Arrhythmia Classification Using Waveform ECG Signals

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Abstract— **An electrocardiogram (ECG) is a non-linear and non-stationary diagnostic biomedical signal that has a great importance for cardiac disorders. The computer-assisted analysis of biomedical signals has become an essential tool in recent years. This study introduces a deep learning application in automatic arrhythmia classification. The proposed model consists of a multi-stage classification system in raw ECG using a Deep belief network (DBN) which has a greedy layer wise training phase. The multistage DBN model classified the MIT-BIH Arrhythmia Database heartbeats into 5 main groups defined by ANSI/AAMI standards. All ECGs are filtered with median filters to remove the baseline wander. ECG waveforms were segmented from long-term ECGs using a window with a length of 501 data points (R peak of the wave is located at the centre of the window). The proposed DBN-based multistage arrhythmia classification has discriminated five types of heartbeats with a high accuracy rate of 95.05%.**

***Keywords*— Arrhythmia, Deep Belief Networks, Deep Learning, AAMI, Raw ECG Waveform**

I. INTRODUCTION

According to the World Health Organization surveys [1], heart diseases are one of the most important reasons which cause death. Heart disease symptoms depend on what type of heart disease you have. An electrocardiogram (ECG) is a non-linear and non-stationary diagnostic signal that is important for cardiac disorders [2]. It is hard to assess a cardiac disorder using ECG because of long processes that need a control in detail and infrequent arrhythmias. In order to overcome these challenges, the computer-assisted analysis of biomedical signals has become an essential method in recent years. The computer assisted diagnosis and analysis systems achieve rapid and advanced assessments in long, and hard to identify processes. Arrhythmia and many cardiac disorders usually need to use long-term ECG in inspection controls [3]. Therefore, computer-based methods and diagnosis systems provide major simplicity and reliability in the diagnosis and treatment of the diseases for cardiologists.

Arrhythmia is a problem concerning the abnormal rhythm and rate of heartbeats. The heart can beat too fast, too slowly, or inconsistently in different types of arrhythmias, which may feel like antagonism affection or fluttering. Arrhythmia may be classified by rate of heartbeats, mechanism (automaticity, re-entry, triggered) or duration of the heartbeats [4]. Several types of arrhythmia are harmless, but some of them refer the cardiac disorders that may cause death. The ECG is a popular diagnosis tool which is of the primary importance for cardiologists [5].

There are many studies that are used for detecting arrhythmias, classifying them and diagnosing cardiac diseases that occur as a result of arrhythmias. These studies can be incorporated into two basic feature extractions: fiducial and non-fiducial methods. The fiducial methods contain the local features such as temporal, morphological, amplitude, duration, interval and segments between two selected waves which are extracted from ECG waveforms. These methods are based on the time-domain features on the ECG [6]. The non-fiducial methods are based on the frequency-domain features such as wavelet transformations, and the other digital signal processing techniques that extract new signal forms, sub-bands and coefficients from ECG waveforms [7].

Deep learning (DL) is an effective and high-performance machine learning algorithm which is gaining popularity. Frequently used analyses of the DL are used in image processing, speech and natural language processing processes. Actually, DL is a neural network structure which addresses the deeper feature levels using more hidden layers [8]. In this study, Deep Belief Networks (DBN), which is an adaptable DL algorithm, is utilized to classify the heartbeats from different classes of arrhythmia using ECG waveform as input of the structure.

The remainder of the paper is structured in the following manner. The database and the arrhythmia types are defined by AAMI standards, pre-processing, and feature extraction from arrhythmia heartbeats are described in detail. The proposed multistage classification system is explained. The experimental results that are obtained using the DBN classifier are presented.

II. Materials and Methods

The general management of medical treatment and assessment systems has become effective and convenient processes because of the recent technological developments in integrated circuit systems and computer-aided intelligent monitoring and diagnosis systems. In this section, information about ECG waveforms and the DBN classifier are described in detail.

