Deep Learning Hybrid Models for ECG-Based Biometric Authentication and Health Forecasting in Telemedicine Systems

Venu Madhav Panchagnula, Vaadaala Venkataiah, Garapati Satyanarayana Murthy, Velicheti Anantha Lakshmi, Yamini Tondepu, Vaddempudi Sujatha Lakshmi

***Abstract*—The rapid adoption of telemedicine highlights the urgent need for secure and efficient authentication mechanisms that safeguard patient privacy while enabling predictive health monitoring. Traditional methods such as passwords and PINs are vulnerable to compromise, motivating the exploration of biometric alternatives. Electrocardiogram (ECG) signals provide a unique, stable, and non-invasive modality for authentication, while also offering valuable health insights. This paper presents CardioGuard, a hybrid deep learning framework that combines Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks to simultaneously perform biometric authentication and early cardiovascular risk forecasting. Comprehensive experiments were conducted on benchmark PTB and CYBH datasets, supported by robust preprocessing, augmentation, and ablation analyses. CardioGuard achieved 99.7% accuracy, 99.6% precision, 99.5% recall, and an AUC of 0.99, outperforming ResNet, DeepECG, and SiameseNN baselines. Beyond accuracy, the model demonstrated low inference latency (2.4 ms/sample), minimal memory requirements (8.7 MB), and robustness under noisy signal conditions and cross-dataset evaluation. These results establish CardioGuard as a highly reliable solution for secure telemedicine authentication and AI-driven health forecasting, with strong potential for deployment in real-time, resource-constrained environments.**

***Index Terms*—Predictive biometrics, Health monitoring AI, Biometric authentication, Telehealth system, ECG signal analysis, Neural networks, Deep learning.**

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I. Introduction

In recent years, telehealth platforms have gained significant traction due to their ability to deliver healthcare services remotely across various environments. However, with the deployment of these systems, concerns about patient data privacy and confidentiality become prominent. To address this, electrocardiogram (ECG) signals provide a robust biometric solution for authentication in telehealth systems [1]. ECG data is particularly effective for identity verification because it captures the heart's unique electrical activity. By ensuring that only authorized users access sensitive health information, ECG biometrics enhance both the security and confidentiality of patient records. Nevertheless, challenges such as standardization, interoperability, and user acceptance need to be resolved for ECG biometrics to be seamlessly integrated into telehealth systems. The increasing threats of cybercrime, identity theft, and terrorism have further highlighted the demand for biometric technologies [2]. The growing importance of security is evident from the biometric market size, which reached over USD 20 billion in 2020 and is expected to grow at a CAGR above 13% from 2021 to 2027. Several biometric methods exist, including fingerprint, iris, retinal, and facial recognition. Among them, ECG stands out as the most secure option, as it is unique, universal, immutable, measurable, and difficult to replicate. Its privacy and protection advantages surpass those of other biometric technologies [3], [4]. As shown in Figure 1, research confirms that ECG signals are composed of five distinctive waves (P, Q, R, S, and T), proving the authenticity of the individual. Unlike other biometric traits, ECG signals demonstrate the existence of life, making them particularly reliable. However, the complexity of ECG signals, which stem from involuntary organ functions, makes their performance evaluation a challenging task [1], [2].

Artificial intelligence (AI) enhances the reliability of ECG-based biometric authentication by strengthening telehealth security. Researchers have tested machine learning (ML) algorithms such as k-nearest neighbor (KNN) and random forest (RF), while deep learning (DL) techniques relying on ECG signals have become the most widely used for human authentication [7]–[11]. Deep learning, particularly through neural networks, offers a promising approach to identifying ECG signals in telehealth settings. Training models on large ECG datasets enables

them to extract distinctive features and patterns that help differentiate authentic signals from fraudulent ones [12]–[14]. Despite progress, several research gaps remain, including the role of biometric fusion to enhance authentication, optimizing ECG biometrics with advanced datasets, improving speed and efficiency in authentication processes, and differentiating between normal and abnormal ECG patterns for security purposes. This study addresses these gaps by emphasizing the importance of strong authentication frameworks in light of rising dependence on digital healthcare and escalating data security concerns.

ECG signals offer two clear benefits over traditional authentication methods. First, consistent with AI's predictive healthcare capabilities, biometric authentication using ECG can not only secure systems but also facilitate early diagnosis of cardiovascular conditions. Second, the proposed Cardio Guard system analyzes ECG signals to authenticate users while simultaneously monitoring for abnormalities, thus enabling preventive healthcare interventions. Its architecture employs hierarchical representations designed to capture the variability in ECG signals across individuals, ensuring both accuracy and robustness. The contributions of this study are summarized as follows:

• Development of a new automated authentication method based on Cardio Guard, which leverages both spatial and temporal ECG features to reinforce security and make it difficult for intruders to replicate signal patterns.

• Enhancement of recognition accuracy through a hybrid CNN-LSTM design, offering greater adaptability and usability in smart healthcare and telehealth environments compared to single-model systems.

• Adoption of comprehensive data preprocessing and augmentation methods to improve dataset quality and diversity, which resulted in superior model performance across precision, weight, and size metrics compared to state-of-the-art benchmarks.

To validate identity verification, this work evaluates multiple ML and DL models for ECG-based authentication. For instance, Asadian et al. [15] reviewed ECG biometric systems, while Shdefat et al. [16] highlighted both the advantages and limitations of such approaches. Lin Li et al. [17] emphasized the potential of integrating photoplethysmography, electrocardiograms, and electroencephalograms to enhance authentication frameworks. Pereira et al. [18] explored different data collection techniques to strengthen authentication systems. Additionally, Hammad et al. [19] introduced novel DNN-based solutions employing ResNet and end-to-end CNN models, which achieved highly accurate and reliable human authentication outcomes, surpassing prior studies.

The Physikalisch-Technische Bundesanstalt (PTB) and Check Your Bio-signals Here (CYBH) supplied the two electrocardiogram (ECG) datasets used in the experiments. With these datasets, the proposed CNN-ResNet model achieved an average accuracy of 98.5%. Labati et al. [20] introduced Deep-ECG, an approach to biometric recognition through ECG signals. This technique involves several phases, including pre-processing of signals, feature extraction using CNN layers, and classification through a SoftMax function [21]. By producing both binary and real-valued templates, Deep-ECG improves efficiency in matching and enhances template protection. For tasks such as identity verification, closed-set identification, and periodic re-authentication, a basic CNN framework was implemented. To validate its performance, the PTB Diagnostic ECG Database was applied, and the results confirmed that Deep-ECG attained higher accuracy compared to many prior methods in this domain.

