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HEARTBEAT OF SECURITY: UNVEILING THE PULSE OF ECG BIOMETRIC AUTHENTICATION

Abstract*: telehealth and remote monitoring improve healthcare accessibility but also expose sensitive data to security and privacy risks, where traditional authentication methods often prove inadequate. The electrocardiogram (ECG) has emerged as a promising biometric modality due to its inherent liveness detection, universality, and individual uniqueness. This paper reviews the ECG authentication pipeline, including signal acquisition through wearables, pre-processing techniques for noise reduction, feature extraction methods (fiducial, non-fiducial, and deep learning), and classification models. Publicly available datasets are examined, alongside key performance benchmarks. Persistent challenges-such as intra-subject variability, computational constraints in wearables, and ethical concerns are discussed, with future directions highlighting multimodal systems, privacy-preserving techniques, and standardized validation. ECG authentication demonstrates strong potential to become a secure and practical component of Telehealth systems.*

Keywords*: ECG biometrics, telehealth security, biometric authentication, healthcare personalization, signal processing, patient identification.*

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ПУЛЬС БЕЗОПАСНОСТИ: РАСКРЫТИЕ ПОТЕНЦИАЛА БИОМЕТРИЧЕСКОЙ АУТЕНТИФИКАЦИИ ЭКГ

***Аннотация**: телемедицина и удаленный мониторинг повышают доступность медицинской помощи, но также подвергают персональные данные угрозам безопасности и конфиденциальности, в то время как традиционные методы аутентификации часто оказываются несовершенными. Электрокардиограмма (ЭКГ) зарекомендовала себя как перспективный биометрический метод благодаря присущим ей скорости, универсальности и уникальности. В этой статье рассматривается канал аутентификации по ЭКГ, включая сбор сигнала с помощью переносных устройств, методы предварительной обработки для снижения шума, методы выделения признаков (фидуциарные, нефидуцированные и глубокое обучение) и модели классификации. Анализируются общедоступные наборы данных, а также ключевые критерии эффективности. Обсуждаются сохраняющиеся проблемы, такие как внутрипредметная вариативность, вычислительные ограничения, связанные с переносными устройствами, и этические соображения, при этом в перспективе выделяются мультимодальные системы, методы сохранения конфиденциальности и стандартизированная проверка. Аутентификация по ЭКГ демонстрирует большой потенциал для того, чтобы стать безопасным и практичным компонентом систем телемедицины.*

***Ключевые слова**: биометрия ЭКГ, телемедицинская безопасность, биометрическая аутентификация, персонализация медицинских работников, обработка данных, идентификация пациента.*

Introduction.

Telehealth and remote patient monitoring have become integral to healthcare delivery, improving access and continuity of care but introducing new security and privacy risks. Traditional authentication methods-passwords, tokens, and even common biometrics such as fingerprints or facial recognition are vulnerable to attacks or spoofing, making them insufficient for safeguarding sensitive health data in remote settings [1].

The electrocardiogram (ECG) has emerged as a promising biometric alternative. Its inherent liveness detection, universality, and uniqueness make it well-suited for secure authentication. With the growth of wearable devices, ECG can also enable continuous and passive identity verification, providing both convenience and resilience. Despite challenges such as variability, noise, and ethical concerns over using diagnostic data for security, ECG authentication offers significant potential to enhance trust and reliability in Telehealth systems [2].

Approaches to ECG-Based Authentication.

ECG-based authentication relies on extracting discriminative information from cardiac waveforms through different methodological paradigms. Fiducial-based approaches detect characteristic points within the ECG signal, such as P-waves, QRS complexes, and T-waves, and use intervals, amplitudes, and slopes as features. These features are physiologically interpretable and computationally lightweight but highly sensitive to noise and errors in delineation. Non-fiducial approaches treat the ECG segment holistically, applying mathematical transforms such as wavelet decomposition, discrete cosine transform (DCT), or autocorrelation to generate robust features without requiring explicit detection of fiducial points [3]. While these methods are generally more resilient to noise, their features are abstract and less physiologically interpretable. More recently, deep learning approaches have emerged as the dominant paradigm, with convolutional neural networks (CNNs), recurrent neural networks (RNNs), and hybrid CNN-LSTM models capable of automatically learning hierarchical features directly from raw signals. These models achieve state-of-the-art accuracy but require large, diverse datasets and considerable computational resources [4].

