ECG Based Biometrics Authentication Using Deep Learning Models

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***Abstract*—This study examines the application of electrocardiogram (ECG) data for biometric authentication through the combination of traditional signal preprocessing and deep learning-based classification and verification models. The system analyzes ECG data using bandpass and notch filtering, heartbeat segmentation, and R-peak recognition prior to inputting them into supervised and unsupervised deep neural networks. Siamese networks, encompassing CNN, LSTM, and Transformer versions, are assessed to tackle inter-session variability and maintain identity preservation. Notwithstanding the issues of overfitting and dataset constraints, the suggested system attains robust verification performance with reduced signal durations. Experimental findings indicate that a 1-minute ECG segment provides an ideal equilibrium between precision and data efficiency, rendering it appropriate for real-time biometric authentication in practical applications.**

***Index Terms*—Electrocardiogram (ECG), Biometric Authentication, Deep Learning, Siamese Networks, Identity Verification.**

I. Introduction

Biometric identification techniques enhance security by utilizing inherent physical or behavioral characteristics to verify an individual's identity. Biometric data, such as fingerprints, iris patterns, or facial features, are distinctive to each individual, rendering them less susceptible to loss, theft, or forgery compared to passwords or physical tokens. However, these traditional methods remain susceptible to presentation attacks and lack real-time liveness detection [1]. Electrocardiogram (ECG) signals, reflecting the heart's electrical activity, have emerged as a viable biometric characteristic due to their inherent vitality, internal origin, and difficulty in external replication. ECG-based biometrics has several unique advantages: they can solely be obtained from living individuals, they encompass both physiological and psychological data, and they remain challenging to replicate artificially. Recent advancements in wearable and contact-based ECG sensors have significantly facilitated their accessibility for authentication purposes. Despite the advantages of these systems, they also present significant challenges: there is a scarcity of high-quality public datasets for identity identification [2], the signals from the same individual may vary considerably between sessions, and there are no standardized experimental methodologies. Numerous prior studies have exclusively analyzed data from a single session, rendering it challenging to extrapolate findings to real-world contexts where conditions evolve over time [3], [4], [5]. This study proposes ECGXtractor, a deep learning framework for using ECGs to identify and authenticate individuals. The system employs standard signal preprocessing in conjunction with both supervised and unsupervised learning methodologies. It employs Siamese networks, including CNN, LSTM, and Transformer variants, to illustrate the potential variations among various sessions. We examine the impact of signal duration on accuracy and determine that 1-minute segments are optimal and most reliable for biometric authentication.

II. Related Work

Many in-depth research have looked at using ECG-based biometric recognition for identification and verification. These studies have used different ways to collect signals and model them. Deep learning methods, notably convolutional neural networks (CNNs), have always outperformed traditional handcrafted feature-based systems by automatically finding complex morphological patterns in ECG data. Many studies have used advanced feature extraction approaches like wavelet decomposition and mutual information analysis to make classification better. The first deep learning frameworks, such cascaded CNN architectures, were very accurate on single-session datasets like FANTASIA because they learned patterns that were stable within each subject. Residual CNNs and hybrid models that feature both convolutional and recurrent layers have also shown promising results when trained on controlled datasets that include healthy people [20], [21]. Most of the time, though, current systems are only tested on records from one session or the same day, which makes it hard for them to apply to several sessions. In multi-session situations, performance often drops a lot since the signals change between sessions because of physiological and environmental factors. Siamese and ensemble networks that use contrastive loss and transfer learning have been utilized in recent projects to improve verification across sessions [22]. For example, a technique that used a parallel multi-scale residual network got an equal error rate (EER) of 0.59 on the healthy subject subset of the PTB dataset. Still, these models are generally tested on small groups who don't have consistent multi-session data, and there aren't any standardized ways

TABLE I: Performance comparison of deep learning-based ECG biometric systems. Session types are reported where available. Acc = Accuracy, EER = Equal Error Rate.

