Jurnal Teknik Informatika (JUTIF) Vol. 6, No. 6, December, 2025, Page. 5632-5648
P-ISSN: 2723-3863 https://jutif.if.unsoed.ac.id
E-ISSN: 2723-3871 DOI: https://doi.org/10.52436/1.jutif.2025.6.6.5299

Early Fusion of CNN Features for Multimodal Biometric Authentication from ECG and Fingerprint Using MLP, LSTM, GCN, and GAT

Muhammad Abdhi Priyatama[1], Dodon Turianto Nugrahadi[*2], Irwan Budiman[3], Andi Farmadi[4], Mohammad Reza Faisal[5], Bedy Purnama[6], Puput Dani Prasetyo Adi[7], Luu Duc Ngo[8]

[1,2,3,4,5]Faculty of Mathematics and Natural Sciences, Lambung Mangkurat University, Banjarbaru, Indonesia
[6]Center of Excellence of Artificial Intelligence for Learning and Optimization, Telkom University, Indonesia
[7]Telecommunication Research Center, National Research and Innovation Agency, Indonesia
[8]Faculty of Information Technology, Bac Lieu University, Bac Lieu, Vietnam

Email: [1]dodonturianto@ulm.ac.id

Received : Nov 24, 2025; Revised : Dec 3, 2025; Accepted : Dec 4, 2025; Published : Dec 23, 2025

Abstract

Traditional authentication methods such as PINs and passwords remain vulnerable to theft and hacking, demanding more secure alternatives. Biometric approaches address these weaknesses, yet unimodal systems like fingerprints or facial recognition are still prone to spoofing and environmental disturbances. This study aims to enhance biometric reliability through a multimodal framework integrating electrocardiogram (ECG) signals and fingerprint images. Fingerprint features were extracted using three deep convolutional networks—VGG16, ResNet50, and DenseNet121—while ECG signals were segmented around the first R-peak to produce feature vectors of varying dimensions. Both modalities were fused at the feature level using early fusion and classified with four deep learning algorithms: Multilayer Perceptron (MLP), Long Short-Term Memory (LSTM), Graph Convolutional Network (GCN), and Graph Attention Network (GAT). Experimental results demonstrated that the combination of VGG16 + LSTM and ResNet50 + LSTM achieved the highest identification accuracy of 98.75 %, while DenseNet121 + MLP yielded comparable performance. MLP and LSTM consistently outperformed GCN and GAT, confirming the suitability of sequential and feed-forward models for fused feature embeddings. By employing R-peak-based ECG segmentation and CNN-driven fingerprint features, the proposed system significantly improves classification stability and robustness. This multimodal biometric design strengthens protection against spoofing and impersonation, providing a scalable and secure authentication solution for high-security applications such as digital payments, healthcare, and IoT devices.

Keywords : *Deep Learning, ECG, Early Fusion, Feature Extraction, Fingerprint, Multimodal Biometric*

1. INTRODUCTION

Traditional authentication methods based on PINs, passwords, or access cards are increasingly insecure. Studies show that knowledge-based systems are unreliable and prone to compromise [1], [2]. Even complex credentials are vulnerable due to users' preference for memorable patterns, exposing them to shoulder surfing [3], smudge attacks [4], and brute-force attacks [5]. Approximately 80% of login credentials can be cracked rapidly using automated tools [4]. These limitations underscore the weaknesses of conventional authentication, necessitating more robust and secure methods.

Biometrics has become a popular alternative to address the limitations of traditional authentication. Modalities such as fingerprints, facial recognition, iris patterns, voice, and handwriting are widely used due to their uniqueness and high identification accuracy [6], [7]. However, unimodal biometric systems still exhibit significant vulnerabilities, for example, fingerprints and facial data are

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prone to spoofing and are affected by environmental factors such as lighting conditions or contaminated finger surfaces [7], [8]. To improve security, recent studies have explored the use of electrocardiogram (ECG) signals as a biometric modality, leveraging the inherent uniqueness of cardiac electrical activity, which is difficult to replicate [8], [9]. Unlike fingerprints and facial features that can be forged or influenced by external conditions, ECG signals are categorized as liveness biometrics, as they can only be obtained from living subjects [7], [8], [10]. Prior studies also reported that synthetic artifacts can achieve fingerprint spoofing [11].

However, relying on a single biometric modality is still considered unsafe because ECG signal noise or poor fingerprint quality can lead to authentication errors [12], [13]. Therefore, multimodal biometric systems that combine two or more modalities, such as ECG and fingerprints, have been developed to improve accuracy and reliability [13], [14], [15]. Integrating ECG with fingerprint data also enables liveness detection, helping to prevent spoofing attempts using artificial fingerprints and enhancing protection against identity impersonation attacks [16], [17].

