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RESEARCH ARTICLE

One-Dimensional Shallow Neural Network Using Non-Fiducial Based Segmented Electrocardiogram for User Identification System

YEJIN KIM[1], GYUHO CHOI[2], AND CHANG CHOI[1], (Senior Member, IEEE)
[1]Department of Computer Engineering, Gachon University, Sujeong-gu, Seongnam-si, Gyeonggi-do 13120, Republic of Korea
[2]Department of Artificial Intelligence Engineering, Chosun University, Dong-gu, Gwangju 61452, Republic of Korea

Corresponding author: Chang Choi (changchoi@gachon.ac.kr)

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ABSTRACT Recent user recognition technologies have focused on biometric signals to remotely identify users in the access management, medical welfare, and public sectors. The electrocardiogram (ECG) signal is an individual's unique electrophysiological signal generated within the body and is difficult to forge or change; thus, it can be used to uniquely identify the user. Existing user identification systems based on ECG signals detect R peaks according to morphological features and use a fiducial-based segmentation process for data normalization. However, this process does not detect a distinct R peak due to motion artifacts generated by the movement of the subject, thereby degrading identification accuracy. To address the problem of decreasing peak accuracy of the fiducial-based segmentation data, this study proposes a user identification system based on one-dimensional neural networks using periodic non-fiducial-based segmentation data that do not overlap in the time domain. The proposed system comprises a preprocessing step for data denoising, a non-fiducial-based and non-overlap segmentation step, and a step for classifying users using a one-dimensional shallow neural network. In the experiment, when using self-acquired 10-second ECG signal data that were divided into non-fiducial and non-overlapping segments, the long short-term memory (LSTM), bidirectional LSTM, and one-dimensional convolutional neural network (CNN) models achieved accuracies of 92.01%, 93.13%, and 95.51%, respectively, with the 1D CNN model exhibiting the best accuracy. The proposed system demonstrated a 25.48% improvement in accuracy on non-fiducial segmented data compared to the 1D CNN model, which achieved an accuracy of 70.03% on fiducial segmented data. Moreover, when tested on publicly available ECG datasets, including MIT-BIH, ECG-ID, and PTB-XL, the proposed system exhibited a user identification accuracy of over 94%, confirming its superior performance.

INDEX TERMS Artificial intelligence, electrocardiogram, non-fiducial-point, one-dimensional convolution network, preprocessing, security, signal processing, user identification.

I. INTRODUCTION

Biometric data areis more challenging to steal than existing patterns or passwords, making biometric technology more convenient to apply to open security frameworks such as access control, medical welfare, and public fields [1]. Biometric technology identifies a user by recognizing the biometric information related to their physical and behavioral characteristics [2]. Representative biometric information for user identification includes fingerprints, irises, and facial features, which can be acquired from outside the body [3]. User recognition systems based on fingerprints or facial recognition have a security vulnerability in that they have a low recognition rate due to the quality or environmental factors concerning fingerprint images [4], along with a high possibility of forgery and tampering due to the development of forgery technologies [5].

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TABLE 1. Research on ECG signal classification system.

Paper	Model	Dataset	Task	Accuracy
Chen et al. [6]	DNN	Medical University Hospital(KMUH) 12-lead ECG Dataset	Arrhythmia Classification	95.68%
Cheikhrouhou et al. [7]	1D CNN	Physionet MIT-BIH Arrhythmia Database	Arrhythmia Classification	99.46%
Abdullah et al. [8]	CNN-LSTM	Physionet MIT-BIH Database	Arrhythmia Classification	98.13%
Kiranyaz et al. [9]	1D CNN	Physionet MIT-BIH Arrhythmia Database	Arrhythmia Classification	98.12%
Saadatnejad et al. [10]	LSTM RNN	Physionet MIT-BIH Arrhythmia Database	Arrhythmia Classification	99.20%
Ramkumar et al. [11]	BiLSTM	Physionet MIT-BIH Database	Arrhythmia Classification	99.00%
Cheng et al. [12]	DCNN+BiLSTM	PhysioNet/CINC challenge Database	Arrhythmia Classification	89.30%

To compensate for these shortcomings, studies are being actively conducted on the applications of bio-signals acquired inside the body, such as the electrocardiogram (ECG) and electromyogram, for user identification systems [13], [14]. User identification systems using ECG signals identify users based on the morphological features of ECG signals which are uniquely determined by the user's heart location and size [15]. The preprocessing steps required to understand the characteristics of an ECG signal include noise removal, feature extraction, feature selection, and segmentation of the ECG signal acquired from the user [16].

