Bulletin of Electrical Engineering and Informatics
Vol. 15, No. 3, June 2026, pp. 2611~2624
ISSN: 2302-9285, DOI: 10.11591/eei.v15i3.10541

Feature extraction and machine learning methods for biometric recognition based on fusion of ECG and fingerprint

Hafiz Ilhami[1], Dodon Turianto Nugrahadi[1], Mohammad Reza Faisal[1], Irwan Budiman[1], Andi Farmadi[1], Dwi Kartini[1], Puput Dani Prasetyo Adi[2], Jumadi Mabe Parenreng[3]
[1]Department of Computer Science, Faculty of Mathematics and Natural Sciences, Lambung Mangkurat University, Banjarmasin, Indonesia
[2]Telecommunication Research Center, National Research and Innovation Agency, Jakarta, Indonesia
[3]Department of Informatics and Computer Engineering, Faculty of Engineering, State University Makassar, Makassar, Indonesia

Article Info

Article history:

Received Apr 21, 2025
Revised Mar 16, 2026
Accepted Mar 31, 2026

Keywords:

Biometric multimodal
Electrocardiogram
Feature extraction
Fingerprint
Machine learning

ABSTRACT

This research introduces a multimodal biometric authentication framework by amalgamating electrocardiogram (ECG) and fingerprint modalities through the utilization of diverse feature extraction methodologies and machine learning classifiers. The proposed methodology aspires to augment precision and mitigate spoofing vulnerabilities in contrast to traditional single-modality systems. Among the feature extraction techniques assessed—grayscale, binary, Sobel edge detection, and minutiae—Naïve Bayes (NB) in conjunction with minutiae features exhibited superior performance, attaining an accuracy rate of 96.25%. Supplementary experiments employing random forest (RF) and support vector machine (SVM) also revealed commendable classification efficacy, underscoring the robustness of the fusion methodology. This investigation provides a pragmatic and secure biometric framework by harnessing complementary biometric characteristics to enhance authentication dependability. The proposed system presents promising applications in real-world contexts, particularly concerning mobile security and healthcare access control. Future research endeavors will tackle challenges associated with ECG signal variability, computational efficiency, and extensive deployment.

Corresponding Author:

Dodon Turianto Nugrahadi
Department of Computer Science, Faculty of Mathematics and Natural Sciences
Lambung Mangkurat University
A. Yani St., KM 36, Banjarbaru, South Kalimantan 70174, Indonesia
Email: dodonturianto@ulm.ac.id

1. INTRODUCTION

Biometric systems have become an integral part of modern security technology, primarily aiming to provide a safer and more efficient method for identity authentication [1]. Various types of biometrics, such as fingerprints, facial recognition, voice, and iris recognition, have been widely used for identity verification [2]. Although fingerprints are one of the most commonly used biometric modalities, fingerprint-based systems are vulnerable to various potential attacks, such as spoofing or data manipulation [3]. To address these vulnerabilities, researchers have explored alternative biometric modalities that are more resilient against forgery. On the other hand, electrocardiograms (ECG) have been identified as a promising biometric modality due to each individual's unique heart signal patterns. However, their application in biometric authentication remains limited. One of the main advantages of ECG over other biometrics, such as fingerprints, facial recognition, handwriting, and iris recognition, is its higher level of security, as it is difficult to counterfeit. ECG signals originate from the heart's electrical activity, which cannot be easily imitated or manipulated like physical biometric characteristics. Despite its advantages, ECG alone has limitations, including signal variability due to physiological conditions and acquisition challenges. To mitigate these issues, combining ECG with another established biometric modality, such as fingerprints, presents an opportunity to develop a more robust authentication system. The uniqueness and resistance of ECG to spoofing make it a potential choice for enhancing security in biometric authentication systems [4]. The problem statement in this study is how to combine two biometric modalities, ECG and fingerprint, to develop a more accurate and reliable identity recognition system using machine learning algorithms [5].

Previous studies on multimodal biometric systems have demonstrated that integrating multiple biometric sources can improve classification accuracy and system reliability [6]. However, there is limited research specifically on the combination of ECG and fingerprints. While some studies have explored multimodal systems with ECG and facial recognition [7], their applicability in various security contexts remains an open question. By integrating ECG and fingerprint data, this study aims to bridge this gap and provide a comparative evaluation of their effectiveness as a combined biometric authentication system. The selection of these two biometrics is based on their complementary characteristics: fingerprints offer high recognition accuracy and are widely used in authentication systems, while ECG provides an additional security layer due to its difficulty to counterfeit. By integrating these modalities, we aim to create a system that balances usability and security.

Several challenges exist in developing a multimodal biometric authentication system based on machine learning using different feature extraction techniques for ECG and fingerprint data. This process faces two main challenges: determining the optimal feature extraction technique to effectively integrate biometric data and selecting a machine learning algorithm capable of providing optimal classification performance based on the combined feature set from both biometric modalities [8].

This study uses five feature extraction approaches to improve fingerprint classification accuracy: grayscale, binary, edge, minutiae, and a combination of all these methods. Each feature extraction method has unique characteristics that can affect classification performance. Grayscale features preserve texture information from the fingerprint image [9], and binary feature extraction extracts binary patterns from the image [10]. Edge feature extraction focuses on the contours and boundaries of the fingerprint [11]. Minutiae feature extraction generates detailed points, such as bifurcations and ridge endings, from fingerprint patterns [12]. Combining all these methods aims to merge the advantages of each approach to improve classification accuracy.

The proposed approach in this study is a multimodal approach that combines information from ECG and fingerprints to enhance individual identification accuracy [13]. In this experiment, we implement and compare four machine learning algorithms: random forest (RF) [14], support vector machine (SVM) [15], Naïve Bayes (NB) [16], and k-nearest neighbors (KNN) [17]. The role of machine learning in multimodal biometric systems is crucial, as it determines how effectively the extracted features from different biometrics can be integrated to achieve high classification accuracy. By evaluating multiple algorithms, this study aims to identify the most suitable classifier for ECG-fingerprint fusion [18].

The originality of this research is manifested in the integration of two biometric modalities—ECG and fingerprint—that have historically been employed independently, as well as in offering a comparative analysis of classical machine learning algorithms pertinent to their fusion. This methodology not only augments authentication accuracy but also enhances resilience against spoofing and other security threats. Ultimately, the proposed approach is anticipated to facilitate the advancement of secure, efficient, and scalable biometric authentication systems that are applicable to real-world contexts such as mobile device security, healthcare access, and the protection of critical infrastructure.

The remainder of this paper is organized as follows: section 2 (dataset and method) presents the datasets used in this study, the preprocessing steps, feature extraction techniques, fusion strategy, and the machine learning classifiers applied. Section 3 (result and discussion) reports the experimental findings and provides an in-depth analysis of the performance of different feature extraction and classification approaches. Section 4 (conclusion) summarizes the key contributions of this research, discusses its practical implications, and outlines potential directions for future work.