Numerous recent studies have emphasized improving preprocessing techniques to enhance data quality before feature extraction and mitigate the limitations of unimodal systems. In fingerprint recognition, low-quality images are refined through methods such as the Inception-CNN architecture, which automatically identifies and removes unusable samples prior to the identification stage [1], [18]. Similarly, for ECG signals, power-line interference is suppressed using notch filtering, while baseline drift is corrected through low-pass filtering [19], producing cleaner and more reliable signals for subsequent analysis.

Following preprocessing, deep convolutional neural networks (CNNs) are widely adopted for feature extraction. Architectures such as VGG16, ResNet50, and DenseNet121 have been extensively evaluated. A comparative study reported that a standard CNN achieved the highest fingerprint recognition performance with an F1-score of 96.5%, outperforming ResNet50 (94.3%) and VGG16 (92.1%) [20]. Similarly, another study designed a compact CNN for ECG-based authentication, achieving 99.9% accuracy on the PTB dataset and 98.2% on ECG-ID [21]. Additional research investigated 1D-CNN, 2D-CNN, and fully connected architectures, including transforming 1D ECG signals into 2D spectrograms for extraction using EfficientNet [22].

After feature extraction, the next stage involves feature fusion and classification. Several studies explored fusion techniques to combine multimodal data before classification [23], [24], [25]. One study compared parallel (score-level fusion) and sequential (decision-level fusion) strategies, achieving the best performance using sequential fusion with a neural network classifier (AUC = 0.985) [16]. Other studies investigated alternative classifiers on multimodal ECG-fingerprint datasets, demonstrating that combining EfficientNet-B3 (fingerprint) with 2D-CNN (ECG) achieved 95.32% accuracy [22]. In another comparison of neural networks, fuzzy logic, and linear discriminant analysis (LDA), neural networks achieved the highest performance with an AUC of 0.951 [26]. These findings highlight the importance of systematically evaluating CNN architectures and classification methods to improve multimodal biometric authentication.

Unlike prior studies that used limited feature sizes and CNN architectures, this work conducts a comprehensive comparison of three CNN models—VGG16, ResNet50, and DenseNet121—combined with four classifiers: Graph Convolutional Networks (GCN), Graph Attention Networks (GAT), Multilayer Perceptrons (MLP), and Long Short-Term Memory (LSTM). The ECG features are segmented at 500, 5000, 7000, and 10,000 based on detected R-peaks, while fingerprint features remain fixed according to CNN outputs (512, 2048, and 1024, respectively). Feature-level early fusion integrates both modalities before classification.

The novelty of this research lies in its ECG preprocessing strategy, which segments signals after R-peak detection, generating multiple feature sizes for comparative evaluation. Fingerprint

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preprocessing includes image enhancement, binarization, and thinning, ensuring consistent input quality. Features from both modalities are extracted using three CNN architectures, fused at the feature level, and classified using GCN, GAT, MLP, and LSTM.

The primary objective of this study is to evaluate and compare CNN architectures and classification methods for ECG-fingerprint multimodal biometric identification. The outcomes of this research contribute to the advancement of secure and intelligent biometric authentication frameworks by identifying optimal CNN architectures and classification models that enhance accuracy, reliability, and resilience against biometric spoofing and cyber intrusion. This provides a significant impact on strengthening cybersecurity in critical applications such as digital payments, IoT devices, and e-government services.

2. METHOD

The research flow of this research is shown in **Figure 1**.

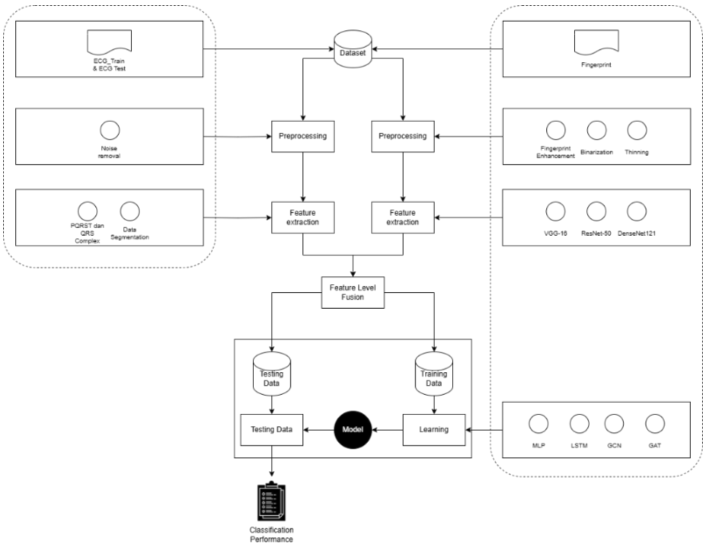

Figure 1. Research flow

2.1. Dataset

This study utilized two publicly available biometric datasets: ECG-ID for electrocardiogram signals and FVC2004 for fingerprint images. These datasets can be accessed online, as summarized in the **Table 1.**

Table 1. Biometric datasets with access links and references.

