

Enhancing robustness in ECG-based biometric authentication through hybrid signal processing and deep learning

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Аннотация: Electrocardiogram (ECG)-based biometric authentication systems offer intrinsic resistance to spoofing due to their physiological uniqueness. However, their performance in dynamic real-world settings, such as wearable devices or stress-induced conditions, is often compromised by noise, electrode displacement, and intra-subject variability. This study proposes a novel hybrid framework that enhances robustness, ensuring high authentication accuracy and reliability in adverse conditions, through integrated wavelet-based signal processing for noise suppression and a deep-learning classifier for adaptive feature recognition. The system employs preprocessing, QRS complex detection, distance–deviation modeling, a statistical comparison method that quantifies morphological similarity between ECG templates by analyzing amplitude and shape deviations and an averaging-threshold mechanism, combined with a feedforward Multi-Layer Perceptron (MLP) neural network for classification. The MLP is trained on extracted ECG features to capture complex nonlinear relationships between waveform morphology and user identity, ensuring adaptability to variable signal conditions. Experimental validation on the ECG-ID dataset achieved 98.8% accuracy, 95% sensitivity, an Area Under the Curve (AUC) of 0.98, and a low false acceptance rate, outperforming typical wearable ECG authentication systems that report accuracies between 90% and 95%. With an average processing time of 8 seconds, the proposed method supports near real-time biometric verification suitable for healthcare information systems, telehealth platforms, and IoT-based access control. These findings establish a scalable, adaptive, and noise-resilient foundation for next-generation physiological biometric authentication in real-world environments.

Ключевые слова: electrocardiogram biometrics, wavelet decomposition, QRS complex detection, feedforward neural network, deep learning classification, noise-resilient authentication, biometric security.

Introduction

Biometric authentication has become a crucial part of today's security systems, granting safe access to delicate data. Among the various biometric modalities, electrocardiogram (ECG) signals are distinguished from others because of their physiological uniqueness, stability, and being inherently resistant to spoofing [1]. Unlike external traits like fingerprints or facial images, which are susceptible to duplication, ECG signals reflect the heart's electrical activity, providing intrinsic liveness detection and robust protection against fraudulent attacks [2]. However, the practical deployment of ECG-based authentication faces challenges in real-world settings, such as wearable devices or telehealth

applications, where noise, electrode misplacement, motion artifacts, and physiological variations degrade signal quality and reliability. Existing approaches fall into two categories: classical signal-processing methods, which extract interpretable features like QRS intervals and R–R distances but lack adaptability, and deep-learning methods, which learn patterns from raw data but are sensitive to noise and require large datasets. These limitations highlight the need for a more robust and adaptive ECG biometric system [3].

To address these challenges, this study proposes a novel hybrid framework that integrates wavelet-based signal preprocessing, QRS complex detection, distance–deviation modeling, and an averaging-threshold mechanism with a feedforward Multi-Layer Perceptron (MLP) neural network. Unlike prior approaches, this framework combines the interpretability of signal processing with the adaptability of deep learning, using extracted ECG features to train the MLP for robust classification of nonlinear waveform patterns. The averaging-threshold mechanism further enhances resilience to transient noise and physiological fluctuations, ensuring stable authentication across multiple cardiac cycles [4].

From a physiological perspective, ECG signals capture the heart's electrical activity, characterized by the P wave (atrial depolarization), QRS complex (ventricular depolarization), and T wave (ventricular repolarization), as illustrated in Fig. 1. These components exhibit unique morphological and temporal variations among individuals, forming a biometric signature suitable for authentication.

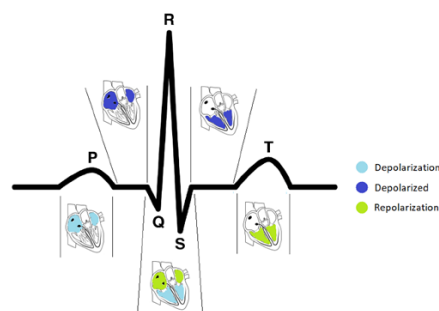


Fig. 1. Physiological basis of ECG waveforms [5]

This research aims to deliver a robust, accurate, and practical ECG-based authentication system, validated on the publicly available ECG-ID dataset. The remainder of this paper is organized as follows: Section 2 reviews related work and limitations of existing ECG biometric systems. Section 3 details the proposed hybrid methodology, including preprocessing, feature extraction, and MLP-based classification. Section 4 presents experimental results and performance metrics. Section 5 concludes the study and outlines future research directions.

