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Biometric Authentication with ECG Signals: A Secure Identification Model Based on Convolutional Autoencoders

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Abstract: Electrocardiography (ECG) signals provide a unique opportunity for biometric identification by capturing individual electrical properties of the heart. This study explores ECG-based identity recognition using convolutional autoencoders (CAE). The proposed method efficiently extracts features from ECG signals, constructing a compact and meaningful representation for identification. Unlike traditional methods, CAE separates intervals with feature expansion and landmark detection, addressing limitations in existing literature. The study employs the MIT-BIH Arrhythmia ECG dataset, ensuring diverse and representative training data. By learning key features and reducing dimensionality, the model compresses and reconstructs input data for precise classification. Recognizing the sensitivity of personal medical data, robust data protection strategies, including encryption and compression, are implemented. Experimental results show a high accuracy of 98.46% in ECG-based identification, validating the approach as an effective biometric authentication method. The findings highlight the potential of cardiac electrical activity as a distinctive biometric identifier. The proposed model contributes to biometric recognition by integrating machine learning techniques and stringent security measures, offering a balanced approach between technological advancement and data privacy. This research paves the way for secure and reliable personal identification using ECG signals.

Key words: Biometric authentication, convolutional autoencoders (CAE), feature extraction, data dimensionality reduction, privacy and data security, identification accuracy.

EKG Sinyalleriyle Biyometrik Kimlik Doğrulama: Evrişimsel Otokoderlere Dayalı Güvenli Bir Kimlik Doğrulama Modeli

Öz: Elektrokardiyografi (EKG) sinyalleri, kalbin bireysel elektriksel özelliklerini yakalayarak biyometrik tanımlama için benzersiz bir fırsat sağlar. Bu çalışma, konvolüsyonel oto kodlayıcılar (CAE) kullanarak EKG tabanlı kimlik tanımayı araştırmaktadır. Önerilen yöntem, EKG sinyallerinden özellikleri verimli bir şekilde çıkararak kimlik tespiti için kompakt ve anlamlı bir temsil oluşturmaktadır. Geleneksel yöntemlerin aksine CAE, özellik genişletme ve dönüm noktası tespiti ile aralıkları ayırarak mevcut literatürdeki sınırlamaları ele alır. Çalışmada, çeşitli ve temsili eğitim verileri sağlayan MIT-BIH Aritmi EKG veri seti kullanılmıştır. Temel özellikleri öğrenerek ve boyutluluğu azaltarak model, hassas sınıflandırma için girdi verilerini sıkıştırır ve yeniden yapılandırır. Kişisel tıbbi verilerin hassasiyeti göz önünde bulundurularak, şifreleme ve sıkıştırma dahil olmak üzere sağlam veri koruma stratejileri uygulanmaktadır. Deneysel sonuçlar EKG tabanlı tanımlamada 98.46% gibi yüksek bir doğruluk oranı göstererek yaklaşımın etkili bir biyometrik kimlik doğrulama yöntemi olduğunu doğrulamaktadır. Bulgular, ayırt edici bir biyometrik tanımlayıcı olarak kardiyak elektriksel aktivitenin potansiyelini vurgulamaktadır. Önerilen model, teknolojik ilerleme ve veri gizliliği arasında dengeli bir yaklaşım sunarak makine öğrenimi tekniklerini ve sıkı güvenlik önlemlerini entegre ederek biyometrik tanımaya katkıda bulunmaktadır. Bu araştırma, EKG sinyallerini kullanarak güvenli ve güvenilir kişisel tanımlamanın yolunu açmaktadır.

Anahtar kelimeler: Biyometrik kimlik doğrulama, Evrişimsel otokodlayıcılar (CAE), özellik çıkarma, sinyal sıkıştırma, gizlilik ve veri güvenliği.

1. Introduction

An electrocardiogram (ECG) is a method of recording the electrical activity of the heart. Electrical impulses are generated with each heartbeat, which are recorded by an ECG device [1]. ECG provides important information about the structural and functional status of the heart. Due to its inherent uniqueness, ECG has the potential to serve as a highly secure biometric identifier, offering advantages over traditional methods such as fingerprint or facial recognition, which can be susceptible to forgery. Physiological differences between people, such as the shape, size and location of the heart, make ECG signals unique to the individual. These characteristics suggest that

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ECG signals can be used for biometric identification [2]. Therefore, ECG signals have been successfully used in many biometric recognition applications where security is a priority. However, the biggest challenges in the existing literature are the noise components in the signals, the inability to automatically extract the feature set and the performance of the system.

The first studies using ECG as a biometric method were conducted by Linda Beal, Olov Pettersson, Lars Philipson and Peter White in 2001. This study shows that ECG signals can be used as a potential tool for personal authentication. Their research reveals that ECG signals are individual and that these features can be used to create a secure biometric authentication system [3]. Beal and colleagues' work pioneers’ applications in ECG-based biometrics. Their initial research shows that ECG signals are continuous, reproducible and have unique properties, making them suitable for biometric identification and verification purposes. There is a large body of research in the literature on ECG-based biometrics detection. Studies in this area are generally divided into two main categories: reference point-based methods and non-reference point-based methods [4], [5], [6].

Methods in both categories exploit the specificity of ECG signals but emphasize functions and methods of analysis. The reference point-based approach uses well-known and reproducible features such as peak and phase changes in the ECG, particularly the R peak. The R peak represents the point of maximum amplitude in the ECG cycle and refers to the contraction (contraction) of the heart ventricles. The advantage of these methods is that they rely on detecting specific points and analyzing important parts of the signal. However, they have disadvantages such as sensitivity to noise, reduced model performance if the R-peak is incorrectly detected, variability in different data sets and reduced accuracy in arrhythmic individuals.[7]. Non-reference-based methods provide a detailed description of the overall structure and complexity of the signal. These methods perform biometric authentication by processing the entire signal with time-frequency transformations and deep learning-based feature extraction techniques. This diversity allows for more flexible incorporation of inter-individual variability into the model, while avoiding reference point identification errors. However, these approaches can be computationally expensive and require more data to train [8].