2. DATASET AND METHOD

This section describes the dataset used in this study and the methods applied for feature extraction and classification in the multimodal biometric authentication system. Figure 1 presents the end-to-end workflow of the proposed multimodal biometric classification framework, integrating ECG signals and fingerprint data from dataset preparation through preprocessing, feature extraction, and feature-level fusion to final classification. The diagram highlights the alternative fingerprint feature representations (grayscale, binary, edge, minutiae, and combined features) and the comparative evaluation of multiple classifiers (RF, SVM, NB, and KNN with different k values) using a consistent train–test split and 5-fold cross-validation. This workflow directly reflects the study's main findings by emphasizing how normalization and discriminative feature choices (particularly minutiae) contribute to improved accuracy and reduced biometric error rates false acceptance rate/false rejection rate/equal error rate (FAR/FRR/EER) within the proposed framework.

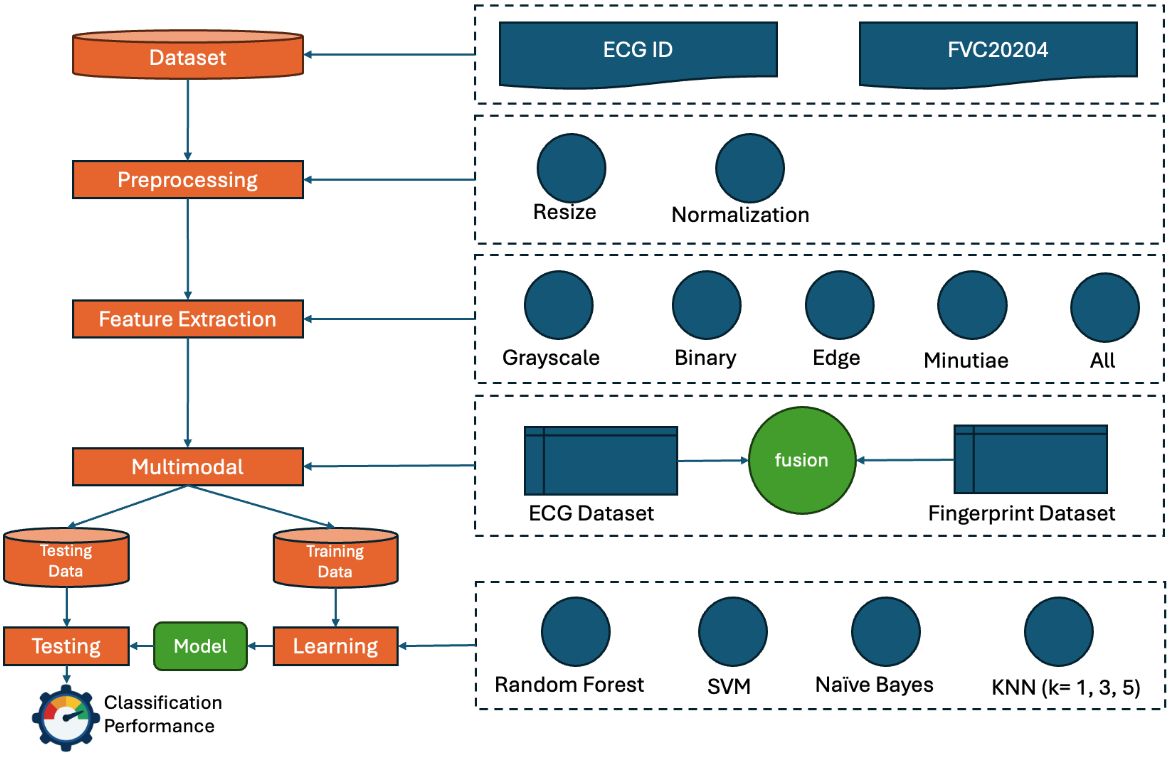


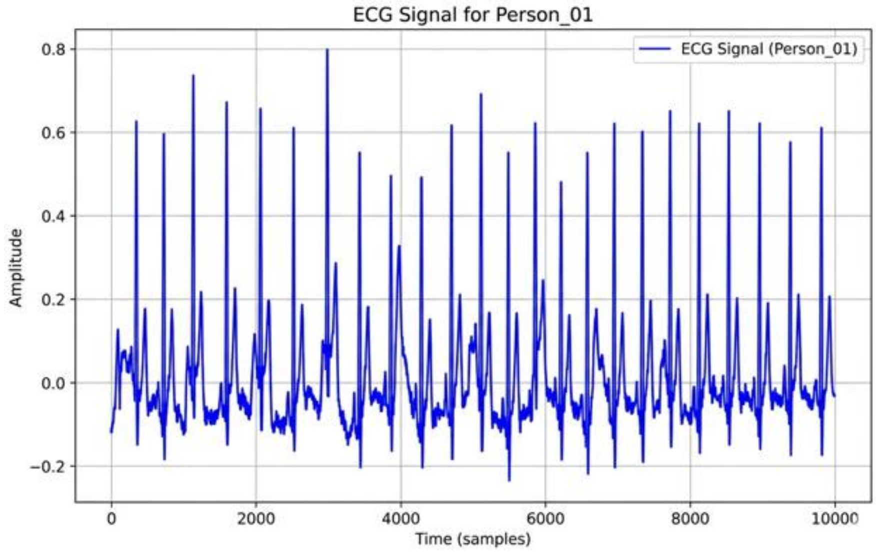
Figure 1. Research procedure program

2.1. Data collection

The data used in this study consists of two main sources, as presented in Figure 2. ECG data was obtained from the ecg_id_raw_filtered subset of the ECG-ID dataset, as shown in Figure 2(a), which contains human heart signal recordings filtered to remove noise [19]. Table 1 presents the ECG dataset, which includes 10,000 features used for training and testing. Each individual has eight data samples, divided into ECG_TRAIN with six samples and ECG_TEST with two samples [20]. Second, fingerprint data is taken from the public FVC2004 dataset [21], as shown in Figure 2(b), which contains fingerprint images from various individuals. Integrating these two data types in this study is expected to improve the accuracy and reliability of biometric predictions through a multimodal approach.

Table 2 presents the division of data into four distinct databases (DB1-DB4) as part of the data processing and validation. Each database contains ten individuals, ensuring a balanced distribution. Furthermore, each database is divided into two subsets: DB Train, which includes six samples per individual, and DB Test, which includes two samples per individual. This structured division is designed to maintain an optimal balance between training and testing data while minimizing the risk of data leakage during model validation.

The integration of ECG and fingerprint data in this study aims to improve the accuracy and reliability of biometric predictions through a multimodal approach. By combining these two distinct biometric modalities, the system is expected to enhance security levels and provide greater resistance to spoofing attacks compared to unimodal methods.