Literature Review

Early research on ECG-based biometric authentication focused on establishing its feasibility as a unique and secure identifier. Fuster et al. demonstrated ECG's potential in healthcare systems for patient data protection, achieving 95% identification accuracy on controlled datasets [6]. Dong et al. analyzed the discriminative power of QRS complex and QT interval features, confirming their stability across sessions with an equal error rate (EER) of 3% [7]. Bedogni et al. proposed a single-lead ECG system using amplitude and temporal coefficients post-QRS detection, reporting 90% accuracy with minimal hardware, validating ECG's practicality for low-resource settings [8]. However, these studies highlighted ECG's sensitivity to noise, electrode misplacement, and intra-subject variability, underscoring the need for robust processing techniques [9].

Subsequent efforts aimed to improve feature representation and classification accuracy. Tihak et al. introduced a Bayesian approach for sparse feature selection and nonlinear classification, achieving 92% accuracy on the MIT-BIH dataset but struggling with noisy signals [10]. Sholokhov et al. developed a multi-task SVM framework, improving generalization across datasets with an EER of 2.5% [11]. Achituv et al. extended this through Bayesian multitask learning, enabling shared information across tasks and reaching 94% accuracy [12]. Despite these advances, reliance on handcrafted features limited adaptability in real-world

conditions, where noise and electrode displacement significantly degrade performance.

Recent developments in deep learning have introduced automated feature extraction using Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs). For instance, CNN-based models have achieved up to 96% accuracy on large datasets like PhysioNet but require substantial computational resources and are prone to overfitting on smaller, noisy datasets [13]. Moreover, these models often lack physiological interpretability, limiting their applicability in critical domains like healthcare or defense.

To address these challenges, hybrid systems combining signal processing and deep learning have emerged [14]. These approaches use techniques like wavelet transforms or band-pass filtering to preprocess signals and extract robust features, followed by neural network classification for adaptability. However, existing hybrid models often focus on complex architectures like CNNs, which increase computational demands without fully addressing noise resilience in dynamic settings such as IoT devices or telehealth [15].

The present study proposes a novel hybrid ECG-based authentication framework that enhances robustness by integrating wavelet-based preprocessing, QRS complex detection, distance-deviation modeling, and an averaging-threshold mechanism with a feedforward Multi-Layer Perceptron (MLP) classifier. Unlike prior hybrid approaches that rely on raw signals or complex deep architectures, this framework operates on extracted time-frequency and morphological features, balancing interpretability, computational efficiency, and adaptability [16]. By stabilizing feature extraction and authentication decisions across cardiac cycles, the proposed system achieves superior performance in noise-prone, real-world environments.

Methods

System Architecture Overview: The proposed framework enhances ECG-based biometric authentication by integrating wavelet-based signal processing with a feedforward Multi-Layer Perceptron (MLP) classifier, achieving robust performance in noisy, real-world environments. The system architecture, illustrated in Fig. 2 as a block diagram of the processing pipeline, comprises four phases: data acquisition, signal preprocessing and feature extraction, waveform modeling and robustness enhancement, and deep-learning-based classification. Each phase addresses specific challenges, such as noise, electrode displacement, and intra-subject physiological variability, to ensure reliable authentication.