The ECG signal is subjected to a segmentation process after feature extraction for use in user identification applications [16]. Generally, segmentation processes applied to ECG signals for user identification systems are divided into fiducial and non-fiducial-based segmentation methods. The ECG signal comprises the P, Q, R, S, and T waveforms; therefore, it can be divided based on the morphological features [17]. The fiducial-based segmentation method segments an ECG signal based on a peak by considering the morphological characteristics of the signal, while the non-fiducial-based segmentation method sets and separates an arbitrary region of the signal without considering the exact peak position and morphological characteristics of the signal. Hamza and Ayed [18] used the Pan-Tompkins algorithm to segment the ECG signal based on the detected R peak. The Pan-Tompkins algorithm detects the QRS complex based on the slope, amplitude, and width of the ECG signal [19]. Although the QRS complex detection performance is high, peak re-detection using the R-R interval should be performed to find the incorrectly detected peak because the subject's motion artifact deteriorates R-peak detection accuracy. Yan et al. [20] implemented a user authentication system using a fiducial-based segmentation method based on a single-lead ECG signal. For fiducial-based segmentation of the ECG signal, peak detection and R peak correction are performed using an adaptive threshold. The fiducial-based segmentation method has the advantage of considering the morphological characteristics of ECG signals. However, the peak detection process of the ECG signals, which includes peak detection and correction, is complicated and is not identified as a factor affecting the accuracy improvement of the user identification system accuracy.

In this study we propose a user identification system based on one-dimensional shallow neural networks which use non-fiducial and non-overlap segmentation data to address the limitations introduced by the complexity of the data segmentation process and the uncertainty of improving accuracy. The proposed system comprises a preprocessing step for denoising ECG signals, a step for non-overlap non-fiducial-based segmentation of ECG signals, and a step for classifying users by employing a one-dimensional shallow neural network. In the experiment, we simplified the preprocessing process and used a lightweight and fast 1D CNN model compared to fiducial-based segmentation. We also wanted to improve the effectiveness of our user recognition system by using short ECG segments. The experimental results exhibited a user identification accuracy of 92.46% on non-segmented self-acquired ECG data, and accuracies of 95.51%, 95.05%, and 91.5% on non-overlap 1-second, 2-second, and 3-second split data, respectively. We validated a user identification accuracy of over 94% using the publicly available MIT-BIH, ECG-ID, and PTB-XL datasets. When using non-overlapping non-fiducial-based segmentation data in the time domain, the identification accuracy improved by at least 9.83% to a maximum of 23.88% compared with the overlapping data. In addition, when using non-fiducial-based segmentation data, the accuracy improved by 25.48% compared to when using fiducial-based segmentation data, confirming the superiority of the proposed method.

The contributions proposed in this paper are summarized as follows.

- Proposal of a non-fiducial point based segmentation method to simplify the preprocessing process
- Proposal to use of short ECG segments to improve the efficiency of user recognition system
- Proposal of a shallow model structure for lightweight model and fast learning speed
- Proves good performance in both self-collected electrocardiogram data and online public data

II. RELATED RESEARCH

A. ECG SIGNAL CLASSIFICATION SYSTEM

Recently, ECG signal classification research has focused on deep learning [6], [26]. Table 1 is a table showing networks used for ECG signal classification. Table 1 shows the types and performance of networks used in ECG classification studies. Convolutional neural networks (CNNs) and long short-term memory (LSTM) models have been validated to

TABLE 2. Research on User identification system using ECG signals.

Paper	Method	Dataset	Task	Accuracy	F1-score
Kim et al. [21]	DNN	Physionet MIT-BIH Database	User Identification	100%	1
Elshahed et al. [22]	1D CNN	ECG-ID, Physionet MIT-BIH Database	User Identification	-	0.96
Li et al. [23]	CNN-LSTM	Physionet Database	User Identification	94.30%	-
Sorvillo et al. [24]	1D CNN	Self-acquired electrocardiogram data	User Identification	88.00%	-
Choudhary et al. [25]	LSTM RNN	Self-acquired electrocardiogram data	User Identification	99.02%	-

have better user identification accuracy than non-network models in conventional machine learning and are applied to network-based ECG signal classification and ECG-based user identification systems [7], [8] [27]. Kiranyaz et al. [9] used one-dimensional CNNs (1D CNN) to classify ECG signals into normal (N), supraventricular ectopic beats (SVEB), ventricular ectopic beats (VEB), fusion beats (F), and unclassifiable beats (Q). ECG signal was classified into five classes and verified with a classification accuracy of 98.12%. The proposed 1D CNN reduced overfitting and dropout caused by the activation function for each convolution layer. The ECG classification system conducted model learning on the Physionet MIT-BIH Arrhythmia Database and was tested on real-world data, demonstrating a performance of 98.07% sensitivity and 98.29% specificity.

