Electrocardiogram Comparison as a Biometric Identifier: A Review

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Abstract

The electrocardiogram (ECG) is a type of biometric data that has recently attracted a lot of attention as a potentially useful biometric trait due to its high discriminatory power. However, precise and consistent biometric identification systems are challenging to deploy because to ECG signals' vulnerability to a wide range of sounds, including baseline wander, powerline interference, and high/low frequency noises. That's why ECG signal denoising is such an important aspect of the preprocessing phase for ECG-based biometric person identification: it removes noise from the raw ECG data. Biometric recognition using ECG signals is a difficult problem involving phases of preprocessing, feature extraction, feature selection, feature modification, and classification. Biometric system analysis also relies heavily on the use of appropriate success measures and a well-organized library of ECG signals. This is especially crucial when considering the fact that researchers rely significantly on freely accessible resources to gauge the efficacy of the algorithms they propose. In this study, we examine most of the approaches that have been taken toward ECG-based biometric verification of humans.

Keywords: ECG biometrics; Applications of biometric; Biometric traits; Feature extraction; Classification; feature fusion; Authentication; Machine learning.

1. Introduction and Related Work

Depending on the level of security required, biometric recognition systems are replacing traditional authentication methods (i.e., keys and personal identification numbers (PINs) [1-5]) in a growing number of fields and applications, including smartphones, banks, websites, and airports. Fingerprint scanners, iris scanners, facial recognition, and voice recognition are all examples of technologies and industries that fall under this category. In order to use biometric features, such as fingerprints, palmprints, iris, voice, and facial recognition, it is essential to enrol these features in a database for feature recognition. Figure 1 clearly demonstrates this.

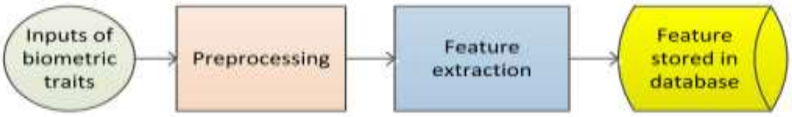

Figure 1: The process required in registering a biometric trait

To improve recognition accuracy and deter forgery, many different devices and systems have combined multiple biometric modalities1 into a single multimodal biometric system [6, 7]. Researchers have already

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begun working on a solution to the spoofing problem in traditional biometric systems like electrocardiogram (ECG) biometrics.

The electrocardiogram (ECG) is being studied as a potential new biometric modality for user authentication and identification [10, 12]. An ECG's recent rise in popularity as a biometric source of security and privacy is nothing short of remarkable. Perhaps the greatest benefit of the ECG-based biometric system is the inherent liveness detection it provides, setting it apart from conventional biometrics [10]. This distinguishing feature will be important in combining ECG signals with other trustworthy biometric modalities to create a spoof-proof biometric system [13], [14]. The studies described in [10] show that electrocardiogram (ECG) biometrics can achieve sufficient identification and authentication accuracy for a number of applications using only the QRS complex of ECG signals. The groundbreaking work of [21] utilised 12 channels of ECG data to complete the recognition, making it the oldest known instance of ECG-based biometric recognition. According to research [22–24], there are unique fingerprints in every person's ECG trace that can be used to identify them.

Classifiers used to perform the recognition task can also be utilized to categorize ECG-based biometric authentication systems [5]. K-nearest neighbor (kNN), linear discriminant analysis (LDA), neural networks (NN), generative models (GM), support vector machines (SVM), and match score classifiers are all examples of such classifiers. (kNN is an abbreviation for "k-nearest neighbor"). All classifier-based recognition approaches, for example [1, [25], [26], rely on a so-called feature extraction strategy, in which important elements from the raw ECG signal are extracted and used as input to a classifier. As such, classifier-based recognition systems rely heavily on feature extraction. However, converting the raw ECG signal into a useful feature vector for classification is a complex task that requires a high level of experience and attention [5]. To get around this problem, several researchers have turned to deep learning, a popular representation learning technique that uses multiple layers to automatically extract features from the raw ECG signal [1, [15-20]]. [1] A common term for deep learning is "supervised learning." Without the prior knowledge of specialists, researchers may now extract unique characteristics from ECG data. Deep learning algorithms use a tiered representation of data, with the lower layers responsible for extracting basic features and the higher levels responsible for more complex ones [19, 20].