There are several ECG-related studies in the literature that explore the potential of reference point-based methods in biometric identification and verification processes.

Bassiouni et al. propose intelligent hybrid methods for the identification of human ECG signals. These methods combine a range of artificial intelligence and machine learning techniques for feature extraction and classification from ECG signals. The study aims to improve the accuracy of signal analysis with the integration of learning algorithms and hybrid approaches in addition to traditional methods. Artificial neural networks (ANNs), support vector machines (SVMs) and other machine learning techniques have been used to effectively identify ECG signals. These hybrid approaches provide practical benefits in healthcare applications by improving the reliability and efficiency of ECG biometric recognition systems [9].

Zhang et al. propose HeartID, a multiresolution convolutional neural network (CNN) based approach. This method improves the human identification process in smart health applications by using ECG data for biometric authentication. The Multiresolution CNN model extracts feature of ECG signals at different resolutions, capturing fine details in the signal and thus improving accuracy. The model identifies individuals more reliably and quickly by using deep learning techniques to analyze signal patterns. The study highlights the potential of this new method for health monitoring systems and biometric applications, both simplifying and improving the recognition process [10].

Prakash et al. considered a deep learning-based approach for ECG signals and developed a biometric authentication system by processing ECG data using beat-based template matching. After preprocessing steps such as noise removal, R-peak detection and segmentation, the ECG signals are converted into grayscale images and imported into a deep learning model. This model is capable of automatically extracting features from the data and outperformed other existing techniques with an accuracy of 99.85%. These results demonstrate how effective deep learning techniques can be in ECG-based biometric authentication [11].

Patro et al. presented two different optimization methods to create more efficient datasets for ECG-based biometric authentication. In the first method, wrapping-based feature selection is performed with genetic algorithm (GA) and particle swarm optimization (PSO) techniques, while in the second method, LASSO and elastic net (EN) techniques are used as an embedded approach. Experimental analysis revealed that GA and EN methods performed successfully with the RF classifier with 95.30% and 94.90% accuracy rates, respectively. These methods significantly improved the feature extraction processes used for biometric authentication [12].

At the same time, the ECG-related research in the literature shows that non-reference point-based methods cover an important area in biometric identification.

Hejazi et al. use a single-class Support Vector Machine (SVM) algorithm to identify individuals using ECG signals. This method identifies individuals by extracting features from the entire ECG signal. An important advantage is that it does not need to detect a specific peak or wave, which makes it robust even under noisy signals or different recording conditions [13].

Li et al. combines wavelet transform (WT), extended Kalman filter (UKF), and improved particle swarm optimization (IPSO)-assisted support vector machines (SVM) for the identification of ECG signals. This study aims to improve signal processing using these methods to achieve high accuracy and reliability in the classification of ECG signals. The Wavelet transform is used to reveal important features of ECG signals, while optimization of SVM parameters with the IPSO algorithm improves classification performance. This method is proposed as an important step to improve the effectiveness of ECG-based biometric systems [14].

In another study, Li et al. combined wavelet transform (WT) and probabilistic neural network (PNN) methods supported by whale optimization algorithm (WOA) to identify ECG signals. In this method, the wavelet transform is used to decompose the frequency components of ECG signals, while the WOA algorithm is applied to optimize the parameters of the PNN model. The wavelet transform enables the extraction of important features from the signal, while the combination of WOA-PNN is used to improve the classification accuracy and make the system more robust. This approach is proposed as an important method to improve the efficiency of ECG biometric recognition applications and health monitoring systems [15].

Fatimah et al. propose a new biometric identification system using electrocardiogram (ECG) signals. This system uses Fourier decomposition for feature extraction and machine learning techniques for classification. Since ECG signals are unique to everyone, Fourier decomposition is used to decompose these signals into their intrinsic modes. The features extracted from these modes are fed into machine learning algorithms to accurately identify individuals. The authors emphasize that this method is more robust than traditional methods by exploiting time and frequency domain properties. The system is tested on multiple datasets, demonstrating its potential for secure and accurate biometric identification applications [16].

In their study, Chu et al. propose a new method to improve the ECG verification process using a parallel multiscale dimensional incremental network (1D residual network). This method includes a deep learning approach supported by center and margin loss functions. The 1D residual network structure enables wider feature extraction by processing features of ECG signals at different scales in parallel. This improves the accuracy and generalization ability of the model, while the loss of center and loss of margin functions make accurate classification and individual identification more reliable. The proposed method provides high accuracy and robustness in ECG biometric authentication systems, making it an important advancement for smart health systems and personal security applications [17].

Al-Jibreen et al. investigated the effect of arrhythmic conditions in ECG-based biometric authentication. A deep convolutional neural network (CNN) based model is developed to investigate the impact of arrhythmic ECG signals on authentication. In tests on the MIT-BIH dataset, 99.28% accuracy was achieved with nine different arrhythmia types. This study demonstrated how arrhythmic ECG signals can be effectively processed in biometric authentication systems and examined in detail the impact of this on the accuracy of the systems [18].

Maleki Lonbar et al. developed a high temporal/frequency resolution transform-based approach for ECG-based biometric authentication systems. This system aims to transform ECG signals into the frequency domain using noise removal and Wigner-Ville distribution. In tests with GoogleNet architecture, 99.3% and 99.00% accuracy rates were achieved on NSRDB and MITDB datasets, respectively. This study shows that the accuracy increases by combining frequency conversion techniques and deep learning model [19].