Dataset	URL	Refference
ECG-ID	https://physionet.org/content/ecgiddb/1.0.0/	[27], [28], [29]
FVC2004	http://bias.csr.unibo.it/fvc2004/databases.asp	[30], [31], [32]

The first is the ECG-ID Database (PhysioNet), comprising 310 lead-I ECG recordings of 20 seconds each, collected from 9 0 subjects (44 males, 46 females; aged 13–75 years). Each recording was converted into 10,000 numerical features (X0–X9999) with identity labels stored in X10000. To maintain consistency with the fingerprint dataset, data from only 40 individuals were selected. The dataset was partitioned into ECG_TRAIN (6 samples per subject) and ECG_TEST (2 samples per subject). The data distribution, including feature dimensions and sample counts, is summarized in

Table 2. A part of the ECG dataset is shown in **Figure 2**.

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Table 2. Description of the Electrocardiogram Dataset

Person	ECG_TRAIN records	ECG_TEST records	Number of ECG features
Person 1	6	2	10000
Person 2	6	2	10000
Person 3	6	2	10000
…	…	…	…
Person 38	6	2	10000
Person 39	6	2	10000
Person 40	6	2	10000

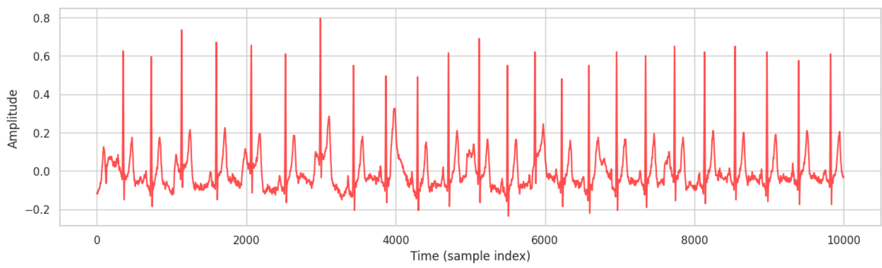

Figure 2. Example of ECG-ID Database

The second dataset is the FVC2004 Fingerprint Database, where each database (DB1–DB4) contains 80 fingerprint images systematically labeled as XXX_Y. Here, XXX denotes the subject ID (101–110, 10 subjects per database), and Y (1–8) represents the impression number, providing eight images per subject. For example, 101_1–101_8 correspond to the eight images of Person 1, while 110_1–110_8 represent those of Person 10. For efficient processing, images from each subject were grouped into dedicated folders (Person 1–Person 10), simplifying labeling, model training, and performance evaluation. The dataset was split into a training set and a test set, with six images (XXX_1–XXX_6) allocated for training and two images (XXX_7–XXX_8) reserved for testing. The complete data partitioning is presented in **Table 3**. A part of the FVC2004 Fingerprint Database is shown in **Figure 3**.

Table 3. Description of the Fingerprint dataset

Database	Individual Range	Total Individuals	Total Training set	Total Testing set	Total Data
DB1	person_01 - person_10	10	60	20	80
DB2	person_01 - person_10	10	60	20	80
DB3	person_01 - person_10	10	60	20	80
DB4	person_01 - person_10	10	60	20	80
Total		40	240	80	320

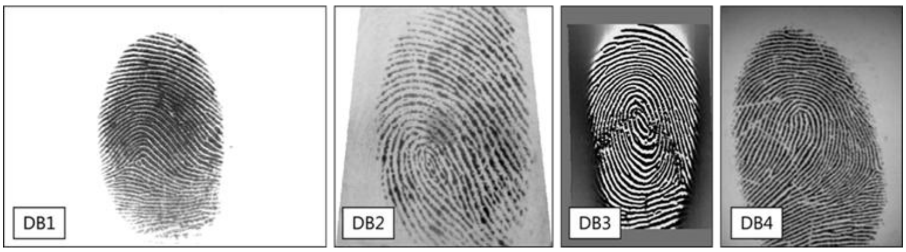

Figure 3. Examples of FVC2004 Fingerprint Database

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2.2. Preprocessing

Preprocessing was conducted separately for four biometric data subsets: ECG_TRAIN, ECG_TEST, Fingerprint_TRAIN, and Fingerprint_TEST. Both train and test subsets were denoised for ECG signals using a Butterworth band-pass filter within the 0.5–45 Hz frequency range [33], preserving relevant cardiac components while removing low- and high-frequency artifacts.

For fingerprint images, the preprocessing stage involved three sequential steps [34]. First, enhancement was applied to clarify the ridge and valley structures by improving image contrast and reducing noise caused by varying finger conditions such as dirt, dryness, moisture, or scars. Next, binarization converted the images into a binary format, representing ridges as black pixels and valleys as white pixels, simplifying the image representation and facilitating subsequent feature extraction. Finally, thinning was performed as a morphological operation to reduce ridge thickness to a single-pixel skeleton, ensuring that minutiae points, such as ridge endings and bifurcations, could be extracted accurately.