(a)

(b)

Figure 2. Sample of dataset; (a) Person_01 of ECG signal data and (b) Person_01 of FVC2004 data

Table 1. ECG data

Person	ECG_TRAIN records	ECG_TEST records	Number of ECG features
person_01	6	2	10
person_02	6	2	10
person_03	6	2	10
person_04	6	2	10
person_05	6	2	10
…	…	…	…
person_35	6	2	10
person_36	6	2	10
person_37	6	2	10
person_38	6	2	10
person_39	6	2	10
person_40	6	2	10

Table 2. Fingerprint data

Database	Individual range	Number of individuals	Train set (6 images/individual)	Test set (2 images/individual)	Total data per DB
DB1	person_01 - person_10	10	60	20	80
DB2	person_11 - person_20	10	60	20	80
DB3	person_21 - person_30	10	60	20	80
DB4	person_31 - person_40	10	60	20	80
Total	person_01 - person_40	40	240	80	320

2.2. Preprocessing

The preprocessing stage is performed to prepare the data for feature extraction. Signal normalization and filtering are applied using appropriate methods. For fingerprint data, images are resized to 200×200 px to maintain dimensional consistency [22]. Before combining features from different data sources (ECG), each modality's data must be normalized to ensure a uniform scale [23]. This normalization process uses StandardScaler, transforming the data into a mean of 0 and a standard deviation of 1 [24].
The feature normalization formula is as (1):

$$X' = \frac{(X - \mu)}{\sigma} \quad (1)$$

where X is the original feature value from the ECG data, μ is the mean of the dataset, and σ is the standard deviation of the ECG data. The normalized feature, denoted as X', is obtained by subtracting the mean μ from the original data X and dividing it by the standard deviation σ.
ECG data normalization is performed using (2):

$$X'_{ECG} = \frac{X_{ECG} - \mu_{ECG}}{\sigma_{ECG}} \quad (2)$$

where X'_{ECG} is the normalized ECG data obtained by subtracting the mean μ_{ECG} from the original ECG data X_{ECG} and then dividing it by the standard deviation σ_{ECG} of the ECG data.
Fingerprint data normalization is performed using (3):

$$X'_{fingerprint} = \frac{X_{fingerprint} - \mu_{fingerprint}}{\sigma_{fingerprint}} \quad (3)$$

where $X'_{fingerprint}$ is the normalized fingerprint data obtained by subtracting the mean $\mu_{fingerprint}$ from the original fingerprint data $X_{fingerprint}$ and then dividing it by the standard deviation $\sigma_{fingerprint}$ of the fingerprint data.

2.3. Feature extraction

At this stage, essential features are extracted from the preprocessed fingerprint data. This feature extraction process includes several key representations, such as grayscale, binary, edge detection (using the Sobel filter), and minutiae. The grayscale conversion is applied to fingerprint images to reduce computational complexity while preserving crucial texture details. This method helps in maintaining contrast variations between ridges and valleys, which are fundamental for feature extraction and fingerprint classification [9], while binarization transforms the grayscale image into a black-and-white format, simplifying the fingerprint structure and enhancing ridge clarity. This step is critical for segmentation and thresholding processes, ensuring more effective extraction of fingerprint patterns [10]. The Sobel filter is employed to highlight ridge edges, enhancing key structural patterns necessary for identification. This technique improves the visibility of fingerprint ridges and valleys by emphasizing significant transitions, making it easier to extract distinguishing features [11]. Additionally, minutiae points, such as ridge bifurcations and terminations, are essential for fingerprint recognition, as they provide unique and invariant features. These points play a critical role in fingerprint matching and biometric authentication, offering high distinctiveness and robustness against noise [12]. Furthermore, all combined features are extracted, integrating grayscale, binary, edge (Sobel filter), and minutiae features into a single representation. Extracting these features is expected to improve the accuracy and reliability of the fingerprint recognition system.

The process described in Figure 3 illustrates the steps involved in feature extraction from fingerprint data, which include several key stages such as dataset processing, grayscale feature extraction, binary feature extraction, edge feature extraction using the Sobel filter, minutiae feature extraction, and extract all combined features. Each type of feature extraction will be added to the training and testing dataset before being stored in CSV format for further analysis [25]. Although this process focuses on fingerprint data processing, future work will expand this approach by integrating ECG data stored in a separate dataset [26]. In this way, both biometric modalities, fingerprint and ECG, will be processed and combined into a multimodal system to enhance the accuracy and reliability of identification. The resulting images from each feature extraction process are shown in Figure 4.