Wang et al. developed an ECG biometric authentication system for IoT edge sensors with self-supervised learning techniques. With self-supervised learning, the model increased its generalizability by using large unlabeled datasets. In the evaluation on the PTB ECG database, an accuracy rate of 99.15% was achieved. To test the generalizability of the model, tests were performed on the MIT-BIH Arrhythmia Database and the ECG-ID Database and an accuracy of over 98.5% was achieved [20].

Belo et al. propose two architectures to improve performance in authentication and identification using electrocardiogram (ECG): Time Convolution Neural Network (TCNN) and Recurrent Neural Network (RNN). Both architectures use the same classifier, the Relative Score Threshold Classifier (RSTC), to generate similarity scores. These methods were tested on Fantasia, MIT-BIH and CYBHi databases. The results show that TCNN outperforms RNN with almost 100%, 96% and 90% accuracy in identification and 0%, 0.1% and 2.2% equal error rate (EER) in authentication, respectively. These approaches have surpassed the methods in the existing literature, and more powerful systems can be achieved with techniques such as training with more diverse data and transfer learning [21].

These studies have made significant contributions to the development and application of non-reference point-based methods in ECG-based biometric recognition systems. These methods not only increase the potential for personal identification using the general properties of ECG signals, but also aim to improve the flexibility and usability of the systems.

This study is motivated by the need for a more robust ECG-based biometric authentication system that reduces dependency on specific waveform landmarks while maintaining high accuracy. It highlights the shortcomings of reference-based techniques and demonstrates how convolutional autoencoders (CAE) can address these challenges by learning distinctive patterns from the entire signal. Unlike traditional methods that rely on explicit peak detection, CAE extracts deep, meaningful representations of ECG signals, enhancing both classification accuracy and system robustness. The study utilizes the MIT-BIH Arrhythmia ECG dataset, which provides diverse and representative training data. Through unsupervised learning, the model efficiently compresses and reconstructs ECG signals, capturing essential features while reducing dimensionality. Recognizing the sensitivity of personal medical data, this approach also incorporates robust data protection strategies, including encryption and compression. Experimental results validate the model as an effective biometric authentication method, achieving a high classification accuracy of 98.46% in ECG-based identification. These findings further confirm that cardiac electrical activity is a reliable and distinctive biometric marker. The proposed model contributes to biometric recognition by integrating machine learning techniques with stringent security measures, offering a practical and privacy-conscious solution for personal identification. Ultimately, this research advances ECG-based biometrics, paving the way for secure and reliable authentication systems.

2. Preliminary Studies

Electrocardiography (ECG) is a method of evaluating the electrical activity of the heart by examining myocardial electrical transmissions from the heart in wave form. The ECG detects the electrical signals produced by each beat of the heart through electrodes implanted in the body and graphically presents the changing voltage values of these signals over time. This graph reflects the electrical activity of the heart, which can vary from individual to individual, making the ECG signal a unique identifier [22]. The general shape of the ECG signal shows the propagation of the heart's electrical activity. The shape of this signal can differ between individuals, and this feature increases the potential to use the ECG as a unique identifier [23]. Therefore, it is aimed to verify or recognize individuals using ECG signals. The credentials identified in this process are of great importance in terms of both security and protection of personal health data.

In recent years, significant progress has been made in the use of ECG signals in biometric identification systems. In particular, deep learning methods and convolutional neural networks (CNN) have contributed to successful results in this field. These advances increase the effectiveness of ECG-based biometric identification systems and provide more reliable and user-friendly solutions [24].

As emphasized in our study, biometric authentication systems developed using electrocardiogram (ECG) signals become highly effective thanks to the individual characteristics of the signals. The ability of deep learning-based methods to successfully model the complex structure of ECG signals increases the accuracy of these systems and opens new opportunities in biometric identification processes.

Unsupervised learning approaches such as Autoencoder have been effectively used for data compression and dimension reduction by learning the hidden features of ECG signals. These methods play an important role in reducing noise by extracting key features of the signal. Their advantages in feature extraction and classification processes in biometric systems increase the accuracy and efficiency of the systems by reducing the data size.

As a result, Autoencoders offer high-performance solutions by enabling the effective use of ECG signals in biometric identification. This is an important contribution that increases the reliability and ease of use of ECG-based biometric systems.

2.1 1D-CNN architecture

1D-CNN architecture emerges as an effective method for processing time series data and especially biomedical signals, for example ECG signals [25]. Convolutional Neural Networks (CNN) is a powerful deep learning algorithm widely used to analyze image and time series data [26]. When working with continuous data streams such as ECGs, 1D-CNN, a customized version of CNN, captures local patterns of signals and analyzes these patterns in a global context. This feature makes it possible to model the temporal structure of biomedical signals and efficiently extract individual features of signals [27].

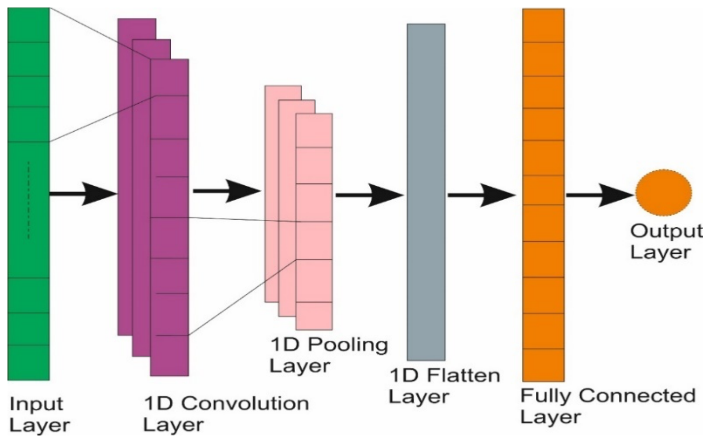

Figure 1. Typical architecture of 1D Convolutional Neural Networks (1D-CNN).