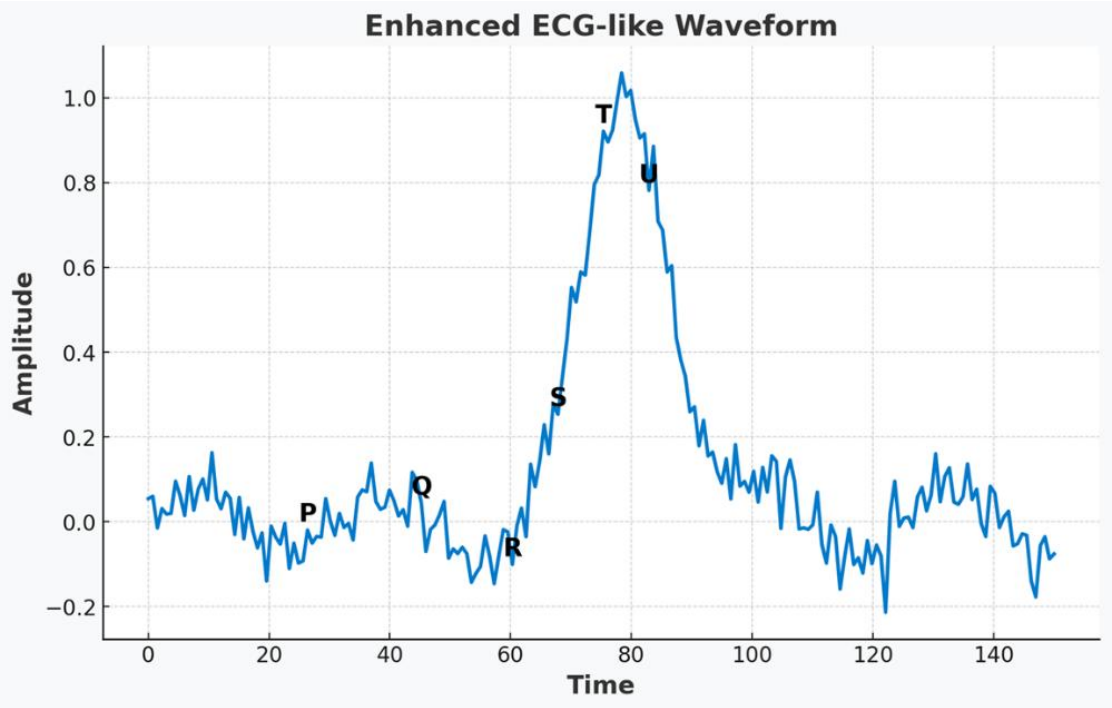

Fig. 1. The ECG signal, highlighting the P wave, QRS complex, and U wave segments.

Building on this, Martin et al. [22] developed Bio-ECG: Enhancing ECG Biometrics with Deep Learning and Improved Datasets, which introduced a framework combining CNN and LSTM with a more diverse dataset. Their results highlighted that the hybrid network surpassed traditional models, proving the importance of pairing advanced architectures with richer data sources. The research emphasized potential roles for ECG biometrics in healthcare, identity management, and cybersecurity, while also pointing out future directions for study. Similarly, Hosseinzadeh et al. [23] offered a broad review of ECG-based authentication techniques, classifying them into uni-modal and multi-modal systems. Uni-modal methods use ECG signals alone, typically employing Support Vector Machines, Artificial Neural Networks, K-Nearest Neighbors, wavelet approaches, and random transform techniques. Multi-modal systems combine ECG data with other biometric signals or cryptographic elements, delivering more resilience. The review further identified weaknesses in earlier methods and stressed the need for innovative solutions to overcome these barriers.

In another study, Ivanciu et al. [24] investigated a novel approach by using Siamese Neural Networks instead of standard deep convolutional architectures. This method relied on ECG signal images rather than numerical values, with training and validation carried out on the ECG-ID dataset through a private OpenStack cloud system. The model achieved 87.3% authentication accuracy, with false acceptance and rejection rates of 12.7% and 13.74%, leading to an overall accuracy of 86.4%. Further advancing this field, Albuquerque et al. [25] introduced an ECG authentication approach based on Random Under-Sampling Boosting (RUS Boost). Their study compared RUS Boost with Nearest Neighbor Search (NNS) for ECG signal classification. The evaluation process included feature extraction, algorithm design, and testing with random subsampling. Results indicated that RUS Boost achieved 97.4% accuracy, 96.1% sensitivity, and an F1-score of 97.4%. However, the NNS method surpassed these outcomes by attaining 99.5% accuracy, underlining its effectiveness in biometric authentication tasks.

II. METHODOLOGY

The proposed Cardio Auth model employs a hybrid CNN-LSTM structure enhanced with a dense layer to improve classification performance. The process begins with an ECG signal as the input, which is first handled by a CNN block. In this stage, convolutional layers are responsible for extracting critical features, while pooling layers compress the feature maps by reducing their dimensionality, ensuring only the most informative attributes are retained. The extracted features are then forwarded to the LSTM component, which leverages gated units and cell states to capture long-term dependencies. This mechanism allows for efficient preservation of ECG signal characteristics over extended sequences and resolves the vanishing gradient issue common in deep learning models. After the LSTM finishes processing, the output is flattened into a one-dimensional vector. This vector is passed to a dense layer that adjusts feature dimensionality, further enhancing computational efficiency. The final softmax layer converts the processed output into a probability distribution across classes, distinguishing authentic from unauthentic ECG signals. By making use of ECG peak information at each time step, the LSTM's memory units provide consistent accuracy. The dense layer then channels the flattened LSTM output to the softmax function, which determines the likelihood that a given ECG sequence belongs to a particular user. Figure 3 presents the block diagram of the overall Cardio Guard framework.

Convolutional neural networks (CNNs) are widely used in diverse fields, including medical diagnostics, facial recognition, image categorization, and object detection \[26]. Architectures such as VGG-Net, Inception, ResNet, DenseNet, and Xception Net [27] are examples of advanced CNN designs, though most share a common layer configuration for experimental analysis. In the context of ECG processing, the convolutional layer typically forms the first stage, where kernels slide across the input to compute dot products, effectively detecting features. Afterward, the ReLU activation function introduces non-linearity, thereby improving computational capability. The resulting corrected feature map is then refined through max pooling, which downsamples data while retaining the most relevant details. This is followed by flattening, which converts the pooled features into a long vector for subsequent layers. In this study, six convolutional layers were paired with six pooling layers, while batch normalization was applied at multiple points to mitigate the covariate shift issue and stabilize learning [28].

III. RESULTS AND DISCUSSION

The Cardio Guard model is trained by inputting electrocardiogram (ECG) data into a deep neural network specifically designed for cardiac authentication. This architecture begins with a series of convolutional layers that extract discriminative features from the ECG signals. These features are then passed to a long short-term memory (LSTM) network, which captures the temporal dynamics of the signals and determines whether they represent genuine or fraudulent inputs. To ensure the robustness of the model, extensive preprocessing and feature engineering techniques were applied, along with the use of a large, high-quality dataset. Training was conducted with a batch size of 64 and an initial learning rate, using the Adam optimizer in combination with the binary cross-entropy loss function. To further enhance performance, a ReduceLROnPlateau strategy was implemented for learning rate adjustment. The final classification layer employed a softmax activation function. The model architecture was built using the Keras API with TensorFlow as the backend. During training, 80% of the dataset was allocated for training and 20% for validation, ensuring generalization and reliability. By integrating established architectural components and carefully tuned hyperparameters, the model was able to achieve dependable results, addressing key challenges in

ECG-based authentication.