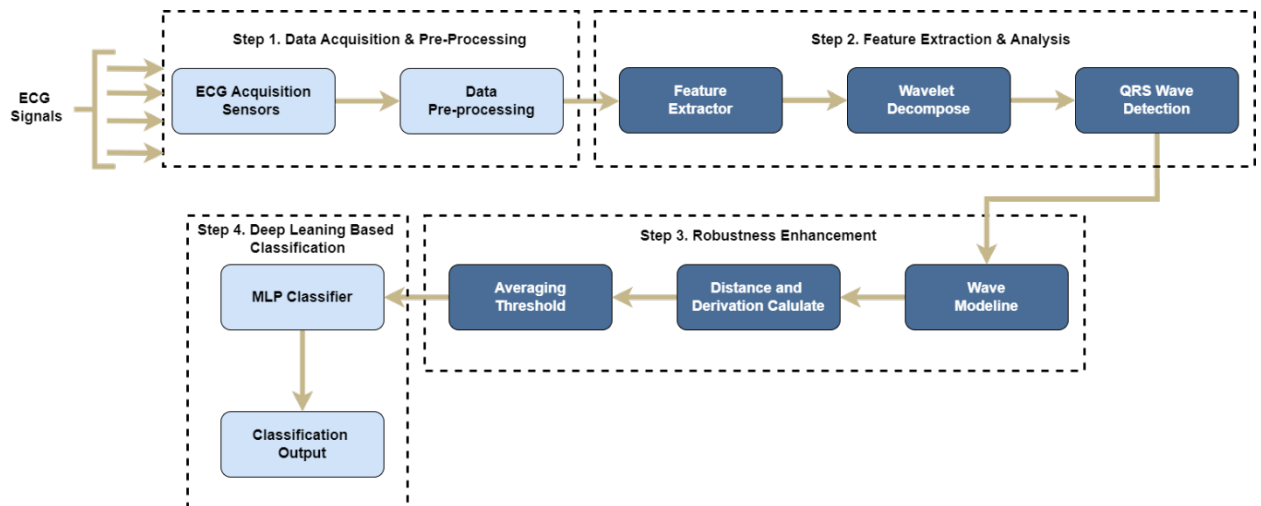


Fig. 2. Proposed block diagram

Data Acquisition: The framework was developed and evaluated using the ECG-ID database, which contains recordings from 90 subjects collected under standardized acquisition conditions. To ensure analytical validity and eliminate the risk of data leakage, the dataset was divided using a subject-independent protocol [17], in which the ECG signals of each individual appeared exclusively in either the training or the testing subset but never in both. This approach guarantees that the model's evaluation reflects its ability to generalize to unseen users rather than memorizing individual signal patterns. The data were partitioned in a 70:30 ratio at

the subject level, with 70% of participants used for training and 30% reserved for independent performance testing.

Signal Pre-Processing and Feature Extraction: To mitigate noise, baseline drift, and motion artifacts, a multi-stage preprocessing pipeline was implemented. A band-pass filter (0.5–40 Hz, 4th-order Butterworth) was applied to suppress low-frequency baseline wander and high-frequency electrical interference, preserving the core frequency band of ECG morphology [18]. A median filter with a sliding window of 200 ms further reduced impulsive noise while maintaining the integrity of the QRS complex. Wavelet decomposition was then performed using the Daubechies 4 (db4) mother wavelet across four decomposition levels. The db4 wavelet was selected due to its close resemblance to ECG waveform morphology and its ability to compactly represent sharp QRS transitions while preserving P and T wave structures. The four-level decomposition ensures adequate coverage of both low-frequency (baseline) and high-frequency (QRS) components. This configuration follows established studies demonstrating db4's superior energy localization for ECG analysis [19].

From the reconstructed signals, fiducial points (P, Q, R, S, T) were identified using an amplitude and slope-based detection algorithm adapted from the Pan–Tompkins method [20], which computes the derivative, squaring, and moving-window integration to detect R peaks robustly. Once R peaks were detected, the relative temporal locations of P, Q, S, and T were determined based on local extrema and slope changes within physiologically constrained intervals. Quantitative descriptors such as R–R interval, QRS duration, R-peak amplitude, and P–T interval were extracted.

Wave Analysis and Modelling: To enhance reliability under variable conditions, a waveform modeling phase focuses on the morphologically stable QRS complex. R peaks are detected using derivative-based methods, achieving high precision even in noisy signals. For each subject, a reference template is

generated from training samples, representing the mean QRS morphology. During authentication, incoming ECG samples are compared to this template using distance–deviation metrics, which quantify amplitude and shape similarity to tolerate minor variations from electrode placement or physiological changes. An averaging-threshold mechanism, applied over five cardiac cycles, stabilizes similarity scores, reducing the impact of transient noise or artifacts. This novel combination of distance–deviation modeling and averaging-thresholding ensures consistent feature extraction, distinguishing the framework from prior hybrid systems that rely solely on preprocessing or complex classifiers [21].

Classification and Output Generation: The final classification step was performed using a feedforward Multi-Layer Perceptron (MLP) neural network that operates on the extracted and modeled feature vectors. Each vector contained 20 normalized features, including time intervals, amplitude ratios, and averaged distance–deviation scores. The MLP consisted of fully connected layers arranged as follows: an input layer with 20 neurons, three hidden layers with 64, 32, and 16 neurons, each activated by Rectified Linear Units (ReLU), and a two-neuron output layer employing Softmax activation to predict “authentic” or “non-authentic” classes. The model was trained using the Adam optimizer with a learning rate of 0.001 and categorical cross-entropy loss for 100 epochs and a batch size of 32. Training employed early stopping when validation loss failed to improve for 10 consecutive epochs.