Saadatnejad et al. [10] proposed an LSTM model-based ECG signal classification algorithm that can solve the time dependency problem. The proposed classification algorithm, which is feasible for wearable devices with low computational cost and limited processing power, was validated with an accuracy of 99.2%. Ramkumar et al. [11] extracted the characteristics of ECG signals using bidirectional LSTM (BiLSTM) networks for ECG signal classification. The proposed network consists of an autoencoder and BiLSTM (AE-BiLSTM) comprising an encoder for feature extraction and a decoder for ECG signal reconstruction. Using this network, ECG signals were classified into six classes: normal (N), atrial fibrillation (AFIB), ventricular bigeminy (B), pacing beat(P), atrial flutter (AFL), and sinus bradycardia (SBR). The experimental results verified the 99% classification accuracy of the proposed method, an improvement of 24.83% and 29.45% over conventional CNNs with LSTM (CNN-LSTM) models and deep code features with LSTM (DCF-LSTM) network models, respectively.

Cheng et al. [12] proposed a network that combines deep-convolutional neural network (DCNN) models with BiLSTM models to classify ECG signals. The proposed network extracts the features of ECG signals using BiLSTM models which account for temporal information and data dependence of ECG signals. We validated the ECG signal classification accuracy as 89.3% using a dataset provided by the 2017 PhysioNet/CINC Challenge. The 1D CNN, LSTM, and BiLSTM models in the classification system were validated with high accuracy using existing ECG in this study. In ECG signal classification studies, networks such as 1D CNN, LSTM and BiLSTM are mainly used. Existing studies indicate that it is effective in classifying ECG signals.

B. ECG SIGNAL-BASED USER IDENTIFICATION SYSTEM

Table 2 is a table that summarizes research on user authentication systems using ECG signals. Kim et al. [21] used LSTM models for ECG-based biometric recognition and classification and proposed preprocessing methods such as derivative filters and moving average filters for fast identification and noise reduction during real-time monitoring. The proposed user authentication system was validated with an ECG signal classification accuracy of 100% and an F1-score of 1 using the MIT-BIH dataset.

The ECG signal must be segmented for application to the user identification system and classification algorithm. Elshahed et al. [22] proposed a user identification system that applied the discrete wavelet composition and Euclidean distance techniques by dividing ECG signals based on non-fiducial points. The method was validated on the ECG-ID and MIT-BIH arrhythmia databases. As a feature extraction method, the performance of F1-score 0.96 was verified by matching the features extracted through the Daubechies wavelet 'db8' using the Euclidean distance algorithm.

Li et al. [23] proposed a CNN-based cascaded CNN to increase user identification efficiency. Cascaded CNNs combine the fully connected neural network (F-CNN) and matching convolutional neural network (M-CNN) models to extract ECG signal features and match them to users. The ECG signal was segmented into fixed lengths based on the R-peak prior to applying the CNN model. The cascaded CNN was trained on the CEBSDB, NSRDB, STDB, and AFDB MIT-BIH databases and tested on the FANTASIA MIT-BIH database, thereby verifying an accuracy of 94.30 %. Sorvillo et al. [24] used the Pan-Tompkins algorithm to detect the R-peak, subdividing ECG signals into single segments. The proposed user identification system employed a support vector machine (SVM) classifier, whereby user identification accuracy of 88% was verified with ECG data obtained from subjects with mental and physical stress.

Choudhary et al. [25] proposed a user identification system employing noise-resistant adaptive variational mode composition (VMD). ECG signals were segmented on a non-fiducial basis without the need for peak detection, and time-frequency features were extracted using VMD. User identification was performed using a back-propagation neural network (BPNN), and 99.02% accuracy was verified. The current study proposes a user identification system using non-fiducial-based segmented ECG signals that do not require peak detection. To solve the problem of complex preprocessing of ECG