2.3. Feature Extraction

After preprocessing, feature extraction was conducted separately for each modality. For ECG signals, fixed-length segmentation was applied to produce feature vectors of 500, 5000, 7000, and 10,000 dimensions, preceded by R-peak detection to ensure feature stability and informativeness [18]. For fingerprint images, three widely adopted Convolutional Neural Network (CNN) architectures VGG16, ResNet50, and DenseNet121 were employed to extract discriminative representations [35]. These models generated feature vectors of 512, 2048, and 1024 dimensions, respectively, reflecting each network's increasing representational depth and complexity.

2.4. Feature Fusion

Extracted features from ECG and fingerprint modalities were combined using feature-level fusion [36]. Early fusion was implemented through direct vector concatenation, mathematically expressed as:

$$F_{fused} = \left[F_{ECG} \,||\, F_{Fingerprint}\right] \qquad (1)$$

where $F_{\mathrm{ECG}} \in \mathbb{R}^{m}$and $F_{\mathrm{FP}} \in \mathbb{R}^{n}$ represent the feature vectors of ECG and fingerprint modalities respectively, and ‖denotes the concatenation operation resulting in a fused vector $F_{\mathrm{fused}} \in \mathbb{R}^{m+n}$. This unified multimodal representation integrates physiological information from ECG signals and spatial fingerprint characteristics into a single embedding. Fusion was performed separately for training and testing sets to maintain distribution consistency.

2.5. Training dan Testing

The training of classification models was conducted using the fused training dataset, employing several deep learning algorithms to compare the performance of the multimodal biometric identification approach. The first model, the Multi-Layer Perceptron (MLP), is a feedforward neural network consisting of an input layer, one or more hidden layers, and an output layer. MLP processes input features through linear transformations followed by nonlinear activation functions applied layer by layer to generate final predictions [36], [37], [38]. The architecture of the MLP model is illustrated in **Figure 4**.

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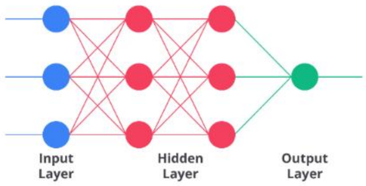

Figure 4. Multi-Layer Perceptron Architecture

The second model, the Long Short-Term Memory (LSTM) network, is a Recurrent Neural Network (RNN) specifically designed to process sequential data while preserving long-term dependencies. LSTM employs memory cells and gating mechanisms—including input, forget, and output gates—to regulate information flow over time, making it particularly effective for capturing temporal patterns in signals such as ECG [39], [40], [41]. The architecture of the LSTM model is presented in **Figure 5**.

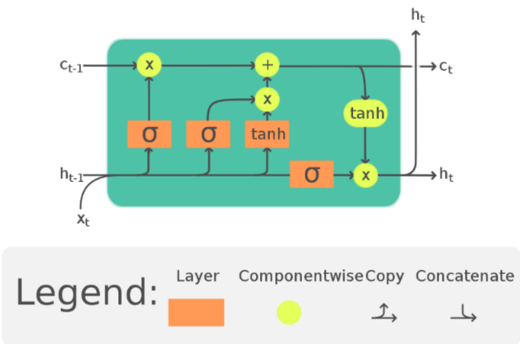

Figure 5. Long Short-Term Memory Architecture

The third model, the Graph Convolutional Network (GCN), extends traditional convolutional operations to graph-structured data. GCN aggregates feature information from neighboring nodes within a graph to learn high-level data representations characterized by relational dependencies [8], [42]. The structure of the GCN model is shown in **Figure 6**.

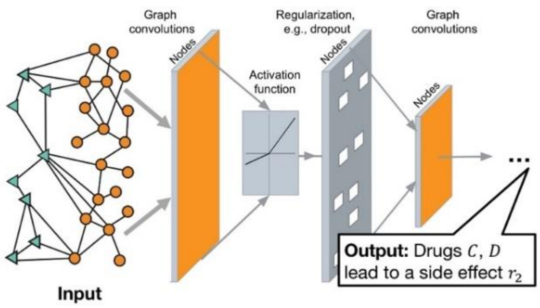

Figure 6. Graph Convolutional Network Architecture

Finally, the Graph Attention Network (GAT) enhances GCN by incorporating a self-attention mechanism that assigns adaptive weights to neighboring nodes during aggregation. This enables GAT to focus on the most informative relationships within a graph, improving its ability to extract discriminative representations based on the relative contributions of each neighbor [43], [44]. The architecture of the GAT model is depicted in **Figure 7**.