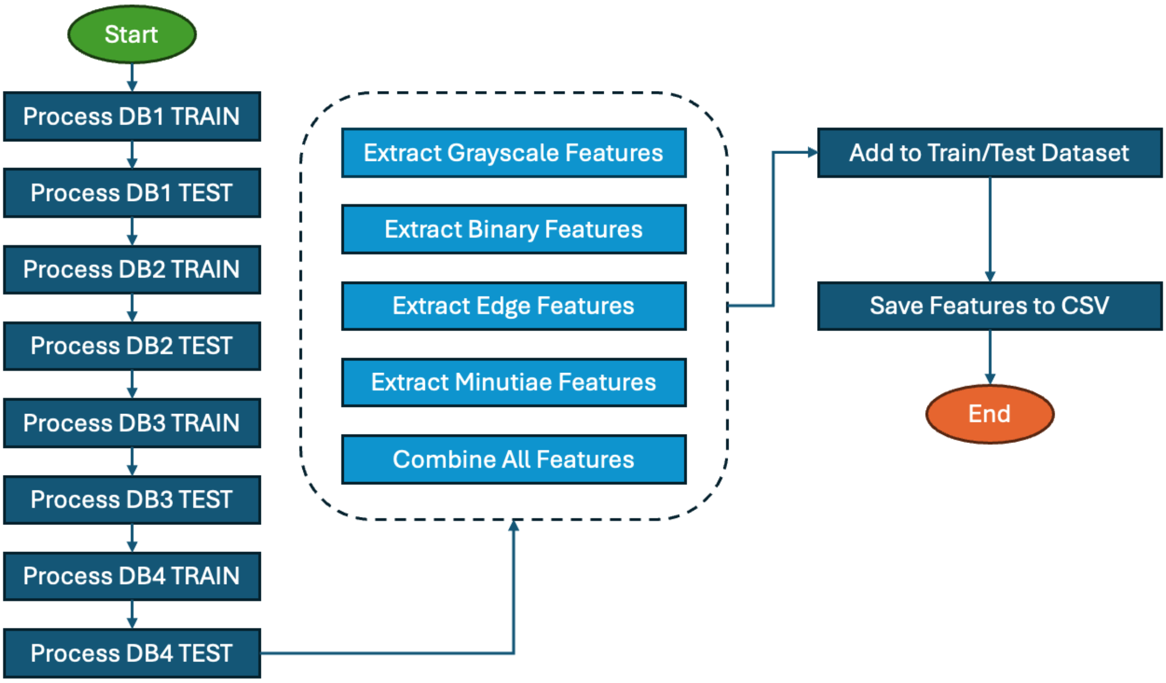


Figure 3. Feature extraction program

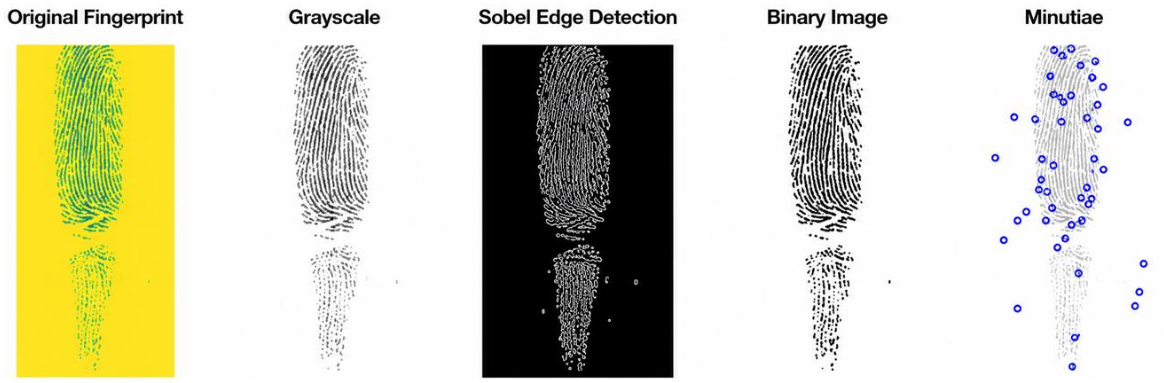


Figure 4. Feature extraction images

2.4. Multimodal

After feature extraction, the ECG and fingerprint data are combined to form a multimodal dataset. Prior to fusion, each feature set is normalized to ensure that all features contribute equally during the learning process and to prevent scale dominance by features with larger numerical ranges. In this study, z-score normalization (standardization) is applied separately to both fingerprint and ECG features. This technique transforms the data to have a mean of zero and a standard deviation of one, thereby improving model stability and classification performance, particularly for distance-based algorithms such as KNN and SVM [27]. Mathematically, the normalization process is expressed as:

$$X' = \frac{X-\mu}{\sigma}$$

where X is the original feature value, μ is the mean of the dataset, and σ is the standard deviation. The normalized feature X' is then used for subsequent fusion.

After normalization, the fingerprint ($X'_{\text{Fingerprint}}$) and ECG (X'_{ECG}) feature vectors are concatenated to form the multimodal dataset, which is then divided into training and testing sets using 5-fold cross validation

[27]. The learning process employs machine learning algorithms such as RF, SVM, NB, and KNN with parameters $n = 1$, $n = 3$, and $n = 5$ to identify the best-performing model.
Mathematically, the feature fusion can be expressed as (4):

$$X_{Multimodal} = [\ X'_{Fingerprint}\ |\ X'_{ECG}\ ] \quad (4)$$

where $X'_{Fingerprint}$ represents the fingerprint features after normalization with dimension $d_{Fingerprint}$, X'_{ECG} represents the ECG features after normalization with dimension d_{ECG} and $X_{Multimodal}$ is the multimodal feature vector that combines both data sources.

2.5. Classification accuracy

In this study, classification accuracy is used as the primary evaluation metric to assess individual identification performance based on multimodal biometric data, namely ECG and fingerprints, by applying four machine learning algorithms: RF, SVM, NB, and KNN. The selection of these algorithms is based on their effectiveness in classification tasks. RF utilizes multiple decision trees to improve accuracy and reduce overfitting [14]. SVM is included as it finds an optimal hyperplane to separate classes with the maximum margin, making it effective for biometric classification [15], NB is selected due to its efficiency in handling probabilistic classification under the assumption of feature independence, making it computationally lightweight and suitable for biometric applications [16]. KNN determines the class based on proximity to the KNN [17], with variations of n=1, 3, and 5 to examine the impact of the number of neighbours on classification accuracy. The classification accuracy of these four methods is compared to determine the best model for individual identification using multimodal biometric data. By evaluating accuracy, this study aims to identify the most effective approach for integrating ECG and fingerprint features into a reliable authentication system.

3. RESULTS AND DISCUSSION

3.1. Result

Based on the classification results of multimodal data consisting of ECG and fingerprint features, the model's accuracy was tested using various machine learning algorithms, including RF, SVM, NB, and KNN with different values of k [28]. Accuracy evaluation was conducted to assess how well each algorithm classifies the data using different feature extraction techniques. Table 3 shows the accuracy of each classification model.

The experimental results demonstrate that the minutiae method with NB and the edge Sobel filter with RF both achieved the highest accuracy, reaching 96.25%, with and without normalization. However, the minutiae method stands out as the more efficient option. It extracts unique fingerprint characteristics, such as ridge endings and bifurcations, which are stable and highly representative, making it particularly effective for fingerprint recognition. NB, a probabilistic classifier, excels at classifying independent features efficiently, further enhancing the performance of the minutiae method. On the other hand, the edge Sobel filter detects texture patterns and intensity contrasts in fingerprint images by highlighting edges, while RF, which uses an ensemble of decision trees, captures complex patterns and is robust to noise. While both methods showed optimal performance, the minutiae method is more computationally efficient due to its relatively smaller feature set (200 features versus 40,000 features in the Sobel method). This makes it a more lightweight and practical choice for fingerprint-based biometric systems, especially when computational resources are a concern.

When comparing our approach with other biometric fusion techniques, such as the VGG16 model for face and ECG fusion [7] and the ensemble classifier for iris and ECG fusion [26], our method achieves competitive results, as shown in Table 4. The VGG16-based approach for face and ECG achieved an accuracy of 98.00%, benefiting from the power of deep learning models for feature extraction. Similarly, the ensemble classifier used in the iris+ECG fusion method achieved 95.65%, which is effective but may not offer the same computational efficiency as our method. On the other hand, the cascade decision-level fusion for fingerprint, fingervein, and face recognition [13] achieved the highest accuracy of 99.43%, though it requires processing multiple biometric traits, which may increase computational complexity.

Our fingerprint+ECG fusion approach using feature fusion and an ensemble classifier, offers a balanced solution by combining relatively efficient feature extraction with robust classification. While the VGG16 and cascade fusion techniques achieve higher accuracy, our method strikes a better trade-off between performance and computational cost, making it a strong candidate for practical, resource-efficient biometric systems, as detailed in Table 4.