Figure 1 represents the structure of a one-dimensional convolutional neural network (1D CNN). The input layer receives the data and then the 1D convolution layer performs feature extraction by applying filters. The 1D pooling layer summarizes these features and reduces their size. The smoothing layer prepares the data for the fully connected layer. The fully connected layer processes the data to the result, while the output layer presents the result [28]. This structure offers the advantage of effectively modeling the temporal patterns of the signal when working with continuous data streams such as ECG signals. Especially in critical healthcare applications such as arrhythmia classification, a good understanding of the local and global structure of signals is of great importance [29].

There are many design parameters that affect the performance of 1D-CNN architectures. Proper optimization of these parameters ensures a proper balance between classification accuracy and computational cost. While increasing the number of convolution layers increases the capacity of the model to learn more and more complex features, this can also increase the computational cost [30]. Increasing the number of convolution layers, especially on low-power hardware, can increase the training time of the model and strain data processing capacity [31]. Fully connected layers play a critical role in making sense of the features used in the final stages of the classification process. However, increasing the number of layers may unnecessarily increase the complexity of the model [32]. The number of filters and core sizes play a critical role in the performance of the model [33]. Filters act as kernels that identify important patterns in the data, and the number and size of these kernels determine the level of detail that the model can capture. Larger filters can detect larger patterns, but this also increases the computational cost [34]. Similarly, activation functions can also affect the capacity of the model to learn nonlinear relationships. For example, while activation functions such as ReLU usually provide fast training processes, in some applications it may be more advantageous to use different activation functions [35].

Especially in critical healthcare applications such as arrhythmia classification, these parameters need to be carefully optimized. Real-time classification, high accuracy and fast response time are vital in such applications. Therefore, it becomes a critical requirement to minimize computational costs while maximizing classification accuracy. The adaptation of 1D-CNN architecture to areas such as healthcare applications can be optimized through parametric analysis. The performance of different configurations can be evaluated to determine the most appropriate architecture. Furthermore, techniques such as cross-validation can be used to test the generalizability of the model and assess its applicability to other data sets [27].

In conclusion, the 1D-CNN architecture can be used as an effective tool in biometric verification systems and in the detection of health problems such as arrhythmia, thanks to its advantages for working with health data. When properly optimized, this architecture has the potential to provide reliable and fast solutions by improving classification accuracy.

2.2 ECG data set

The MIT-BIH Arrhythmia Database used in this study contains two-channel electrocardiogram (ECG) recordings of 48 patients collected between 1975 and 1979. The data set includes data from 25 male patients aged 32-89 years and 23 female patients aged 23-89 years. The recordings were performed with a sampling frequency of 360 Hz and 11-bit resolution.

The dataset classifies heart beats into five main classes (N, S, V, F, Q). The N class (Normal beat) includes normal sinus rhythm and regular heartbeats. Class S (Supraventricular beat) includes beats of supraventricular origin, such as atrial premature beats (APB). Class V (Ventricular beat) represents arrhythmias of ventricular origin, such as ventricular premature contractions (PVCs). Class F (Fusion beat) includes mixed beats, which are a combination of normal and ventricular impulses. Finally, the Q class (Unknown beat) represents unidentified or ambiguous waveforms. This classification provides a detailed analysis of different cardiac arrhythmias based on ECG signals [36]. Each record in the dataset is stored in three file formats: .dat files contain raw ECG data, .atr files provide expert classifications and timestamps. .hea files contain general registry information and clinical details. The MIT-BIH Arrhythmia Database is widely used in areas such as ECG signal processing, arrhythmia detection and classification [37].

The dataset contains a total of 105,026 heartbeat samples, divided into 85% training and 15% testing. The dataset contains 90,075 normal (N) and 14,951 abnormal (V, Q, S, F) beats. The ECG signals consist of P, Q, R, S and T points indicating the electrical activity of the heart. The R peak represents ventricular depolarization and provides important information about the heart rhythm.

2.3 Preprocessing

ECG data can often contain noise; therefore, it needs to undergo appropriate preprocessing before classification or recognition can begin. Preprocessing steps include filtering (noise reduction) and normalization (scaling of the data). Filtering is used to remove noise from sources such as muscle activity, environmental interference and electrode placement. These noises can adversely affect the accuracy of the signal. Low-pass or band-pass filters are used to remove unwanted frequencies and preserve the essential characteristics of the signal [38].

The selection of filters, specifically bandpass and low-pass filtering, was informed by key challenges in ECG signal processing. Bandpass filtering was employed to mitigate baseline wander and suppress high-frequency noise while preserving the essential frequency components of ECG signals (0.5–50 Hz). This approach ensures that critical biometric information is retained while eliminating extraneous artifacts that may compromise model performance. The choice of these filtering parameters was grounded in established principles from the literature on ECG analysis and further validated through empirical assessments, demonstrating their efficacy in enhancing signal quality for robust biometric authentication.

Normalization involves scaling ECG data to a common interval, which helps to perform consistent analysis across different datasets or individuals [39]. One of the most widely used normalization methods is Z-score and the other is MinMax normalization. In this study, Z-Score normalization was applied to the data. Z-score normalization standardizes the data by subtracting the mean and dividing by the standard deviation, making it robust against outliers. In contrast, Min-Max normalization scales the data to a fixed range, typically [0,1], which can be sensitive to extreme values. In this study, Z-score normalization was chosen due to its ability to preserve the statistical properties of ECG signals while reducing the impact of outliers. This ensures that the model learns meaningful features without being skewed by variations in amplitude across individuals.