A. Database

There are several arrhythmia databases in the literature. In this study, the MIT-BIH arrhythmia database (MADB) is utilized [9]. This database has been used for evaluating arrhythmia detection and classifying the arrhythmia types. MADB contains 48 long-term ECGs from 25 men aged 32–89 years, and 22 women aged 23–89 years; each has 11-bit resolution with 360 Hz sampling frequency. The heartbeats are labelled as five main arrhythmia types defined by the Association for the Advancement of Medical Instruments (AAMI) standard. AAMI standardizations provide an objective, understanding, and dividual assessments and monitoring processes of the arrhythmia types for clinical treatments and an increased capability of testing and training abilities for supervised learning phases [10]. AAMI classifies heartbeats into normal beats (N), supraventricular ectopic heartbeats (S), ventricular ectopic heartbeats (V), fusion heartbeats (F), and unknown heartbeats (Q). The testing and training dispersions of the heartbeats from the MADB are seen in Table I.

TABLE I
DISPERSION OF MADB ACCORDING TO AAMI STANDARDS AND QUANTITIES OF TEST AND TRAINING SETS

AAMI classes	MIT-BIH heartbeat classes	Train Set	Test Set
N	Normal beat Left bundle branch block beat Right bundle branch block beat Nodal escape beat Atrial escape beat	350 350 350 114 8	250 250 250 113 8
S	Aberrated atrial premature beat Premature or ectopic supraventricular Atrial premature contraction beat Nodal premature beat	74 1 350 42	74 1 250 41
V	Ventricular flutter wave beat Ventricular escape beat Premature ventricular contraction beat	236 53 350	236 53 250
F	Fusion of ventricular and normal beat	350	350
Q	Paced beat Unclassifiable beat Fusion of paced and normal beat	350 17 350	250 16 250

Long-term ECG signals can be contaminated by several types of noise, such as motion during ECG recording, electromyogram noise, contact noise, clinician artefacts, coughing, position of patient, baseline wandering, etc. All ECGs are filtered with two median filters to remove the baseline wander [11]. 6077 short-term ECGs were segmented from long-term ECGs using a window with a length of 501 data points (R peak of the wave is located at the center of window). All data points are normalized to a [0, 1] range.

B. ECG Waveform

The ECG is a method that finds out the regularity or irregularity of heart beats and heart rates using the electrical activity of the heart. The recorded electrical activities of the heart represent for a waveform on the clinical assessments. These waveforms may have different forms according to the lead of the ECG [11], [12]. The use of the ECG in medical assessment processes is very important in detecting the different waveforms and various cardiovascular heart diseases.

In the entire body only the heart muscle has the ability to contract spontaneously. Polarity is the event of discharge of electrical charge of heart tissue. Depolarization is the positive charging case of electrical activation in heart tissue [13].

The ECG has 0 mV to 5 mV amplitude and a frequency band between 0.5 Hz and 100 Hz [2], [13]. P, Q, R, S, T and U waves appear over the baseline in the signal, respectively. If the amplitude of Q, R and S waves is less than 5 mV, the wave is referred to using small capitals (q, r, and s). The remaining portion between the waves is a segment; the distance between the waves is an interval [12].

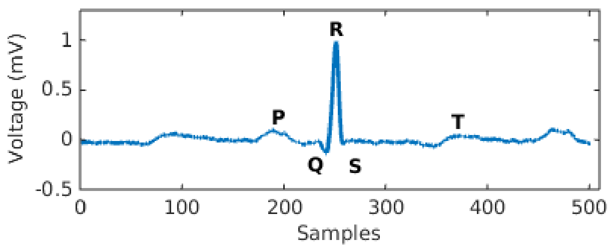

Fig. 1 ECG waveform with P, Q, R, S, and T waves

A P wave occurs as the result of the depolarization of the atrium. First, the right atrium then the left atrium depolarizes. Therefore, the first part of the P wave occurs when the right atrium depolarizes; second part of the P wave occurs when the left atrium depolarizes. Although it depends on the time of the year, the duration of the P wave is about 0.11 seconds; the amplitude of the P wave is between 0.18 mV and 0.22 mV on a normal lead [2].