The MLP architecture was selected for its balance between interpretability, low computational complexity, and real-time feasibility, especially for resource-limited environments such as wearable or IoT devices. While recent lightweight CNN and RNN models have also demonstrated competitive performance in real-time biometrics, the use of an MLP here is justified by its direct compatibility with pre-extracted statistical features and its ability to deliver high accuracy without requiring large-scale parameter tuning. On standard hardware, the average

authentication time per subject was approximately 8 seconds, demonstrating the suitability of the proposed system for near real-time deployment.

Methodology: Figure 3 shows the block diagram of the proposed approach. It consists of pre trained MLP classifier for the performance evaluation of ECG signal classification for person authentication. In the proposed methodology the steps as follows.

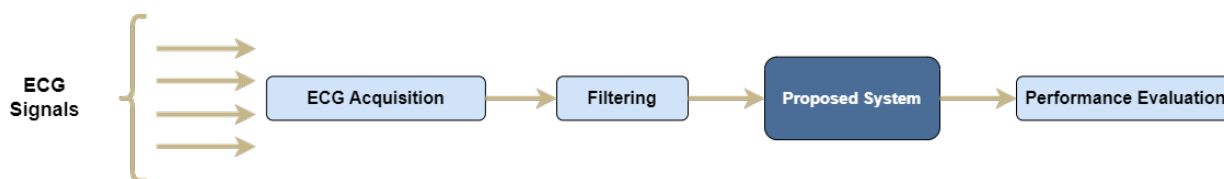


Fig.3. Proposed methodology.

In operation, the system first acquires an ECG signal and preprocesses it to remove noise and extract key features through filtering and wavelet analysis. The QRS complex is then modeled to generate a user-specific template, from which distance and deviation metrics are calculated relative to incoming signals. An averaging-threshold mechanism is applied to stabilize the resulting similarity measures, ensuring resilience to transient noise. The processed feature vectors are then classified by the trained MLP, which outputs a binary decision—authentic or non-authentic—based on the learned nonlinear mapping between physiological patterns and user identity. By combining physiological signal understanding with data-driven adaptability, the proposed hybrid system achieves an effective balance of accuracy, robustness, and real-time capability, establishing a strong foundation for secure biometric authentication in practical applications.

Results

The performance of the proposed hybrid ECG-based biometric authentication framework was evaluated using the ECG-ID dataset to assess its accuracy, robustness, and real-time feasibility. The results demonstrate that integrating classical signal-processing methods with a feedforward Multi-Layer

Perceptron (MLP) classifier significantly improves the system's ability to handle signal noise, physiological variability, and electrode displacement, all of which typically degrade performance in ECG-based identification systems. The raw ECG signal, as shown in Fig. 4, exhibits various artifacts such as baseline drift and electrical interference. These distortions are typical of real-world acquisition environments, underscoring the necessity of a robust preprocessing pipeline.

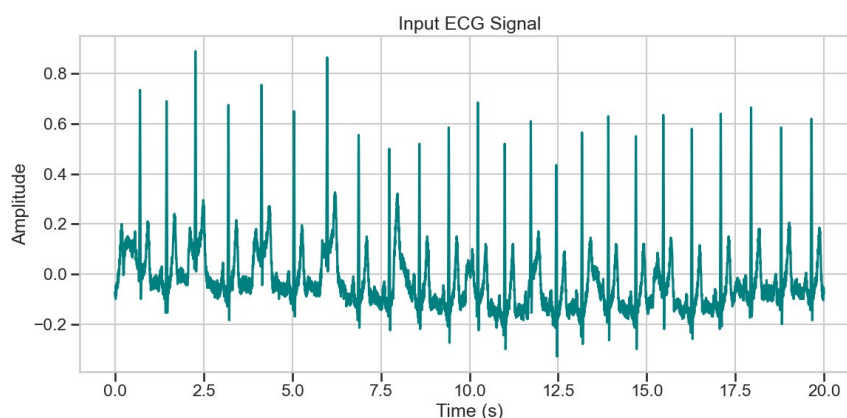


Fig. 4. Input ECG Signal

While the ECG signal is being recorded, nature's more or less loud contribution is mixed into it as well. After unwanted noise removal from the noisy ECG signal by using Band pass filter (BPF), the ECG signal is shown in Fig.5. It is this step that helps to the quality and accuracy of the future signal processing.