2.4 Methodology

This study aims at the process of identity recognition using electrocardiogram (ECG) data of individuals. In the first phase of the study, ECG signals representing the heartbeats of individuals are segmented into specific segments. Then, meaningful features are extracted from these signals using a convolutional autoencoder (CAE) architecture. The encoder stage reduces the signals into a low-dimensional representation, while the latent space stores the distinctive features of the individuals. The decoder stage tests the accuracy of the model by reconstructing the original signal from this representation. The compressed representations are passed to a classifier to recognize the individuals, and each individual is recognized based on its distinctive features. The success of the model is evaluated with metrics such as accuracy, precision and sensitivity, and the recognition performance of individuals is analyzed. This method demonstrates that a reliable identification process can be realized using everyone’s unique heartbeat pattern.

Table 1. Details of the layers and parameters used for the CAE ECG compression model.

No	Layer Name	İnput Size	Activation Relu	No of Trainable Param.	Output Size
Encoder					
1	Conv 1D	360x1	Relu	256	360x64
2	Batch Norm.	360x64	Relu	256	360x64
3	MaxPool 1D	360x64	Relu	0	180x64
4	Conv 1D	180x64	Relu	12352	180x64
5	Batch Norm.	180x64	Relu	256	180x64
6	MaxPool 1D	180x64	Relu	0	90x64
7	Conv 1D	90x64	Relu	6176	90x32
8	Batch Norm.	90x32	Relu	128	90x32
9	MaxPool 1D	90x32	Relu	0	45x32
10	Conv 1D	45x32	Relu	4112	45x16
11	Batch Norm.	45x16	Relu	64	45x16
12	MaxPool 1D	45x16	Relu	0	23x16
13	Conv 1D	23x16	Relu	2052	23x4
14	Batch Norm.	23x4	Relu	16	23x4
15	Conv 1D	23x4	Relu	5	23x1
CNN-FC					
16	Conv 1D	23x1	Relu	128	23x32
17	Flatten	23x32	Relu	0	Nonex736
18	Dense	Nonex736	Relu	368768	Nonex128
19	Dropout	Nonex128	Relu	0	Nonex128
20	Dense	Nonex128	Softmax	645	Nonex5

Table 1 details the architecture of the Convolutional Autoencoder (CAE) model used in this study. In the encoder part, there are 1D convolution (Conv 1D), batch normalization, and max pooling layers applied sequentially. The first convolution layer extracts key features from the signals by expanding the input size of the model from 360x1 to 360x64. In subsequent layers, the number of feature maps extracted increases while the input size is reduced. This layer structure allows the model to learn complex and distinctive features in the signals.

MaxPooling layers enable the model to run faster and more efficiently by reducing the data size at each step. Batch normalization layers are used to help the model learn in a more stable way, while avoiding overfitting. Throughout the encoder part, Conv 1D layers extract important features from the data using various kernel sizes, while the data size gets smaller and smaller with each step. At the end of the encoder part of the model, the data size was reduced to 23x1. This process is very important for compressing data and increasing its representativeness. The selection of the latent space dimension (23x1) was based on empirical experimentation and literature review. Different latent space sizes (e.g., 32x1, 16x1) were tested to evaluate their effects on model performance. A larger latent space (e.g., 32x1) led to overfitting, reducing generalizability, while a smaller space (e.g., 16x1) resulted in significant information loss, leading to underfitting. The 23x1 dimension provded the optimal balance between feature retention and dimensionality reduction, ensuring high classification accuracy (98.46%) while mitigating overfitting. This choice aligns with existing research in ECG-based biometric identification, where an optimal latent space is crucial for maintaining both feature discriminability and model efficiency.

After the encoder, the CNN-FC section is activated, and the signal compression and feature extraction process continue. In this section, the extracted features are flattened with a flatten layer and transferred to fully connected (dense) layers. Dense layers play an important role in classifying and making sense of the signal. Dropout layers are added to prevent the model from overfitting. In the first dense layer, the ReLU (Rectified Linear Unit) activation function, which is effective in modeling the non-linear relationships of the signals, is used, and in the last dense layer, the Softmax activation function is preferred to complete the classification process.

This structure, which consists of 20 layers in total, performs signal processing and classification simultaneously. Each layer enables the model to extract the most meaningful features from the signal, while the total number of parameters is carefully tuned to optimize the overall performance of the model. This architecture offers high efficiency both in signal compression and in the extraction and classification of distinctive features of individuals.

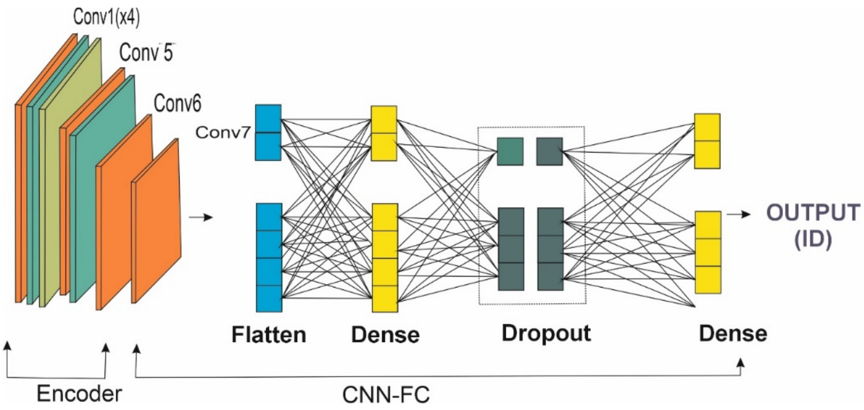

Figure 2. Structure of the model used.