Feature sets are either saved in a database or sent to a classifier for identification after the feature extraction procedure is complete. The following are the main components of the method used to analyze an ECG for biometric purposes: Processing and detecting QRS pulses in incoming signals; Extracting, Choosing, Transforming, and Classifying Features [14], [27]. Electrocardiogram (ECG)-based biometric systems for human authentication [14, 25], [28] make use of a variety of approaches developed to extract relevant information from an ECG. Examples include [23], [25], [29] that use fiducials, don't use fiducials, or just partially use fiducials. The fiducial-based method uses interval, amplitude, angle, and area as biometric parameters, and relies on accurate localization of reference points within each cardiac trace, including the P wave, QRS complex, and T wave [23], [25], [29]. These characteristics can be used to uniquely identify a person. Although many fiducial-based ECG biometrics recognition algorithms have been devised to meet biometric identification necessary criteria [25, 29], [30], accurate localization of fiducial sites remains a challenging topic.

However, the detection of fiducial sites is not always necessary when using the non-fiducial based ECG biometrics detection approach [29]. Wavelet coefficients [14, 25, 28], autocorrelation coefficients [22, 23], and principal components [22, 23] are a few examples. Only the R-peaks (of the QRS complex) can be located using partially fiducial approaches, which combine fiducial and non-fiducial techniques. ECG signals are segmented using these techniques into individual heartbeat waveforms so that information can be extracted as features in either the time domain or the frequency domain. Since it is generally agreed that the R peaks are the tallest and most distinguishable of the fiducial points. The study published in [5], for instance, extracts the QRS-complex from ECG data and gives a QRS vector to each of the four QRS complexes it detects. Recently, deep neural networks (DNNs) have gained popularity as a means of classifying electrocardiogram (ECG) signals and extracting ECG-related information. When applied to ECG-enabled biometric systems, these techniques reliably identify and authenticate individuals. One major limitation of these methods, especially when applied to the matching problem, is their limited generalizability [18], [19]. That is to say, without first validating a person's identity, these methods often provide inconclusive predictions.

2. ECG Basics

It is common practice to place electrodes on a patient's skin in order to record the changes in the electrical potential of the heart as they are sensed by the skin. These electrodes record voltage changes brought on by

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the depolarization and repolarization of heart cells in order to promote cardiac contraction and relaxation. Widespread ECG data collecting has resulted from the widespread availability of relatively affordable portable ECG sensors. These sensors have been employed in previously uncharted domains such as fitness monitoring and wearable biometric authentication systems. The electrocardiogram (single lead) for one cardiac cycle is illustrated in figure 2, and we will now provide it to you. If you are interested in learning more about the physiological principles underlying cardiac electrophysiology, you can refer to. P, QRS (a wave complex), and T are the three waves that make up a normal ECG waveform. Each of these waves represents a separate event that occurs during one cycle of the heart's electrical cycle.

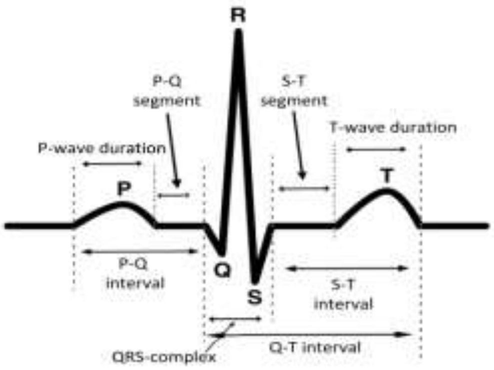

Figure 2: A representation of a typical cardiac cycle with the related waves of a single-lead ECG signal.

