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Accurate and Secure Person Identification Using ECG Signals and Deep Neural Networks

Short Paper

Sandeep Tripathi[1]

[1]Research Scholar, Department of Computer Science and Engineering, Bansal Institute of Engineering and Technology, Lucknow, Affiliated to AKTU, Lucknow, U.P. INDIA

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Abstract:

Person identification based on Electrocardiogram (ECG) signals has gained significant attention in biometric applications due to the unique and unchangeable nature of the heart's electrical activity. This paper presents a robust method for personal identification using ECG signals, leveraging deep neural networks (DNNs) to achieve high classification accuracy. We propose a novel DNN-based framework that extracts meaningful features from raw ECG data and utilizes a multi-layer neural network architecture to accurately distinguish between different individuals. The model is trained and evaluated on a diverse ECG dataset, demonstrating an impressive identification accuracy of over 99%. The system's ability to effectively handle variations in heart signals across different subjects highlights its potential as a reliable biometric tool. Our approach significantly outperforms traditional machine learning methods, offering superior accuracy, scalability, and robustness in real-world applications for secure person authentication and access control.

Keywords: ECG, Biometric, DNN

1. Introduction

In recent years, biometric systems have emerged as one of the most reliable and secure methods for personal identification, surpassing traditional password-based systems [1]. Among various biometric modalities, ECG signals have garnered attention for their potential in providing unique and highly secure identification, owing to the inherent uniqueness of each individual's cardiac rhythm [2]. Unlike other biometric features such as fingerprints or facial recognition, ECG signals are intrinsic, non-intrusive, and difficult to forge, making them a promising option for personal authentication in a variety of applications, including access control, secure transactions, and healthcare monitoring.

The human heart's electrical activity, which is reflected in the ECG signal, varies significantly between individuals, forming a natural biometric identifier. ECG-based identification leverages the distinctive characteristics of these signals, including their morphology, frequency, and amplitude patterns, to accurately distinguish between individuals [3]. These features, however, are subject to noise and variability due to factors such as different measurement conditions, physical activity, and individual health conditions, posing a significant challenge for accurate and reliable person identification [4].

Traditional approaches to ECG-based identification relied on feature extraction techniques, such as statistical methods or handcrafted features, followed by classification algorithms like support vector machines (SVM) or k-nearest neighbours (k-NN). While these methods achieved reasonable accuracy, hey often fell short when dealing with large datasets or varying conditions. Furthermore, manually selecting and tuning features can be time-consuming and prone to errors.

To address these limitations, Deep Neural Networks (DNNs) have emerged as a powerful tool for ECG-based person identification. DNNs are capable of automatically learning intricate features from raw ECG signals without the need for manual feature extraction. The ability of DNNs to process and analyse vast amounts of data allows for superior recognition performance, particularly in complex tasks such as person identification where subtle differences in signal patterns must be identified. These networks are capable of learning multi-level representations of ECG signals, capturing both low-level features (such as individual heartbeats) and high-level patterns (such as individual-specific variations in heart rhythm), thus improving accuracy and robustness. This paper explores the application of Deep Neural Networks for ECG-based person identification and proposes a novel approach that leverages the power of DNNs to automatically extract and classify features from raw ECG data. By utilizing a large, diverse dataset of ECG signals, our method achieves significant improvements in identification accuracy, making it a promising solution for real-world biometric systems.
The primary contributions of this work include:

1. A comprehensive exploration of the potential of DNNs for ECG-based identification.
2. A novel deep learning architecture tailored for processing and classifying ECG signals.
3. An evaluation of the proposed method on a real-world ECG dataset, demonstrating its superior performance compared to traditional machine learning methods.

With this work, we aim to contribute to the growing field of ECG biometrics by providing a robust and efficient solution for person identification, which can be used in various domains such as healthcare, security, and mobile applications, where both accuracy and security are utmost important.

