SpacSec 2026

ITMO

Robust ECG Biometric Authentication Using a Hybrid Deep Learning Model with Adaptive Beat Aggregation

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OCT 28, 2026

MOTIVATION

- Convenient alternative to traditional passwords.
- Rapid market growth.
- Expanding applications across sectors.
- Increasing need for reliable authentication.

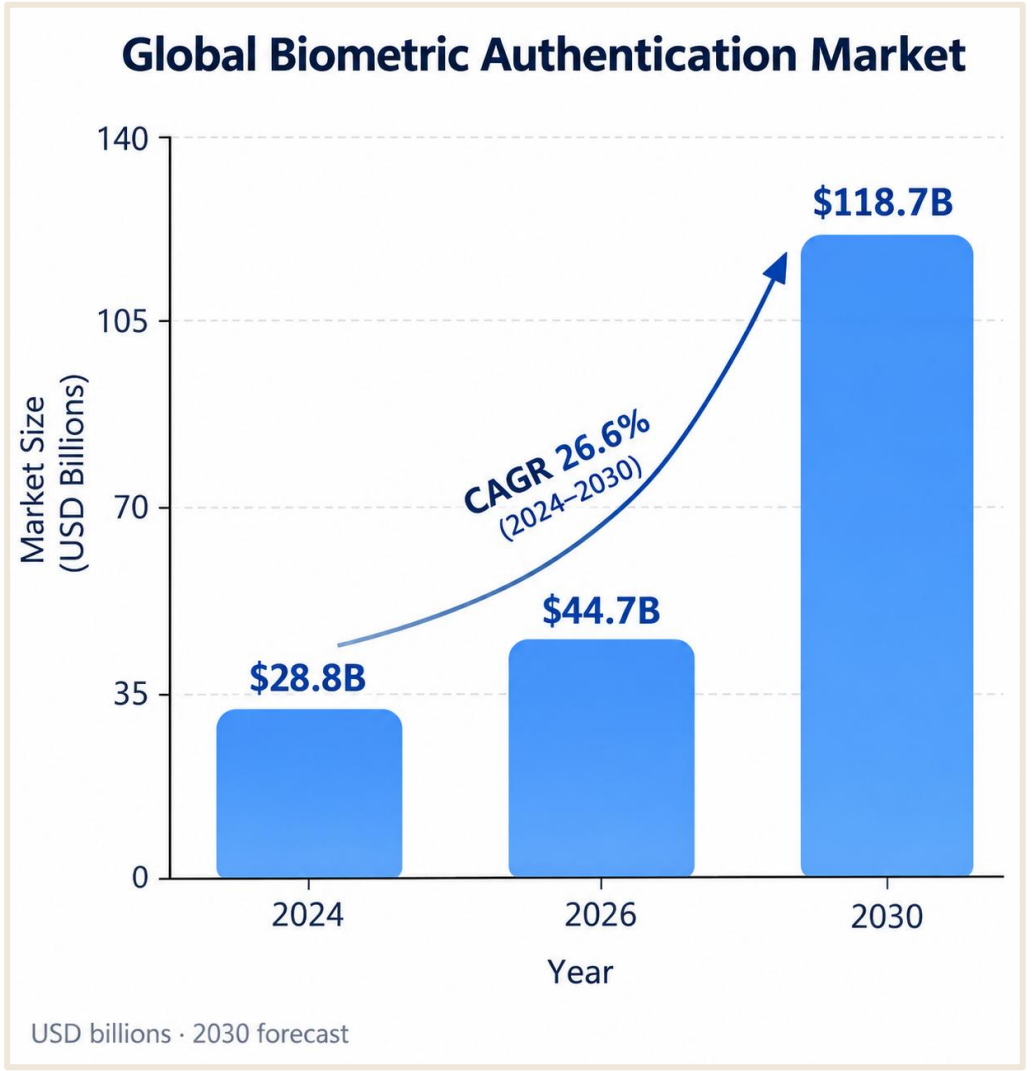


Fig.1. Global Biometric Market [1]

[1] https://www.grandviewresearch.com/industry-analysis/next-gen-biometric-authentication-market-report