The atrial contraction coincides with the P wave, which has a duration of 0.06-0.12 seconds and indicates depolarization of the left and right atrium. A ventricular depolarization is represented by the Q, R, and S waves of the QRS Complex. This complex consists of the Q, R, and S waves, as the name suggests. The Q wave is an initially negative deflection of the QRS complex because it is short-lived (lasting no more than 0.030 seconds) and deflects in a downward direction. This slanting indicates that the septum has become depolarized. The R wave is a result of depolarization at the top of the left ventricle. The S wave is typically short, descending, and negative to reflect the depolarization of the basal and posterior regions of the left ventricle. Between 0.06 and 0.09 seconds is a possible duration for the QRS complex. One technique to determine the ventricular rate is to count the number of seconds that pass between QRS complexes.

Potentially having no value at all, the PQ segment depicts the time lag experienced by the impulse as it travels through the auriculoventricular node. The PQ interval represents the delay time experienced at the auriculoventricular node prior to the commencement of the depolarization process in the ventricles, as well as the time required to depolarize the auricular muscle. More precisely, the PQ-interval spans from the onset of the P wave to the onset of the QRS complex. It's worth noting that the amplitude of the auricular T-wave, or repolarization wave, is typically relatively tiny and goes unnoticed in healthy individuals. Common locations for its incorporation are the PQ-segment and the QRS complex. This means that the PQ interval is the result of electrical activity in the auricle.

The electrocardiogram's ST segment shows how long the ventricles were depolarized. During this time, chemical processes that led to depolarization are actively working to go in the opposite direction, preparing for the repolarization phase that follows. Normally, the ST terminal has no potential. However, it is not impossible for it to go up or down beyond the zero potential baselines. The T wave, which represents the ventricles' repolarization, has a duration of 0.1 to 0.25 seconds. The ST interval is the period that elapses between when ventricular depolarization is fully completed and when ventricular repolarization is fully completed. It is the overall time it takes for the ventricles to depolarize and subsequently repolarize that is represented by the QT interval. The QT interval, in other words, spans from the onset of the QRS complex to the termination of the T wave.

3. ECG Signal in Biometrics

Characteristics of the cardiac trace on an electrocardiogram (ECG) are listed in detail. A total of 29 participants were studied over the course of 7 sessions of data collection, with each session lasting only 120

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seconds. The results provided here show that the recovered features do not change depending on the person's level of anxiety or where the sensors are placed. An electrocardiogram-based recognition system that uses Bayes' theorem to analyze data from 502 ECG recordings. Here, utilizing a dataset of 234 ECG recordings from 74 individuals, we demonstrate an electrocardiogram (ECG)-based biometric recognition system. The system just requires 10 seconds for each measurement.

An ECG-based biometric identification system has been published. Over the course of three data-gathering sessions, the system was applied to 50 unique individuals, and 95% accuracy in categorization was attained. An ECG-based biometric identification system was proposed by the authors of [22]. A total of 43 people were used to test the device, and ECG records were taken as they performed seven 2-minute exercises. The eigenPulse method, detailed in [22], uses principal component analysis (PCA), a method common in conventional biometrics such as fingerprinting and iris scanning. applying 65 participants across 6 data recording sessions, we found that applying a principal component analysis (PCA) technique, called eigenpulse, to measure the quality of each segmented heartbeat led to a significant increase in recognition accuracy. Eigenpulse is used in this technique to assess the integrity of each individual heartbeat segment.

We present a single-lead electrocardiogram (ECG)-based biometric that combines a short-time frequency technique with robust feature selection, based on data collected from 269 people over the course of 7 months and collected on three separate occasions. An EER verification of 5.58 percent, a rank-1 recognition accuracy of 76.7 percent, and a rank-15 recognition accuracy of 93.5 percent were all attained by this biometric. This biometrical information was gathered from a sizable data set of 269 individuals. The short-time frequency technique combined with rigorous feature selection has been applied to the electrocardiogram (ECG) to create a biometric based on a single lead. Using only 90 seconds of data from each of 168 individuals recorded during a single session, this biometric is able to achieve a rank-1 recognition accuracy of 98%.