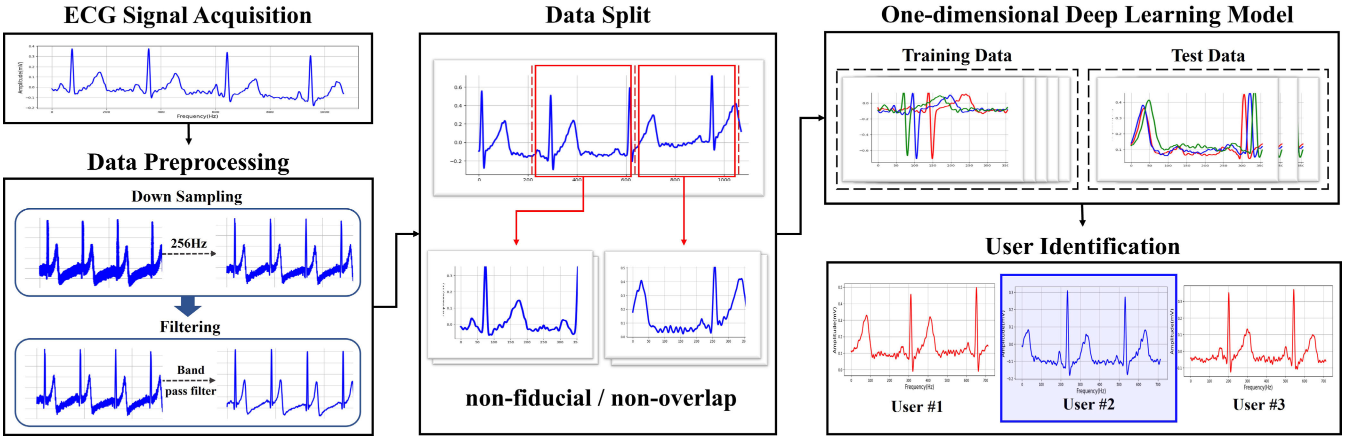


FIGURE 1. User Identification system step.

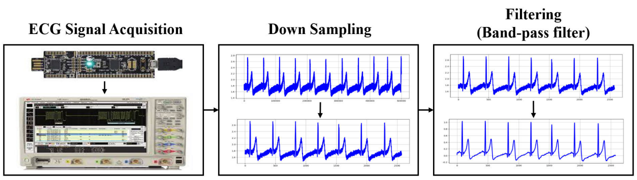
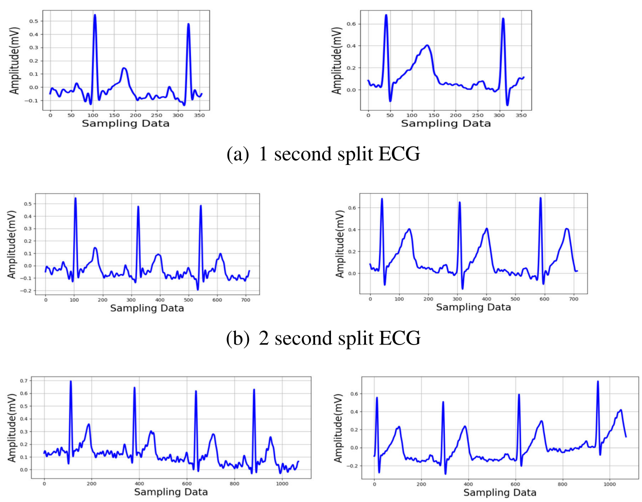


FIGURE 2. ECG signal preprocessing process.



(a) 1 second split ECG

(b) 2 second split ECG

(c) 3 second split ECG

FIGURE 3. Segmentation of ECG signals based on non-fiducial-point by length.

signals, a user identification system for fiducial-based segmented ECG signals must be studied.

III. USER IDENTIFICATION SYSTEM USING A ONE-DIMENSIONAL SHALLOW NEURAL NETWORK

The proposed user identification system is illustrated in Figure 1. It consists of a signal preprocessing step to remove noise from the self acquired ECG signal, a non-overlapping segmentation process for non-fiducial based ECG signals, a one dimensional neural network model construction, and a user authentication process.

A. PREPROCESSING FOR NOISE REMOVAL OF ECG SIGNALS

The ECG introduces baseline and interference noise during the acquisition process. Representatively, noise is caused by the measuring equipment and motion artifacts. Because a noisy ECG signal degrades the performance of the user identification system, a noise-removing process for the ECG signal is essential [28]. The ECG signal was downsampled and the noise was removed using a bandpass filter. The preprocessing method used in this study is shown in Figure 2.

The ECG was downsampled to 256 Hz to reduce the throughput of data learning for user identification while maintaining the morphological characteristics of the ECG signals obtained at a sampling rate of 500,000 Hz. When obtaining the ECG signals, a bandpass filter was applied to remove noise corresponding to high and low frequencies. A bandpass filter passes frequencies within a specific range and removes other frequencies [29]. During the filtering using a bandpass filter, frequencies other than those in the interval of 0.05-40 Hz were removed based on the specified noise frequency band.

B. ECG SIGNAL SEGMENTATION BASED ON NON-FIDUCIAL POINT

This study used segmented ECG signals based on non-fiducial points without peak detection and R peak detection for fiducial-based segmentation of ECG signals.