BIOMETRIC MODALITIES

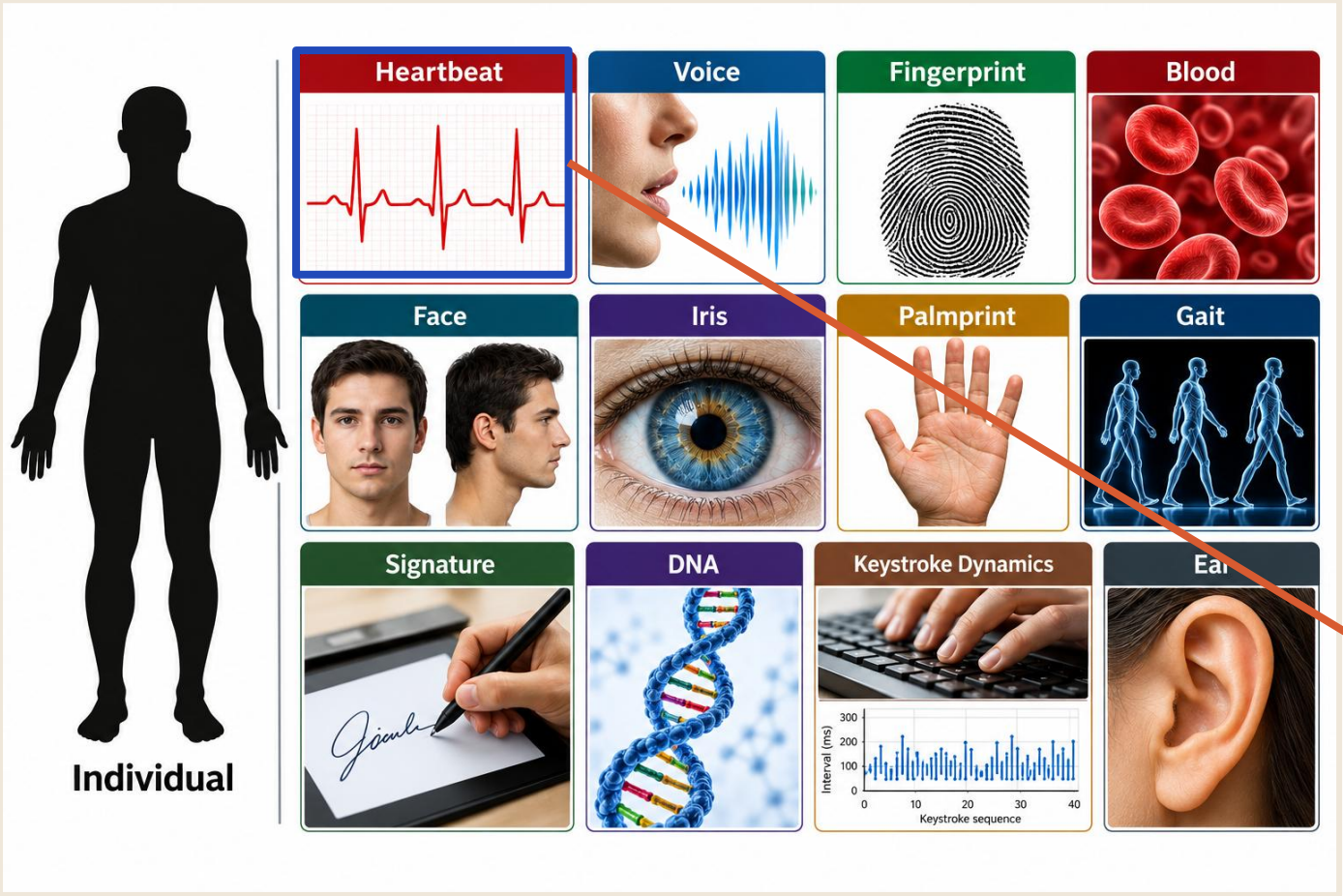


Fig. 2. Example of Biometric Modalities. [3]

Why ECG ?

- Focus on ECG signals as the primary biometric trait.
- ECG morphology and timing contain individual-specific characteristics.

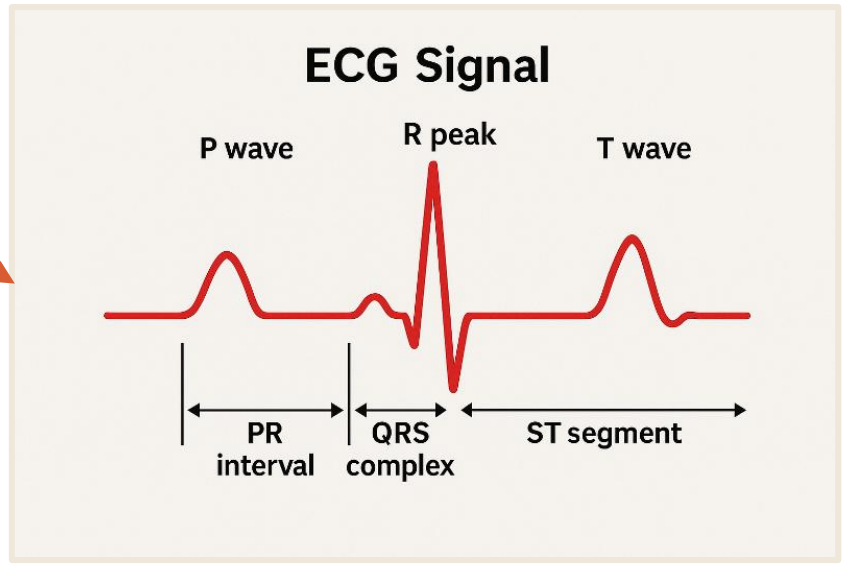


Fig.3. Illustrative P–QRS–T Cardiac Cycle

[2] 50 years of biometric research: Accomplishments, challenges, and opportunities

RESEARCH PROBLEM

- ECG heartbeats from the same person can vary in morphology.
- Noise, motion artifacts, and physiological changes introduce variations.
- Uniform averaging assigns equal weights to all enrollment heartbeats.
- Noisy or atypical heartbeats can distort the enrollment template and reduce authentication reliability.

