods for ECG biometrics in open-set recognition scenarios. They were sourced primarily from high-impact journals and conferences.

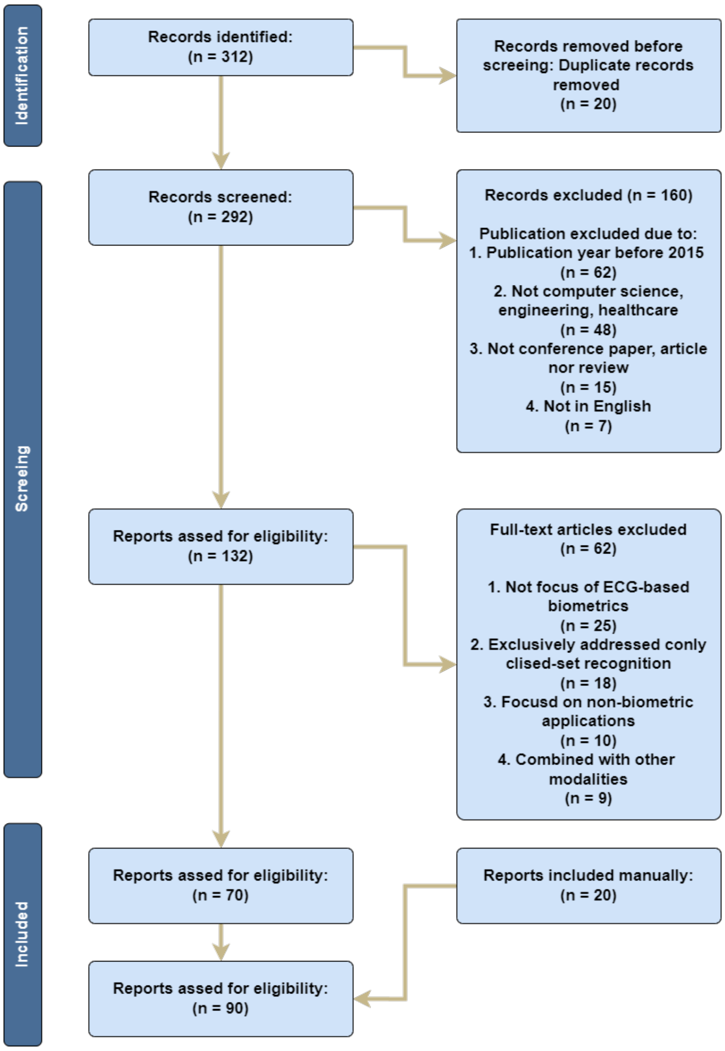

Fig. 4. Flow diagram of the literature research process (adapted from Prisma Guidelines [49])

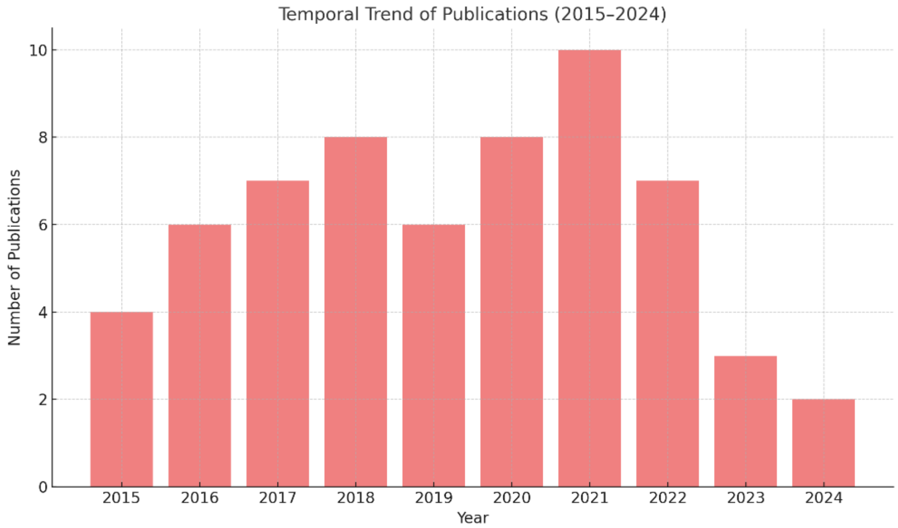

Fig. 5. The annual distribution of included publications from 2015 to 2024

Research Questions

This systematic review focuses on addressing the following key research questions (RQs) related to open-set recognition in ECG-based biometrics. Each question is designed to uncover specific aspects of the topic, guiding the review and identifying areas for future research and practical implementation.