Study	**Input Type**	**Dataset(s)**	**Performance**	**Session Protocol**
Chu et al. (2019) [6]	Pairwise heartbeats	ECG-ID, PTB	Acc = 98–100%, EER = 0.59–2.00%	Not stated
Donida et al. (2019) [7]	QRS complex vectors	PTB, E-HOL	Acc = 100%, EER = 1.05–2.15%	Within-session (short gaps)
Ihsanto et al. (2020) [8]	6–8 heartbeat segments	ECG-ID, MIT-BIH	Acc = 100%	Multi (same-day), Single
Ingale et al. (2020) [9]	Hybrid template (fiducial + non-fiducial)	ECG-ID, PTB, CYBHi	EER = 0.25–2.30%	Not specified
Li et al. (2020) [10]	Voting on individual beats	FANTASIA, CEBSDB, etc.	Avg Acc = 97.7–100%	Single-session
Srivastva et al. (2021) [11]	Triple-beat windows	PTB, CYBHi	Acc = 99.6%, EER = 0.00%	Single and multi-session
AlDuwaile et al. (2021) [12]	CWT-transformed heartbeats	PTB, ECG-ID	Acc = 97.3–100%	Mixed (single/multi)
ArNet-ECG (2022) [13]	Deep learning on raw ECG signals	53,753 hours of continuous ECG	F1 = 0.96	Focused on raw ECG performance; limited interpretability
RawECGNet (2023) [14]	Deep learning on raw single-lead ECG	RBDB, SHDB	F1: 0.91–0.94	Robust to population variability; morphology-driven
Risk Prediction DNN (2023) [15]	12-lead ECG with deep neural network	Clinical ECG records	AUC = 0.845	Predictive model for future AF risk, not just diagnosis
M-XAF (2024) [16]	Knowledge-fused XAI framework	Clinical AF data	Acc = 0.9719	Semantic + medical knowledge fusion; strong explainability focus
AF-GCN (2024) [17]	Graph neural network on heartbeat correlation graphs	MIT-BIH AFDB, Challenge AFDB	Precision/Recall $\geq$50%	GNN-based approach; emphasizes relational learning
CNV-NeXt-v2 (2025) [18]	ConvNeXt-v2 on ECG spectrograms	MIT-AFDB, MIT-ADB	F1 = 0.986, Sensitivity = 0.968, Precision = 0.944	Guided-CAM interpretation; efficient inference
DeepBoost-AF (2025) [19]	DCAE + Gradient Boosting fusion	Raw ECG	F1 = 95.2%, Sensitivity = 99.9%	Hybrid unsupervised + boosting; inference latency 4s
Propsed work	Aggregated multi-beat template	PTB, ECG-ID	Acc = 96.5–100%, EER = 0.15–2.06%	Multi-session protocol

to do this. Ben-Moshe et al. presented ArNet-ECG [13], a comprehensive deep learning model trained on more than 53,000 hours of raw ECG data, attaining an F1-score of 0.96. This was then expanded to RawECGNet [14], which exhibited strong generalization across external datasets like RBDB and SHDB, enhancing performance in cross-population assessments. In 2023, a risk-prediction deep neural network was introduced, utilizing typical 12-lead ECGs to anticipate the probability of atrial fibrillation development, attaining an AUC of 0.845 and underscoring the prognostic value of ECG-based artificial intelligence. In a similar vein, Jahmunah et al. [16] introduced M-XAF, a semantic knowledge-integrated explainable AI system aimed at harmonizing AI outputs with clinical reasoning. These works underscore the significance of practicality and interpretability, two critical factors for clinical adoption. Graph-based models have arisen as potent instruments for elucidating inter-beat connections. Han et al. [17] presented AF-GCN, a graph neural network that utilizes heartbeat correlation matrices for arrhythmia classification, attaining intermediate precision and recall while providing relational explainability. Recently, CNV-NeXt-v2 [18] utilized ConvNeXt-v2 on spectrogram representations, attaining state-of-the-art performance (F1 = 0.986) and offering guided-CAM visuals for feature attribution. DeepBoost-AF [19] integrated deep convolutional autoencoders with gradient boosting techniques, achieving an F1-score of 95.2% and exceptional sensitivity (99.9%), while ensuring efficient inference appropriate for clinical applications. In conclusion, deep models have improved performance within a single session, however there is still not enough research on multi-session ECG biometric verification. We have created ECGXtractor, a deep learning framework that is particularly designed for session-invariant identification. It uses a combination of CNN, LSTM, and Transformer-based Siamese networks and has been tested under strict multi-session protocols. A summary table is given as Table I.