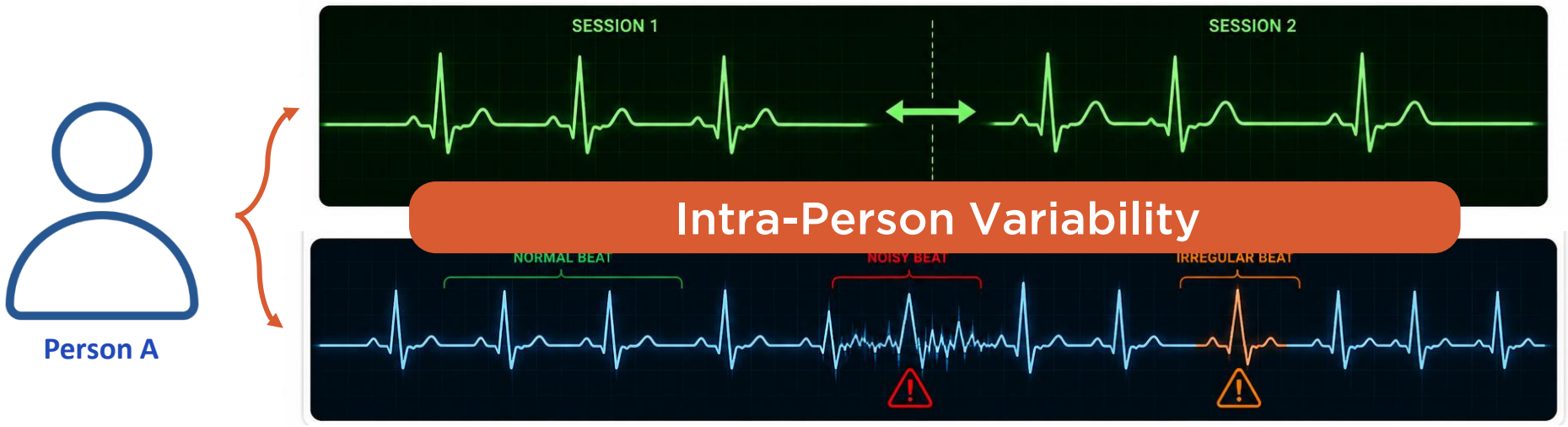


Fig.4. Challenges in ECG Biometric Authentication [3]

[3] M. Ingale, R. Cordeiro, S. Thentu, Y. Park and N. Karimian, "ECG Biometric Authentication: A Comparative Analysis," in IEEE Access

RESEARCH GOAL

Goal

- Develop more reliable ECG enrollment templates by assigning adaptive weights based on heartbeat consistency.

Objectives

- Extract discriminative heartbeat features using a CNN.
- Estimate heartbeat reliability based on embedding consistency.
- Construct stable enrollment templates using adaptive reliability weights.
- Evaluate authentication accuracy and robustness using Siamese-based verification.

PROPOSED METHODOLOGY

- The framework combines CNN feature extraction, quality-aware heartbeat aggregation, and Siamese-based identity verification.