Figure 3 shows separated data for non-overlapping ECG signals in the time domain. The length of the acquired data is 10 seconds. We divided the ECG signal into 1 second, 2 second, and 3 second units to improve user identification performance with only short ECG segments. The user identification performance according to the length of the ECG signal was analyzed using the divided data. In addition, the

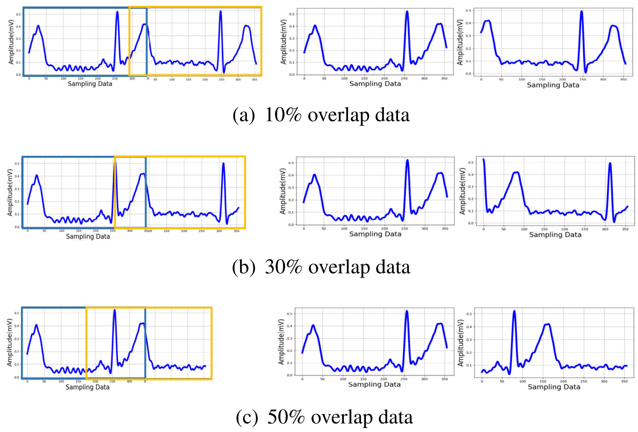


FIGURE 4. ECG signal of 1s with 10%, 30%, and 50% overlap.

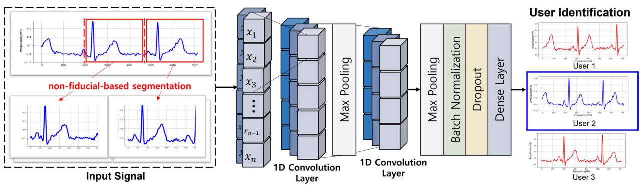


FIGURE 5. Shallow 1D-CNN model-based human identification.

effect of overlapped time-domain data on user identification was analyzed using an ECG signal that applied overlap to the segmented data.

Figure 4 shows the ECG signal data divided into 1-second units for the non-fiducial-based segmentation method with10%, 30%, and 50% overlaps applied. Figure 4(a) shows 10% overlap applied in the time domain, and Figures 4(b) and 4(c), 30% and 50% overlaps, respectively, are applied in the time domain.

C. IMPLEMENTATION OF A USER IDENTIFICATION SYSTEM USING ECG SIGNALS

The proposed user identification system was implemented using a shallow 1D CNN model. The 1D CNN model is a representative model for learning one-dimensional data; time- series data and is widely used to process sequential data, including one-dimensional signals such as in natural language processing, time- series analysis, speech recognition, and arrhythmia classification [30], [31].

Figure 5 shows the proposed 1D CNN model, which comprises a shallow 1D CNN with a dense final layer. A non-fiducial segmented ECG signal was input, and a rectified linear unit was applied as an activation function to each layer. The proposed model configuration, batch normalization, and dropout reduced overfitting. The filter size of each 1D convolution layer was set to 4096 sizes, and the padding process was omitted. Consequently, the model comprised two 1D convolution layers, max pooling, batch normalization, and a dense layer.

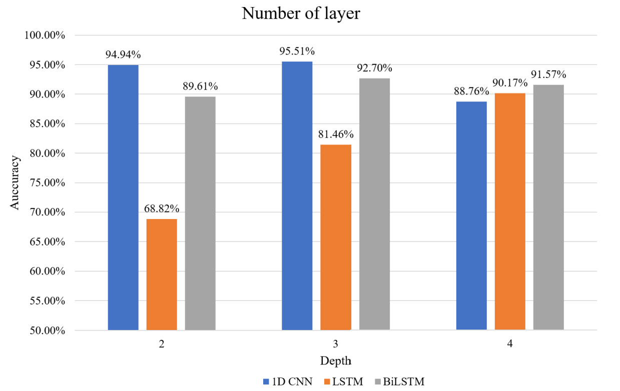


FIGURE 6. Accuracy of user identification based on the number of layers.

IV. EXPERIMENT RESULTS

The experimental environment for verifying the user identification system consisted of Python 3.8.8 on personal computers powered by Intel Core i9 processors. The CU-ECG DB consisted of private data acquired in 2016 using ARM Cortex-M3 Psoc-5LP and Keysight MSO 9104 equipment with the subjects in a relaxed state where all 100 people were seated in chairs. The signals were measured 60 times for each person for 10 s and were collated into a dataset with 500,000 Hz sampling rate of a single lead-I type. To evaluate the user identification system using ECG signals, the model performance was verified using accuracy and F1-score. Accuracy uses true positive (TP), true negative (TN), false positive (FP), and false negative (FN) to calculate the proportion of correctly classified labels for the entire prediction, as shown in (1). For the F1-score, the harmonic mean is calculated as shown in (4) using precision and recall.

$$Accuracy = \frac{TN + TP}{TN + FP + FN + TP} \tag{1}$$

$$Precision = \frac{TP}{FP + TP} \tag{2}$$

$$Recall = \frac{TP}{FN + TP} \tag{3}$$

$$F1score = 2 \cdot \frac{precision \cdot recall}{precision + recall} \tag{4}$$

The neural network used in the user identification system for ECG signals was applied by analyzing user identification accuracy and training time according to filter size, depth, and data length for optimization. The user identification system proposed in this study used a 1-second non-fiducial ECG signal segment with no overlap and 1D CNN architecture.