RQ1: What are the main challenges in implementing open-set recognition for ECG biometric systems? This question aims to systematically categorize the barriers hindering the effective deployment of open-set ECG biometric systems, enabling a targeted approach to addressing these issues.

RQ2: What methods and techniques have been proposed to address open-set challenges in ECG biometrics? The goal of this question is to review existing methodologies, compare their effectiveness, and identify innovative techniques that show promise in overcoming the identified challenges.

RQ3: What role do signal acquisition, pre-processing, and feature extraction play in improving ECG biometrics for open-set environments? This question seeks to evaluate how these components contribute to the robustness and accuracy of ECG biometric systems and to identify best practices for optimizing these processes.

RQ4: How can advanced technologies like deep learning and multimodal systems contribute to open-set ECG biometrics? This question aims to explore the role of emerging technologies in advancing ECG biometrics, focusing on how they can improve generalization, feature representation, and decision-making in open-set contexts.

Results

Open-set recognition in ECG biometrics poses several challenges that hinder its widespread adoption and real-world applicability [50]. This is one of the most crucial problems since ECG is known to be a highly variable signal. For example, stress, physical activity, or a change of position entails intra-individual variability which leads to variations that complicate the classification of signals [15]. Additionally, inter-individual variability, which stems from anatomical and physiological differences, further complicates the development of reliable models. Environmental factors, including noise, electrode placement, and acquisition conditions, exacerbate these issues, highlighting the need for robust techniques that can handle such variability [51].

Another significant challenge lies in the generalization capabilities of existing classifiers. Traditional models, such as k-Nearest Neighbors (k-NN) and Support Vector Machines (SVMs), often fail to reject unknown inputs effectively, leading to high false acceptance rates [52][53]. While advanced classifiers like OpenMax and Extreme Value Machines (EVMs) show promise, they still require further refinement to balance the trade-off between accurately identifying known classes and rejecting unknown ones [54]. Moreover, the scarcity of diverse and standardized datasets limits the ability to train and evaluate these models. Existing datasets often lack representation across different demographics, health conditions, and acquisition settings, making it difficult to ensure the generalizability of developed systems [55].

The inadequacy of traditional evaluation metrics further complicates the development of open-set recognition systems. Metrics such as accuracy and precision, which are widely used in closed-set scenarios, fail to capture the system's ability to reject unknown classes. This further emphasizes the need to use open-set specific measures including the Open-Set Identification Rate (OSIR) and Generalized Accuracy.

Despite these challenges, several techniques have been proposed to address the limitations of open-set recognition in ECG biometrics. Feature extraction methods have evolved from relying solely on fiducial points, such as the R peak and QRS complex, to non-fiducial approaches that leverage statistical and frequency-domain analysis. Hybrid techniques that combine both fiducial and non-fiducial methods have demonstrated improved robustness and accuracy [56][57]. Advanced classifiers, including OpenMax and EVMs, are designed to handle unknown classes by creating flexible decision boundaries. Deep learning models, such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), have further enhanced classification by learning complex, high-dimensional representations of ECG signals [58][59].

Data augmentation strategies, such as the use of Generative Adversarial Networks (GANs), have also played a vital role in addressing the lack of diverse datasets. By generating synthetic ECG signals that simulate real-world variability, these methods enable models to generalize better to unseen scenarios. The integration of these techniques has paved the way for significant advancements in the field, although challenges remain in achieving consistent performance across diverse conditions [60][61].

The applications and potential use of open-set ECG biometrics are numerous and significant. In secure access systems, ECG biometrics can be considered as attractive solutions for the access authentication in the secure environment because the false reject rate in the system is close to zero. In healthcare, ECG-based identification facilitates secure access to patient records and enhances the privacy of sensitive medical information. The integration of ECG biometrics into IoT devices and wearables enables continuous authentication, providing personalized services while maintaining user security [62][63]. In the financial sector, ECG biometrics are being explored as a secure, contactless method for transaction authentication. Additionally, multimodal systems that combine ECG biometrics with other modalities, such as facial recognition or fingerprints, further enhance system reliability by leveraging the strengths of multiple traits [15][64].