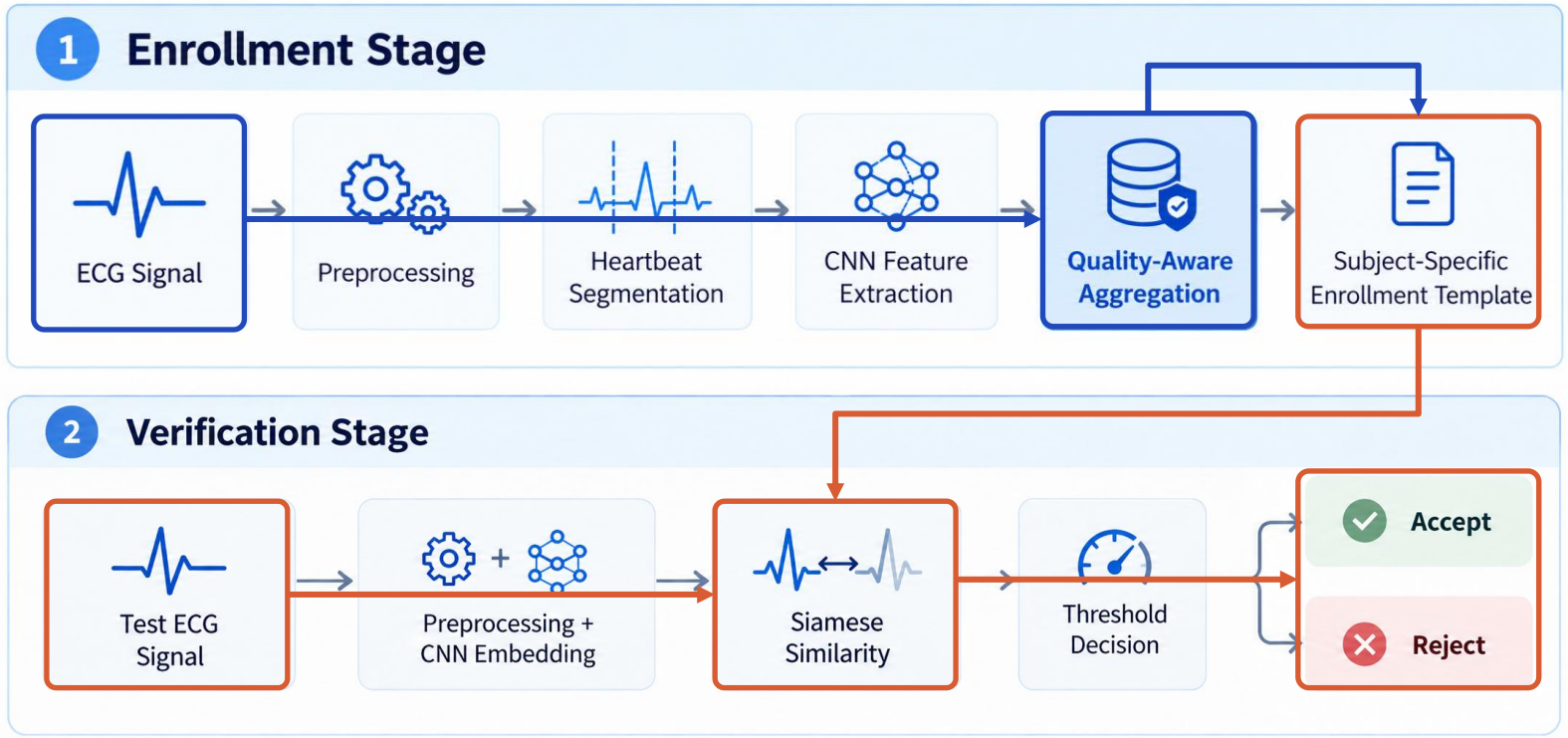


Fig.5. Overall Architecture of the Proposed ECG Authentication Framework

BEAT AGGREGATION

- Consistent heartbeat embeddings receive higher weights, producing more reliable enrollment templates.

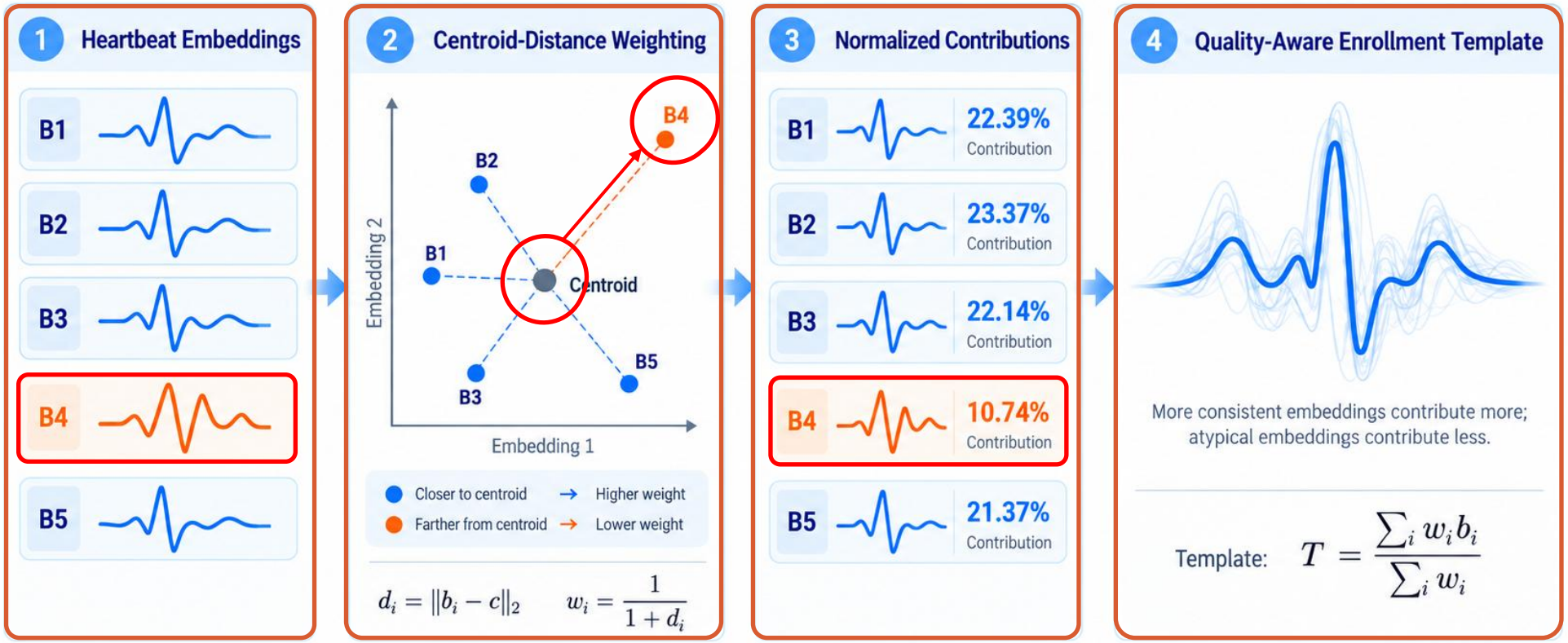


Fig.6. Quality-Aware Heartbeat Aggregation Process

DATASET

PTB Diagnostic ECG Database

- PTB Diagnostic ECG Database[4] with multi-subject clinical recordings.