III. Methodology

A. Dataset and Prepreocessing

The study utilizes ECG recordings from 47 individuals, each of whom provided many sessions. We collected signals from standard leads (MLII and V1) and partitioned them into non-overlapping intervals of varying durations (30 seconds, 1 minute, and 10 minutes) to evaluate the impact of segment length on the model's performance. The ECG data file structure for a given time interval is given in Table II. We employed a 0.5–40 Hz bandpass filter and a notch filter (50/60 Hz) to eliminate baseline drift and powerline noise from the raw ECG data. The Pan-Tompkins technique identified R-peaks, enabling the data to be consistently segmented into heartbeats or fixed-length intervals. This preparation preserved the morphological characteristics essential for identity recognition.

B. Feature Extraction and Model Architecture

We employed two deep learning techniques to extract features:

- Unsupervised Feature Learning: A one-dimensional convolutional autoencoder acquired compact identity embeddings from ECG segments without the utilization of labels.
- Supervised Feature Learning: A baseline 1D-CNN was employed to categorize the data. Dropout, early halting, and variable learning rate schedules were employed to enhance generalization.

We utilized Siamese architectures to compare embeddings from pairs of ECGs for biometric authentication. Every component of the Siamese network utilized common weights and produced fixed-length representations. The contrastive loss function was employed to minimize the distances between embeddings of the same individual while maximizing the distances between embeddings of different individuals. We created three distinct versions of Siamese.

- Siamese 1D Convolutional Neural Network for the acquisition of spatial information.
- Siamese LSTM for identifying temporal relationships.
- Siamese Transformer for simulating long-range dependencies via self-attention.

C. Different Models

1) Siamese Transformer: To address the limitations of traditional CNNs and enhance generalization in identity recognition, a Siamese Transformer architecture was implemented. Unlike standard classifiers, it learns similarity-based representations, ideal for biometric tasks with subtle intra and inter-person variations. The model features twin Transformer encoders with self-attention to capture long-range dependencies in ECG signals. Trained using contrastive loss, it minimizes embedding distances for the same person and maximizes them for different individuals. The model achieved almost 100 accuracy in both identification and verification, demonstrating strong generalization, robustness to noise, and suitability for cross-session and multi-device authentication.

2) Siamese 1D-CNN: This architecture comprised 1D convolutional layers designed to capture local morphological features in ECG waveforms. It processed beat segments through shared convolutional filters and produced embeddings optimized via contrastive loss. While effective in capturing amplitude-based spatial patterns, it lacked temporal modeling capabilities.

3) Siamese LSTM: Built on Long Short-Term Memory (LSTM) units, this model emphasized temporal dependencies across ECG beats. It learned rhythm-based identity cues by analyzing the sequential nature of heartbeat intervals. This approach was particularly effective in modeling timing variations inherent in cardiac activity.

4) Hybrid CNN: The Hybrid CNN combined convolutional layers with recurrent or residual modules to jointly model spatial and temporal patterns in ECG signals. While the model achieved up to 97 accuracy on the test set, it exhibited signs of overfitting and failed to consistently predict correct identities. This suggests the model had learned session-specific artifacts rather than robust, identity-preserving features.

5) Baseline 1D-CNN: A conventional 1D CNN served as the baseline. The model comprised multiple convolutional and pooling layers followed by dense layers for classification. However, it performed poorly, achieving only 5 accuracy. This result underscored its inability to capture identity-specific ECG features due to Lack of sequential modeling , Overfitting to non-generalizable patterns , Insufficient feature extraction capability. All Siamese models were trained with contrastive loss to minimize intra-class embedding distances while maximizing inter-class separation. This emphasizes the necessity of more sophisticated architectures like Siamese or attention-based models in biometric systems.

D. Hybrid Decision Fusion and Experimental Protocol

Decision Fusion and Experimental Protocol: To make it more reliable, a hybrid fusion method integrated similarity scores from Siamese models with probability outputs from classifiers. This was done using metrics like cosine and Euclidean distances. Experiments followed strict rules for separating sessions to mimic real-world deployment situations. A full evaluation was done, looking at identification and verification using metrics including accuracy, precision, recall, F1-score, ROC-AUC, and Equal Error Rate (EER). Table III summarizes the deep learning models evaluated in this study, highlighting their architecture and intended purpose

IV. Experiments and Results

A. Experimental Setup

Data was divided into training and testing sets with strict session separation to simulate real-world conditions. Multiple segment durations (30 seconds, 1 minute, 10 minutes) were evaluated to assess performance relative to recording length. Each model was trained using early stopping and learning rate scheduling to mitigate overfitting. Performance was assessed using standard metrics: accuracy, precision, recall, F1-score,