In conclusion, the outcomes of this review confirm the recent advances in the solutions to the issues with the open-set recognition of ECG biometrics but stress the further potential research. Application of modern approaches, such as hybrid solutions and deep learning models, are being introduced as possible solutions, but these techniques' performance relies heavily on the obstacles posed by data shortages as well as the development of better methods to evaluate the results of the methods. By addressing these gaps, ECG biometrics can be placed at the foundation of sound authentication solutions in various fields. Table 3 provides various classification techniques and their characteristics, showing how emerging classifiers can improve the authentication under open-set recognition environments.

Table 3. Comparison of different classification techniques.

Classification Technique	Type	Key Feature	Applications
k-Nearest Neighbors (k-NN)	Traditional	k-NN predicts data based on its tag similarity with the majority class of the nearest neighbors of data using the training set and a distance measure without modeling.	k-NN is used in biometric systems for applications such as face recognition, fingerprint verification, and gait recognition.

Support Vector Machines (SVM)	Traditional	SVMs optimize class separation by maximizing margins, excelling in high-dimensional spaces for both linear and nonlinear tasks.	Applications of SVM in biometric systems include fingerprint verification, face recognition, and other biometric identification tasks.
Linear Discriminant Analysis (LDA)	Traditional	LDA projects data onto a lower-dimensional space, maximizing class separability by optimizing the ratio of between-class to within-class variance.	LDA is used in biometric systems for applications such as face recognition, fingerprint verification, and disease diagnosis in healthcare
Convolutional Neural Networks (CNNs)	Emerging	CNNs automatically learn features from images, handle spatial hierarchies, provide translation invariance, and are robust to variations in input data	Face recognition, fingerprint verification, and multimodal biometric systems that combine different types of biometric data
Recurrent Neural Networks (RNNs)	Emerging	RNNs use hidden states to retain context from previous inputs, enabling effective processing of variable-length, sequential data with feedback loops	RNNs excel in biometric authentication, speech recognition, ECG biometrics, and expression analysis by processing sequential data effectively
OpenMax	Emerging	OpenMax replaces softmax in neural networks, using Extreme Value Theory (EVT) to detect unknown classes and compute probabilities.	OpenMax supports biometric systems like face recognition and fingerprint verification, identifying known individuals while recognizing and rejecting unknown ones.
Extreme Value Machines (EVMs)	Emerging	The Extreme Value Machine (EVM) applies EVT for probabilities, enabling open-set classification and recognizing inputs from unseen classes effectively.	EVM is applied in biometric systems for face recognition and fingerprint verification, improving the accuracy and scalability of open-set recognition tasks.

Conclusion

ECG-signature-based biometric authentication thus proposes a novel solution to secure and accurate person identification based on the intrinsic and distinctive features of ECG signals. However, actual applications are not limited to the closed-set identification; in the real-world setting, it may be necessary for the system to perform open-set identification in which new subjects or even imposters can appear. This review has outlined the design aspect, problem, and possible solution of ECG biometric systems in such a dynamic environment. The transition from closed-set to open-set recognition triggers the following challenges – variability in ECG signal, generalization of classifiers to unseen subjects, and the constraints of existing datasets and assessment methodologies. Insights have revealed that other essential features include the use of sophisticated classifier architectures, deep learning algorithms, aspects of data augmentation, and features engineering as helpful in overcoming these challenges. Additionally, ECG biometrics together with multimodal systems and real-time applications, can be improved in terms of robustness and scalability. Despite the progress made, significant gaps remain in open-set ECG biometrics. The future work should focus on the improvement of adaptive classifiers, the establishment of unified and assorted databases, as well as the investigation of novel technologies including blockchain and IoT. Questions of ethical and legal nature like data privacy violation and tendency in following the legalities that govern such systems must also be talked of to support responsible use of these systems. Thus, ECG biometrics might be used effectively to meet the emerging challenge of developing efficient and flexible systems for personal identification and authentication. The opportunities identified and discussed in this review shall be pursued to assist the researchers and practitioners to overcome some of the difficulties outlined above and develop solutions that can lead to better systems that operate effectively in open-set conditions. These enhancements will help in redefining the use of ECG biometric systems from the Healthcare and IoT sector to financial securities and Critical Infrastructure.

Literature:

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