	PTB Database
Subjects	290
Sampling	1000 Hz
Leads	Lead I
Annotations	Subject ID
Format	WFDB (.dat / .hea)

- Database captures diverse physiological conditions; enables robust model training and realistic authentication performance assessment.

[4] https://physionet.org/content/ptbdb/1.0.0

EXPERIMENTAL SETUP

- Filtering, normalization and heartbeat segmentation.
- Subject-level partitioning: 60% training, 20% validation, and 20% testing.

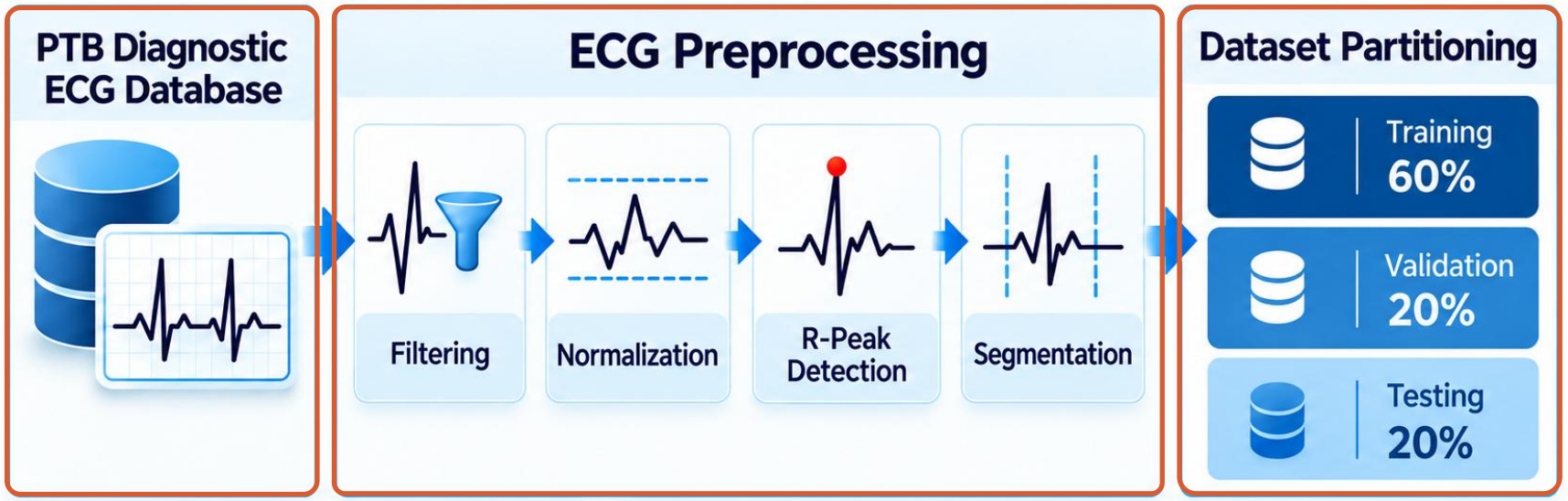


Fig.7. ECG Preprocessing and Experimental Data Partitioning

IMPACT OF BEAT SIZE

- Performance improves rapidly up to 5 enrollment beats, after which the gains become marginal.