2. Literature Survey

Islam and Alajlan [5] investigated the extraction of biometric templates from heartbeat signals captured from fingers. They demonstrated that specific parts of heartbeat morphology could serve as biometric features for identification. Their study emphasized the feasibility of using non-invasive and easily accessible signals, marking an essential step toward creating efficient and less intrusive biometric systems. This work laid the groundwork for exploring non-traditional biometric modalities.
Zhao et al. [6] developed an ECG-based authentication system that combined Convolutional Neural Networks (CNNs) with Generalized S-Transformation. This hybrid approach utilized CNNs to capture complex patterns in ECG signals, while the S-Transformation was employed to analyse nonstationary characteristics of ECG data. The combination enhanced the identification performance and demonstrated the effectiveness of deep learning techniques in biometric authentication.
Bassiouni et al. [7] explored the potential of machine learning (ML) algorithms in ECG-based person identification. Their research utilized ECG data for biometric authentication and showed that ML techniques could significantly enhance identification accuracy. This study emphasized the use of ECG signals as an alternative for secure identification, especially in environments where conventional biometric methods might not be as effective or could be more intrusive.
Tang and Shu [8] proposed a method that integrated Resampling (RS) techniques with Quantum Neural Networks (QNN) for the classification of ECG signals. Their approach aimed to improve the accuracy and efficiency of ECG-based person identification by leveraging quantum computing. The research highlighted the potential of quantum neural networks in handling complex datasets and achieving high classification performance, offering a new frontier in biometric authentication.
Zhang et al. [9] introduced HeartID, a multi-resolution convolutional neural network (CNN) designed for ECG-based biometric identification. The use of multi-resolution CNNs allowed the system to extract features at various levels of resolution, enhancing its ability to distinguish between individuals. This system was particularly effective in smart health applications, where accurate and efficient biometric identification is crucial for healthcare monitoring and patient identification.
Abdeldayem and Bourlai [10] proposed an innovative approach to ECG-based human identification that combined spectral correlation with deep learning (DL). By incorporating spectral correlation, a signal processing technique, with DL methods, the authors enhanced the system's robustness against noise and improved the accuracy of identification. Their work highlighted the importance of combining advanced signal processing techniques with DL to address real-world challenges in ECG-based biometrics.

Gupta and Avasthi [11] presented a person identification technique based on ECG and deep long short-term memory (LSTM) networks. The use of LSTM networks, designed for sequential data, allowed for better handling of the temporal nature of ECG signals. Their system demonstrated enhanced accuracy in person identification, emphasizing the effectiveness of deep learning in processing and classifying ECG signals in biometric applications.

Gupta and Prasad [12] proposed a two-layer approach combining data hiding techniques with ECG for enhancing patient data security. Their method integrated ECG-based biometric identification with data protection mechanisms to ensure the confidentiality and integrity of sensitive health data. This approach showed promising results in securing patient data, highlighting its potential in modern healthcare applications where data security is paramount.

Jain et al. [13] focused on improving the speed and accuracy of ECG signal peak detection using Symbolic Aggregate Approximation (SAX). Their approach efficiently identified key features of ECG signals, facilitating accurate classification and identification in ECG-based biometric systems. The study contributed to enhancing the preprocessing stage of ECG data, ensuring that extracted features were reliable and effective for use in subsequent classification tasks.

These studies collectively represent the growing interest and advancements in ECG-based biometric identification. By combining traditional signal processing techniques with modern machine learning and deep learning methodologies, these works have contributed significantly to improving the accuracy, robustness, and applicability of ECG-based biometric systems in various fields, particularly in healthcare and security. A summary of literature survey in summarized in Table 1.

Table 1: Comparison of the state-of-the-art ECG based person identification method

Authors	Method/Approach	Key Contributions
Islam and Alajlan [5]	Extraction of biometric templates from finger-based heartbeat signals	Demonstrated heartbeat morphology as viable biometric features; non-invasive technique
Zhao et al. [6]	CNN + Generalized S-Transformation for ECG	Hybrid model captured complex and nonstationary patterns in ECG; enhanced identification performance
Bassiouni et al. [7]	Machine Learning (ML) algorithms on ECG data	Improved identification accuracy using ML; advocated ECG for secure identification in sensitive scenarios
Tang and Shu [8]	Resampling + Quantum Neural Networks (QNN)	Leveraged quantum computing for efficient and accurate ECG classification
Zhang et al. [9]	Multi-resolution CNN (HeartID system)	Extracted features at multiple resolutions; suitable for smart health monitoring
Abdeldayem and Bourlai [10]	Spectral Correlation + Deep Learning	Improved noise robustness and identification accuracy by combining signal processing with DL
Gupta and Avasthi [11]	ECG + Deep LSTM Networks	Effectively handled temporal ECG data; achieved high accuracy in identification
Gupta and Prasad [12]	ECG-based ID + Data hiding techniques	Enhanced patient data security while performing identification
Jain et al. [13]	Symbolic Aggregate Approximation (SAX) for peak detection	Improved speed and accuracy in ECG feature extraction