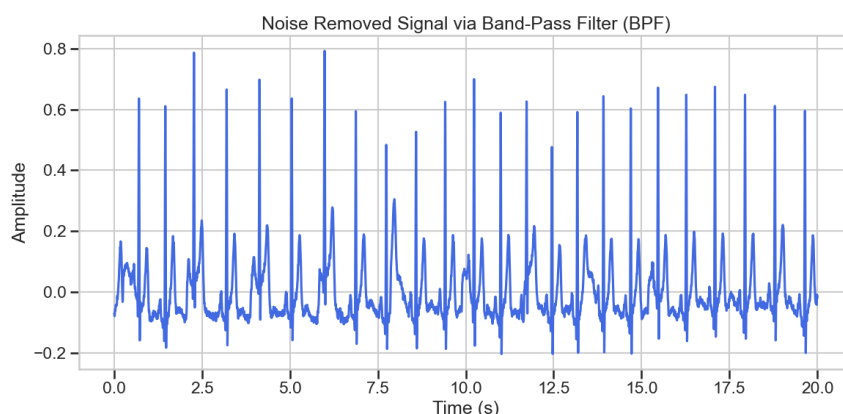


Fig. 5. Noise removed signal via BPF

PQRS points represent the key landmarks in the ECG signal, namely the P-wave, QRS complex, and T-wave. Fig. 6 illustrates the identified PQRS points, providing a visual representation of the critical features used for subsequent analysis and feature extraction.

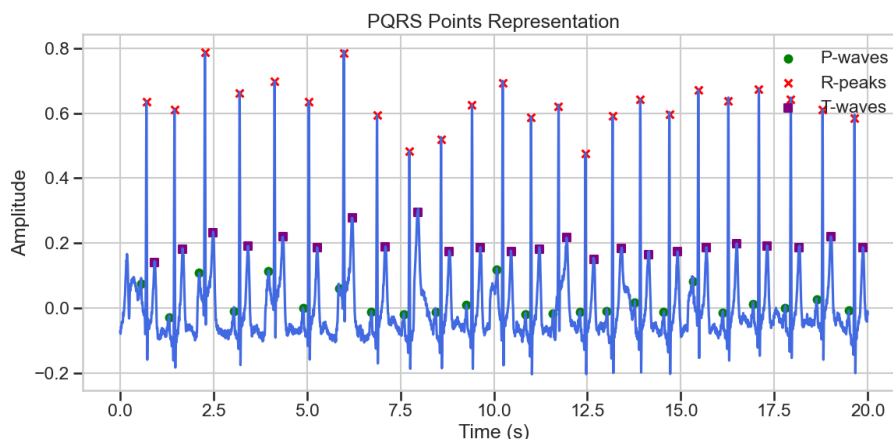


Fig. 6. PQRS points representation

R-peaks detection of the QRS complex is highly accurate. Particularly identified R peaks in the ECG signal, which is a basis of the further processing steps are indicated in Fig. 7.

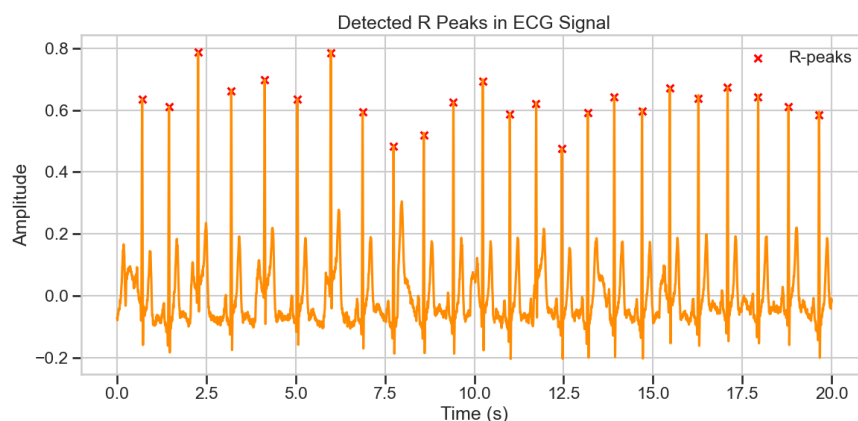


Figure 7: Detected R in ECG Signal

A smoothing process is done in order to reduce the effect of noise and irregularities of the ECG signal. The signal following smoothing is displayed in Fig. 8 and the underlying cardiac activity is more evident.