A. ANALYSIS OF IDENTIFICATION ACCURACY ACCORDING TO LAYER DEPTH

Figure 6 shows the results of verifying the user identification system based on the layer depth for each model. The LSTM model was validated with 90.17% accuracy at four depths, whereas the 1D CNN and BiLSTM models were validated with accuracies of 95.51% and 92.70%, respectively, at three

TABLE 3. Accuracy based on the number of overlapping data points.

	Overlap	Non-overlap	Overlap 10%		Overlap 30%		Overlap 50%	
	Number of data	360	360	420	360	540	360	780
Model	1D CNN	95.51%	84.27%	89.61%	82.87%	89.04%	79.21%	88.48%
	LSTM	90.17%	67.13%	76.40%	63.48%	75.56%	58.43%	70.51%
	BiLSTM	92.70%	82.87%	83.99%	71.63%	83.71%	68.82%	72.19%

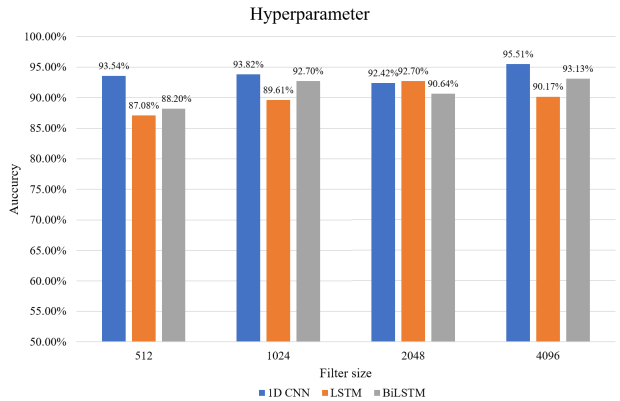


FIGURE 7. Accuracy of user identification based on hyperparameters.

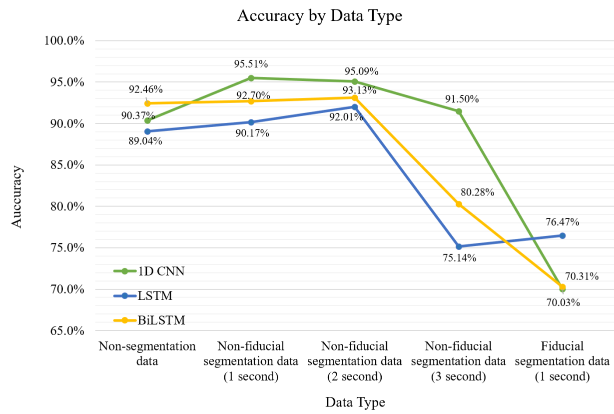


FIGURE 8. Accuracy of identification by data length and segmentation method.

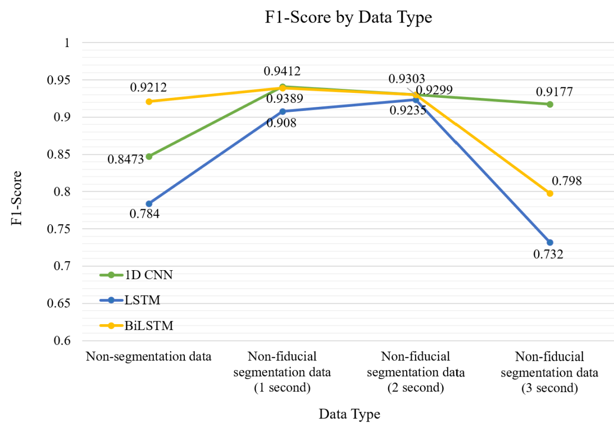


FIGURE 9. F1-Score by data length.

depths. The LSTM model requires a large depth for high identification accuracy, but the 1D CNN model used in the system proposed in this study showed the best performance with only three depths.

B. ANALYSIS OF IDENTIFICATION ACCURACY ACCORDING TO FILTER SIZE

Because the model is not deep, the larger the filter size, the shallower and broader the configuration of the model to increase accuracy.

Figure 7 shows that the accuracies of the 1D CNN and BiLSTM models have improved by as much as 2.8%, as filter size increases. In contrast, the accuracy of the LSTM model decreases as filter size increases up to a specific size or greater. Accuracies of 95.51%, 93.13%, and 92.70% were verified when using a filter size of 4096 for the 1D CNN model and BiLSTM models and a filter size of 2048 for the LSTM model, respectively.