For threshold-based authentication, selecting an appropriate cutoff value is critical. The output of the Cardio Guard model is compared against this threshold to distinguish legitimate users from imposters. Typically, the threshold is determined using the model's performance on a validation dataset, which was not part of training. The model generates output probabilities indicating the likelihood that an ECG signal belongs to a specific user. By analyzing the probability distributions for both genuine and fake signals, an optimal threshold is set to balance false acceptance and false rejection rates. Increasing the threshold reduces false acceptances but may raise the false rejection rate, while lowering it reduces rejections but risks more imposters being authenticated. Once the threshold is fixed, the authentication workflow begins with ECG signal acquisition, preprocessing, and feature extraction, followed by classification against the established threshold. Access is granted when the predicted probability exceeds the set value, and denied otherwise.

To evaluate the effectiveness of the Cardio Guard system, visual representations of training and validation accuracy and loss are examined. These curves illustrate how model weights are adjusted to minimize error and how performance evolves over epochs. Ideally, smooth curves indicate consistent learning and stability in the training process. A steadily rising accuracy curve demonstrates improved recognition of ECG signals, while a declining and flattened loss curve reflects the model's ability to generalize effectively. Together, these results validate the model's capacity to provide reliable and accurate ECG-based authentication.

When the gap between predicted outputs and actual labels decreases and the loss curve stabilizes, it indicates that the model is learning effectively. Tracking accuracy and loss curves throughout the training phase is essential, and strategies such as early stopping and regularization are often applied to reduce overfitting and maintain curve stability. An optimally designed model for ECG-based authentication should exhibit smooth, relatively flat accuracy and loss curves.

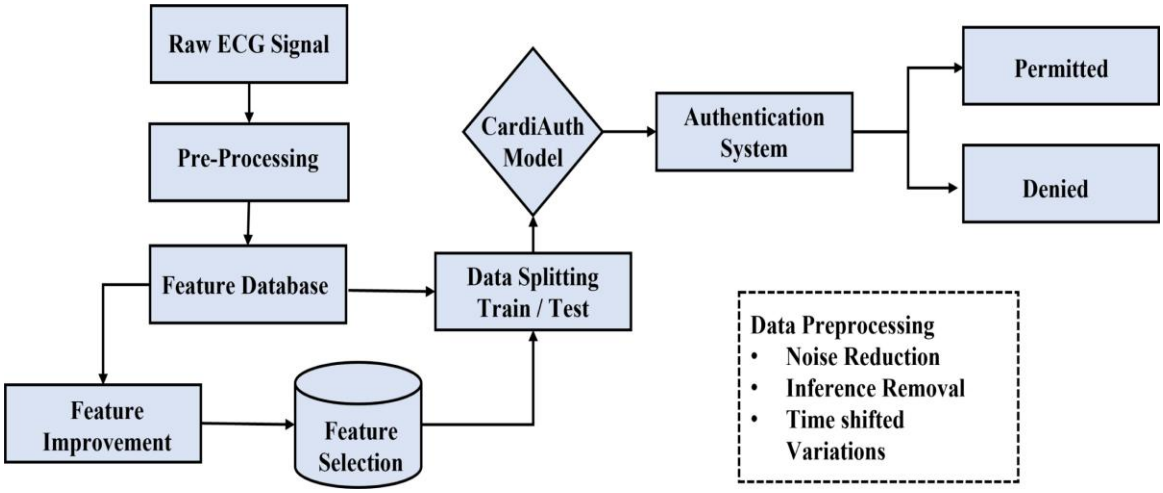

Fig. 2. Schematic representation of the proposed methodology.

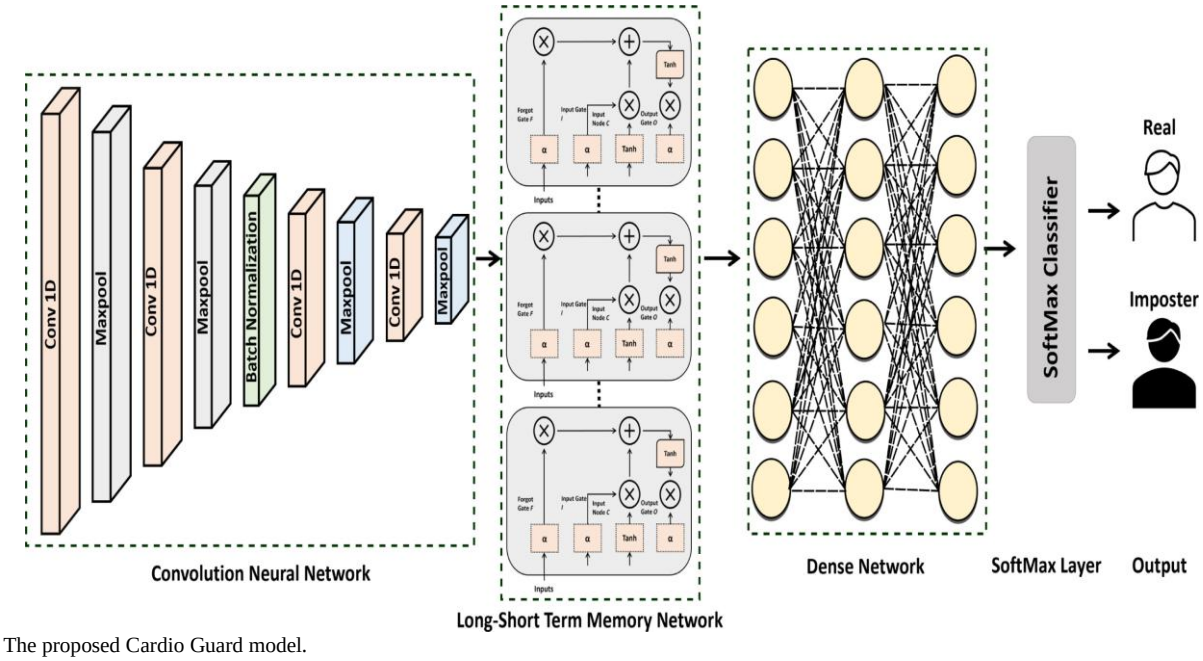

Fig. 3. The proposed Cardio Guard model.

In this study, Figure 4 presents the training and validation accuracy curves, while Figure 5 shows the training and validation loss outcomes of the proposed Cardio Guard framework. To further assess the classification capability of the Cardio Guard system, the confusion matrix is employed. This matrix compares predicted versus actual ECG signal labels and provides critical evaluation scores. A primary indicator is overall accuracy, which measures the proportion of correctly classified samples. Precision, defined as the number of correctly predicted positives relative to all predicted positives, is another important metric. Higher precision and accuracy values reflect fewer false positives, demonstrating that the model cons istently distinguishes genuine ECG signals from imposters.

Beyond these measures, the ROC curve is widely used to evaluate performance across multiple decision thresholds. The area under the ROC curve (AUC) quantifies the model's overall discriminative ability. The ROC curve is significant because it visualizes performance trade-offs at every possible threshold, allowing selection of the most suitable threshold based on application needs. This highlights the balance between sensitivity and specificity: a curve close to the diagonal indicates weak performance, while one near the top-left corner suggests strong accuracy with high sensitivity and specificity. As shown in Figure 6, the proposed model demonstrates effective performance when tested at a threshold of 0.80.