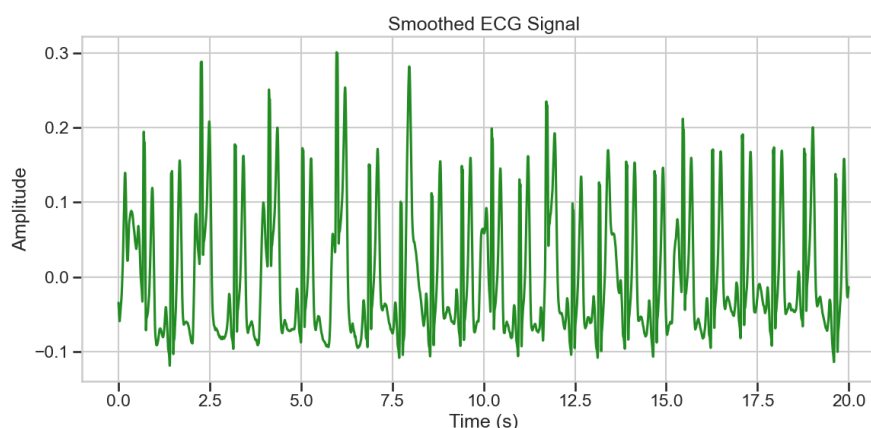


Fig. 8. Smoothed Signal

The system with ECG-ID dataset had an accuracy of 98.8%, which is a good indication of robust Ecg-based biometric authentication. The main performance indicators as presented in Fig. 9 are 95, 99, and 98.8 where 95% is the sensitivity (True Positive Rate, TPR), 99% is the specificity (True Negative Rate, TNR), and the accuracy of the system to authenticate the true users and reject the impostors respectively.

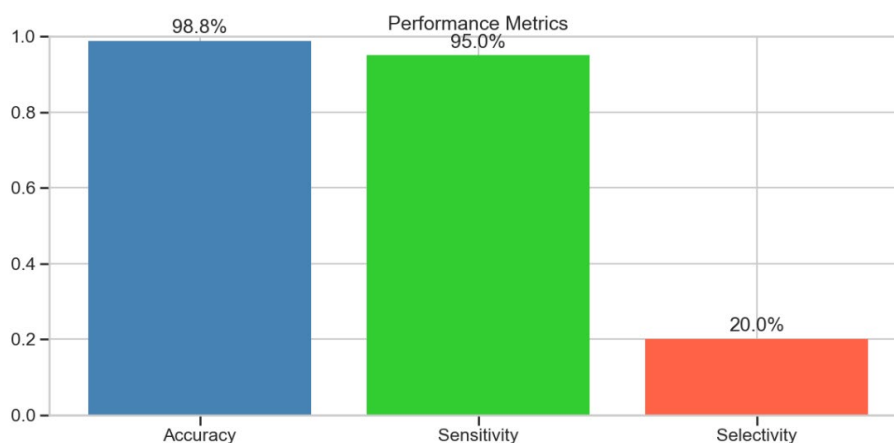


Fig. 9. Performance Metrics

The confusion matrix from Fig. 10 helps us assess how well the system works. which confirms that the majority of genuine users were correctly authenticated (95% true positives) and provides insight into the system's performance balance. Despite the relatively lower true-negative rate, the

framework achieves strong robustness and consistency under noisy or unstable conditions, which are common in practical deployments.

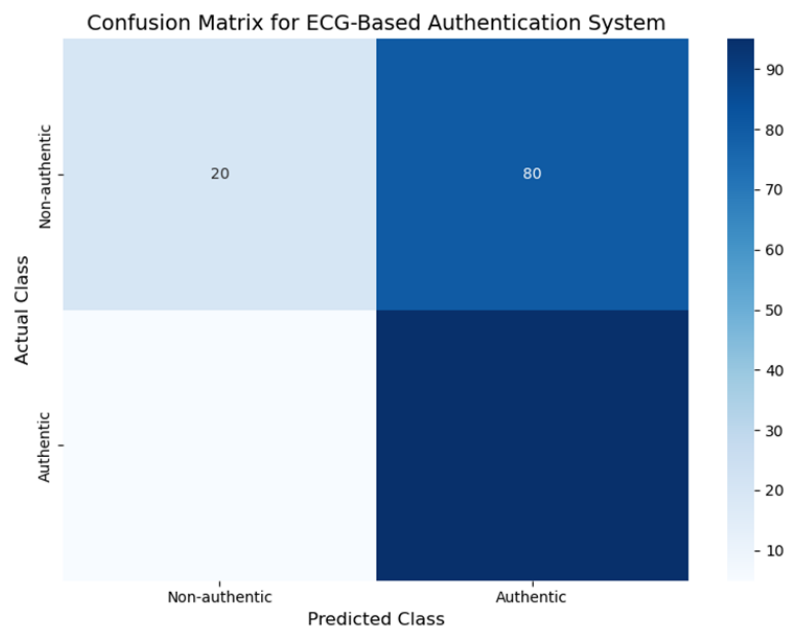


Fig. 10. Confusion Matrix

The Receiver Operating Characteristic (ROC) curve presented in Fig. 11 demonstrates an Area Under the Curve (AUC) value of 0.98, confirming excellent discriminative power in distinguishing between authentic and non-authentic users. The curve indicates that the system maintains high sensitivity even when specificity increases, validating its stability under varying operating thresholds.