Table 3. Accuracy of classification models

Extraction feature	Machine learning algorithm	Accuracy (%) with normalization	Accuracy (%) without normalization
Grayscale (40.000) feature	RF	90	**90**
	SVM	**93.75**	21.25
	NB	55	50
	KNN n=1	78.75	16.25
	KNN n=3	62.5	11.25
	KNN n=5	53.75	11.25
Binary (40.000) feature	RF	**93.75**	**95**
	SVM	91.25	43.75
	NB	16.25	13.75
	KNN n=1	80	22.5
	KNN n=3	47.5	13.75
	KNN n=5	46.25	12.5
Edge (sobel filter) (40.000) feature	RF	**96.25**	**96.25**
	SVM	82.5	17.5
	NB	11.25	6.25
	KNN n=1	46.25	3.75
	KNN n=3	38.75	1.25
	KNN n=5	25	6.25
Minutiae (200) feature	RF	95	95
	SVM	95	83.75
	NB	**96.25**	**96.25**
	KNN n=1	93.75	77.5
	KNN n=3	63.75	53.75
	KNN n=5	52.5	42.5
All extraction (120.200) feature	RF	**86.25**	**87.5**
	SVM	68.75	23.75
	NB	16.25	6.25
	KNN n=1	37.5	13.75
	KNN n=3	31.25	6.25
	KNN n=5	23.75	5

Table 4. Comparison with related works

Source	Biometric	Method	Performance accuracy (%)
[7]	Face+ECG	VGG16	98
[26]	Iris+ECG	Ensemble classifier	95.65
[13]	Fingerprint+fingervein+face	Cascade decision level fusion	99.43
Our	Fingerprint+ECG	Feature fusion+ensemble classifier	96.25

3.2. Discussion

This section discusses the experimental results, highlighting the impact of data normalization, feature extraction techniques, and classification algorithms on the model's performance in processing multimodal biometric data.

a. Impact of normalization

Figure 5 delineates the influence of normalization on the efficacy of classification performance. The process of data normalization resulted in a significant augmentation of the mean classification accuracy, ascending from 37.46% to 62.29%, along with a concomitant diminution in both the FAR and the FRR, thereby yielding a lower EER. Through the standardization of feature scales, normalization guarantees that no single feature exerts undue influence over the learning process, thus facilitating the model's capacity to more effectively discern relevant patterns. This phenomenon is particularly pronounced in distance-based algorithms, such as KNN and SVM, which are heavily dependent on feature magnitude. In the absence of normalization, inconsistencies in feature scales can distort distance computations, thereby elevating the FAR and undermining model stability. These observations substantiate the assertion that normalization constitutes an essential component of multimodal biometric preprocessing, enhancing not only accuracy but also the robustness and security performance of the system.

b. Analysis of feature extraction techniques

Figure 6 illustrates a comparative analysis of various fingerprint feature extraction methodologies, both with and without the application of normalization techniques. Among the diverse methodologies evaluated, minutiae-based features demonstrated the highest efficacy, attaining an average accuracy of 82.71% post-normalization alongside the lowest EER of 2.1%, thereby reflecting exceptional discriminative capabilities. Minutiae features, which encapsulate ridge endings and bifurcations, offer a compact yet remarkably distinctive representation of fingerprint characteristics. This is particularly congruent with probabilistic classifiers such as NB, which operate under the assumption of feature independence and exhibit superior performance on lower-dimensional, non-redundant feature collections.

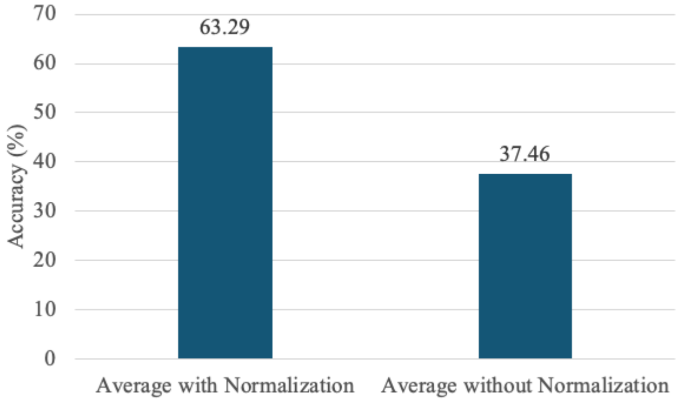


Figure 5. Comparison of average classification accuracy with and without data normalization

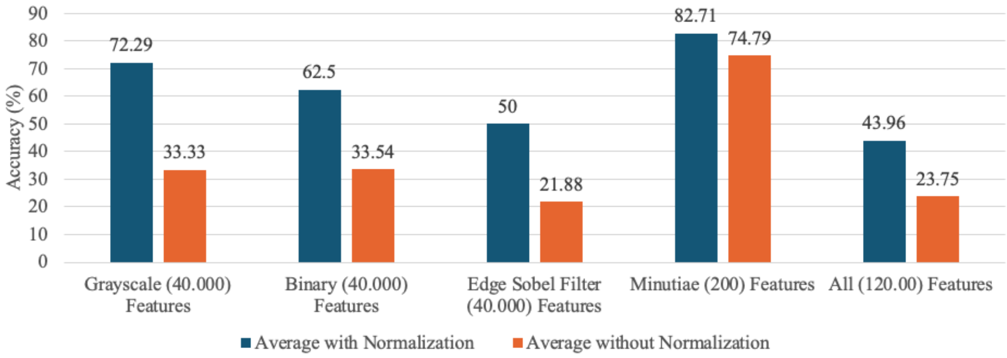


Figure 6. Comparison of average extraction feature with and without data normalization

Conversely, edge detection utilizing the Sobel filter manifested the least effective performance (EER=8.3%), indicating that an exclusive dependence on contour data is inadequate for establishing robust fingerprint recognition systems. The combined extraction methodology—despite its richness in informational content—yielded a marginally elevated EER (5.7%) and diminished overall efficacy attributed to feature redundancy and the inherent curse of dimensionality, which may precipitate overfitting alongside heightened computational demands. This observation underscores the notion that compact and discriminative features confer greater advantages for biometric systems compared to extensive, redundant feature sets.

c. Performance of classification algorithms

Figure 7 delineates a comparative analysis of classification algorithms predicated on their accuracy metrics and biometric error rates. The RF algorithm exhibited the most superior accuracy of 92.25% when normalization was applied, coupled with a minimal EER of 1.9%, thereby illustrating its efficacy in managing heterogeneous and intricate feature distributions via ensemble learning methodologies. Furthermore, an analysis of feature importance within RF indicates that minutiae features significantly enhance model performance, thereby highlighting their intrinsic discriminative attributes. The SVM secured the second position, achieving an accuracy of 89.75% alongside an EER of 2.8%, thereby reflecting stable performance and commendable generalization capabilities.