This article details a biometric system that use the Birge-Massart algorithm to analyze electrocardiograms (ECGs). Only a subset of the wavelet coefficients will be used for the signal difference/similarity measurements. Thirty patients' electrocardiogram (ECG) recordings were collected over the course of two sessions. An ECG-based recognition method that incorporates the periodicity transform (which is robust while dealing with heart rate changes) to enhance the autocorrelation / LDA feature extraction approach. When applied to data from 52 subjects with ECG recordings across 1.2 recording sessions using tiny measures of 180 seconds in duration, the system achieves a 92.3% accuracy rate. For the purpose of performance evaluation, the authors provided the University of Toronto ECG Database (UofTDB) using brief measures of 180 seconds in duration with 1012 patients throughout 1.6 data recording sessions. Electrocardiogram (ECG) data was published, which was collected from the palms and fingers of the hands using dry silver/silver chloride (Ag/AgCl) electrodes and electrolycra strips, and was included in both the short-term and long-term public datasets presented by the authors. One hundred and twenty-eight people were used over the course of 1.5 sessions of data collection, and quick measurements lasting only 120 seconds were used.

A proposed 1D convolutional long short-term memory neural network for an electrocardiogram-based biometric system can be found on the Physionet public database. An EER of 0.41% and a rank-1 identification accuracy of 99.58% were found after analyzing data recorded from 109 participants using 16 channels of ECG signals and brief measures of 1 second in duration. Using eigenvector centrality, an electrocardiogram (ECG)-based biometric system with data from 109 patients was able to obtain a rank-1 recognition accuracy of 92.60% and an error rate (EER) of 4.40% on a public physionet database. This was achieved by collecting ECG signals from 64 different electrodes for a total of 12 seconds of data collection. The concept of "ECG-based subject identification" (ES1D) is a network architecture proposal. The ES1D network is a refinement of the classic CNN that leverages Welch's power spectral density estimation of ECG signals from the public database DREAMER, including data from 23 participants, to achieve an accuracy of 94.01%. It took 23 participants to successfully test this network.

With the use of a data augmentation technique, we propose a deep convolutional neural network (CNN)-based ECG biometric system and test it on the Physionet ECG Database [26], which includes readings from 109 people. In order to reduce the EER recognition (verification mode), this system employs 64 ECG channels, each of which is sampled at 0:16 kHz. The study's authors [16] proposed a biometric approach that uses raw ECG data and a CNN to identify individual patients. Using the BCIT database, the system was evaluated on 100 subjects with a 12-second subsequence of equal length, and it achieved 97% Rank-1 accuracy. Using a FuWai ECG database consisting of 722 patients, with 12 ECG channels across 2 data recording sessions, we demonstrated a dynamical radial basis function (RBF) neural network-based ECG

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recognition system. The system was built with the help of a FuWai electrocardiogram database. In this scenario, a 12-channel ECG is used with a sample rate of 1000 hertz. The proposed approach has a recognition accuracy of 91.4% at a resolution of 16 bits. Using deep CNN and two publicly available datasets, the authors of this study [5] demonstrated an innovative biometric detection method for ECGs. Intercity Digital Electrocardiogram Alliance-IDEAL (E-HOL-03-0202-003) and Physionet (PTB Diagnostic ECG Database) were the datasets used in this study [30]. 52 patients' electrocardiogram (ECG) signals were recorded over the course of 5 sessions. A total of 12 ECG channels were used. The slots were 10 seconds long, and the sampling rate was 1000 Hz. The EER result of 2.90 was within acceptable range. Voice, keystroke, stride, and signature are all examples of cognitive or behavioral modalities, while ECG, DNA, iris, fingerprint, and earlobe are all examples of physiological modalities. There are commonalities between the various biometric modalities.

(a) All members of the sample population should exhibit the trait under investigation.
a) The biometric feature in question needs to be enough different between individuals for it to be regarded unique.
(c) Longevity: The biometric trait in question must be relatively invariant (i.e., stable and enduring) over a considerable amount of time for the matching condition to be met.
(d) Collectability: The biometric feature in question must be able to be obtained and digitalized with the aid of suitable equipment in order to be utilized for future authentication of a user.
(e) Acceptability: the biometric identifier should be widely recognized as a reliable means of authentication or identification, and the acquisition methodology should be secure. The biometric identifier must also remain unchanged.
(f) Circumvention: It should be difficult to trick the biometric system by utilizing fraudulent methods to imitate the feature. This is a security measure to ensure that no one can cheat the system.