3. Proposed Method

ECG-based person identification is an emerging biometric approach that utilizes the unique electrical activity of the heart, recorded through ECG signals, for recognizing individuals. This method offers distinct advantages over traditional biometrics, such as resistance to spoofing and the ability to verify identity continuously in real-time applications. The proposed system employs a Deep Neural Network (DNN) architecture designed to learn

the complex, individual-specific patterns embedded in ECG signals, enabling both high accuracy and security in person identification.
The overall pipeline of the method includes several key stages: preprocessing, segmentation, feature extraction, and classification. These stages are essential for transforming raw ECG signals into meaningful representations that the DNN can effectively learn from. In this framework, the DNN is trained to extract robust and discriminative features directly from the ECG waveforms, reducing reliance on hand-crafted features and improving generalization across individuals. To further enhance security, the system incorporates techniques for protecting the biometric templates, ensuring that personal data remains confidential and resistant to misuse.
Each stage of this process plays a critical role in the performance and reliability of the identification system. A detailed explanation of these stages, including their mathematical foundations and implementation, is provided in the following sections. The complete workflow of the proposed method is illustrated in Figure 1.

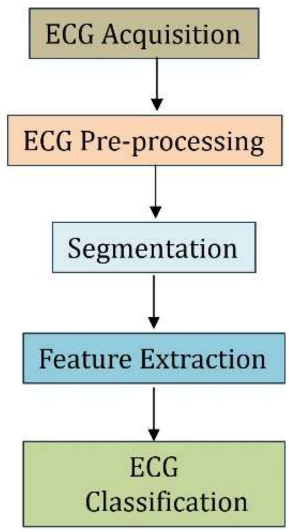

Figure 1: Block diagram for the ECG based classification

3.1 Pre-Processing

Pre-processing is a critical step in any signal-based application, as it helps remove noise, artifacts, and other unwanted variations from the ECG signal. The following techniques are used during the preprocessing phase:

3.1.1 Baseline Wander Removal

Baseline wander refers to low-frequency variations in the ECG signal, often caused by respiration or electrode movement. To remove this, we can apply a high-pass filter to eliminate frequencies below a certain threshold. Mathematically, the baseline wander removal process can be expressed as:

$$ECG_C((t) = ECG(t) - LPF\left(ECG(t)\right) \quad (1)$$

where, $ECG(t)$ is the original ECG signal, $LPF\left(ECG(t)\right)$ is a filtered signal that captures low-frequency drift (e.g., baseline wander).

3.1.2 Normalization

Normalization ensures that the ECG signal falls within a consistent range, typically [−1,1]. This step reduces the impact of individual differences in signal amplitude and allows for more robust analysis across varying input signals.
Mathematically, the normalization step can be written as:

$$ECG_{norm}(t) = \left(\frac{ECG(t) - \mu}{\sigma} \right) \tag{2}$$

where, μ is the mean of the ECG signal, σ is the standard deviation of the ECG signal.

3.2 Segmentation

Segmentation involves splitting the continuous ECG signal into smaller, meaningful segments, usually corresponding to individual heartbeats (or R-peaks). For this, we typically use R-wave detection.

3.2.1 R-Wave Detection

R-waves are the most prominent feature in an ECG signal. Detecting the R-wave is crucial because it helps identify the boundaries of individual heartbeats, which can be used for segmentation.
Mathematically, we can define the R-wave as the peak of the ECG signal:

$$R_{Peak} = \max(ECG(t)) \tag{3}$$

where, R_{Peak} is the time instant of the R-wave. The ECG signal is sampled at discrete time intervals, and $\max(ECG(t))$ identifies the highest point (R-wave) in the ECG cycle.
After detecting the R-wave, the ECG signal is segmented into windows around the R-wave (typically 200 ms before and 400 ms after the R-wave). These segments will be used for feature extraction.