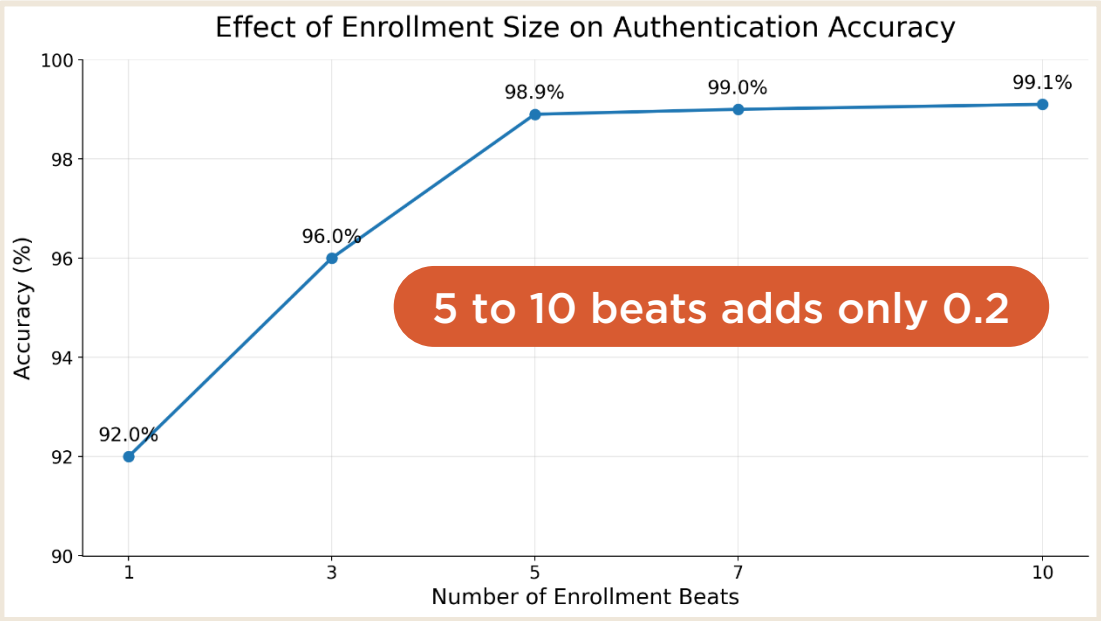


Fig.8. Effect of enrollment size on authentication accuracy (%)

Impact of Beat Size on Authentication

	Proposed accuracy (%)	Proposed EER (%)
1	92.0	8.00
3	96.0	4.00
5	98.9	1.20
7	99.0	1.00
10	99.1	0.9

AUTHENTICATION PERFORMANCE

- Quality-aware aggregation achieved 98.8% authentication accuracy while reducing both false acceptance and false rejection rates.

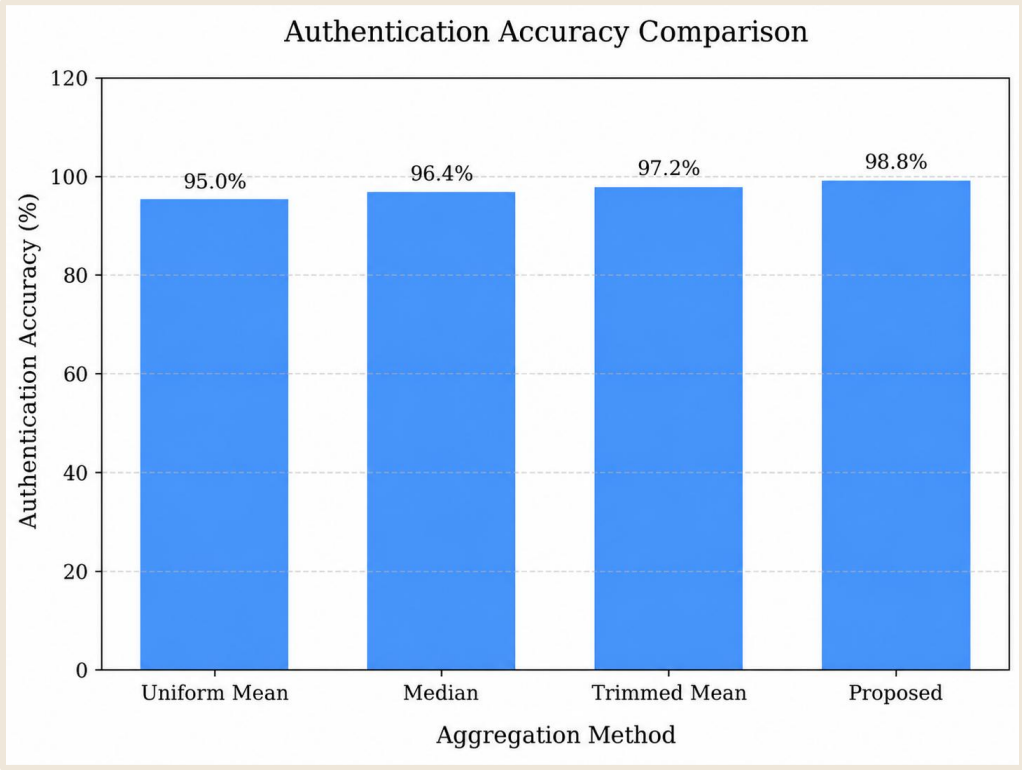


Fig.9. Authentication accuracy (%)

Authentication Performance Metrics

	Uniform	Median	Trimmed	Proposed
Acc. (%)	95.00	96.40	97.20	98.80
FAR (%)	4.50	3.20	2.50	0.80
FRR (%)	5.50	4.00	3.10	1.60
EER (%)	5.00	3.60	2.80	1.20
AUC	0.985	0.990	0.994	0.998

ROBUSTNESS UNDER NOISE

- Gaussian noise was introduced into selected enrollment heartbeats.
- Corruption levels ranged from 0% to 30%.
- The proposed method maintained higher accuracy across all evaluated conditions