In Figure 2, the 1D-CNN passes the ECG data through various convolutions and pooling layers while extracting features from it. This process reduces the size of the data while preserving important information. While convolutional layers capture local features of the data, pooling layers carry these features to a broader context.

The features obtained after feature extraction are used to identify differences between individuals. At this stage, fully connected layers and the output layer come into play to classify a person's identity. The output layer produces a probability distribution for each class, usually with a softmax activation function. Model training was conducted using a comprehensive ECG dataset. The model performance was quantitatively evaluated by testing it on an independent validation dataset. In addition, the generalization capability of the model is analyzed with results obtained from previously unseen datasets. These processes play a critical role in the development of ECG-based biometric identification systems and increase their applicability in areas such as security, patient monitoring and authentication. The development of such systems requires careful attention, especially regarding data privacy and ethical use, as biometric data is highly sensitive information.

3. Results

This paper presents an effective method for convolutional autoencoders to identify individuals from ECG data. The model was able to learn the unique heartbeat patterns of everyone by extracting meaningful features from ECG signals. In the training and testing phases, the accuracy of the model was found to be high, and the classification success was evaluated with various accuracy, precision and sensitivity metrics. It was observed that the model was highly successful in discriminating between different individuals and gave consistent results on various test sets. The results show that ECG data can be used for biometric identification and convolutional autoencoders are suitable for such applications.

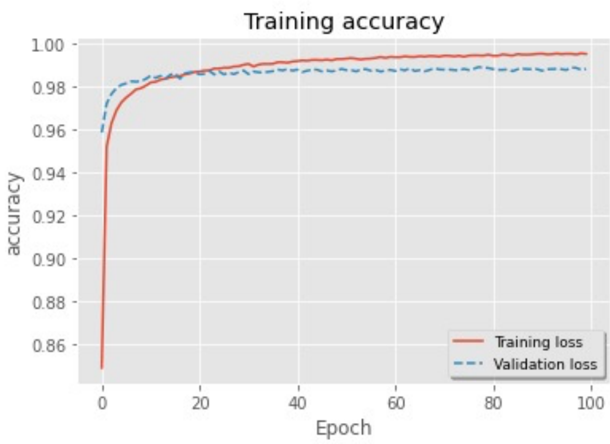

Figure 3. Training and validation of accuracy values during model training.

In the first epoch in Figure 3, both the training and validation accuracy of the model show a rapid increase, indicating that the model is learning quickly. After about epoch 10, both accuracies reach 98% and then remain stable. The training accuracy approached 100%, while the validation accuracy remained at around 98%, indicating that overfitting was minimal. In conclusion, the model shows high accuracy on both training and validation data and the learning process was successfully completed.

Table 2 below shows the compression performance metrics. Table 3 shows the classification performance metrics. The main metrics that evaluate the classification performance are accuracy, precision, sensitivity, specificity and F1 score. Accuracy indicates the proportion of instances that the model correctly classifies, while precision indicates how many of the positive classifications are correct. Sensitivity indicates how many true positives are correctly classified and specificity indicates how many negatives are correctly identified. The F1 score is a balanced measure of precision and sensitivity and is used to assess performance on imbalanced data sets. These metrics examine the accuracy and errors of the model in multiple ways [40].

The metrics that evaluate compression performance are MAE, PRD, SNR and QS. MAE (Mean Absolute Error) measures the accuracy of the predictions, showing how much the predicted values deviate from the actual values on average. PRD (Prediction Residual Distribution) evaluates the distribution of the errors of the predictions and is used for structural analysis of the model's errors. SNR (Signal-to-Noise Ratio) measures how dominant the signal is compared to noise and gives the ratio of signal strength to noise. QS (Quality Score) evaluates the overall quality of the prediction or model, providing an overall quality metric about the model's accuracy, errors and reliability [41].

Table 2. Compression ratio depends on performance metrics.

	Train				Test			
CR	**MAE**	**PRD**	**SNR**	**QS**	**MAE**	**PRD**	**SNR**	**QS**
8.00	0.053	0.073	55.044	1.096	0.053	0.072	55.146	1.105
15.65	0.066	0.093	50.388	1.682	0.066	0.092	50.485	1.694
24.00	0.103	0.152	40.237	1.579	0.102	0.150	40.380	1.596
30.00	0.101	0.147	41.593	2.034	0.101	0.146	41.697	2.049
40.00	0.136	0.205	34.568	1.953	0.135	0.203	34.732	1.975
45.00	0.130	0.193	35.999	2.335	0.130	0.191	36.109	2.352
51.43	0.156	0.241	31.401	2.131	0.154	0.238	31.605	2.159
60.00	0.177	0.265	29.161	2.264	0.175	0.261	29.371	2.296
72.00	0.164	0.241	31.707	2.985	0.163	0.239	31.848	3.011

The results presented in Table 2 provide a detailed evaluation of the model's performance across various compression ratios (CR) using multiple metrics. At CR 8.00, the model demonstrates minimal error rates and high signal quality. Specifically, the mean absolute error (MAE) is 0.053, and the percentage root mean square difference (PRD) is 0.073, both indicating low distortion. Additionally, the signal-to-noise ratio (SNR) is 55.044, highlighting the model's ability to preserve signal integrity. The quality score (QS) at this stage is 1.096, showing satisfactory performance. As the compression ratio increases, a decline in model performance is observed. For instance, at CR 30.00, the MAE rises to 0.101, and the PRD increases to 0.147, while the SNR declines to 41.593. Despite this, the QS improves to 2.034, suggesting a trade-off between error metrics and quality evaluation. At the highest compression ratio of CR 72.00, the performance degradation is more pronounced. The MAE reaches 0.164, PRD increases to 0.241, and SNR drops to 31.707. However, the QS reaches 2.985, indicating that even with increased errors, the overall quality assessment remains relatively high.