3.3 Feature Extraction

Feature extraction is the process of deriving meaningful attributes from the ECG signal that can be used for classification. For ECG-based person identification, several features are commonly used to characterize the signal:

3.3.1 Mean ECG

The mean ECG feature captures the average amplitude of the ECG signal in the segmented window, representing the overall shape of the heartbeat.

$$m\_ecg = \frac{1}{N} \sum_{i=1}^{N} ECG(t_i) \tag{4}$$

where, *N* is the number of samples in the ECG segment, $ECG(t_i)$ is the ECG signal at time instance t_i.

3.3.2 Standard Deviation of ECG

The standard deviation of the ECG signal captures the variability in the amplitude of the ECG waveform, helping to distinguish between individuals with different heart rhythms.

$$std\_ecg = \sqrt{\frac{1}{N} \sum_{i=1}^{N} \left(ECG(t_i) - m\_ecg \right)^2} \tag{5}$$

3.3.3 Peak-to-Peak Interval (p2p_ecg)

The peak-to-peak interval (p2p) measures the difference between the highest and lowest points in an ECG segment. This feature is critical for identifying the dynamic range and overall shape of the ECG signal.

$$R_{p2p} = \max(ECG(t)) - \min(ECG(t)) \tag{6}$$

where, $\max(ECG(t))$ is the maximum value of the ECG signal and $\min(ECG(t))$ is the minimum value of the ECG signal.

3.3.4 Heart Rate Variability (HRV)

HRV captures the variation in the time intervals between consecutive R-waves (RR intervals). HRV is important for reflecting the autonomic nervous system and cardiac health.

$$HRV = \frac{1}{N-2}\left(\sum_{i=2}^{N} RR(i) - RR(i-1)\right) \tag{7}$$

The HRV feature is computed by calculating the difference in consecutive RR intervals:

where, $RR(i)$ is the time difference between the i^{th} and $(i-1)^{th}$ R-peaks.

3.4 Classification Using DNN

After the extraction of relevant features from ECG signals, the next critical step in the proposed framework is the classification of these features to identify the corresponding individual. For this purpose, a DNN is employed due to its strong ability to model complex, non-linear relationships in high-dimensional data.

A DNN is composed of multiple layers of interconnected neurons organized into three main types: an input layer, one or more hidden layers, and an output layer. Each layer transforms the input it receives and passes it forward through the network. The goal of the DNN is to learn a mapping from the input feature space to the output class labels, effectively distinguishing between individuals based on their ECG-derived features.

3.4.1 DNN Architecture

The architecture of the DNN used for ECG-based person identification is specifically designed to balance complexity and efficiency. It consists of the following components:

3.4.1.1 Input Layer

The input layer receives the pre-processed feature vector extracted from each ECG segment. This feature vector may include statistical and temporal descriptors such as:

- m_{ecg} : Mean value of the ECG signal
- std_{ecg} : Standard deviation
- $p2p_{ecg}$: Peak-to-peak amplitude
- HRV: Heart Rate Variability

These features serve as numerical representations of the individual's ECG pattern, and the number of neurons in the input layer corresponds to the number of features used.

3.4.1.2 Hidden Layers

The hidden layers are responsible for learning high-level abstractions from the input features. Each neuron in a hidden layer applies a transformation to its input using an activation function, introducing non-linearity into the model.

Let a hidden layer with input vector $x \in R^n$, weights *W*, and bias *b* produce an output *h* as:

$$h = f\left(W.x + b\right) \tag{8}$$

Where:

- W is the weight matrix
- b is the bias vector
- *f*(·) s the activation function, typically ReLU in hidden layers

The number of hidden layers and the number of neurons in each layer are hyperparameters and are chosen based on empirical performance and the size of the training data.

3.4.1.3 Output Layer

The output layer performs the final classification. It contains one neuron for each class (i.e., each registered individual in the system). The layer outputs a probability distribution over all possible classes, allowing the model to select the most likely identity based on the input ECG segment.