As Figure 1 illustrates, the ECG authentication pipeline consists of four stages: signal acquisition, pre-processing, feature extraction, and classification. Signal acquisition can be achieved either through clinical “on-the-person” electrodes or consumer wearables that enable unobtrusive capture in daily settings. Pre-processing reduces noise and normalizes variability, while feature extraction generates discriminative representations for classification. The final stage applies machine learning or deep learning models to distinguish between genuine users and impostors, producing the authentication decision [5].

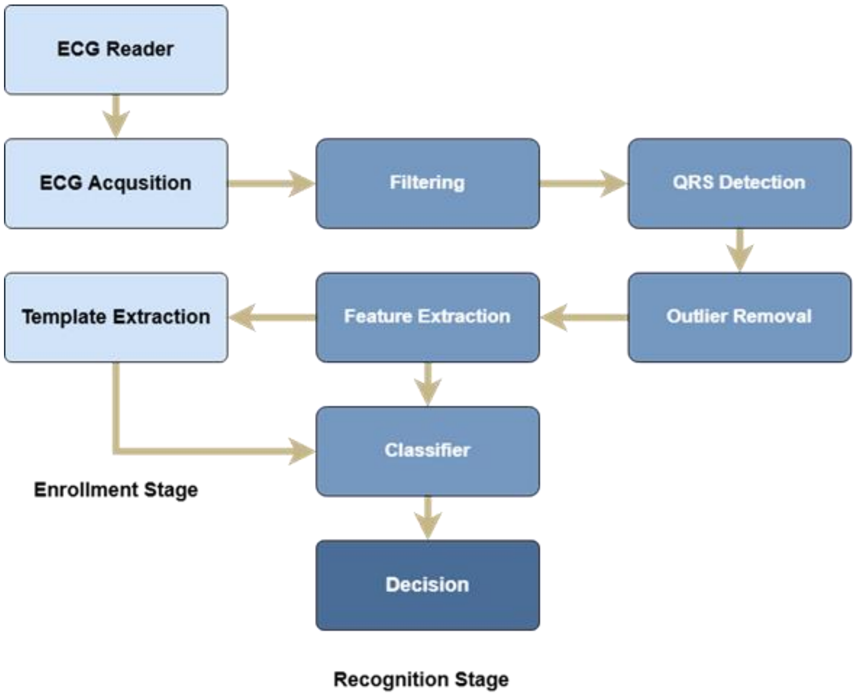

Fig. 1. A diagram of the various applications

Challenges in Implementing ECG Biometrics.

While ECG biometrics demonstrates strong potential, several challenges hinder its adoption in real-world applications. A major issue is intra-subject variability, as ECG signals are influenced by physiological state, emotional stress, physical activity, and aging [6]. This variability undermines the permanence expected from a biometric trait. Noise and motion artifacts, particularly from wearable devices, further complicate signal quality and reduce reliability [7]. Pathological conditions such as arrhythmias present another difficulty, as they may significantly alter ECG morphology and bias system performance if not adequately represented in training datasets [8]. Scalability also remains a barrier. While small-scale laboratory experiments achieve very low error rates, performance often degrades in large, unconstrained populations [9]. Additionally, ECG signals contain diagnostic information beyond identity, raising concerns about privacy and ethics. Unauthorized access to raw ECG data could reveal sensitive health conditions, underscoring the need for privacy-preserving methods and regulatory safeguards [10].

Conclusion.

ECG biometric authentication combines liveness detection, universality, and high discriminative power, making it an attractive solution for secure and seamless identity verification. Deep learning methods have demonstrated exceptional accuracy, and wearables enable passive, user-friendly integration. Nevertheless, practical deployment faces challenges including intra-subject variability, noise, scalability, and ethical concerns related to the dual diagnostic and biometric nature of ECG signals [11].

The future viability of ECG authentication depends on developing adaptive algorithms, privacy-preserving techniques, and standardized validation protocols. By addressing these challenges, ECG biometrics has the potential to become a trusted and integral component of secure digital ecosystems, particularly within Telehealth, where reliable authentication is essential for protecting sensitive patient data.

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