TABLE II: ECG Data File Structure for a Given Time Interval

Component	Description
Subject Directory	`/Subject_ID/` (e.g., `/201/`, `/305/`)
Session Subfolder	`/Session_N/` per subject, indicating different recording sessions
Segment Files	Fixed-length ECG segments (e.g., 30s, 1min), stored as individual files
File Format	Each segment stored in `.csv` or `.npy`, containing raw or preprocessed signals
Sampling Info	Each file includes metadata: sampling rate, lead type (MLII/V1), and duration
Example Path	`/201/Session_2/segment_001_MLII_1min.csv`

TABLE III: Summary of Model Architectures for ECG-Based Biometric Verification

Model	Architecture	Key Features and Purpose
1D-CNN (Baseline)	Conv + Pool + Dense Layers	Learns spatial features; limited temporal modeling; used for identity classification.
CNN Autoencoder	Encoder–Decoder (Unsupervised)	Extracts compressed identity embeddings; unsupervised feature representation.
Siamese 1D-CNN	Twin CNN branches with contrastive loss	Captures local waveform features; effective for pairwise ECG verification.
Siamese LSTM	Twin LSTM branches	Models temporal dependencies in heartbeat intervals; useful for sequential identity cues.
Siamese Transformer	Twin Transformer encoders	Uses self-attention to learn long-range signal dependencies; robust to session variability.
Hybrid CNN	CNN + RNN or residual blocks	Combines spatial and temporal patterns; used for robust identity representation.

ROC-AUC, and Equal Error Rate (EER). All experiments were repeated across multiple folds for statistical robustness.

B. Results and Discussion

TABLE IV: Verification Accuracy and EER for Different Models and Segment Durations

Model	Segment Duration	Accuracy (%)	EER (%)
Siamese Transformer	1 min	100.00	0.00
Siamese 1D-CNN	1 min	98.19	1.11
Siamese LSTM	1 min	97.85	1.42
Hybrid CNN	1 min	97.00	2.10
Siamese 1D-CNN	30 sec	97.69	1.38
Siamese 1D-CNN	10 min	96.15	2.47
1D-CNN (Baseline)	1 min	5.00	45.00

Table IV presents a comparison of various deep learning models explored during the study, along with their respective descriptions. The performance readings shown in Table 1.5 were specifically obtained using the Siamese 1D-CNN model, as it offered significantly faster execution compared to the other models evaluated. This efficiency enabled deeper experimentation and analysis, leading to several important conclusions throughout the investigation. These insights were derived using the Siamese 1D-CNN model, chosen for its faster execution time compared to other architectures explored during the study. Across all ECG signal durations tested—ranging from 30 seconds to 10 minutes—Person 201 consistently emerged as the top predicted identity. This strong consistency highlights the presence of distinctive and stable ECG features for Person 201, as well as the model's robust capability to recognize certain individuals regardless of the time scale used. Based on this consistency, it can be concluded that the minimum, efficient, and effective time interval for ECG data in a biometric authentication system should be 1 minute. Interestingly, even short ECG durations can yield high accuracy. With only 1 minute of data, which amounts to approximately 72 heartbeats, the Siamese 1D-CNN achieved the highest observed verification accuracy of 98.19. This result demonstrates the effectiveness of the signal preprocessing and feature extraction methods applied, and validates the feasibility of using short-duration ECG recordings for real-time biometric systems. However, an unexpected trend was noted with longer recordings. When the duration was increased to 10 minutes, the verification accuracy dropped to 96.15, the lowest among all durations tested. This suggests that longer signals may introduce redundant information or accumulate noise, potentially leading to overfitting or diminishing returns in model performance despite the larger dataset. Overall, the 1-minute ECG segment appears to be the most effective trade-off as shown in Table V, providing the highest accuracy along with a reasonable data size of 72,500 samples per person. This balance makes it ideal for practical deployment, combining performance with data efficiency. Even very short durations, such as 30 seconds (equivalent to 36 heartbeats), were found to be viable. At this duration, the model still maintained a high accuracy of 97.69. Person 201 continued to be correctly identified, although the confidence score was lower at 0.5394, indicating a slightly reduced certainty in prediction while still remaining highly functional.