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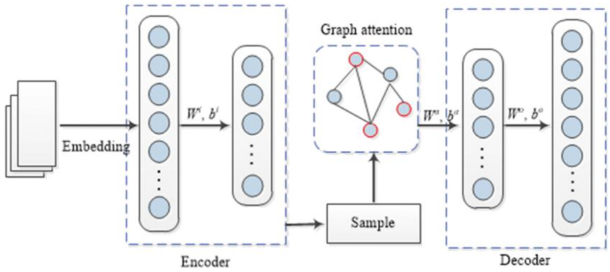

Figure 7. Graph Attention Network Architecture

2.6. Evaluation

The performance of each model was evaluated using classification accuracy as the primary metric [45], [46]. Accuracy was selected because the dataset was balanced across all classes, with an equal number of samples per subject in both training and testing sets. This eliminates class imbalance bias and makes accuracy a reliable indicator of model performance. The evaluation process was conducted by computing the accuracy on the test set based on the predicted class labels generated by each model [45]. Classification accuracy was calculated using the standard formula:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (2)$$

where TP, TN, FP, and FNrepresent true positives, true negatives, false positives, and false negatives, respectively. The accuracy value was obtained by comparing the predicted labels with the ground-truth labels using the accuracy_score function [46]. The evaluation results revealed notable variations in performance, which depended on the combination of ECG feature dimensions, fingerprint feature representations, and the chosen CNN architecture and classification algorithm. Although accuracy was the only metric explicitly calculated, the results provide a general indication of the effectiveness of each model in classifying the fused multimodal features derived from ECG and fingerprint data.

3. RESULT

This section presents the results of the entire experimental workflow, including preprocessing, feature extraction, feature fusion, and classification.

3.1. Post-Preprocessing Data Quality

In the ECG preprocessing stage, noise was removed using a Butterworth band-pass filter in the frequency range of 0.5–45 Hz, producing a clean dataset that retained the relevant cardiac signal components. An example of the ECG signal after preprocessing is shown in **Figure** 8. Similarly, the fingerprint preprocessing stage involved enhancement, binarization, and thinning to improve ridge and valley visibility and optimize feature extraction. Examples of preprocessed fingerprint images are presented in **Figure 9**.

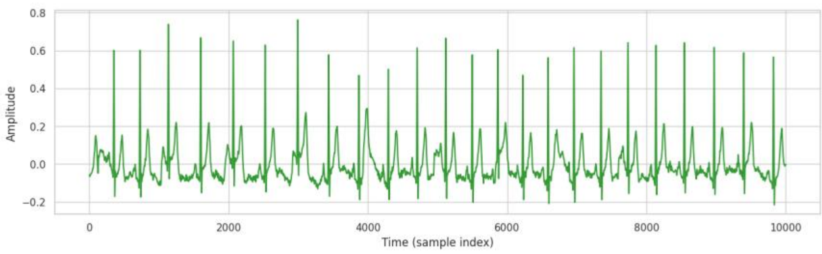

Figure 8. Example of ECG Signal after Preprocessing

Jurnal Teknik Informatika (JUTIF)
P-ISSN: 2723-3863
E-ISSN: 2723-3871

DOI: https://doi.org/10.52436/1.jutif.2025.6.6.5299

Figure 9. (a) Fingerprint Image after CLAHE Enhancement, (b) Fingerprint Image after Otsu Binarization, and (c) Fingerprint Image after Thinning (Skeletonization)

3.2. Extracted Feature Profiles

Following preprocessing, feature extraction was performed separately for each modality. For the ECG dataset, R-peaks were detected and fixed-length segmentation was applied, generating feature vectors of 500, 5000, 7000, and 10,000 dimensions. Three widely used CNN architectures VGG16, ResNet50, and DenseNet121 were employed for fingerprint images, resulting in feature vectors of 512, 2048, and 1024 dimensions, respectively.

3.3. Feature-Level Fusion Summary

After extraction, features from both modalities were concatenated to form the fused multimodal dataset, as summarized in **Table 4**.

Table 4. Description of Feature Fusion Results

Fingerprint Feature Extraction	Number of Fingerprint Features	Number of ECG Features	Total Combined Features
VGG16	512	500	1012
		5000	5512
		7000	7512
		10000	10512
ResNet50	2048	500	2548
		5000	7048
		7000	9048
		10000	12048
DenseNet121	1024	500	1524
		5000	6024
		7000	8024
		10000	11024

3.4. Classification

The fused features were then classified using four deep learning algorithms: Multi-Layer Perceptron (MLP), Long Short-Term Memory (LSTM), Graph Convolutional Network (GCN), and Graph Attention Network (GAT). The comparative classification performance of these models across different CNN feature extractors is reported in **Table 5**.

P-ISSN: 2723-3863
https://jutif.if.unsoed.ac.id
E-ISSN: 2723-3871
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Table 5. Comparison of Accuracy for Each Model