The electrocardiogram (ECG) biometric modality stands out as the most promising when compared to the other biometric modalities in Table 1. The ECG biometric modality excels in the vast majority of the characteristics that define the quality of a biometric modality. Due to its unique properties, it is immune to spoofing attacks, and the inherent liveness detection ensures that the ECG-based biometric system is not being overloaded. In comparison to physical biometric identifiers like fingerprints or facial features, which have a two-dimensional data representation, the EKG is made up of relatively low-frequency impulses and only has a one-dimensional data representation. Given the computational advantages of electrocardiograms over video or image-based biometric systems, they are increasingly being used for continuous recognition systems that rely heavily on speedy judgements.

Table 1: Advantages and disadvantages of the ECG compared to other biometric modalities

Biometric	Advantages	Disadvantages
ECG	University, specialness, longevity, and vitality confidence, inconspicuous charac easy acquisition	needs interaction; human actions produce variation
Palmprint	Consistent and dependable performance time; rapid recognition; works well with low-resolution imaging hardware	requires direct interaction with t device
Fingerprint	The matching procedure is quick, memor efficient, cheap, dependable, and accurate a high degree.	Needs user interaction; precisio affected by factors including cut scars, dust, grime, and twists
Voice	Easy implementation, less expensive and convenient to use	Simpler to implement, cheaper, more user-friendly.
Iris	Quick turnaround time, low sample size, no direct human interaction	Infectious diseases threaten precision in high-priced machine
Gait	Equipment is cheap, there is no distance limitation, and taking pictures is simple.	Low precision and high computational cost
Face	No direct contact is necessary; results in simpler statistics; the necessary equipme cheap and readily available; and the identifying procedure may be completed quickly.	Depending on the face's visibilit and lighting, aging, accidents, a time can all cause noticeable changes.

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Retina	The trait cannot be forges, highly accurat	The quality is unforgeable and v precise.

4. ECG Signal Classification

In order to use an electrocardiogram (ECG) as a biometric identifier for human authentication, it is essential that features be extracted from ECG waveforms. An integral aspect of this procedure is the categorization of ECG data. Classifying electrocardiogram (ECG) data presents challenges due to the subjective nature of the data. Some of the major obstacles in ECG classification jobs include the lack of standardization of ECG characteristics, the absence of appropriate classification rules for ECG classification, the distinctiveness of the ECG patterns, variability among the ECG features, and variability in the subject ECG waveforms. An enrollment phase is required at the outset of an ECG-based identification system, with the goal of acquiring and storing the unique characteristics of the individual being recognized. This preprocessing is performed before the data is saved to remove background noise and artifacts and to extract useful features. The identification procedure can proceed once identifying features of subjects have been recorded. The unidentified ECG input to the system during the signal identification phase requires preprocessing to remove noise. Then, similar to the enrollment phase, feature extraction and transformation must be executed. Furthermore, the extracted features are used by a specific classification approach to identify which subject's data in the database is the best match for those qualities. After that, we'll dive deep into the many classification strategies that may be applied to ECG data in order to identify individuals.

A. ANN Classification Models

ANNs, which are well-established as a biologically-inspired paradigm, are a viable machine learning method for the categorization of non-linear ECG data for biometric recognition. Learning methodologies such as supervised learning, unsupervised learning, and reinforcement learning are used in the ANN implementation processes. Different neural network models have been used by different researchers to classify ECG signals. Data-driven, non-linear, accurate, fast, noise-resistant, and easily scalable best describe the ANN models. They are also non-linear. Among the many benefits of ANN are the ones listed below.

- It can be used to address non-linear issues like the classification of ECG data by producing a non-linear mapping between inputs and outputs via activation functions like sigmoid. An instance of an activation function is the sigmoid.

- Results can be on par with, or even better than, those produced using deterministic or statistical approaches. Statistical approaches, which are built on the premise that the time series being analyzed would be linear, fail miserably when used to non-linear problems yet shine when dealing with linear ones.

- The ECG's low frequencies can be modeled adaptively by means of ANN, notwithstanding their inherent nonlinearity. When using ANN, it is simpler to filter out the ECG signal's time-varying and non-linear noise.