The NB classifier attained an accuracy of 96.25% when utilizing minutiae features; however, it demonstrated diminished performance with alternative features, thereby substantiating that its independence assumption is most effectively realized with compact and structured representations. This methodology also benefits from a comparatively lower computational complexity in relation to RF and SVM, rendering it particularly advantageous for real-time applications. Conversely, the performance of the KNN algorithm was observed to decline as the number of neighbors (nn) increased, with optimal results recorded at n=1 (EER 4.2%) and a degradation in accuracy noted at n=5, thereby indicating a diminished discriminative capability under broader neighborhood assumptions.

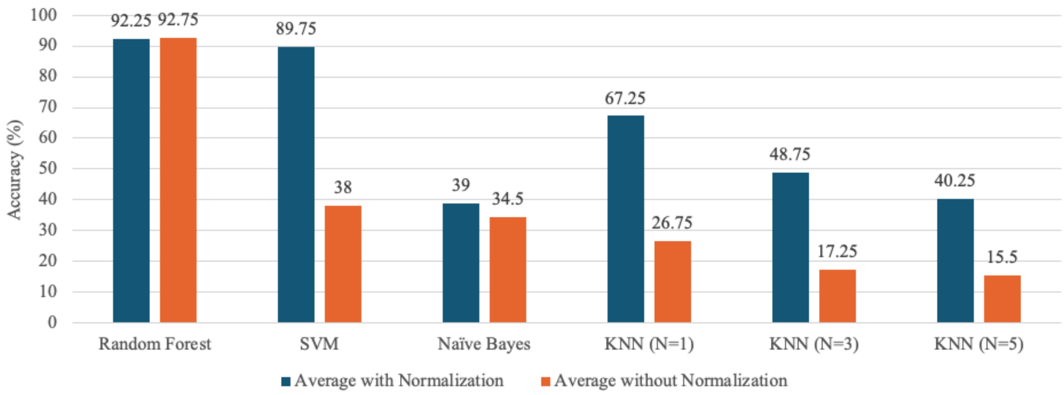


Figure 7. Comparison of average classification algorithm with and without data normalization

To furnish a more nuanced understanding, confusion matrices were generated for both the most effective (NB+minutiae) and the least effective (KNN+edge) models. The resultant data corroborates that the majority of classification inaccuracies transpired within classes characterized by subtle ridge variations, thereby indicating potential pathways for enhancing intra-class discrimination.

d. Interpretation and broader implications

These findings indicate that the combination of ECG and fingerprint modalities significantly enhances accuracy, decreases error rates, and improves resistance to spoofing. Multimodal fusion achieved an average EER reduction exceeding 5% compared to unimodal approaches, underscoring its effectiveness in bolstering authentication reliability. Furthermore, the integration of minutiae-based features with NB demonstrates a commendable equilibrium among accuracy, error rate, and computational efficiency, rendering it particularly advantageous for resource-limited environments like mobile authentication or wearable security systems.

Nonetheless, this research uncovers various limitations and challenges. Firstly, the application of high-dimensional feature representations—especially from edge-based and combined extraction techniques—did not produce optimal outcomes. The heightened dimensionality resulted in feature redundancy, likely leading to model overfitting and diminished generalization capabilities, particularly for algorithms like KNN and SVM that are sensitive to feature space complexity. This also resulted in extended training durations and increased computational expenses, rendering such methods less feasible for real-time applications. Secondly, the dataset employed in this investigation is relatively controlled, potentially failing to encapsulate real-world variances such as ECG signal noise due to movement artifacts, sensor discrepancies, or environmental disturbances. These elements may influence robustness in practical deployment scenarios.

From a more profound analytical standpoint, the exceptional performance of minutiae-based features with NB underscores the significance of compact and discriminative representations rather than merely augmenting feature quantity. It also implies that the independence assumption of NB harmonizes well with structured, low-dimensional biometric features, whereas more intricate classifiers like SVM or KNN exhibit heightened sensitivity to high-dimensional redundancy. Additionally, while the fusion process enhances accuracy, optimal fusion methodologies and post-fusion normalization strategies were not exhaustively investigated in this study and represent a prospective research avenue for performance optimization.

Lastly, the incorporation of physiological data such as ECG raises privacy and security concerns. Given that ECG signals may disclose sensitive health information, future systems must incorporate robust encryption, anonymization, and explicit user consent protocols to comply with ethical and legal requirements. Addressing these issues will be pivotal for the scaling of multimodal biometric authentication in high-security real-world applications.

4. CONCLUSION

This study indicates that the combination of ECG and fingerprint modalities, using minutiae feature extraction and NB classification, achieves a maximum accuracy of 96.25%, surpassing unimodal baselines. This finding validates the efficacy of merging discriminative fingerprint characteristics with physiological ECG signals to establish a more resilient and secure multimodal biometric system. The normalization of data further improves classification efficacy, ensuring model stability and enhanced reliability across various algorithms. The primary contribution of this research is the integration of ECG and fingerprint biometrics using diverse feature extraction methods and classical machine learning models, yielding a lightweight yet efficient authentication solution. This system exhibits significant potential for practical applications, such as mobile device security, healthcare access control, and high-security environments.

Future investigations will concentrate on dimensionality reduction and feature selection to mitigate high-dimensional redundancy, alongside cross-dataset validation and adversarial testing to bolster generalization and robustness. These measures are critical for advancing this multimodal biometric framework towards viable and scalable implementation.

Overall, the findings of this study highlight the practical significance of integrating ECG and fingerprint modalities as a reliable, efficient multimodal biometric approach, contributing to the development of more robust, secure, and deployable authentication systems for real-world applications.

FUNDING INFORMATION

This research was financially supported by Lambung Mangkurat University Research Grant year 2024 with grant number 1374. 33/UN8.2/PG/2024.

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Hafiz Ilhami	✓	✓	✓	✓	✓	✓		✓	✓	✓			✓	
Dodon Turianto Nugrahadi	✓	✓		✓	✓	✓		✓	✓	✓	✓	✓		✓
Mohammad Reza Faisal	✓	✓		✓	✓	✓		✓	✓	✓	✓			
Irwan Budiman	✓	✓	✓		✓			✓	✓					
Andi Farmadi	✓			✓		✓	✓			✓				
Dwi Kartini	✓			✓	✓					✓				
Puput Dani Prasetyo Adi	✓		✓			✓	✓		✓					
Jumadi Mabe Parenreng	✓		✓			✓	✓		✓					

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors state no conflict of interest.

DATA AVAILABILITY

The dataset used in this study is publicly available and can be accessed through the following link:

- ECG-ID: https://physionet.org/content/ecgiddb/1.0.0/
- FVC2004: http://bias.csr.unibo.it/fvc2004/download.asp

REFERENCES

[1] R. Ryu, S. Yeom, S. H. Kim, and D. Herbert, "Continuous Multimodal Biometric Authentication Schemes: A Systematic Review," *IEEe Access*, pp. 34541-34557. 2021, doi: 10.1109/ACCESS.2021.3061589.