TABLE V: Effect of ECG Segment Duration on Verification Accuracy

Duration	Approx. Heartbeats	Accuracy (%)
30 seconds	36	97.69
1 minute	72	98.19
10 minutes	720	96.15

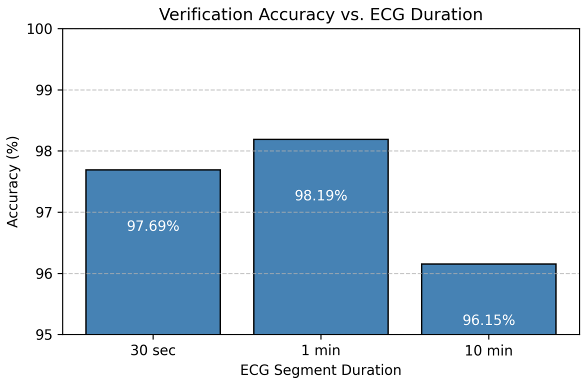

Fig. 1: Verification accuracy of the Siamese 1D-CNN model across ECG segment durations. One-minute segments yield the highest performance, balancing feature richness and efficiency.

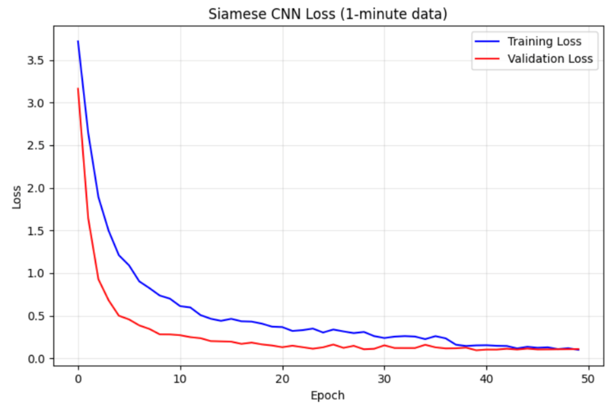

Fig. 5: Training and validation loss of Siamese CNN using 1-minute ECG segments. Validation loss stabilizes below 0.1 after 30 epochs, confirming model convergence.

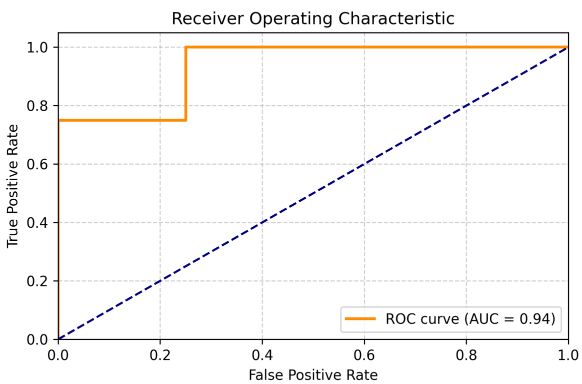

Fig. 3: Receiver Operating Characteristic (ROC) curve of the Siamese model for ECG verification. The area under the curve (AUC) is 0.94, demonstrating strong separability between genuine and impostor pairs.

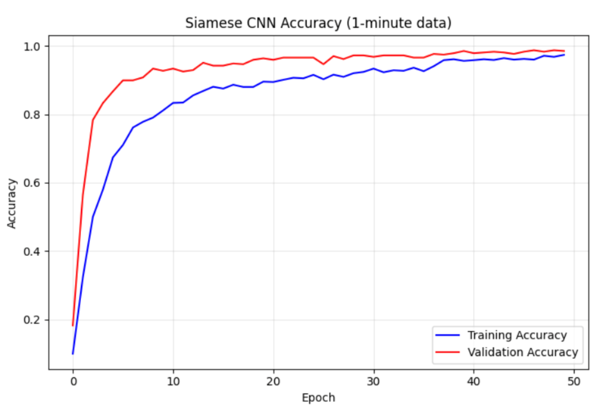

Fig. 4: Training and validation accuracy of Siamese CNN with 1-minute ECG segments. The model converges to above 95% accuracy after $\tilde{2}0$ epochs.

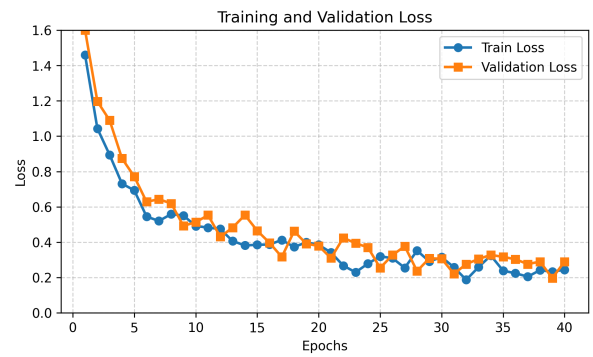

Fig. 6: Training and validation loss curves across 40 epochs. The loss steadily decreases and stabilizes, with the validation loss plateauing slightly earlier, indicating effective learning with minimal overfitting.