The QRS complex occurs as the result of the depolarization of the ventricles. One of the waves (R) forming the QRS complex is positive; the other two waves (Q and S) are negative. The Q wave represents the first negative wave after the P wave; the R wave represents the first positive wave after the P wave and the S wave represents the next negative wave after the R wave. The QRS monitored complex varied in different leads. The QRS samples show significant differences even among normal individuals. R and S waves refer to the contraction of the myocardium. The QRS complex indicates the current causing the left and right ventricle contraction [14]. The QRS complex has the maximum amplitude between the ECG forms. The duration of the QRS complex does not exceed 0.11 seconds and has an amplitude value up to 2-3 mV [2].

The T-wave occurs as a result of ventricular re-polarization. The T-wave may have a pointed or flat view and positive, negative or biphasic value on various leads. The duration of the T wave that belongs to a normal subject is between 0.10 and 0.25 seconds. It takes place after about 300ms from the QRS complex. The positions of these waves vary according to the heart rhythm. The T wave is closer to the QRS complex when the heart rhythm accelerates [14].

C. Deep Belief Networks

This study introduces a deep learning (DL) application for automatic arrhythmia classification. The proposed model consists of a multi-stage classification system of raw ECG using DL algorithms. The DBN is one of the most effective DL algorithms which has a greedy layer wise training phase [15]. The DBN is composed of both Restricted Boltzmann Machines (RBM) or an autoencoder based layer-by-layer unsupervised pre-training procedure and neural network based supervised training [8], [16]. Considering RBM with input layer activations v (for visible units) and hidden layer activations h (hidden units), bias of the visible unit b, bias of hidden unit c:

$$E(v,h) = -hWv - bv - ch \quad (1)$$

$$P(v,h) = \frac{e^{-E(v,h)}}{\sum e^{-E(v,h)}} \quad (2)$$

$P(v,h)$ represents the joint distribution of the RBM and $E(v,h)$ represents the energy function of the distribution. RBM is used for calculating the conditional distribution of the visible and hidden units. Each adjacent two layers create an RBM. The first visible unit is the input feature vector and the other RBM parameters $\theta = (W, b, c)$ are denoted by depending on the first visible unit [17].

In the unsupervised training phase, the sub-network's hidden layer serves as the visible layer for the next adjacent layer applying contrastive divergence and the probabilistically reconstruction of the shared weights is implemented [8]. In the supervised training phase of the DBN, the calculated shared weights and the structure of the DBN are unfolded to a neural network structure for fine-tuning all the parameters of the deep structure such as the weights and the biases [15]. The DBN consists of at least two hidden layers (latent variables) in the neural network. The number of the hidden layers is related to the deep analysis of the input features in detail [15], [17].

III. Experimental Results

The morphological features are the ones most used in clinical trials for the diagnosis of the arrhythmia types. The robust and steady detection of arrhythmia is a common need for all the cardiac diseases. Each arrhythmia type can be related to different types of cardiac and pulmoner diseases. That's why detection and classification of the arrhythmia types are so important in the early diagnosis and early treatment processes. Considering the importance of the classification of the arrhythmia types, a computer-aided classification of the 5 arrhythmia types is implemented using a DBN-based multistage classification. Figure 2 depicts the structure of the arrhythmia classification model.