[2] A. A. Aleidan *et al.*, "Biometric-Based Human Identification Using Ensemble-Based Technique and ECG Signals," *Applied Sciences*, vol. 13, no. 16, Aug. 2023, doi: 10.3390/app13169454.

[3] N. Ammour, Y. Bazi, and N. Alajlan, "Multimodal Approach for Enhancing Biometric Authentication," *Journal of Imaging*, vol. 9, no. 9, Sep. 2023, doi: 10.3390/jimaging9090168.

[4] A. N. Uwaechia and D. A. Ramli, “A Comprehensive Survey on ECG Signals as New Biometric Modality for Human Authentication: Recent Advances and Future Challenges,” *Institute of Electrical and Electronics Engineers Inc*, 2021, doi: 10.1109/ACCESS.2021.3095248.

[5] A. Sharma, D. P. Yadav, H. Garg, M. Kumar, B. Sharma, and D. Koundal, “Bone Cancer Detection Using Feature Extraction Based Machine Learning Model,” *Computational and Mathematical Methods in Medicine*, 2021, doi: 10.1155/2021/7433186.

[6] S. P. Singh and S. Tiwari, “A Dual Multimodal Biometric Authentication System Based on WOA-ANN and SSA-DBN Techniques,” *School of Computer Science*, vol. 5, no. 1, Mar. 2023, doi: 10.3390/sci5010010.

[7] S. Madduluri and T. Kishorekumar, “Multimodal Biometric Authentication System for Military Weapon Access: Face and ECG Authentication,” *International Journal of Computational and Experimental Science and Engineering*, vol. 10, no. 4, pp. 952–961, Oct. 2024, doi: 10.22399/ijcesen.565.

[8] N. Bala, R. Gupta, and A. Kumar, “Multimodal biometric system based on fusion techniques: a review,” *Information Security Journal: A Global Perspective*, vol. 31, no. 3, pp. 289–337, 2022, doi: 10.1080/19393555.2021.1974130.

[9] A. M. Bazen, “Fingerprint Identification-Feature Extraction, Matching and Database Search,” [Online]. Available: https://www.researchgate.net/publication/239851652.

[10] Z. Han, M. Lu, “Improved Pattern-based Fingerprint Image Preprocessing and Binarization Algorithm.” in *2012 International Conference on Computer Application and System Modeling*, 2012, pp. 1040-1043, doi: 10.2991/iccasm.2012.264.

[11] K. M. R. A. Utama, R. Umar, and A. Yuhdana, “Edge detection comparative analysis using Roberts, Sobel, Prewitt, and Canny methods,” *Jurnal Teknologi dan Sistem Komputer*, vol. 10, no. 2, pp. 67–71, 2022, doi: 10.14710/jtsiskom.2022.14209.

[12] S. Bakheet, S. Alsubai, A. Alqahtani, and A. Binbusayyis, “Robust Fingerprint Minutiae Extraction and Matching Based on Improved SIFT Features,” *Applied Sciences (Switzerland)*, vol. 12, no. 12, Jun. 2022, doi: 10.3390/app12126122.

[13] E. Mehdi Cherrat, R. Alaoui, and H. Bouzahir, “A multimodal biometric identification system based on cascade advanced of fingerprint, fingervein and face images,” *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 18, no. 1, pp. 1562–1570, 2020, doi: 10.11591/ijeecs.v18.i1.pp1562-1570.

[14] M. Kropf, D. Hayn, and G. Schreier, “ECG classification based on time and frequency domain features using random forests,” in *2017 Computing in Cardiology (CinC)*, 2017, pp. 1–4, doi: 10.22489/CinC.2017.168-168.

[15] O. M. A. Ali, S. W. Kareem, and A. S. Mohammed, “Evaluation of Electrocardiogram Signals Classification Using CNN, SVM, and LSTM Algorithm: A review,” in *2022 8th International Engineering Conference on Sustainable Technology and Development (IEC)*, 2022, pp. 185–191, doi: 10.1109/IEC54822.2022.9807511.

[16] V. B. Shtino and M. Muça, “Comparative Study of K-NN, Naive Bayes and SVM for Face Expression Classification Techniques,” *Balkan Journal of Interdisciplinary Research*, vol. 9, no. 3, pp. 23–32, Dec. 2023, doi: 10.2478/bjir-2023-0015.

[17] E. Laksono, A. Basuki, and F. Bachtiar, “Optimization of K Value in KNN Algorithm for Spam and Ham Email Classification,” *Jurnal RESTI (Rekayasa Sistem dan Teknologi Informasi)*, vol. 4, no. 2, pp. 377–383, 2020, doi: 10.29207/resti.v4i2.1845.

[18] S. A. El-Rahman and A. S. Alluhaidan, “Enhanced multimodal biometric recognition systems based on deep learning and traditional methods in smart environments,” *PLoS One*, vol. 19, no. 2, Feb. 2024, doi: 10.1371/journal.pone.0291084.

[19] D. T. Nugrahadi, M. R. Faisal, R. Herteno, I. Budiman, F. Abadi, and I. Sutedja, “An Effective Preprocessing Data on Performance of Machine Learning for ECG-Based Personal Authentication,” in *ACM International Conference Proceeding Series*, Association for Computing Machinery, Oct. 2023, pp. 581–588, doi: 10.1145/3626641.3626943.

[20] P. Melzi, R. Tolosana, and R. Vera-Rodriguez, “ECG biometric recognition: Review, system proposal, and benchmark evaluation,” *IEEE Access*, vol. 11, pp. 15555–15566, 2023, doi: 10.1109/ACCESS.2023.3244651.

[21] D. Maio, D. Maltoni, R. Cappelli, J. L. Wayman, and A. K. Jain, “FVC2004: Third fingerprint verification competition,” *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, vol. 3072, pp. 1–7, 2004, doi: 10.1007/978-3-540-25948-0_1.

[22] R. Thanki and K. Borisagar, “Novel Approach for Fingerprint Recognition Using Sparse Representation,” *International Journal of Advanced Networking Applications (IJANA)*, pp. 77-82.

[23] M. F. Safdar, R. M. Nowak, and P. Pałka, “Pre-Processing techniques and artificial intelligence algorithms for electrocardiogram (ECG) signals analysis: A comprehensive review,” *Computers in Biology and Medicine*, vol. 170, 2024, doi: 10.1016/j.compbiomed.2023.107908.

[24] Z. L. Thakker and S. H. Buch, “Effect of Feature Scaling Pre-processing Techniques on Machine Learning Algorithms to Predict Particulate Matter Concentration for Gandhinagar, Gujarat, India,” *International Journal of Scientific Research in Science and Technology*, pp. 410–419, Feb. 2024, doi: 10.32628/ijsrst52411150.