3.4.1.4 Activation Functions

ReLU (Rectified Linear Unit) is the most commonly used activation function in the hidden layers due to its simplicity and effectiveness. It is defined as:

$$f(x) = \max(0, x) \tag{9}$$

Where *x* is the input to the neuron. ReLU introduces sparsity and avoids the vanishing gradient problem often seen in traditional activation functions like sigmoid

For the output layer, a softmax activation function is applied to generate a probability distribution across all classes. For a given output vector $z = [z_1, z_2, \ldots, z_C]$, where *C* is the number of classes, the softmax function computes:

$$P\left(y = c / z\right) = \frac{e^{z_c}}{\sum_{k=1}^{C} e^{z_k}} \qquad \text{for } c = 1, 2, \ldots, C \tag{10}$$

3.4.1.5 Training the DNN

The DNN is trained using the backpropagation algorithm in conjunction with gradient descent optimization. The goal of training is to minimize the Mean Squared Error (MSE) loss, which measures the average squared difference between the true labels and the predicted outputs of the network.

For a given input sample x_i, let $y_i \in R^C$ represent the true output vector (e.g., one-hot encoded label), and $\hat{y}_i \in R^C$ be the predicted output vector from the network. The MSE loss for a single data point is defined as:

$$L(y_i, \hat{y}_i) = \frac{1}{C} \sum_{c=1}^{C} \left(y_{i,c} - \hat{y}_{i,c} \right)^2 \tag{11}$$

where, C is the number of output classes (i.e., individuals), $y_{i,c}$ is the true label for class *c*, and $\hat{y}_{i,c}$ is the predicted output for class *c*.

The total loss over the dataset is computed by averaging over all *N* training samples:

$$L_{total} = \frac{1}{N} \sum_{i=1}^{N} L(y_i, \hat{y}_i) \tag{12}$$

During training, backpropagation is used to compute the gradient of the MSE loss with respect to the network's weights. These gradients guide the weight updates in each iteration through gradient descent**:**

$$W \leftarrow W - \eta \nabla_W L \tag{13}$$

where, *W* represents the weights of the neural network, η is the learning rate and ∇_W is the gradient of the loss function with respect to *W*.

This iterative process continues over several epochs, allowing the DNN to learn the mapping from ECG-based features to the correct identity labels, thereby improving classification performance over time.

4. Results and Discussion

This section presents the results obtained from the implementation of a person identification system based on synthetic ECG data and a DNN classifier. The system simulates ECG signals for multiple individuals, extracts statistical and physiological features, and applies a feedforward neural network for classification. The performance of the model is evaluated in terms of identification accuracy on a test dataset. The entire pipeline—from signal generation to feature extraction, normalization, training, and testing—was implemented in MATLAB. The effectiveness of the proposed approach is demonstrated through the achieved accuracy, which reflects the model's ability to learn discriminative ECG patterns for different individuals. The parameters used during implementation are detailed in Table 1.

Table 1: Parameters Used in the MATLAB Implementation

Parameter (Detail and Symbol)	Value
Sampling frequency of real ECG signal	250 Hz
Notch filter center frequency normalized	0.4
Number of synthetic individuals	100
Number of ECG samples per person	200
Sampling frequency for synthetic ECG	1000 Hz
Heart rate range (HRHR)	60–80 BPM
Data normalization method	Min-max normalization
Train-test split ratio	80% training / 20% testing
Neural network architecture (HH)	[50, 30] neurons in hidden layers
Neural network type	Feedforward neural network