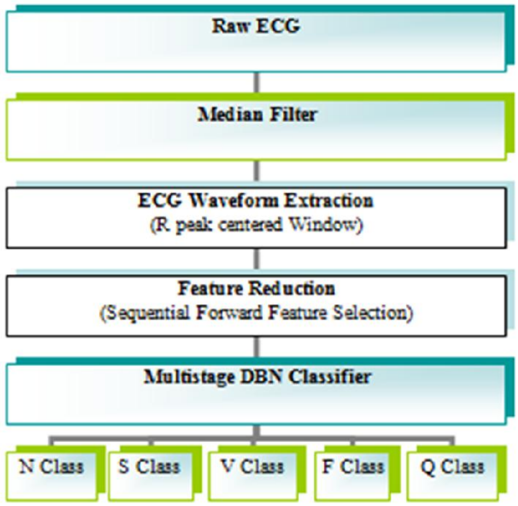

Fig. 2 Structure of proposed Arrhythmia Classification Method

Two median filters are applied to remove the noise and the baseline wanders to raw ECGs. Analysis of the long-term ECGs is a demanding process for clinicians and also for computer-aided systems. Considering this situation, ECG waveforms were extracted from long-term ECGs using the moving window analysis technique. The R peak centred window with 501 data points was moved to extract ECG waveforms. 6077 of ECG waveforms were obtained from long-term ECGs. ECG waveforms with 501 data points were directly used as features. Having a great number of the feature dimensionality causes long and deceiving training processes for the supervised machine learning algorithms. Feature dimensionality reduction for the provides for the extraction of more meaningful classification rules, the elimination of the pointless feature vector for machine learning algorithms, the improvement of generalization capabilities using fewer parameters and reduced complexity and run-time and for the evaluation and prediction of accuracy for classifiers [18]. The sequential forward feature selection algorithm is utilized in the proposed method to reduce feature dimensionality [19]. The algorithm selects a subset of features which are not yet selected from 501 data points and the best predict the arrhythmia types by sequentially selecting features until there is no improvement in the prediction. The highest accuracy is achieved using 106 features from the ECG waveforms. The reduced feature vector is normalized to 0-1. The proposed DBN-based multistage classifier was trained using 106 data points. Selected data points on the ECG waveform are seen in Figure 3 with the red asterisk.

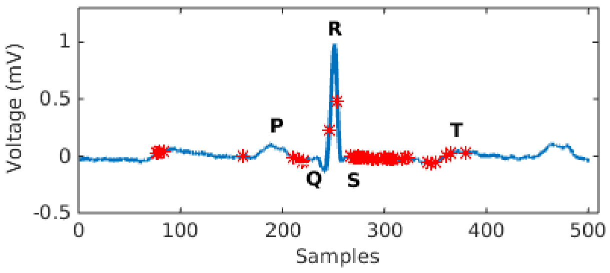

Fig. 3 Selected data points from ECG waveforms after feature dimensionality reduction (Red asterisk)

The proposed multistage DBN model separates N, S, V, F, and Q types of arrhythmias, respectively. 4 of the DBN models are used in the proposed system. The RBM based greedy layer-wise pre-training is used in this model at the unsupervised learning stages of all DBNs with 5 epochs. The parameters of the RBM were denoted by iterations. The models were tested with a limited number of the parameters and the highest classification performances are given. The learning rate of the model is 3 and the softmax output function was utilized constantly. The proposed multistage arrhythmia classification model consists of 4 DBN structures with various numbers of hidden units. The DBN1 has 2 hidden layers with 100-260 hidden units; the DBN2 has 3 hidden layers with 230-520-210 hidden units; the DBN3 has 2 hidden layers with 120-240 hidden units; and the DBN4 has 2 hidden layers with 70-190 hidden units. The four DBN structures are connected sequentially and have the ability to separate five classes of arrhythmia types defined by ANSI/AAMI.

The training set of the DBN-based automatic arrhythmia classification model includes 4,077 of ECG waveforms from various types of heartbeat classes distributed homogeneously. The DBN-based multistage model is tested using 2,000 of ECG waveforms. The confusion matrix of the classifier is seen in Table II.

TABLE II
CONFUSION MATRIX OF MULTISTAGE CLASSIFIER

Labels		***Predicted heartbeats***				
		N	***S***	***V***	***F***	***Q***
True heartbeats	***N***	**489**	2	8	9	3
	S	0	**290**	7	3	8
	V	2	0	**472**	2	5
	F	4	5	9	**179**	13
	Q	5	3	4	7	**471**