The following are some of the most serious problems associated with ANN:

- The ANN training approach cannot typically guarantee a globally minimal set of weights.
- ANN may not be the best option for the complete 12-lead ECG categorization process in most circumstances.

B. Deep Learning Methods Applied As Classification

Classification of electrocardiogram (ECG) data has recently been explored using Deep Learning, a branch of AI and ML. Structured deep learning is another name for deep learning. The first implementation of deep learning was the creation of DBNs5 within a machine learning framework. Data classification, feature extraction, and manipulation are all possible because to the system's multi-stage non-linear information processing architecture. This is the era that saw the birth of deep learning. In particular, deep learning methods are designed to build feature hierarchies, wherein features learned at a higher level are defined in terms of those learned at a lower level. DNNs have been the focus of most recent algorithmic improvements in ECG classification. The successful deep learning architecture is the primary inspiration for these enhancements. Although many works have shown improvement in performance, they still use a simplistic implementation of DNNs. There is room for expansion and adjustment in the ECG training method and model architectural enhancements because they have not been researched in depth.

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To further improve the overall performance of ECG classification tasks after the introduction of DBNs, a number of additional unsupervised deep learning models have been provided. One example is the sparse autoencoder network, which can be used to learn overcomplete features with few missing ones. It accomplishes this by (1) using an autoencoder-based greedy layer-wise unsupervised learning technique, and (2) using a linear encoder and a linear decoder preceded by a sparsifying non-linearity that changes a code vector into a quasi-binary sparse code vector.

The following are examples of several deep learning methods: Novel optimization techniques have led to the development of three distinct types of deep learning training: DSL, DSSL, and DUL. These developments mark significant advances in the field of deep learning.

(a) DSL: Discriminative deep networks aim to improve classification accuracy by providing more detailed descriptions of the posterior distributions of classes acquired from the available data. Supervised deep learning (DSL) and supervised deep networks are other names for these types of systems. For the purposes of supervised learning, target label data are always accessible, albeit in varying forms. Because of their superior training and testing efficacy, more design flexibility, and suitability for end-to-end learning of complex systems, DSL models are becoming increasingly popular. It is possible to differentiate between the following types of DSL: Television stations like CNN and RNN.

One common DNN design is the Convolutional Neural Network (CNN), which is typically trained with a gradient-based optimization strategy. CNN typically consists of multiple stacked layers that are fed forward into one another. Using Convolutional Neural Networks (CNNs) as classifiers for ECG biometric authentication has been proposed in only a small number of previous articles. A multimodal biometric system with many fusion modes has been designed for authentication. CNN and Q-Gaussian multi-SVM work together in this system to ensure reliable outcomes. The EER was 3.2% when using the PTB database, and 2.9% when using the CYBHi database. CNN was also used to generate the feature template, which was subsequently retained via a matrix operation technique employed by the authors. After delivering the QG-MSVM classifier, they were successfully authenticated. They managed a 3.5% EER with the help of the PTB database. The electrocardiogram (ECG) has inspired a new type of authentication system that combines manual features with convolutional neural networks. The system you see here was created.

They employed CNN to categorize the data after employing feature extraction methods including scanning and deleting. They were able to get an EER of 4.47% using the CYBHi database and 1.63% using the PTB database. It is suggested to construct a deep convolutional neural network (CNN) using a PTB database of 109 people and all 64 ECG channels, with several data augmentation techniques being explored for the training process. Using data from Physionet, they calculated an EER of 0.19 percent. For the goal of biometric recognition, [5] introduced DeepECG, a CNN-based biometric approach for ECG signals. They used stochastic gradient descent with momentum to train the model. When their approach was utilized for authentication with the PTB database, the associated error rate (EER) was 2.90%. Few studies have applied deep-CNN techniques to ECG analysis beyond its usage in biometric recognition. These analyses, however, have only concerned themselves with determining if particular cardiac rhythms are healthy or not.