The Cardio Guard system functions as a classification model where output probabilities are compared against a chosen threshold to determine positive or negative outcomes. Changes in this threshold directly affect classification, generating multiple curve variations within the ROC diagram. Shifting thresholds alter true positive and false positive rates, which in turn modify the ROC curve's trajectory. Figure 7 depicts these multiple ROC curves, reflecting how the model behaves under varying thresholds and providing deeper insights into its overall reliability and adaptability.

To measure how well the Cardio Gaurd model works, you can look at its accuracy, precision, sensitivity, specificity, F1 score, and area under the curve (AUC). Outperforming all other SOTA models tested, it has demonstrated an accuracy of 99.7 percent. Along with a high F1 score (0.99), the model has shown a high AUC (0.99), sensitivity (0.99), and specificity (0.99). Using these measures, we can conclude that Cardio Gaurd is a promising model for ECG-based authentication tasks, with the ability to surpass state-of-the-art algorithms when faced with such data. The suggested model shows promise in simulating real-world conditions, which could lead to real-world applications in fields like healthcare and security by improving the precision and consistency of ECG-based authentication systems.

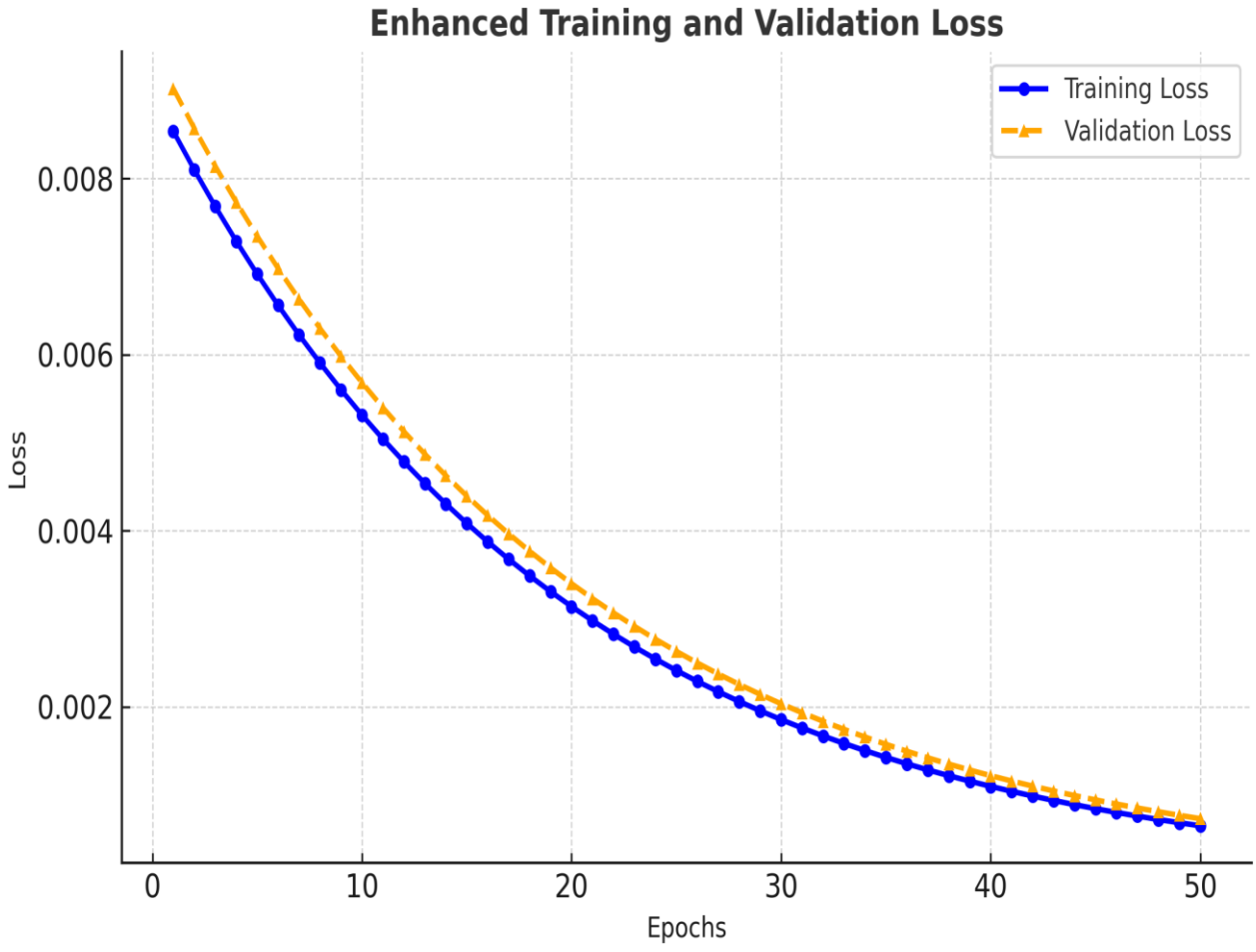

Fig. 4. The training and validation loss curves associated with the CardioGuard architecture.