C. ACCURACY ANALYSIS BASED ON ECG SIGNALS TYPE

Figure 8 shows the user identification accuracy of the model structure based on the above experiment for non-segmentation data, fiducial-based segmentation data, and non-fiducial-based segmentation data. The accuracy of the BiLSTM model was validated at 92.46% accuracy for non-partitioned ECG signals.

However, the identification accuracy improved by 5.14% when applying the 1D CNN model to segmented ECG signals. The user identification system proposed in this study was validated with an identification accuracy of 95.51%; these results were obtained when using short-length ECG signals suitable for real-time user ECG identification systems that require fast results.

R-peak detection was performed using the Pan-Tompkins algorithm to compare user identification accuracy on fiducial-based segmentation data. The ECG signal was divided based on the detected R-peak. As a result of the segmented ECG signal by the R-peak, an identification accuracy of 70.03% in the 1D CNN model, 76.47% in the LSTM model, and 70.31% in the BiLSTM model was verified. When using the 1D CNN model for non-fiducial-based segmentation data, the accuracy improved from a minimum of

TABLE 4. Accuracy comparison of proposed methods.

Method	Model	w/o fiducial point detection	Database	Accuracy
Sorvillo et al. [24]	SVM	Fiducial point detection	Self-acquired electrocardiogram data	88%
		Non-fiducial point detection		62%
Zhang et al. [32]	1D CNN	Non-fiducial point detection	MIT-BIH Database	93.50%
Abdeldayem et al. [33]	CNN	Non-fiducial point detection	PTB Database	94.90%
Ours	1D CNN	Non-fiducial point detection	Self-acquired electrocardiogram data	95.51%
			PTB-XL	94.79%
			MIT-BIH	95.29%
			ECG-ID	94.39%
	LSTM	Non-fiducial point detection	Self-acquired electrocardiogram data	90.17%
			PTB-XL	75.55%
			MIT-BIH	77.84%
			ECG-ID	86.37%
	BiLSTM	Non-fiducial point detection	Self-acquired electrocardiogram data	92.70%
			PTB-XL	94.39%
			MIT-BIH	76.45%
			ECG-ID	94.85%

21.47% to a maximum of 25.48% compared to when using fiducial-based segmentation data.

Figure 9 shows the F1-score when non-fiducial-based segmentation data were used. With the 1D CNN model, the user identification F1-score for one-second ECG signals was validated as highest at 0.9412 among the non-fiducial-based segmentation data.

D. USER IDENTIFICATION ACCURACY ANALYSIS BY DATA OVERLAP

To analyze the impact of overlap on the user identification system, we verified user identification accuracy using non-fiducial-based segment ECG signals with overlap. The experiment was conducted using data to which the overlap was applied at 10%,30%, and 50% in the time domain. Table 3 lists the accuracy of user identification using data to which overlap was applied. The user identification performance using the 1D CNN model was found to be the highest for all overlap data, and it was confirmed that the performance improved as the amount of data increased. Hanil et al. [34] proposed a two-dimensional electrocardiogram biometric method that extracts attributes from overlapped ECG signals. Using the PTB-XL database, the identification accuracy was validated at 85.71% for the ACDCT image and at 80.95% for the CC image after fiducial-based segmentation. In this study, the identification accuracy was 3.9% higher when redundant data were included in the 1D CNN model. However, the performance was reduced by at least 11.24% compared to non-overlapping data. Data overlap was found to adversely affect user identification accuracy. In this study, a user identification system was implemented for non-overlapping data.

E. TRAINING TIME ANALYSIS OF IDENTIFICATION SYSTEM ACCORDING TO ECG DATA LENGTH

Table 5 compares the data learning speeds of the user identification system for each model. Using an optimized neural network architecture, it was found that the 1D CNN model was the fastest to learn from all the data, twice as fast as the LSTM model and more than three times faster than the BiLSTM model.

TABLE 5. Research on respiration data classification.

Model	Non-segmentation data	Non-fiducial segmentation data		
	10 second	1 second	2 second	3 second
1D CNN	45ms	20∼30ms	30ms	35ms
LSTM	200ms	80ms	100ms	250ms
BiLSTM	380ms	90ms	130ms	450ms

Li et al. [35] compared the time costs of the 1D CNN model and the LSTM and BiLSTM models. While both the 1D CNN, LSTM and BiLSTM models require a time cost of one minute or more in the proposed user identification model, the 1D CNN model proposed in this paper takes only 20 to 30 ms to perform the task and improves the identification accuracy by 12.61%. This indicates advantages in both time cost and accuracy.

F. COMPARISON WITH EXISTING METHOD

Table 4 compares the performance of the proposed method with that of existing methods. Sorvillo et al. [30] validated a user recognition system with 88% identification accuracy by detecting R peaks using the Pan-Tompkins algorithm and segmenting the ECG signal into a single segment. Zhang et al. [32] and Abdeldayem et al. [33] validated accuracies of 93.5% and 94.9 %, respectively, by applying CNN models to non-fiducial-based segmented ECG signals.