A proposed incorporating CNNs into the development of an ECG-based person recognition system. The 1-D CNN and 2-D CNN were used to generate the ECG features, with the raw ECG signal approach and the heartbeat spectrogram representation strategy being used, respectively. Then, they used a fusion at the score level to combine the sum rule, the mean rule, and the multiplication rule, which are all score-level fusion procedures. They were able to reduce the EER of a 1-D CNN to 15.60%, that of a 2-D CNN to 20.48%, and the EER of fusing two CNN models to 13.93%. A proposed incorporating CNNs into the development of an ECG-based person recognition system. The 1-D CNN had an EER of 1.53 percent when tested on the PTB database. When they looked at the data from the CYBHi database, however, they saw that the EER was much lower, at 0.27%. In the study documented in [11], a biometric recognition system based on 1-D convolutional neural networks (CNNs) was developed to authenticate humans. Using eight PhysioNet datasets (CEBSDB, WECG, FANTASIA, NSRDB, STDB, MITDB, and AFDB), the authors evaluated their method and found it to be effective. The 1-D CNN achieved an average detection rate of 93.5% after being tested on eight separate ECG datasets. Only a small number of research have combined CNNs with other methods. In [341], the generalized S-transformation and CNN methods are presented as part of an ECG-based biometric identification system to boost classification precision. This is because CNN is more forgiving of background noise than other methods. They found 100% accuracy using the ECG-ID database, 98% accuracy using the Physionet database's Atrial fibrillation (AF) ECG signals, and 99% accuracy using the Physionet database's noisy ECG signals.

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The connections between the nodes in a recurrent neural network (RNN) constitute a directed graph in which the edges represent timestamps. The use of RNNs with more complex architectures, such as LSTM and GRUs for learning extended dependencies, has led to major improvements in a wide range of tasks, such as the implementation of ECG-based biometric recognition. The fundamental idea behind these networks is the deployment of several gates to regulate the information flow between preceding and current processing steps. A mapping from one location to another can be learned by any recurrent unit using gates. LSTM is widely used for time series signal analysis, including ECG data categorization. A bidirectional deep recurrent neural network that employs late-fusion in order to construct a real-time system for ECG-based biometrics recognition and classification has been developed.

Here, we present the results of an evaluation of the proposed model using two publicly available datasets, the MIT-BIH Normal Sinus Rhythm (NSRDB) and the MIT-BIH Arrhythmia (MITDB) databases. Researchers achieved good overall classification accuracy on both datasets. The proposed LSTM-based deep RNN model, trained on the MIT-BIH normal sinus rhythm database and the MIT-BIH arrhythmia database, obtained overall precision of 100% (and 99.8%), recall of 100% (and 99.8%), accuracy of 100% (and 99.8%), and F1-score of 1 (and 0.99). These findings are in contrast to the prior findings of this model, which had a 100% (and 99.8%) success rate. The above-mentioned study [69] shown that LSTM performs better than GRUs at identifying and classifying ECG biometrics. For the identification challenge, they achieved nearly perfect classification accuracy on the ECG-ID dataset and saw comparable outcomes on the MITDB dataset.

b) DUL (also known as unsupervised deep networks) are pre-trained with generating models like RBMs, and then fine-tuned with conventional supervised learning techniques. This method is all-encompassing. The next step was to test the classifications on the validation dataset. To be more precise, DUL techniques operate in the absence of labeled classes while yet capturing high-order correlation. Autoencoder-based methods, deep Boltzmann networks (DBNs), and deep Boltzmann machines (DBMs) are the three most used DUL model designs.

Autoencoder-Relying Methods: Autoencoders are neural networks used to automatically extract and identify features for classification from electrocardiogram (ECG) data that has been labeled with beat positions. Autoencoders can pick up intricate representations of the data through training. In particular, AE has been used to pre-train other deep learning networks like CNNs and to learn lower-dimensional representations of the initial input. In [1], a deep neural network (DNN) was pre-trained using an autoencoder to actively classify electrocardiogram (ECG) signals for biometric recognition. An ECG-based biometric identification system that uses a deep autoencoder for feature learning to classify ECG signals is proposed.