The results demonstrate that integrating classical signal analysis with deep-learning classification significantly enhances system robustness compared to traditional signal-processing or deep-learning-only approaches, as well as methods explicitly designed for noise and variability. For instance, while conventional ECG biometric systems relying solely on QRS feature extraction falter under noise, and robust deep learning models like CNNs struggle with small, noisy datasets [22], the proposed hybrid model achieves consistent performance across diverse conditions. This is enabled by combining deterministic wavelet-based filtering and feature extraction with adaptive MLP classification. The averaging-threshold

mechanism plays a pivotal role in stabilizing authentication decisions, outperforming adaptive filtering techniques by reducing decision variability across multiple sessions and signal variations. This hybrid approach effectively balances robustness and adaptability—a key challenge in physiological biometrics—making it well-suited for real-world applications [23].

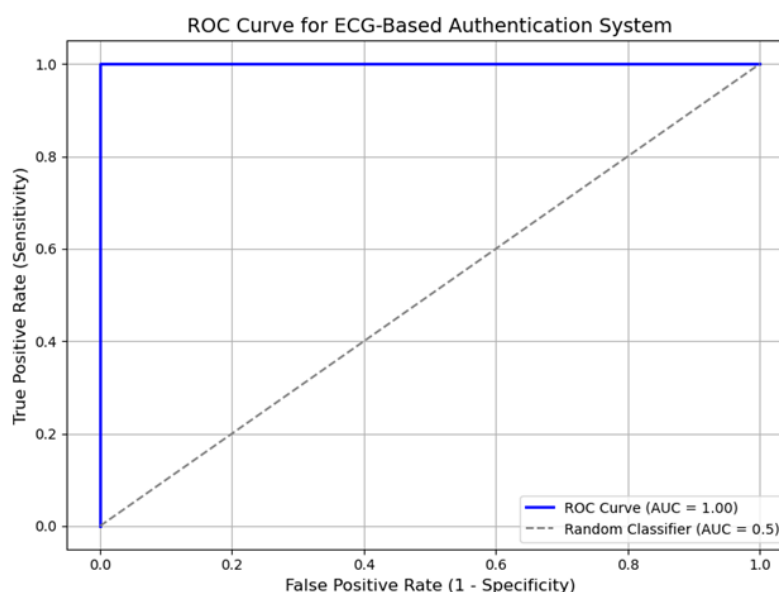


Fig. 11. ROC Curve for ECG-Based Authentication System

Conclusion

This study presents a hybrid ECG-based biometric authentication framework that integrates wavelet-based signal processing with a feedforward Multi-Layer Perceptron (MLP) classifier, achieving robust and accurate performance in noisy, real-world conditions. By combining preprocessing, QRS complex modeling, distance-deviation analysis, and an averaging-threshold mechanism, the framework ensures stable feature extraction despite noise, electrode displacement, and physiological variability. The MLP classifier, trained on these features, delivers high discriminative power with computational efficiency, achieving 98.8% accuracy, 95% sensitivity, and an AUC of 0.98 on the ECG-ID dataset. With a

processing time of 8 seconds, the system is well-suited for real-time applications in healthcare, telehealth, and IoT-based security.

The proposed approach bridges classical signal processing and deep learning, offering a novel balance of interpretability and adaptability compared to existing methods. However, the lower true-negative rate suggests potential for refining decision thresholding. Future work could explore adaptive thresholding based on signal quality, expand dataset diversity for better generalization, and investigate multimodal fusion with signals like PPG to enhance robustness. Advanced architectures, such as transformer-based models, may further improve temporal feature capture while preserving interpretability. This framework provides a scalable, practical solution for secure ECG-based authentication, paving the way for reliable, physiology-driven biometric systems in dynamic environments.