Zhang et al. used inter-beat features, amplitude morphology and morphological distance features for separating 4 types of arrhythmia by the Support Vector Machines (SVM) classification algorithm with 86.66%, 93.81%, and 98.98% for accuracy, sensitivity, and selectivity, respectively [20]. Melin et al. utilized cycle features and fiducial features with an Artificial Neural Network (ANN) and Learning Vector Quantization based multistage classification algorithm and classified 15 types of arrhythmia with an accuracy rate of 99.16% [21]. Thomas et al. extracted wavelet based coefficients from 4th and 5th scale of Wavelet transform, high order statistics and fiducial features using the QRS complex from the ECG with ANN and presented an accuracy rate of 94.64% and a sensitivity rate of 94.60% for 5 classes of arrhythmia types [22]. Batra et al. utilized invariant features and Principle Component Analysis features using the SVM classifier with the cross validation technique and achieved an accuracy rate of 84.82% for 11 classes of arrhythmia types [23]. Leutheuser et al. compared the Naive Bayes and k-NN classifier algorithms using statistical and high order statistical features, heartbeat features and template based features from segmented ECGs for the real-time classification of 2 types of arrhythmias on android-based mobile devices with reported accuracies of 93.30% and 56.10% for k-NN and Naive Bayes classifiers, respectively [24]. Alajlan et al. extracted morphological features, high order statistical features and non-fiducial features applying the Discrete wavelet transform, S transform and classified arrhythmia types into 2 classes using the SVM machine learning algorithm with high performances of 93.49%, and 93.14% for accuracy, and sensitivity, respectively [25].

DL algorithms, especially the DBN, are being effectively used in ECG analysis. The DBN is utilized at both feature extraction [26], [27] and classification stages [16], [28]. Huanhuan et al. used the DBN-based learning features from complete waveforms and R-R timing interval features with a multi-stage (5 stages) SVM classifier model. They achieved an accuracy rate of 98.82% for 6 classes of arrhythmia types [27]. Rahhal et al. extracted temporal features, morphological features and DBN-based features using stacked denoising autoencoders. They fed the all features to the SVM for training and classification. They classified 2 classes of arrhythmia types defined by ANSI/AAMI with an overall accuracy rate of 98.49% [26]. Yan et al. utilized R-R interval features, beat features and raw ECG signals from multi-lead to feed the DBN classifier and achieved a high accuracy rate of 98.82% for 12 classes of arrhythmia types [16]. There are lots of studies based on different types of arrhythmia classification. We focused on the arrhythmia types defined by ANSI/AAMI and the considerable studies are compared in Table 3.

TABLE III
COMPARISON OF THE RELATED WORKS FOCUSED ON ARRHYTHMIA DETECTION DEFINED BY AAMI

Related Works	**Features**	**Classifier**	**Accuracy**
Owis et al. [29]	Correlation dimension, Lyapunov exponents	k-NN	86.67%
Martis et al. [30]	DWT, LDA, PCA	PNN	99.28%
Kim et al. [31]	CWT, Morphological feature, DWT, PCA, LDA	ELM	97.94%
Tadejko et al. [32]	Morphological features, Wavelet Transform	SVM	97.82%
Llamedo et al. [33]	Wavelet Transform, Morphological features	LD	78.00%
Alvarado et al. [34]	Pulse based features	LD	93.60%
Ye et al. [35]	Interval Features, Wavelet Transform, ICA, PCA	SVM	86.40%

Proposed	ECG Waveform	DBN	95.05%

CWT: Continuous Wavelet Transform, LD: Linear Discriminant, ELM: Extreme Learning Machines, PNN: Probabilistic Neural Network, DWT: Discrete Wavelet Transform

It is hard to compare the studies in a stable way, because of reasons such as the different number of subjects, different number of the arrhythmia types, different subjects, different databases and different classification types. High classification performances are reported in the literature. In this study, the efficiency of the DL algorithms has been proven with high classification performances of 95.05%, 93.87%, and 94.51% for accuracy, sensitivity, and selectivity, respectively.

IV. CONCLUSIONS

PQRS complexes and T waves plots a regular form in normal sinus rhythm. Any obvious changes occurring in the PQRST lines indicate the irregularity or arrhythmia in heartbeats. Since the determination of the features such as intervals, segment measurements, heart rate, and the frequency of R waves have great benefits for clinicians to identify the cardiac diseases and arrhythmias, the physiology and the morphology of the ECG waveforms have frequently been used in clinical trials [12], [14]. The meaningful data points for arrhythmia classification are thickened between S-T waves and P-Q waves for the proposed DBN-based multistage classification model.

The proposed DBN-based multistage arrhythmia classification has discriminated five types of heartbeats with a high accuracy rate of 95.05%. The achievements prove the success and efficiency of the DBN algorithm in raw ECG signals.

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