Fingerprint Feature Extraction	Number of Fingerprint Features	Number of ECG Features	Deep Learning Algorithm	Accuracy (%)
VGG16	512	500	GCN	46.25%
			GAT	41.25%
			MLP	91.25%
			LSTM	65.00%
		5000	GCN	66.25%
			GAT	57.50%
			MLP	93.75%
			LSTM	95.00%
		7000	GCN	67.50%
			GAT	61.25%
			MLP	95.00%
			LSTM	98.75%
		10000	GCN	75.00%
			GAT	62.50%
			MLP	95.00%
			LSTM	97.50%
ResNet50	2048	500	GCN	32.50%
			GAT	18.75%
			MLP	83.75%
			LSTM	78.75%
		5000	GCN	60.00%
			GAT	58.75%
			MLP	97.50%
			LSTM	98.25%
		7000	GCN	62.50%
			GAT	60.00%
			MLP	97.25%
			LSTM	98.75%
		10000	GCN	70.00%
			GAT	23.75%
			MLP	97.50%
			LSTM	96.25%
DenseNet121	1024	500	GCN	32.50%
			GAT	23.75%
			MLP	92.50%
			LSTM	85.00%
		5000	GCN	71.25%
			GAT	58.75%
			MLP	96.25%
			LSTM	95.00%
		7000	GCN	67.50%
			GAT	65.00%
			MLP	98.75%
			LSTM	97.50%
		10000	GCN	70.00%
			GAT	62.50%
			MLP	95.00%
			LSTM	93.75%

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4. DISCUSSIONS

This study proposes a multimodal biometric identification system by integrating electrocardiogram (ECG) signals and fingerprint features to enhance classification accuracy. The primary objective is to evaluate the effectiveness of three CNN-based feature extractors VGG16, ResNet50, and DenseNet121 in combination with four classification algorithms, namely MLP, LSTM, GCN, and GAT. Experimental results demonstrate that the proposed multimodal fusion approach significantly improves identification performance, achieving the highest accuracy when using 7000 ECG features. The best configurations were obtained with VGG16 + LSTM and ResNet50 + LSTM, both reaching an accuracy of 98.75%, while DenseNet121 + MLP achieved a comparable accuracy of 98.75%. **Figure 10** illustrates the average performance of each algorithm evaluated in this study, showing that MLP and LSTM consistently outperform GCN and GAT, with MLP demonstrating slightly better overall performance than LSTM. These findings highlight the importance of aligning classifier selection with the nature of extracted features, where LSTM effectively captures temporal dependencies in sequential ECG data. In contrast, MLP excels in processing high-dimensional and structured feature embeddings.

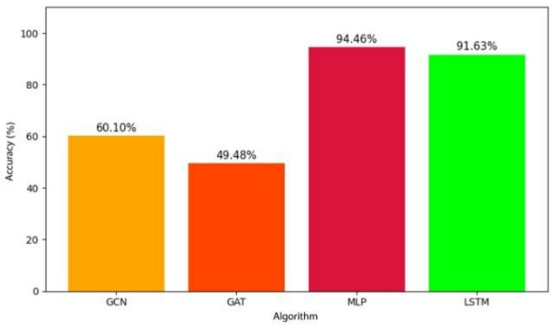

Figure 10. Comparison of average accuracy by algorithm

To better understand why MLP and LSTM outperform graph-based models, an in-depth analysis of classifier performance is presented. The superior performance of MLP and LSTM compared to GCN and GAT in multimodal biometric classification is primarily due to the nature of the extracted features. ECG signals contain strong temporal dependencies, which LSTM effectively captures through its memory cells and gating mechanisms, enabling superior sequential pattern learning and achieving state-of-the-art accuracy [47], [48], [49]. Meanwhile, MLP performs optimally on high-dimensional, structured embeddings generated by CNNs, efficiently processing fixed-length feature vectors without requiring temporal modeling [50], [51]. In contrast, GCN and GAT are designed for data with explicit graph structures, whereas CNN-derived embeddings from ECG and fingerprint data are continuous vectors without inherent topological relationships [44]. As a result, forcing such embeddings into graph representations without adaptive graph construction limits their discriminative power, explaining the inferior performance of graph-based models in this study.

To contextualize the contribution of this work, **Table 6** presents a comparison with several prior studies on unimodal and multimodal biometric systems. Unlike traditional approaches that use unimodal data or late fusion, the proposed method adopts early fusion and deep learning-based classification, achieving the highest reported accuracy. This demonstrates the potential of combining ECG and fingerprint features at the representation level to build more discriminative and robust biometric systems.

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Table 6. Comparison with Related Works

Reff	Biometric	Fusion Type	Classifier	Best Accuracy (%)
[52]	ECG	-	1D-CNN + PQRST Segment	91.57%
[53]	Fingerprint	-	CNN + DeepFKTNet	98.9%
[16]	ECG + Fingerprint	Sequential Fusion + Parallel Fusion	Neural Network (NN), Fuzzy Logic (FL), Linear Discriminant Analysis (LDA), CNN	98.5%
[22]	ECG + Fingerprint	Early Fusion	EfficientNet-B3 + 2D-CNN	95.32%
Our Proposed Method	ECG + Fingerprint	Early Fusion	- MLP (Multilayer Perceptron) - LSTM (Long Short-Term Memory) - GCN (Graph Convolutional Network) - GAT (Graph Attention Network)	98.75% (LSTM and MLP)

As presented in Table 6, the proposed method achieves the highest accuracy among existing multimodal approaches. While fingerprint-only systems, such as DeepFKTNet, reached a slightly higher accuracy of 98.9%, unimodal ECG models using 1D-CNN and PQRST segmentation attained only 91.57%. Other multimodal systems based on traditional fusion techniques achieved up to 98.5%, and early fusion methods using EfficientNet-B3 with 2D-CNN reported 95.32%. In comparison, our proposed method, which integrates ECG and fingerprint features through early fusion and utilizes LSTM and MLP classifiers, achieves 98.75% accuracy. These results demonstrate that our system provides a competitive and balanced performance, combining the strengths of multiple biometric sources to deliver robust and highly accurate identity verification.