The use of DBNs, or dynamic Bayesian networks, DBNs are complex visual generative models with several layers. Typically, stacked RBMs form the basis of the DBN design. The RBM is a Markov random field model with two layers: the first is the input layer, which is transparent, and the second is the representation of the latent features, which is concealed. By extracting low-dimensional latent properties and choosing important channels, DBN is able to use ECG data to identify emotional states. DBN's bidirectional connections make this possible whenever an input vector is used. In addition, a linear classifier is added to the DBN's top layer so that each layer can be trained with unsupervised data before being fine-tuned with supervised optimization. The seminal work by introduced the concept of a random-bit-model (RBM), an undirected model for binary random variables. Its goal was to model distributions over data with only two possible values. A RBM's data layer consists of visible units, whereas the hidden feature learning layer comprises of units that capture higher-order correlations and learn to represent the features. The layer with the observable units is where the data are represented. The DBN, which is a simulation of random variables across time and is itself composed of numerous RBM layers, was also introduced in the seminal work. A major breakthrough in the area had just been made. In this architecture, the outputs of one layer's RBM are fed into the inputs of the next layer's RBM. Therefore, training DBNs involves training RBMs in a bottom-up fashion, one layer at a time. In [19], it is suggested that RBM be used in conjunction with DBN for the classification of single-lead ECG data. This occurs after single-lead ECG has identified ventricular and supraventricular heartbeats. Using the MIT-BIH database, they found that both RBM and DBN could achieve above-average recognition accuracies of 93.63 and 95.57 percent, respectively, at a relatively low sampling rate of 114 Hz.

Deep Belief Networks (DBNs): a different type of pre-training technique wherein a DBN's weights are initially established with a stack of tweaked RBMs. These results show that DBM can be taught reliable generative models and put to good use in recognition applications.

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Adding labeled input to an otherwise unsupervised learning process is what Deep Semi-Supervised Learning (DSSL) is all about. Hybrid deep networks is another term for this method. The DSSL methods use both generative model components (which do not need labeled data) and discriminative model components (which do need labeled data). The GANs serve as a model of the DSSL in operation.

To create deep representations of ECG signals for classification without extensive annotations of training data, we may employ Generative Adversarial Networks (GANs). Classification with GANs is an example of an unsupervised machine learning technique. A GAN's generator and discriminator compete with one another while being trained. The generator and the discriminator make up the two main parts of a GAN. The job of the discriminators is to tell the difference between true samples and false samples, whereas the generators' job is to use random data to make samples that approximate the real data distribution. To enhance the model's generalization abilities, game training is used to fine-tune the weight parameters between the generator and discriminator networks. With GAN, the generator selects samples at random from a latent distribution and transforms them into the background data space. In the meantime, the adversarial discriminator works to identify genuine and fabricated samples. The adversarial training technique is also used to fine-tune the optimization of both modules. The use of GANs in ECG signal analysis has been investigated. After the signals have been examined, they can be added to the classifier's training set to improve its accuracy. The produced signals significantly enhance ECG classification, according to empirical investigations.

6. Conclusion

During a single heartbeat, an electrocardiogram (ECG) signal is composed of numerous waveforms, including P waves, QRS complexes, and T waves. However, the signals from an ECG are extremely vulnerable to the effects of outside factors. One form of technology that has been actively developed to improve the safety and security of the workplace is referred to as a biometric recognition system. Techniques such as pattern recognition, machine learning, and deep learning are responsible for the entire progression. We provided a comprehensive survey of ECG signals as a new biometric modality for human authentication by using a variety of methods, such as ECG preprocessing, feature extraction, feature selection, feature transformation, feature classification, databases, and performance measures for evaluating the accuracy of the ECG classifier. In doing so, we aimed to answer the question, "How can we authenticate humans using ECG signals?" In particular, fiducial and non-fiducial techniques, both of which are essential methodologies, have been examined for ECG-based biometric recognition in the feature extraction component of this research. The use of fiducial methods to the process of feature extraction on relatively small datasets has demonstrated surprisingly high performance. Non-fiducial techniques, on the other hand, do not require the discovery of fiducial sites that are included by the ECG signal, and they offer reasonably good efficiency for a large population. This is because non-fiducial procedures do not use fiducial markers.

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