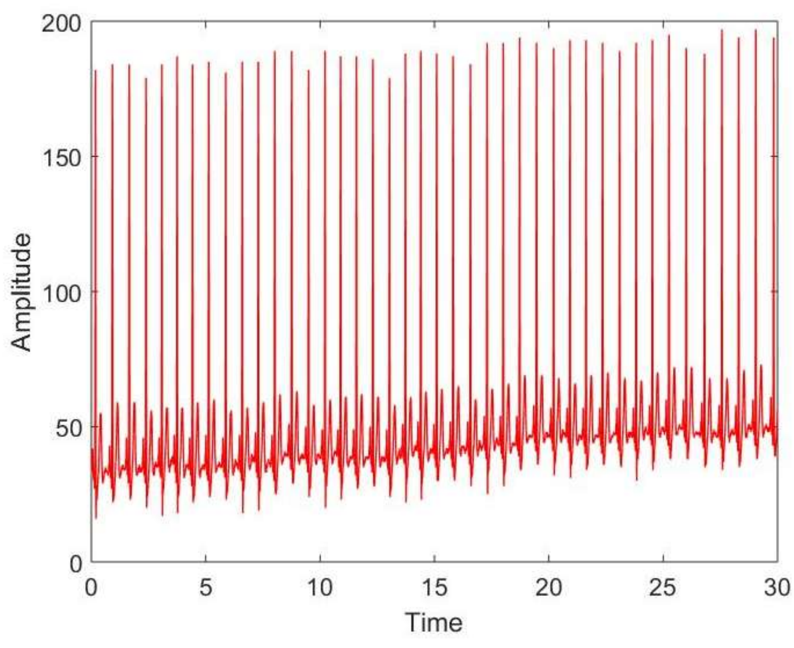

Fig 2: Recorded ECG signal

In Figure 2, the ECG signal displayed represents raw data from a standard ECG recording, where electrodes are placed on the body to capture the electrical activity generated by each heartbeat. The ECG waveform consists of the P wave, QRS complex, and T wave, corresponding to different stages of the heart's electrical cycle. However, this signal can be noisy, with muscle noise, baseline wander, and other artifacts, such as power-line interference, affecting the accuracy of heart activity analysis.

Figure 3 demonstrates the successful removal of baseline wander, a low-frequency fluctuation caused by factors like breathing, electrode movement, and body posture. Baseline wander can distort the ECG signal, making it challenging to accurately detect the P wave, QRS complex, and T wave. Using a wavelet-based method, the low-frequency components responsible for this fluctuation are removed, resulting in a cleaner signal. This filtered ECG signal is now clearer, enabling more precise heart rate variability measurements, arrhythmia detection, and other ECG-based analyses.