In this study, we evaluated user identification accuracy using not only self-acquired data but also representative public ECG datasets, including MIT-BIH, ECG-ID, and PTB-XL. Using a non-fiducial based segmentation method, we observed user identification performance of over 94% in the ECG-ID and PTB-XL datasets, and over 95% in the

MIT-BIH dataset in the 1D CNN model. The results showed that using the 1D CNN model performed better than the method used in previous studies. To reduce preprocessing complexity and improve user identification accuracy, we used a non-fiducial based segmentation method to show better performance than the method used in previous studies. Based on these results, we can conclude that the method proposed in this study shows superior performance compared to user identification systems for fiducial-based segmented ECG signals.

V. CONCLUSION

Biometrics is a method for user identity verification and authentication, reducing risk of identity theft and improving convenience, as an alternative to existing authentication methods such as patterns or passwords. However, biometrics using fingerprints or face recognition have disadvantages, such as a low recognition rate and a high possibility of forgery and alteration. To solve these problems, we studied a user identification system using an ECG to identify an individual's unique electrophysiological signal. The ECG signal was segmented for application in the user identification system. In existing user identification systems using fiducial-based segmentation, the morphological characteristics of ECG signals are considered. However, there is a problem in that the required peak detection process, becomes complicated. To address the complexity of the fiducial-based segmentation process, this study proposes a one-dimensional shallow neural network user identification system for non-fiducial-based segmentation of ECG signals with fixed non-overlapping intervals. The proposed user identification system consists of preprocessing for noise removal from ECG signals using downsampling and bandpass filtering, and the implementation of a one-dimensional neural network-based user identification system for non-fiducial-based segmented ECG signals. In the experimental results, the proposed system showed an accuracy improvement of 21.47%-25.48% compared with the user identification system using landmark-based segmented ECG signals. The shallow architecture of the 1D CNN applied to the proposed system was more than twice as fast as those of the LSTM and BiLSTM models, and the best user-identification performance was validated at an accuracy of 95.51% using self-acquired data. Additionally, an accuracy of over 94% was verified in the 1D CNN model using publicly available datasets, such as MIT-BIH, ECG-ID, and PTB-XL. The proposed 1D CNN model in this study achieved high user identification accuracy despite its lightweight and fast architecture, by utilizing baseline-free segmentation. These results suggest that our model can be useful in real-world applications. In the future, we plan to study a stable high-performance user identification system that considers various user states and ECG signal acquisition environments.

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YEJIN KIM received the B.S. degree in computer engineering from Gachon University, Seongnam, South Korea, in 2022, where she is currently pursuing the M.S. degree. Her research interests include signal processing, one-dimensional neural networks, artificial intelligence, and biometrics.

GYUHO CHOI received the B.S. and Ph.D. degrees in electronics engineering from the Department of Control and Instrumentation Engineering, Chosun University, Gwangju, South Korea, in 2015 and 2021, respectively. He is currently an Assistant Professor with the Department of Artificial Intelligence Engineering, Chosun University. His research interests include biometrics, pattern recognition, artificial intelligence, and computer vision.

CHANG CHOI (Senior Member, IEEE) received the B.S., M.S., and Ph.D. degrees in computer engineering from Chosun University, in 2005, 2007, and 2012, respectively. Since 2020, he has been an Assistant Professor with Gachon University. He has authored more than 100 publications including papers in prestigious journal/conferences, such as *IEEE Communications Magazine*, IEEE TRANSACTIONS ON INDUSTRIAL INFORMATICS, IEEE TRANSACTIONS ON INFORMATION FORENSICS AND SECURITY, IEEE TRANSACTIONS ON SUSTAINABLE COMPUTING, IEEE INTERNET OF THINGS JOURNAL, *Information Sciences*, and *Future Generation Computer Systems*. His research interests include intelligent information processing, semantic web, smart IoT systems, and intelligent system security. He has served or is currently serving on the organizing or program committees for international conferences and workshops, such as ACM RACS, EAI BDTA, IE, ACM SAC, and IEEE CCNC/SeCHID. He received the Academic Awards from the Graduate School, Chosun University, in 2012. He also received a Korean Government Scholarship for graduate students (Ph.D. course), in 2008. He has also served as the Guest Editor for high-profile journals, such as IEEE TRANSACTIONS ON INDUSTRIAL INFORMATICS, *Future Generation Computer Systems*, *Applied Soft Computing*, *Multimedia Tools and Applications*, *Journal of Ambient Intelligence and Humanized Computing*, *Concurrency and Computation: Practice and Experience*, *Sensors*, and *Autosoft*.