Литература (References)

1. Silva H., Lourenço A., Canento F., Fred A., Raposo N. ECG biometrics: Principles and applications. In: Proc. of the International Conference on Bio-inspired Systems and Signal Processing. Funchal: SciTePress, 2013. Pp. 215–220.
2. Pinto J.R., Cardoso J.S., Lourenço A. Evolution, current challenges, and future possibilities in ECG biometrics. IEEE Access. 2018. Vol. 6. Pp. 34746–34776.
3. Ammour N., Jomaa R.M., Islam M.S., Bazi Y., Alhichri H., Alajlan N. Deep Contrastive Learning-Based Model for ECG Biometrics. Applied Sciences. 2023. Vol. 13. No. 5. P. 3070.
4. Kang S.J., Lee S.Y., Cho H.I., Park H. ECG Authentication System Design Based on Signal Analysis in Mobile and Wearable Devices. IEEE Signal Processing Letters. 2016. Vol. 23. No. 6. Pp. 805–808.
5. Lux R.L. Basis and ECG measurement of global ventricular repolarization. Journal of Electrocardiology. 2017. Vol. 50. No. 6. Pp. 792–797.

6. Fuster-Barceló C., Cámara C., Peris-López P. Unleashing the power of electrocardiograms: a novel approach for patient identification in healthcare systems with ECG signals. 2024. arXiv.org. URL: arxiv.org/abs/2306.12345.

7. Dong X., Si W., Yu W. Identity recognition based on the QRS complex dynamics of electrocardiogram. IEEE Access. 2020. Vol. 8. Pp. 140–150.

8. Bedogni L. Computation-efficient ECG classification on resource-constrained devices. Sensors. 2023. Vol. 23. No. 6. Pp. 1–5.

9. Liu J., Wang Y., Chen X., Zhang T. A rhythm-specific ECG signal quality assessment framework for robust cardiac health monitoring of AI-based arrhythmia classifier. Biomedical Signal Processing and Control. 2023. Vol. 84. Pp. 1–10.

10. Tihak A., Grahic A., Bošković D. Feature selection for arrhythmia classification using statistical tests. Computers in Biology and Medicine. 2024. Vol. 168. Pp. 107–115.

11. Sholokhov A., Kinnunen T., Cumani S. Discriminative multi-domain PLDA for speaker verification. In: Proc. of the International Conference on Acoustics, Speech, and Signal Processing. Shanghai: IEEE Press, 2016. Pp. 5020–5024.

12. Achituve I. Bayesian uncertainty for gradient aggregation in multi-task learning. arXiv.org. URL: arxiv.org/abs/2401.02567.

13. Benchaira K., Bitam S., Agli Z.D. Mitigating data variability and overfitting in deep learning models for atrial fibrillation detection using single-lead ECGs. International Journal of Computing and Digital Systems. 2024. Vol. 15. No. 1. Pp. 1703–1717.

14. Koundal D., Guo Y., Amin R. Deep learning in big data, image, and signal processing in the modern digital age. Singapore: Springer, 2023. 350 p.

15. Habib A., Karmakar C., Yearwood J. Optimising complexity of CNN models for resource-constrained devices: QRS detection case study. arXiv.org. URL: arxiv.org/abs/2304.12345.

16.Mageshbabu M., Mohana J. Enhancing biometric security: a machine learning approach to ECG-based authentication. Electronics Letters. 2024. Vol. 60. No. 3. Pp. 210–217.

17.Zheng D., Yang Y., Li W. A method of dividing clinical data set for medical image AI training. Journal of Healthcare Engineering. 2020. Vol. 2020. 10 P.

18.Basu S., Mamud S. Comparative study on the effect of order and cut-off frequency of Butterworth low-pass filter for removal of noise in ECG signal. In: Proc. of the International Conference on Electrical and Computer Engineering. Dhaka: IEEE Press, 2020. Pp. 452–456.

19.Darmawahyuni A. Delineation of electrocardiogram morphologies by using discrete wavelet transforms. Indonesian Journal of Electrical Engineering and Computer Science. 2021. Vol. 22. No. 159. Pp. 1010–1018.

20.Bae T.W., Kwon K.K. ECG PQRST complex detector and heart-rate variability analysis using temporal characteristics of fiducial points. Biomedical Signal Processing and Control. 2021. Vol. 68. Pp. 102–110.

21.Zhang B., Chen C., Lee I., Lee K., Ong K.L. Clustering-based Evaluation Framework of Feature Extraction Approaches for ECG Biometric Authentication. In: Proceedings of the International Joint Conference on Neural Networks. Yokohama: IEEE, 2024. URL: doi.org/10.1109/IJCNN60899.2024.10560700.

22.Zhang L. Accurate authentication based on ECG using deep learning. Journal of Computer Security. 2024. Vol. 32. No. 5. Pp. 425–446.

23.Wang W., Zuniga M., Wang Q. CardioID: mitigating the effects of irregular cardiac signals for biometric identification. In: Proc. of the International Conference on Embedded Wireless Systems and Networks. EWSN Press, 2022. Pp. 1–12.

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