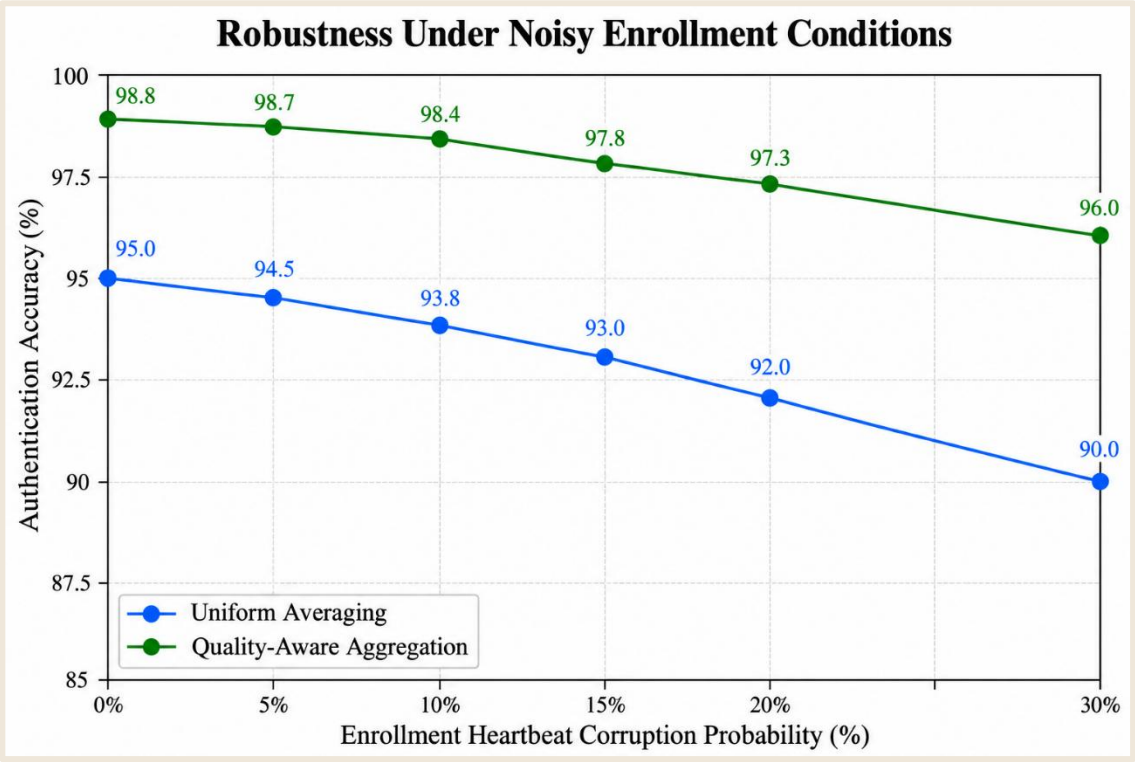


Fig.10. Authentication Robustness Under Noisy Enrollment Conditions

CONFUSION MATRIX ANALYSIS

- Quality-aware aggregation reduces both false acceptances and false rejections, improving verification reliability.