[25] M. Shabana, J. P. Kumar, and K. Masthan, “Image Forgery Detection Using Sobel Edge Detection, Feature Extraction,” in *Disruptive Technologies in Computing and Communication Systems*, CRC Press, 2024, pp. 253–258.

[26] K. Ashwini, G. N. Keshava Murthy, S. Raviraja, and G. A. Srinidhi, “A Novel Multimodal Biometric Person Authentication System Based on ECG and Iris Data,” *BioMed Research International*, vol. 2024, p. 8112209, 2024, doi: 10.1155/2024/8112209.

[27] D. Jagadiswary and D. Saraswady, “Biometric Authentication Using Fused Multimodal Biometric,” *Procedia Computer Science*, pp. 109–116, 2016, doi: 10.1016/j.procs.2016.05.187.

[28] M. J. Nayeem, S. Rana, F. Alam, and M. A. Rahman, “Prediction of Hepatitis Disease Using K-Nearest Neighbors, Naive Bayes, Support Vector Machine, Multi-Layer Perceptron and Random Forest,” in *2021 International Conference on Information and Communication Technology for Sustainable Development (ICICT4SD)*, Feb. 2021, pp. 280–284, doi: 10.1109/ICICT4SD50815.2021.9397013.

BIOGRAPHIES OF AUTHORS

Hafiz Ilhami originates from Hulu Sungai Utara, South Kalimantan. He has been involved in the academic world since 2021 as a student in the Department of Computer Science at Lambung Mangkurat University. His current research focuses on data science. Additionally, his final assignment involves research on the comparison of machine learning algorithms for multimodal biometric identification based on fingerprint and ECG signals to identify individuals using a combination of fingerprint and ECG data. He can be contacted at email: 2111016210011@mhs.ulm.ac.id.

Dodon Turianto Nugrahadi is a lecturer in the Department of Computer Science at Lambung Mangkurat University. His research interest is centered on data science and computer networking. He completed his Bachelor's degree in Informatics Engineering in the Petra Christian University, Surabaya, in 2004. After that, he pursued a master's degree in Information Engineering at Gajah Mada University, Yogyakarta, in 2009. His current area of research revolves around network, data science, the internet of things (IoT), and network quality of service (QoS). He can be contacted at email: dodonturianto@ulm.ac.id.

Mohammad Reza Faisal was born in Banjarmasin. After graduating from high school, he pursued his undergraduate studies in the Department of Informatics at Pasundan University in 1995 and later majored in Physics at Bandung Institute of Technology in 1997. After completing his Bachelor's degree, he gained experience as a training trainer in information technology and software development. Since 2008, he has been a lecturer in Computer Science at Universitas Lambung Mangkurat while also pursuing his master's degree in Informatics at the Bandung Institute of Technology in 2010. In 2015, he furthered his education by pursuing a doctoral degree in Bioinformatics at Kanazawa University, Japan. To this day, he continues his work as a lecturer in Computer Science at Lambung Mangakurat University. His research interests encompass data science, software engineering, and bioinformatics. He can be contacted at email: reza.faisal@ulm.ac.id.

Irwan Budiman completed his Bachelor's degree in the Department of Informatics at the Islamic University of Indonesia. Subsequently, he assumed the role of a lecturer in Computer Science at Universitas Lambung Mangkurat starting in 2008. In 2010, he pursued a master's degree in Information Systems at Diponegoro University. He is the chair of the Computer Science study program at Universitas Lambung Mangkurat. His area of research expertise lies in data science. He can be contacted at email: irwan.budiman@ulm.ac.id.

Andi Farmadi completed his undergraduate studies at Hasanuddin University and his graduate studies at Bandung Institute of Technology. He is a senior lecturer in Computer Science at Universitas Lambung Mangkurat since 2008. He currently serves as the Head of the Data Science Laboratory since 2018. His research area, focuses on data science. He can be contacted at email: andifarmadi@ulm.ac.id.

Dwi Kartini received her Bachelor's and master's degrees in Computer Science from the Faculty of Computer Science, Putra Indonesia "YPTK" University, Padang, Indonesia. She teaches various subjects such as linear algebra, discrete mathematics, and research methods. Her research interests include the applications of artificial intelligence and data mining. Currently, she holds the chair position for the Computer Science study program at Lambung Mangkurat University. She can be contacted at email: dwikartini@ulm.ac.id.

Puput Dani Prasetyo Adi received the Bachelor's degree in Informatic Engineering (S. Kom.) from STMIK AKAKOM Yogyakarta in 2008, now Universitas Teknologi Digital Indonesia (UTDI), Indonesia; a Master's degree (M.T.) from Hasannudin University Makassar, Indonesia, in 2011, and a Ph.D. (Dr.Eng.) from Kanazawa University, Japan, in 2020. He joined the Microelectronics Laboratory (MeRL), Kanazawa University, Japan, under Professor Akio Kitagawa from 2018 to 2020. In 2020, he received a Dean's Award from Kanazawa University, Japan. Also in 2020, he also received the Best Paper Award at the IEEE ICITACEE 2020 conference for the paper titled "Finger Robotic control using M5Stack Board and MQTT Protocol". He is a lecturer at Universityas Merdeka Malang East Java, Indonesia, in the Department of Electrical Engineering. The focus of the research is on low power wide area (LPWA) and low power wide area networks (LPWAN), which use long-range (Lora) radio frequency and another type of RF. Currently, the research focuses on agriculture and healthcare, which is IoT-based. He joins the National Research and Innovation Agency at the Telecommunications Research Center starting February 2022. On 23-25 August 2022, at the IEEE XPlore International Conference, The 11th Electrical Power, Electronics, Communications, Control, and Informatics Seminar (EECCIS), he received the Best Presenter Award EECCIS 2022. He received the Best Paper Award titled "Spreading Factor of IoT-LoRa Effect for Future Smart Agriculture", at the 2022 International Conference on Information Technology Research and Innovation (ICITRI), IEEE Conferences, on November 10, 2022. He can be contacted at email: pupu008@brin.go.id.

Jumadi Mabe Parenreng is an academic and researcher in the Informatics and Department of Computer Engineering at Universitas Negeri Makassar. He earned his Bachelor of Applied Science (S.ST.) degree from the Electronics Engineering Polytechnic Institute of Surabaya in 2004 and his Master of Computer Science (M.Kom.) degree from the Sepuluh Nopember Institute of Technology. He research focuses on wireless sensor networks (WSN). One of his notable publications is "Resource Optimization Techniques and Security Levels for Wireless Sensor Networks Based on the ARSy Framework," published in the Sensors Journal in 2018. Additionally, he has developed several applications and information systems, including "Designing a Web-Based Employee Management Information System (Simpeg) at Universitas Negeri Makassar," published in 2021. He also holds several copyrights related to application development, such as "UNM Community Service Management Information System Application," registered in 2023. He can be contacted at email: jparenreng@unm.ac.id.