Figure 2 shows how the models learn over time. The training and validation losses in all of the deep models show a continuous and even drop. The convergence plot of Siamese 1-D CNN model is given in Figure 6. By epoch 30, the Siamese CNN (Fig. 5) has quickly converged, and the validation loss has stabilized around 0.1, which means there is not much generalization error. The Transformer-based Siamese model (Fig. 4) also shows consistently high training and validation accuracy, with little divergence. This suggests that the model is well-regularized and has a lot of different types of data. Figure 3 shows how well the models can verify things. The Siamese architecture has an AUC of 0.94, which means it can tell the difference between positive and negative ECG pairs quite well. The high AUC matches the observed accuracy measures and shows that the system is strong enough to work in real life. Figure 1 shows that the length of a segment has a big effect on accuracy. The 1-minute ECG segments are the best balance between having enough data and having a good model, with an accuracy of 98.19%. Shorter segments (30 seconds) have a success rate of 97.69%, which makes the system good for use in real time. Notably, longer parts (10

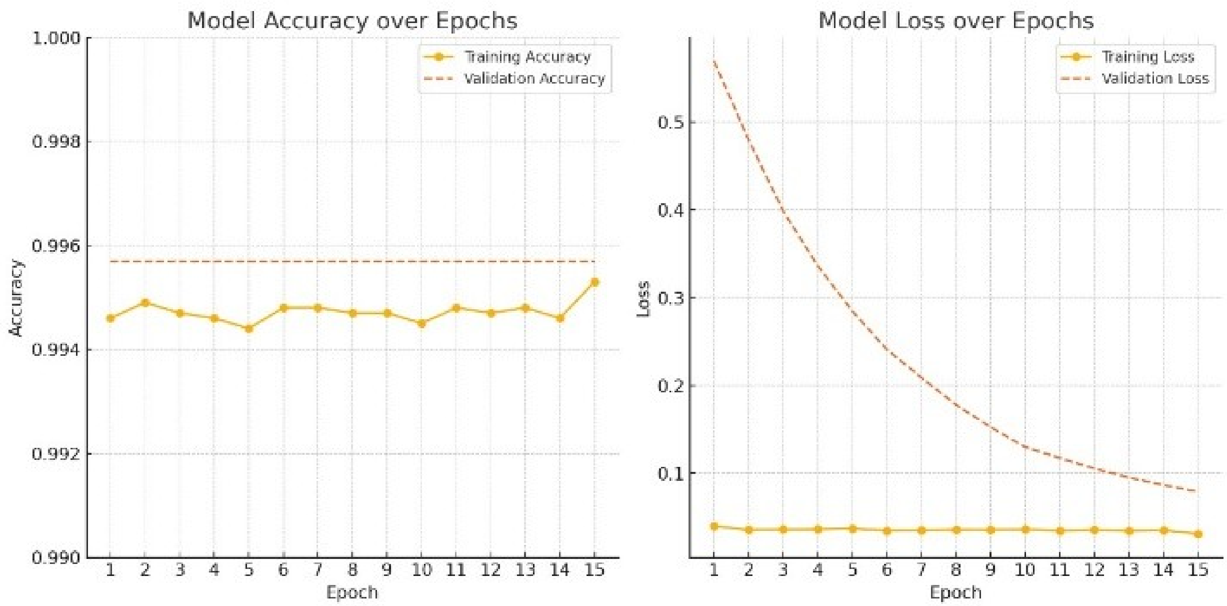

Fig. 2: Accuracy and loss evolution of the Transformer-based Siamese model over 15 epochs. Accuracy remains stable above 99.4% with minimal variance.

minutes) make accuracy a little worse, perhaps because noise and other time irregularities pile up.

V. Conclusion and Future Work

This research illustrates that ECG signals may function as a legitimate biometric characteristic when analyzed via deep learning frameworks. Among the assessed models, Siamese networks especially those using Transformers demonstrated robust generalization across sessions. A 1-minute ECG segment was identified as the optimal compromise between accuracy and computational demand, attaining superior verification performance with less data. To augment dependability, subsequent research will investigate bigger, multi-session datasets, multimodal integration with additional biosignals, and the deployment of lightweight models for real-time authentication on edge devices.

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