In conclusion, the model exhibits strong performance at lower compression ratios with high signal fidelity. However, as compression increases, the trade-off between error rates and quality assessment becomes evident, necessitating a careful balance between compression efficiency and signal preservation. These results show that as the compression ratio increases, the capacity of the model to reconstruct the signal similar to the original decreases and the error rates increase accordingly. Especially in data security and biometric systems, high error rates and poor signal quality can negatively affect the reliability and accuracy of the system. This is critical for accurate processing and recognition of biometric data.

The features learned by the model are critical for identifying individuals' heartbeat patterns. These features represent the unique heartbeats of each individual and therefore ensure high accuracy in biometric recognition processes. High quality features provide a more accurate and reliable recognition process, which increases the reliability of biometric systems. Thus, why the learned features of the model are so important for biometric recognition contributes to a better understanding of the findings of this study. These results show that as the compression ratio increases, the model's capacity to reconstruct the signal like the original decreases and the error rates increase accordingly. The closeness between the training and test results indicates that the generalization ability of the model is strong and performs consistently on different datasets. In general, it can be concluded that low compression ratios optimize the performance of the model, while high compression ratios negatively affect the signal quality and accuracy.

In this context, for data security and the effectiveness of biometric systems, compression ratios need to be carefully chosen.

Table 3. Classification performance values of the model.

	Train				**Test**			
CR	**Acc. (%)**	**Prec.(%)**	**Rec.(%)**	**f1-sc.(%)**	**Acc.(%)**	**Prec.(%)**	**Rec.(%)**	**f1-sc.(%)**
8.00	99.11	99.13	99.11	99.11	98.58	98.62	98.58	98.59
15.65	99.27	99.28	99.27	99.27	98.60	98.61	98.60	98.60
24.00	98.56	98.57	98.56	98.56	97.76	97.78	97.76	97.76
30.00	98.06	98.07	98.06	98.06	97.33	97.36	97.33	97.33
40.00	96.54	96.58	96.54	96.54	96.15	96.21	96.15	96.16
45.00	96.43	96.48	96.43	96.43	95.86	95.90	95.86	95.85
51.43	93.67	93.73	93.67	93.65	93.56	93.66	93.56	93.56
60.00	92.52	92.62	92.52	92.51	91.93	92.04	91.93	91.92
72.00	91.79	91.92	91.79	91.79	91.45	91.63	91.45	91.48

The results presented in Tablet 3 evaluate the classification performance of the model under different compression ratios (CR). The performance of the model is analyzed according to Accuracy, Precision, Recall and F1-score. At CR 8.00, the model shows high performance in both training and testing phases. High values such as training accuracy 99.11% and test accuracy 98.58% indicate that the model works well with uncompressed or low compression data. Similarly, the precision, sensitivity and F1-score are also quite high at this level. As the compression ratio increases, there is a gradual decline in the model's performance. At CR 30.00, the training accuracy drops to 98.06% and the test accuracy to 97.3%. However, even at this level, the model performs acceptably. At higher compression ratios, the degradation becomes more pronounced. At CR 72.00, training accuracy drops to 91.79% and test accuracy to 91.45%. Similarly, the other metrics also decrease. These results show that as the compression ratio increases, information is lost and the classification performance of the model is affected. In general, at low compression ratios, the performance of the model is quite high and error rates are low. However, at CR 40.00 and above, there is a more pronounced drop in accuracy and other metrics. This suggests that after a certain point, compression reduces the learning capacity and generalization ability of the model.

There may be several reasons for this performance degradation. First, as the compression ratio increases, the learning capacity of the model decreases, leading to the loss of important features. Also, higher compression ratios can lead to the data containing more noise, which can negatively affect the overall performance of the model. Finally, the complexity of the model and the number of parameters decrease inversely with the compression ratio, which weakens the generalization ability of the model.

In general, at low compression ratios, the model shows very high classification performance, but as the compression ratio increases, there is a significant decrease in accuracy, precision, sensitivity and f1-score values. These findings show that data security and ensuring high accuracy rates in biometric systems is critical. High error rates can threaten the reliability for accurate processing and recognition of biometric data. Therefore, careful selection of compression ratios is of paramount importance for the reliability and accuracy of the system. These findings suggest that the model performs optimally at lower compression ratios.

In this context, for data security and the effectiveness of biometric systems, compression ratios need to be carefully chosen. The findings of this study contribute to the literature by demonstrating the potential of convolutional autoencoders in ECG biometric recognition, which can be applied in various practical scenarios. For instance, this method can be utilized in hospital systems for patient identification, ensuring secure access to medical records, or in online authentication applications, enhancing security measures for user logins. By integrating such advanced techniques, the reliability and accuracy of biometric systems can be significantly improved, paving the way for broader adoption in critical applications.

4. Discussion

The results in the table clearly demonstrate the effectiveness of various methods and approaches for ECG biometric recognition. The fact that the proposed work performs similarly or better compared to other high performing methods in the existing literature demonstrates the potential of CAE in ECG recognition. However, the effectiveness of these methods can be further strengthened by testing on more datasets and different scenarios.

Table 4. Comparison table.