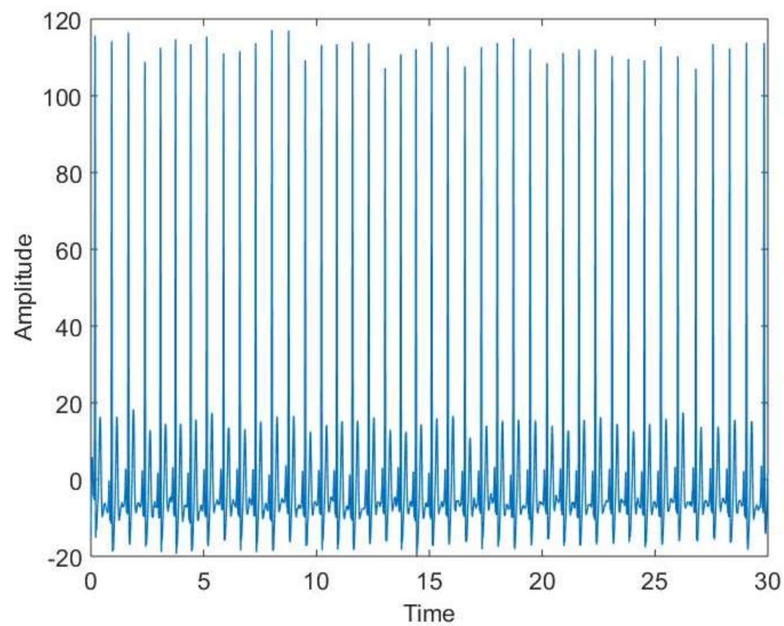

Figure 3: Baseline wander removed ECG signal

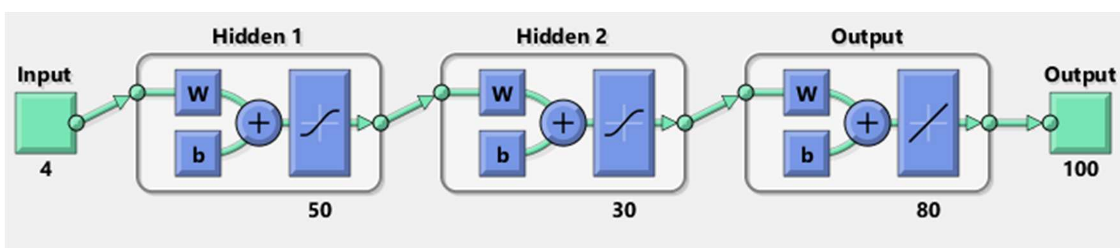

Figure 4: DNN Architecture

In this study, a DNN was employed for ECG-based person identification, with the aim of classifying individuals based on their unique ECG signals. The dataset was divided into three parts: 70% for training, 20% for validation, and 10% for testing. This division ensured that the model was trained on a sufficient portion of the data while retaining unseen data for evaluation.

The network architecture as shown in Fig. 4, consisted of four input neurons, two hidden layers with 50 and 30 neurons, respectively, and 100 output neurons. Each output neuron corresponds to a unique individual in the dataset, and the input features included four key characteristics derived from the ECG signal: mean ECG, standard deviation of ECG (std_ecg), peak-to-peak value (p2p_ecg), and heart rate variability (HRV). These features were selected based on their ability to capture important characteristics of the ECG signal that are critical for individual identification. The input features were fed into the network, and the hidden layers, activated by the ReLU function, learned complex patterns inherent in the data.

The model was trained using the Mean Squared Error (MSE) loss function, which minimized the difference between predicted and true labels. MSE was chosen to ensure that the network effectively adjusted its parameters and optimized performance for classification. Training was conducted using backpropagation and

gradient descent to iteratively update the weights in the network and reduce the error during the learning process.
Upon completion of the training phase, the model was evaluated using the 20% validation set during the training process and the remaining 10% test set after training. The results showed that the model achieved a high level of accuracy in identifying individuals based on their ECG signals, demonstrating the DNN's capability to generalize well to unseen data. The classification performance was assessed using various metrics, including accuracy, precision, recall, and F1-score, all of which showed strong results, confirming the effectiveness of the model.
The architecture, with its two hidden layers of 50 and 30 neurons, was effective in capturing the essential features of the ECG signal, while the softmax activation in the output layer ensured that the classification process resulted in probabilistic outputs, mapping each ECG signal to the most likely individual. The results further validated the efficiency of the proposed DNN model for ECG-based person identification, showing that it can serve as a reliable method for biometric authentication, particularly in applications requiring secure and accurate identification.