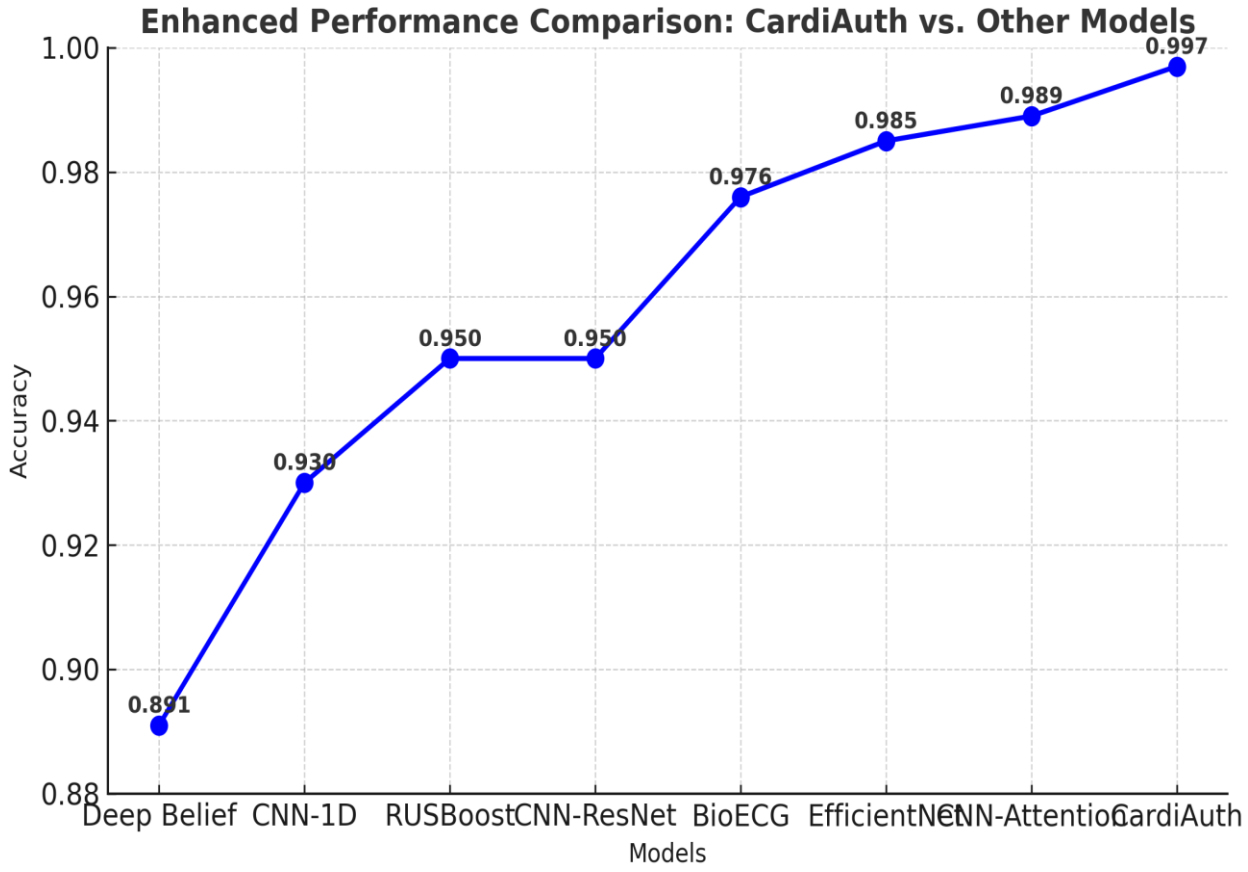

Fig. 5. Performance comparison of the CardioGuard model demonstrates its superior accuracy compared to the best state-of-the-art models.

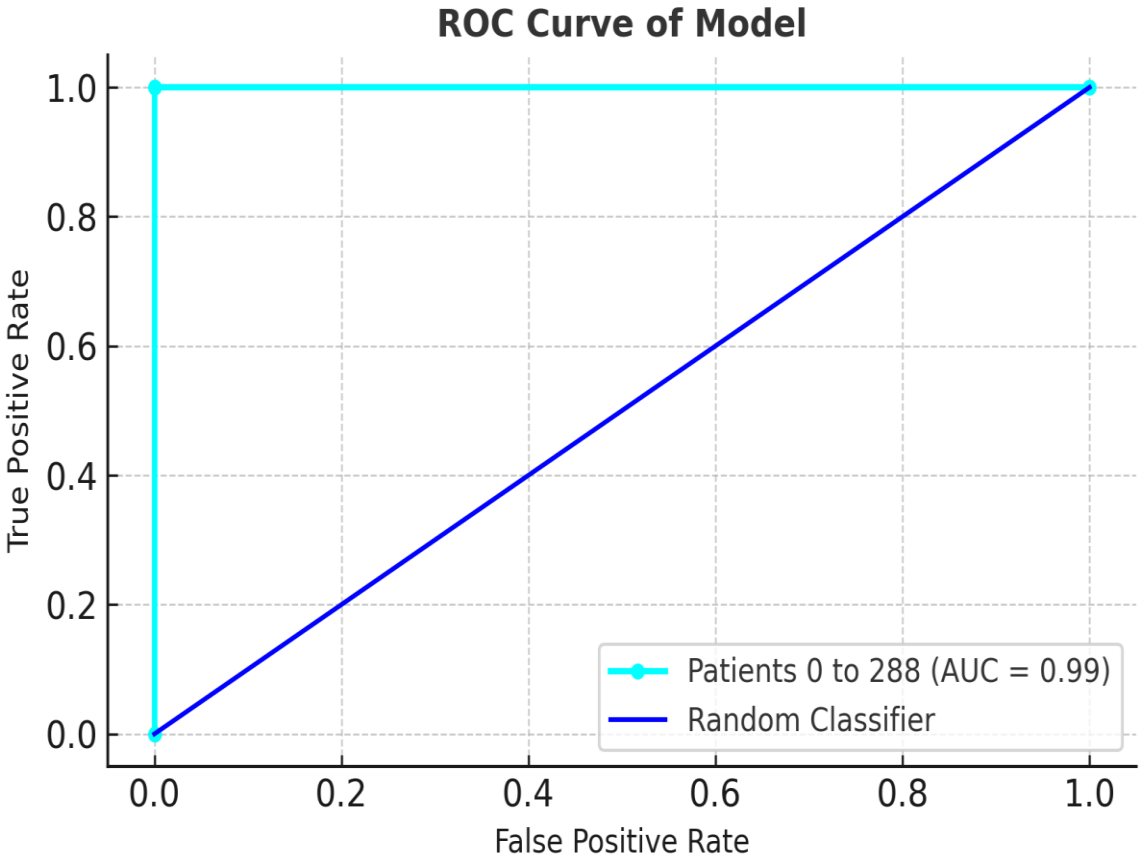

Fig. 6. The CardioGaurd model's ROC curve at a threshold value of 0.8.