Study	Database	Method	Performance (Accuracy-%)
Jyotishi et al. [42]	PTB MIT-BIH Arrhythmia ECG-ID CYBHi	LSTM	97.3 96.81 93.11 79.37
Li et al.[15]	MIT-BIH Arrhythmia	PNN/ WOA-PNN	98.08- 98.54
Abdeldayem et al. [43]	PTB	2D-CNN	94.9
Fatimah et. Al. [16]	MIT-BIH Arrhythmia CYBHi ECG-ID	Random Forest	97.92 99.45 98.45
Zhang et al.[10]	MIT-BIH Arrhythmia	1D-CNN	93.5
Chu et al. [17]	MIT-BIH Arrhythmia	CNN	95.99
Singh et al. [44]	MIT-BIH Arrhythmia	Using Eigenbeat Features	91.42
Bassiouni et al. [9]	PTB	SVM/KNN/ANN	99- 98.1-95.3
Li et al.[14]	MIT-BIH Arrhythmia	WT-UKF and IPSO-SVM	98.44
Önerilen Çalışma	MIT-BIH Arrhythmia	CAE	98.46
Prakash ve ark. [11]	ECGID	Beat Template Matching	99.85
Wang et al. [20]	PTB, MIT-BIH, ECG-ID	CNN	99.15, 98.5, 98.5
Maleki Lonbar et al. [19]	NSRDB, MITDB	GoogleNet	99.3, 99.00
Al-Jibreen et al. [18]	MIT-BIH Arrhythmia	CNN	93.81
Patro et al. [12]	ECGID	GA, EN	95.30, 94.90
Belo et al. [21]	Fantasia, MIT-BIH, CYBHi	TCNN	100, 96, 90

Table 4 provides important insights on arrhythmia classification and ECG biometric recognition by comparing the performance of different machine learning methods on ECG databases. The results of the proposed model demonstrate the effectiveness of the deep learning based Convolutional Autoencoder (CAE) architecture when compared to other works in the literature.

The proposed work achieved 98.46% accuracy with CAE on the MIT-BIH Arrhythmia database. CAE provides advantages in data compression and extraction of important features and is an effective method to reduce noise and complex waveforms in the signal. Thanks to the deep learning architecture, the learning capacity of the model increases and gains the ability to learn more complex relationships. This improves the overall performance of the model, allowing it to achieve high accuracy rates in arrhythmia classification.

The analysis of other studies reveals the strengths and limitations of different methods. For example, the LSTM model proposed by Jyotishi et al. [42] achieved accuracy rates of 97.3% and 96.81% on the PTB and MIT-BIH Arrhythmia databases, respectively. However, its low performance of 79.37% on the CYBHi database indicates that while LSTM may perform better on certain datasets, it may fall short on others. The PNN and WOA-PNN methods proposed by Li et al.[15] stand out with 98.08% and 98.54% accuracy rates, respectively. The potential of these methods to achieve high accuracy rates with fewer parameters and the ability to prevent overlearning are very close to the performance of the proposed model.

The Random Forest method used by Fatimah et. al. [16] achieved 97.92% and 99.45% accuracy on the MIT-BIH Arrhythmia and CYBHi databases, respectively. This finding shows that traditional machine learning methods can be as effective as deep learning methods under certain conditions. However, CAE's deep learning architecture offers an advantage in that it has the capacity to learn more complex relationships and generalize better.

The 1D-CNN and CNN models developed by Zhang et al.[10] and Chu et al. [17] achieved accuracy rates of 93.5% and 95.99% respectively, on the MIT-BIH Arrhythmia database. These accuracy rates are below the performance of the proposed model. Although CNN-based approaches can provide successful results thanks to their deep learning architecture, the advantages of feature extraction and data compression offered by CAE increase the overall performance of the model. SVM, KNN and ANN methods proposed by Bassiouni et al. [9] are remarkable with accuracy rates of 99%, 98.1% and 95.3% respectively. Traditional methods can provide high accuracy rates for certain types of data. However, CAE's deep learning architecture offers the capacity to deal with more complex data more effectively, which gives it an advantage over traditional methods.

Prakash ve ark. [11] proposed the Beat Template Matching method, which has a very high accuracy rate of 99.85%. However, it should be noted that this method may be optimized for a specific application and thus may lack the flexibility offered by CAE as a general model. Similarly, the CNN model developed by Wang et al. [20] achieved accuracy rates of 99.15%, 98.5% and 98.5% on PTB, MIT-BIH and ECG-ID databases, respectively. Although these results are quite high, the advantages of the proposed CAE model stand out when looking at the balance of the model's performance on different databases.

In conclusion, the proposed CAE model proves to be an effective method for ECG analysis and arrhythmia classification, offering high accuracy rates compared to existing methods in the literature. Thanks to its deep learning-based architecture, the model is capable of learning more complex relationships and generalizes better. The analysis of other works in the literature reveals the advantages and limitations of different methods, contributing to the identification of the most suitable approaches for the analysis of ECG data. In this context, the proposed model stands out as a powerful alternative for arrhythmia classification with its high accuracy and advanced feature extraction capabilities.

For future studies, the use of larger and more diverse datasets in the field of ECG analysis and arrhythmia classification is recommended. Datasets representing different patient groups and various clinical conditions can contribute to more robust and reliable results by increasing the generalization ability of the model. Moreover, more complex deep learning architectures, e.g. hybrid models or structures incorporating attention mechanisms, have the potential to further improve the performance of the model. Such innovative approaches may increase the capacity to learn more complex relationships of the signal, allowing for higher accuracy rates in arrhythmia classification. Finally, optimization and acceleration of the model for real-time applications could enable it to be used more effectively in clinical settings. These proposals are considered as important steps to support progress in the field of ECG biometric recognition and arrhythmia classification.

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