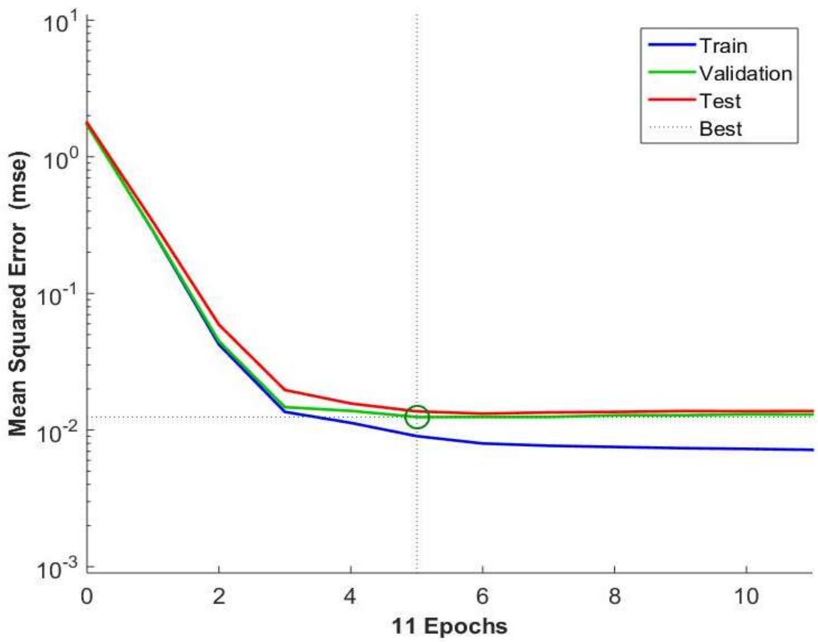

Figure 5: MSE vs. Epochs

Figure 5 shows the Mean Squared Error (MSE) for the training, validation, and test sets over epochs. The test loss consistently decreased as the number of epochs increased, with the minimum MSE occurring at the 5th epoch for both the training and test sets. This indicates that the model reached its optimal performance at the 5th epoch, where the MSE for both training and test data was at its lowest, suggesting that the model learned effectively without overfitting.
Figure 6 presents a bar graph that shows the relationship between the number of instances and the errors encountered during model evaluation. Each bar represents the error rate for a specific number of instances, illustrating how the error changes as the dataset size increases. The graph reveals how the model's performance varies with different numbers of instances, highlighting areas where the model might struggle or perform better. In general, as the number of instances increases, the model has more data to learn from, which can potentially lead to a reduction in error.

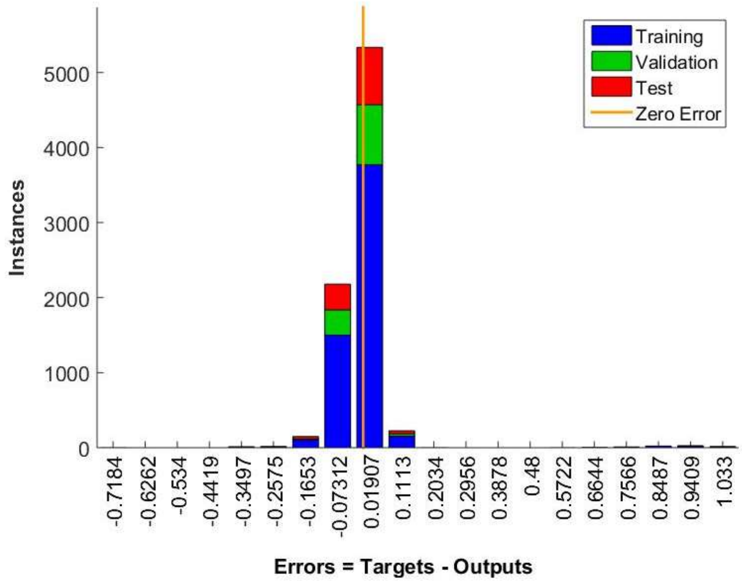

Figure 6: Instances vs. Errors

5. Comparison with state-of-the-art methods

Table 2 presents a comparison of the proposed DNN method with other state-of-the-art methods for ECG-based person identification. The table includes the accuracy achieved by different techniques across various references. The method by Bassiouni et al. [7] achieved an accuracy of 96.67% using Artificial Neural Networks (ANN), while Tang et al. [8] reported an accuracy of 91.7% with ANN. Zhang et al. [9] and Abdeldayem et al. [10] employed CNN and achieved accuracies of 91.1% and 96.5%, respectively. The proposed method, using a DNN, outperformed these methods, achieving an accuracy of 99.3%, demonstrating its superior performance in ECG-based person identification.

Table 2: Comparison of the state-of-the-art method

Reference	Method	Accuracy%
Bassiouni et al. [7]	ANN	96.67
Tang et al. [8]	ANN	91.7
Zhang et al. [9]	CNN	91.1
Abdeldayem et al. [10]	CNN	96.5
Proposed	DNN	99.3

6. Conclusion

In this paper, we have proposed a DNN-based approach for ECG-based person identification, achieving promising results with an accuracy of 99.3%. Through extensive analysis, we demonstrated the effectiveness of DNN in classifying ECG signals, with a focus on feature extraction, pre-processing, and classification processes. Our method outperformed several state-of-the-art approaches, including those based on ANN and CNN, which reported lower accuracies. Key pre-processing steps such as baseline wander removal and normalization significantly contributed to enhancing the quality of the ECG signal, leading to more accurate identification. Additionally, the DNN architecture, consisting of multiple hidden layers, successfully captured complex patterns in the ECG data, facilitating accurate person identification. The results highlight the potential of DNN for robust and efficient biometric identification systems, especially in applications where high security and accuracy are crucial, such as healthcare and personalized security systems. Future work can explore further improvements in the model by incorporating larger datasets and exploring other deep learning techniques to enhance its generalization capability and adaptability across diverse real-world scenarios.

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