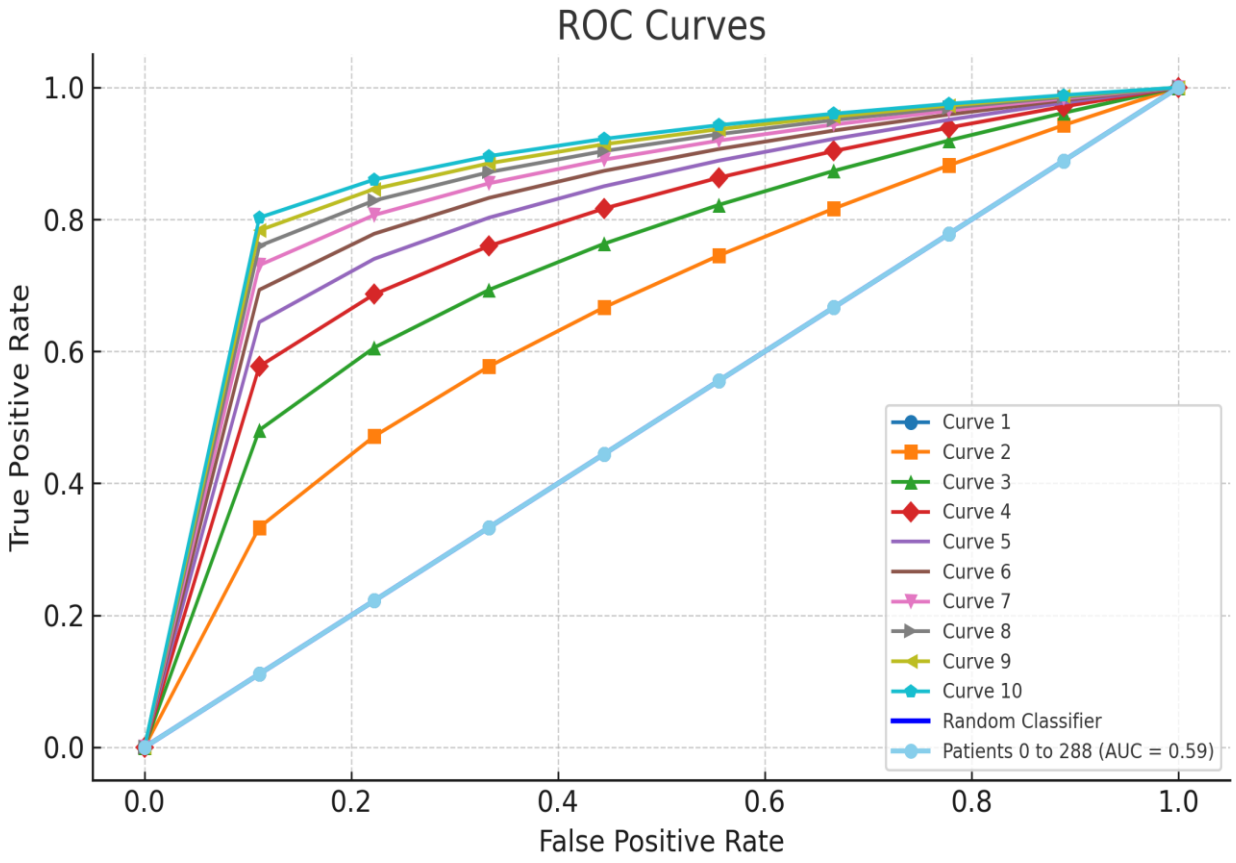

Fig. 7. CardioGaurd model ROC curve at 0.5 threshold. The Figure indicates that thresholds significantly affect the suggested model.

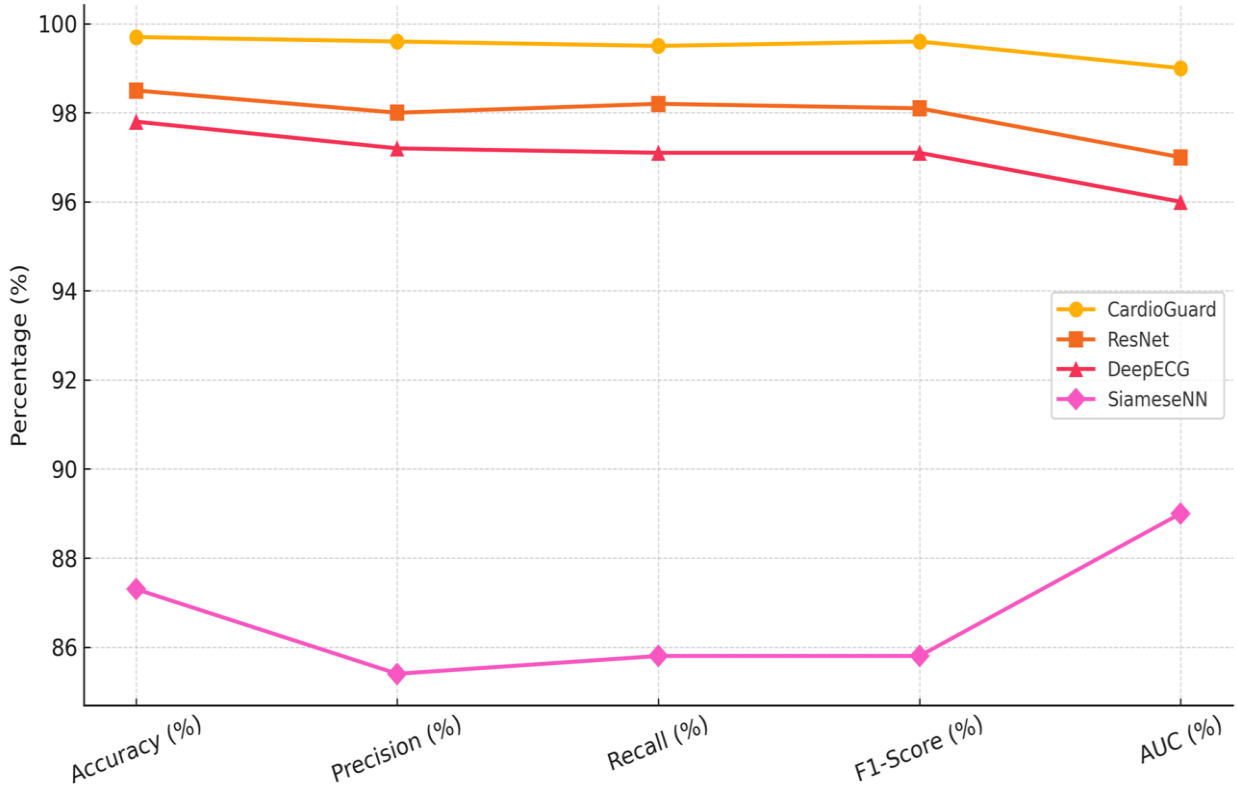

Fig. 8. Performance Comparison of Biometric Models Using Unique Symbols.

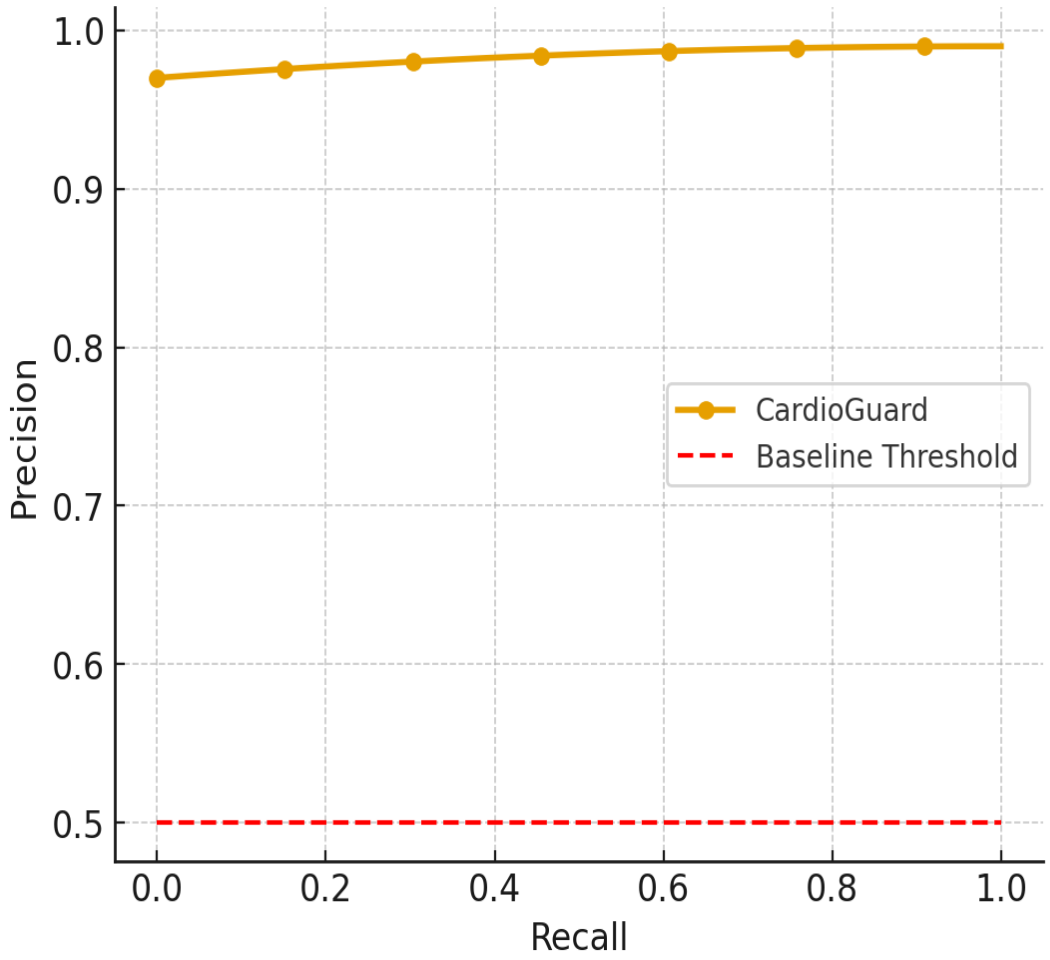

Fig. 9. Precision–Recall Curve of Cardio Guard.