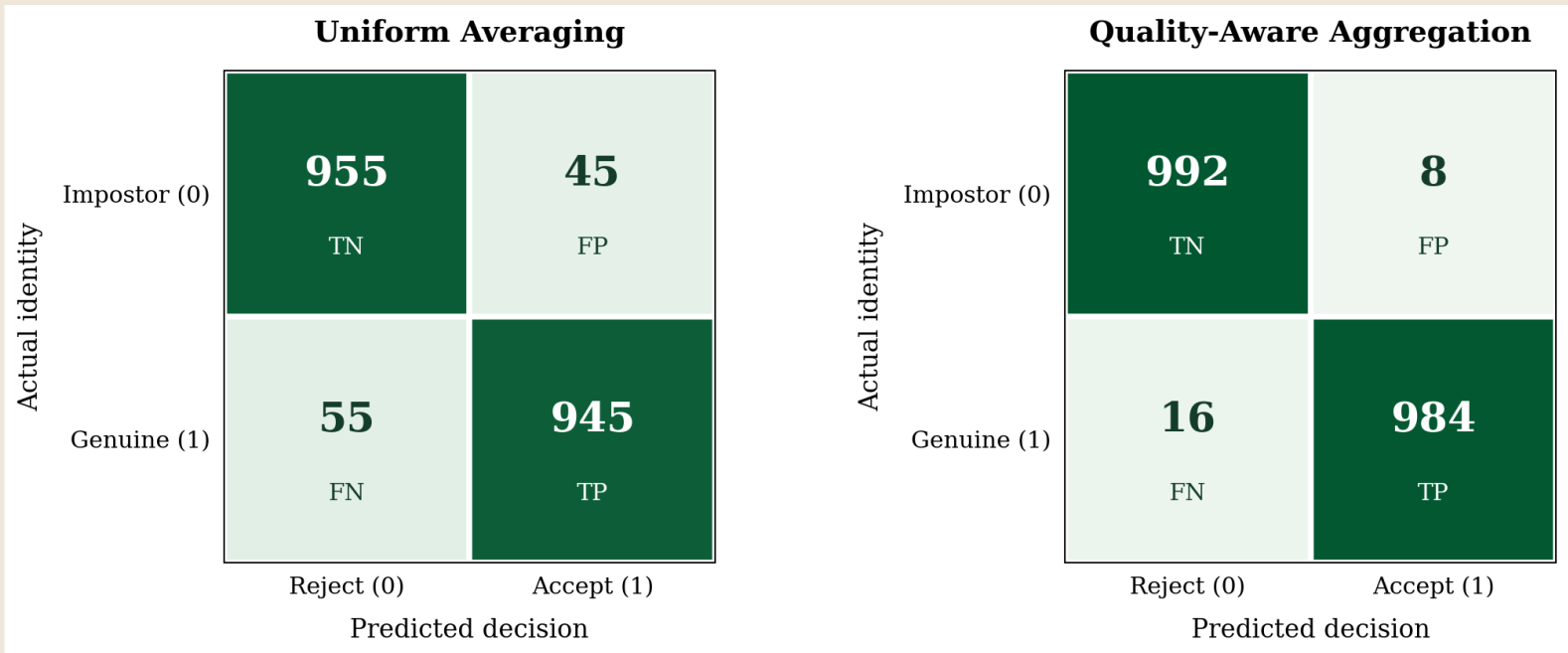


Fig.11. Confusion Matrix Comparison of ECG Authentication Methods

COMPARISON WITH EXISTING METHODS

- The proposed method achieved 98.8% accuracy, outperforming selected PTB-based authentication benchmarks.

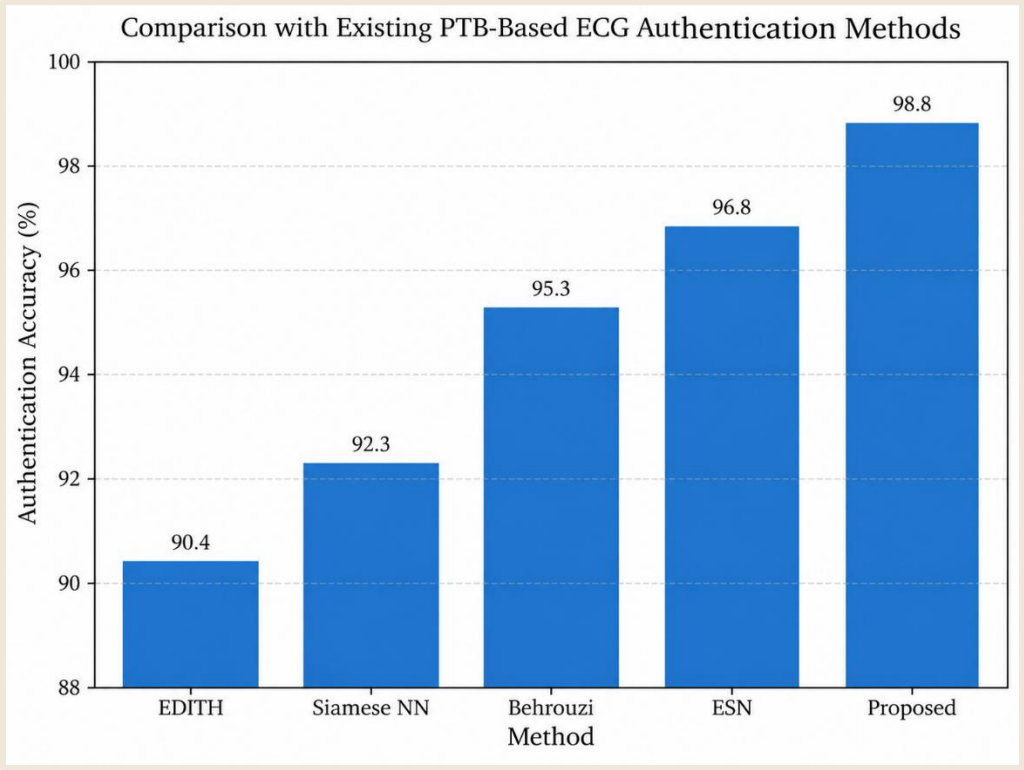


Fig.12. Comparison with Existing PTB-Based ECG Authentication Methods

Comparison of PTB-Based Methods

	Method	PTB Accuracy (%)
Ibtehaz et al.	EDITH — Deep Learning Authentication	90.4
Ivanciu et al.	Siamese Neural Network	92.3
Behrouzi et al.	Siamese ECG Authentication	95.3
Hazratifard et al.	Ensemble Siamese Network	96.8
Proposed method	Quality-Aware Aggregation	98.8

CONCLUSION & FUTURE WORK

Conclusions

- Quality-aware aggregation improves enrollment template reliability without modifying the CNN–Siamese architecture.
- The proposed method achieved 98.8% accuracy and 1.2% EER.
- Accuracy remained 96.0% with 30% corrupted enrollment heartbeats.

Future Work

- Validate across different ECG datasets and recording sessions.
- Investigate open-set and continuous authentication.
- Optimize computational efficiency for wearable and embedded devices.

THANK YOU
FOR YOUR ATTENTION !

SAINT PETERSBURG, 2026

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