To further analyze the contribution of each CNN-based feature extractor, this study evaluated fingerprint feature extraction using VGG16, ResNet50, and DenseNet121, which generated 512, 2048, and 1024 feature dimensions, respectively. The experimental results demonstrate that the best-performing models were obtained using VGG16 + LSTM, ResNet50 + LSTM, and DenseNet121 + MLP. As shown in **Figure 11**, the average performance across models based on the CNN architecture used for feature extraction indicates that VGG16-based features consistently achieved the highest accuracy, despite producing the smallest feature dimension.

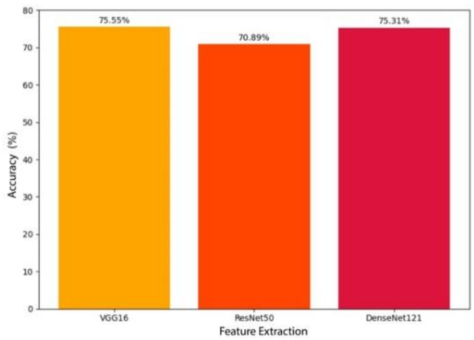

Figure 11. Comparison of average classification performance by fingerprint feature

This superior performance of VGG16 can be attributed to the nature of its extracted representations. Although VGG16 produces only 512-dimensional embeddings, these representations tend to be more compact and discriminative than those derived from deeper architectures such as ResNet50 and DenseNet121. VGG16 employs stacked convolutional layers with small 3×3 kernels

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repeatedly applied within each block, enabling the extraction of localized and focused spatial features. Such compact feature representations are well-suited for capturing the fine-grained fingerprint texture patterns while maintaining computational efficiency. Moreover, these smaller and more discriminative embeddings simplify the learning process for classification models like LSTM and MLP, allowing them to effectively learn decision boundaries without the overhead of processing excessively high-dimensional vectors.

In contrast, ResNet50 and DenseNet121 generate larger embeddings of 2048 and 1024 dimensions, respectively. While high-dimensional embeddings are typically richer in information, they may introduce the risk of overfitting, especially when the training dataset size is relatively limited. VGG16's 512-dimensional features balance representational richness and model complexity better, resulting in improved generalization performance on small to medium-sized multimodal datasets.

In this study, an investigation was also conducted regarding the variation in the number of ECG signal features. The total number of features in the ECG data is 10,000. As mentioned earlier, this study proposes a segmentation technique starting from the first R-peak with three variations of feature lengths: 500, 5000, and the longest at 7000. **Figure 12** illustrates the model's performance using ECG signal inputs with these four feature length variations.

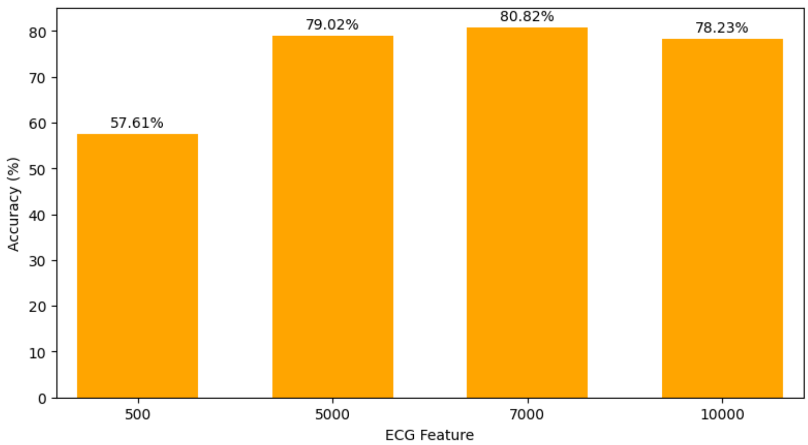

Figure 12. Comparison of average performance by length of the ECG signal

Generally, the model's performance is proportional to the length of the ECG signal features, ranging from 500 to 7000. These three feature variations share a common characteristic: they are segmented starting from the first R-peak. The results show that using more R-peak-based features improves the classification algorithm's ability to recognize patterns. On the other hand, using the full-length signal with 10,000 features results in lower performance compared to classification models that utilize 7000 features.