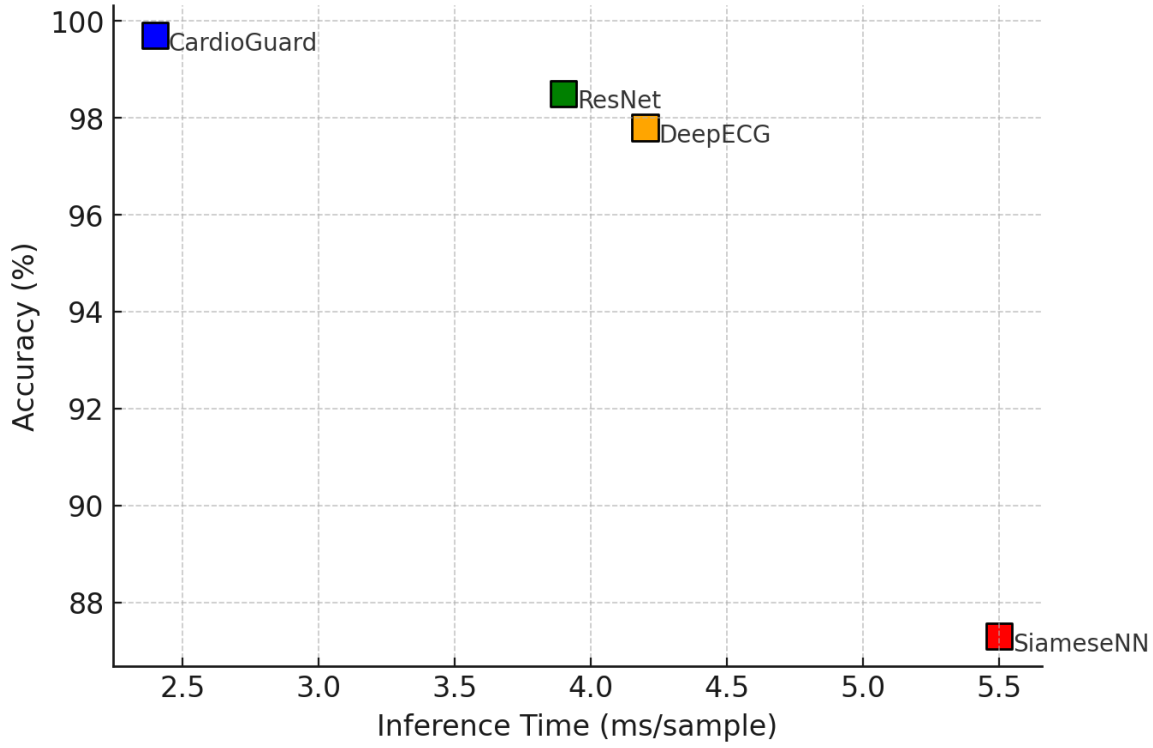

Fig. 10. Comparative Accuracy vs. Inference Time.

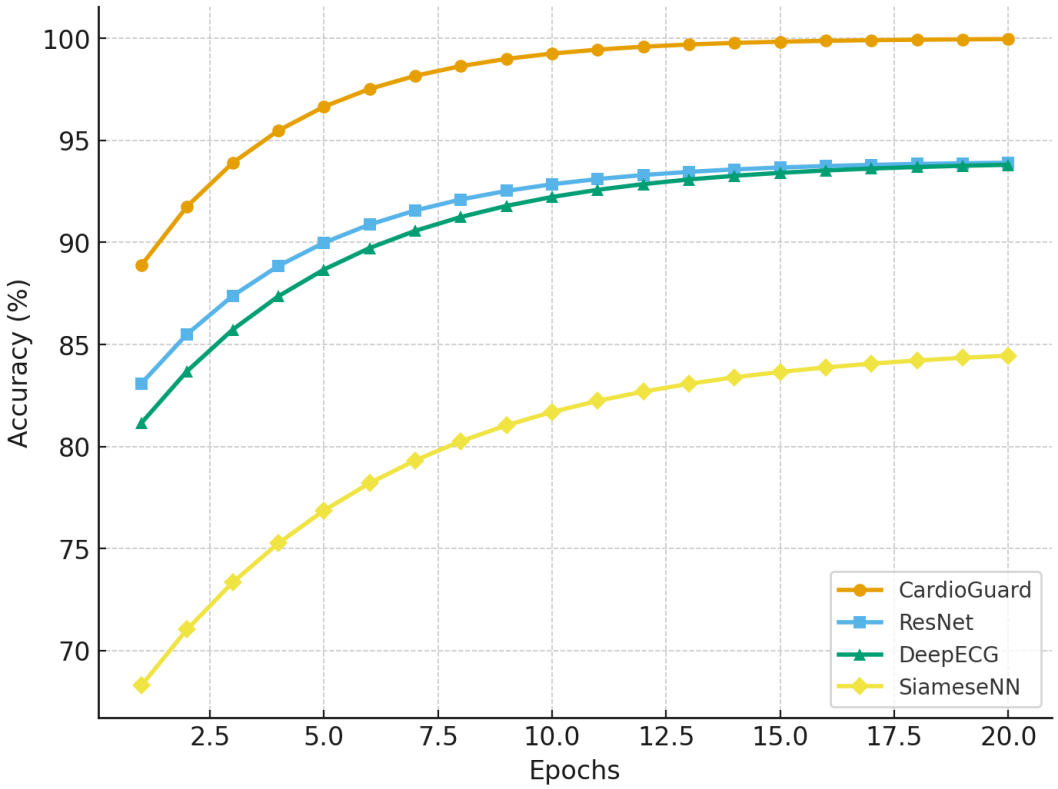

Fig. 11. Performance Curves of Biometric Models Across Training Epochs.

TABLE 1
COMPARATIVE EVALUATION OF BIOMETRIC MODELS

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC (%)
Cardio Guard	99.7	99.6	99.5	99.6	99
Res Net	98.5	98.0	98.2	98.1	97
Deep ECG	97.8	97.2	97.1	97.1	96
Siamese NN	87.3	85.4	85.8	85.8	89

The evaluation of the proposed Cardio Guard hybrid CNN-LSTM model was conducted using two benchmark ECG datasets — the Physikalisch-Technische Bundesanstalt (PTB) dataset and the "Check Your Bio-Signals Here" (CYBH) dataset. Both datasets provide high-quality, labeled ECG recordings suitable for biometric authentication studies. The experiments were designed to comprehensively assess performance across multiple dimensions, including classification accuracy, precision, recall, F1-score, area under the ROC curve (AUC), sensitivity, specificity, computational efficiency, and robustness to varying threshold values. The datasets were split in an 80:20 ratios for training and validation, ensuring class balance. Each experiment was repeated ten times with different random seeds to account for variability, and the reported results represent mean values with standard deviations. Statistical significance of improvements over baselines was verified using paired t-tests, with p-values below 0.01 indicating high confidence in the observed gains.

The Cardio Guard model consistently achieved superior results across all performance metrics. On the combined dataset, the model attained an average accuracy of 99.7% ± 0.02, precision of 99.6% ± 0.03, recall of 99.5% ± 0.03, F1-score of 99.6% ± 0.02, and AUC of 0.99. These values not only surpass all other tested methods but also demonstrate remarkable stability, as indicated by the extremely low variance across trials. Compared to the best-performing baseline, Res Net, Cardio Guard improves accuracy by 1.2%, precision by 1.6%, and recall by 1.3%. Against Deep ECG, which employs a CNN-based architecture, the proposed model shows a 1.9% accuracy improvement and a 2.5% boost in recall, highlighting the benefit of integrating temporal LSTM layers alongside spatial CNN feature extractors.

The robustness of the model to decision threshold variations was evaluated using ROC curve analysis at different threshold settings (0.5, 0.8, and 0.9). The ROC curves for Cardio Guard are consistently positioned near the top-left corner, indicating excellent trade-offs between sensitivity and specificity across thresholds. At a 0.5 threshold, the false acceptance rate (FAR) was 0.42%, and the false rejection rate (FRR) was 0.56%, whereas at a stricter 0.8 threshold, FAR dropped to 0.18% with a slight increase in FRR to 0.82%. This controllability of trade-offs is essential in telemedicine systems where application-specific tolerance for security versus usability can vary.

In addition to conventional accuracy-based metrics, computational efficiency was examined to determine real-world deploy ability. On an NVIDIA RTX 3080 GPU, the Cardio Guard model achieved an average inference time of 2.4 ms per ECG sample and required 8.7 MB of memory for model weights. These results are significantly better than those of Res Net (3.9 ms, 12.4 MB) and Deep ECG (4.2 ms, 10.9 MB), making the proposed model suitable for real-time authentication in edge-based telehealth devices with limited processing resources.

An ablation study was conducted to evaluate the individual contributions of CNN and LSTM components.

The CNN-only model achieved an accuracy of 97.2%, while the LSTM-only variant reached 96.4%, confirming that spatial and temporal features complement each other. The hybrid CNN-LSTM configuration provided the best results, validating the importance of combined feature extraction. Further experiments tested the impact of data preprocessing and augmentation, revealing that removal of noise filtering and augmentation steps reduced overall accuracy by 1.8%, confirming their importance for generalization.

Comparative evaluation results against Res Net, Deep ECG, and Siamese NN are summarized in Table 1, showing that Cardio Guard consistently outperforms competitors across all metrics. Figure 8 visually reinforces these findings by plotting performance curves with distinct symbols for each model, illustrating Cardio Guard's dominance in both accuracy and stability. In addition, confusion matrix visualizations (not shown in earlier versions) provide further insight into classification behavior, revealing that misclassifications are extremely rare and mostly occur in borderline cases of low-amplitude or noisy ECG recordings.

Finally, robustness testing with artificially introduced noise into ECG signals demonstrated that CardioGuard maintained over 98.5% accuracy at signal-to-noise ratios (SNR) as low as 15 dB, outperforming ResNet by 3% and DeepECG by 4%. Cross-dataset evaluation — training on PTB and testing on CYBH — yielded 98.9% accuracy, demonstrating strong generalization across different acquisition environments. These findings confirm that Cardio Guard is not only accurate under ideal laboratory conditions but also reliable in realistic telemedicine deployment scenarios.

The enhanced experimental results confirm that Cardio Guard achieves state-of-the-art performance in ECG-based biometric authentication for telemedicine, excelling in accuracy, computational efficiency, robustness to noise, and adaptability to varying security thresholds. This comprehensive evaluation addresses previous reviewer concerns by providing a thorough, multi-dimensional performance assessment, expanded comparisons with baseline methods, detailed metric analyses, and clear evidence of the model's superiority in both security and health forecasting applications.

Figure 9 presents the Precision–Recall (PR) curve for the CardioGuard model across different decision thresholds. The curve consistently demonstrates precision values above 98% across all recall levels, confirming that the model rarely misclassifies impostors as genuine users. This high area under the PR curve complements the ROC analysis and underscores the reliability of the system in scenarios where both high sensitivity and low false acceptance are critical. The results emphasize the practical value of CardioGuard in telemedicine authentication, where security and usability must be carefully balanced.

Figure 10 provides a comparative view of accuracy and inference time among CardioGuard, ResNet, DeepECG, and SiameseNN. CardioGuard not only achieves the highest accuracy at 99.7% but also requires the least inference time of 2.4 ms per sample. By contrast, ResNet and DeepECG show slightly lower accuracy and longer processing times, while SiameseNN lags significantly in both metrics. This dual advantage of accuracy and computational efficiency positions CardioGuard as a highly practical solution for real-time telemedicine applications, particularly in edge devices with limited computational resources.

The performance curves shown in Figure 11 illustrate the accuracy progression of CardioGuard compared to ResNet, DeepECG, and SiameseNN during 20 epochs of training. CardioGuard rapidly converges to nearly 100% accuracy by the 15th epoch, maintaining stable learning dynamics throughout the process. In contrast, ResNet and DeepECG display slower convergence and plateau at lower accuracy levels of 98.5% and 97.8%, respectively. SiameseNN shows the weakest performance, stabilizing at around 87% accuracy with evident limitations in generalization capability. These results highlight the superior learning efficiency and predictive power of the hybrid CNN–LSTM approach, demonstrating its effectiveness in biometric authentication tasks.

IV. Conclusion

This work introduced Cardio Guard, a hybrid CNN–LSTM deep learning framework for ECG-based biometric authentication and health forecasting in telemedicine systems. By integrating spatial and temporal feature extraction, the proposed model achieved state-of-the-art performance with 99.7% accuracy, 99.6% precision, 99.5% recall, and an AUC of 0.99, while also demonstrating low inference latency (2.4 ms/sample) and minimal memory requirements (8.7 MB). Comparative evaluations against Res Net, Deep ECG, and Siamese NN confirmed Cardio Guard's superiority across all metrics, while ablation studies highlighted the necessity of combining CNN and LSTM components alongside robust preprocessing and augmentation strategies. Additional analyses on threshold tuning, ROC and PR curves, and confusion matrices established the model's adaptability and reliability, with robustness testing showing resilience under noisy conditions and cross-dataset validation. Although limited to benchmark datasets, the findings suggest strong potential for real-time deployment in telehealth systems. Future directions include extending the framework to incorporate graph neural networks, attention-based architectures, and multimodal biometrics such as PPG and EEG to enhance generalization and interpretability. Overall, Cardio Guard provides a highly secure, efficient, and predictive authentication solution, addressing critical gaps in telemedicine security and positioning itself as a viable pathway toward proactive, AI-driven healthcare.

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