Segmenting the ECG signal starting from the R-peak yields better classification performance than using the entire ECG signal. This is because the R-peak is the most stable fiducial marker within a cardiac cycle, indicating the beginning of the QRS complex, representing the most informative part of the signal [54], [55]. By segmenting and aligning the signal based on the R-peak, the model can better focus on diagnostically relevant regions while reducing noise and irrelevant variability in other parts of the signal. Conversely, using the entire ECG signal introduces feature redundancy, increases computational overhead, and raises the risk of overfitting, as less-informative regions may overshadow the critical features needed for accurate classification [56], [57].

Despite the promising results achieved in multimodal biometric identification using ECG and fingerprint data, several limitations remain. First, graph-based classifiers such as GCN and GAT yielded inferior performance compared to MLP and LSTM, likely due to the absence of adaptive graph

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construction mechanisms that could better exploit the continuous feature embeddings derived from CNNs. Without such optimization, valuable discriminative information within the multimodal features may remain underutilized. Second, this study did not investigate the effect of noise on ECG signals, even though such disturbances are common in practical settings and can substantially degrade classification reliability. Third, the ECG signal segmentation was conducted based on a single R-peak reference point. While effective, incorporating R–R–R interval-based segmentation could provide richer temporal context across multiple cardiac cycles, potentially improving signal representation and model performance. Lastly, the use of high-dimensional feature embeddings—particularly those generated from CNN-based fingerprint and ECG inputs—may increase the risk of overfitting and sensitivity to noise. Future work may benefit from implementing feature selection or dimensionality reduction methods to enhance model generalization, reduce computational complexity, and maintain classification accuracy.

From a practical standpoint, the proposed method offers a valuable contribution to biometric security systems by increasing resistance to spoofing and impersonation. The combination of ECG signals, which are inherently liveness-based, with fingerprint patterns enhances the robustness and reliability of identity verification processes. This is particularly relevant in real-world applications such as secure access control, financial authentication, and healthcare systems, where high accuracy and resilience to attacks are critical requirements.

5. CONCLUSION

This study proposed a multimodal biometric identification system integrating electrocardiogram (ECG) signals and fingerprint features to investigate classification accuracy using various CNN-based feature extractors and classifiers. Specifically, three CNN architectures—VGG16, ResNet50, and DenseNet121—were combined with four classification algorithms: MLP, LSTM, GCN, and GAT. Experimental results demonstrated that the proposed multimodal fusion approach achieved the highest classification accuracy of 98.75% using VGG16 + LSTM and ResNet50 + LSTM, while DenseNet121 + MLP achieved a comparable accuracy of 98.75%. Across all evaluated classifiers, MLP and LSTM consistently outperformed GCN and GAT, underscoring the importance of aligning classifier selection with the characteristics of extracted features. Moreover, segmenting ECG signals starting from the first R-peak yielded better classification performance than using the full-length ECG signals, demonstrating that focusing on diagnostically informative regions within the cardiac cycle improves classification outcomes.

Despite these promising results, several limitations were identified. First, graph-based models such as GCN and GAT exhibited lower performance than MLP and LSTM, partly due to the absence of adaptive graph construction, which could exploit CNN-derived continuous feature representations more effectively. Second, this study did not analyze the impact of noise on ECG signals, even though noise is commonly encountered in real-world biometric applications and can significantly affect classification accuracy. Third, ECG segmentation was performed using only a single R-peak point, potentially limiting the temporal information captured from multiple cardiac cycles. Furthermore, the system produces high-dimensional feature embeddings—especially from CNN-based fingerprint extractors and ECG representations—making the model more susceptible to noise and potential overfitting.

From a security perspective, the proposed system offers a practical and effective solution for biometric authentication by combining liveness-based ECG signals with unique fingerprint textures. This fusion enhances the system's ability to resist spoofing attacks, identity impersonation, and unauthorized access, making it highly suitable for implementation in high-security domains such as financial transactions, access control, and critical infrastructure protection.

Future work is encouraged to overcome the current limitations and enhance the robustness and scalability of multimodal biometric identification systems. Implementing adaptive graph construction could significantly improve the performance of graph-based classifiers by capturing complex intermodal relationships more effectively. Additionally, evaluating preprocessing techniques that are resilient to noise, as well as testing model performance under different signal quality scenarios, would offer valuable insights for practical applications. Introducing R–R–R-based segmentation may further enrich the temporal features of ECG signals by utilizing information from multiple cardiac cycles, thereby improving classification outcomes. Moreover, applying dimensionality reduction or feature selection approaches—such as PCA, LDA, or autoencoder-based methods—can help simplify high-dimensional embeddings, lower computational overhead, and boost the model's ability to generalize without sacrificing accuracy.

ACKNOWLEDGEMENT

The authors sincerely thank Lambung Mangkurat University, Indonesia, for providing access to their laboratory facilities. We sincerely appreciate the financial support from the National Research Program of Indonesia's Ministry of Higher Education, Science, and Technology. Main Contract Number: 075/C3/DT.05.00/PL/2025, Derivative Contract Number: 1432/UN8.2/PG/2025.

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