

A Multistage Deep Belief Networks Application on Arrhythmia Classification

Gokhan ALTAN*¹, Yakup KUTLU², Novruz ALLAHVERDI³

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Abstract: An electrocardiogram (ECG) is a biomedical signal type that determines the normality and abnormality of heart beats using the electrical activity of the heart and has a great importance for cardiac disorders. The computer-aided analysis of biomedical signals has become a fabulous utilization method over the last years. This study introduces a multistage deep learning classification model for automatic arrhythmia classification. The proposed model includes a multi-stage classification system that uses ECG waveforms and the Second Order Difference Plot (SODP) features using a Deep Belief Network (DBN) classifier which has a greedy layer wise training with Restricted Boltzmann Machines algorithm. The multistage DBN model classified the MIT-BIH Arrhythmia Database heartbeats into 5 main groups defined by ANSI/AAMI standards. All ECG signals are filtered with median filters to remove the baseline wander. ECG waveforms were segmented from long-term ECG signals using a window with a length of 501 data points (R wave centered). The extracted waveforms and elliptical features from the SODP are utilized as the input of the model. The proposed DBN-based multistage arrhythmia classification model has discriminated five types of heartbeats with a high accuracy rate of 96.10%.

Keywords: Arrhythmia, Deep Belief Networks, DBN, Deep Learning, AAMI, ECG Waveform, Second Order Difference Plot, SODP.

1. Introduction

The heart is the organ that has the most vital importance to maintain the life for most of living beings. The heart stands for pumping the blood, and feeding the other organs in the body with oxygen and nutrients by rhythmic contractions. As the heart feeds the body, coronary arteries need oxygen and the nutrients for itself, too. Any problem that may occur in the coronary arteries can cause heart disorders. The heart disorders are in a wide range of ubiquitous death-causing problems. Cardiac disorders are at the first rows of the world's fatalist diseases list in the world health organization reports [1]. The most essential diagnostic tool is electrocardiogram (ECG) nowadays. ECG is a non-stationary and non-linear biomedical signal type that is often utilized in the computer-aided diagnosis of the cardiac disorders [2]. Sudden changes in long-term ECG waveforms, non-synchronous oscillations and different frequency rates in various signal channels are important in diagnosis of cardiac diseases such as arrhythmia, heart failure and more. The difficulties on controlling and analysing of long-term processes benefit directing the researches and developments on computer-based methods, medical diagnosis and decision support systems [3]. Computer-based diagnosis systems provide simplicity and convenience for cardiologists and clinicians in the assessments of various cardiac disorders and early onset of treatment.

Arrhythmia means irregular heartbeats. The heart beats 60 to 100 times per minute in normal circumstances and may increase the

number of the beats to 150 times per minute by physical activity such as exercise and running or excitement conditions. If the heart, which works in a quite rhythmic oscillation, loses this order for various reasons, it is called arrhythmia, which is called as rhythm disorder. Arrhythmia may be in two forms such as abnormal fast (tachycardia), abnormal slow (bradycardia) [4]. Arrhythmias can be either a bit regular naturally in its irregularity or can be completely irregular when in normal, fast or slow heart rates. It is essential that identifying the cause of arrhythmia or rhythm disorders correctly for guiding treatment processes of the disorders. There are different reasons of arrhythmia such as damage of heart muscles by narrowing or blockage of in heart-feeding vessels with coronary artery disorders, high blood pressure, hypertension, heart attacks, myocardial infarction, cardiac muscle inflammation (myocarditis and cardiomyopathy), balance disorders, healing process after heart surgery, inherited traits, and more [5]. The calvinic stimulation system forms the number of heartbeats, or heart rate, and each heart rate can be determined using the specific biomedical ECG signals. There are sixteen types of arrhythmia, the most common types are:

- Tachycardia: The rate of the heart rhythm is higher than 100 beats per minute.
- Bradycardia: The rate of the heart rhythm is slower than 60 beats per minute.
- Supra-ventricular Arrhythmia: The arrhythmia type that is arising from atrium.
- Ventricular Arrhythmia: The rhythm disturbances that is arising from ventricular.
- Brady arrhythmia: The stimulus system of the heart begins with sinoatrial node, and followed by antioventricular node and purkinje fibers. Tachycardia or bradycardia may not always be the sign of a disease in the stimulus systems. For example during an exercise, it is normal for sinus tachycardia increasing the heart rate by pumping the blood for providing enough oxygen to cells [4].

¹Mustafa Kemal University, Turkey

²Iskenderun Technical University, Turkey

³Kto Karatay University, Turkey

* Corresponding Author: Email: gokhan_altan@hotmail.com

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The studies in literature based on classifying the different arrhythmia types into various classes, detecting the arrhythmia on long-term ECG signals and using some arrhythmia types to diagnose different cardiac disorders. The studies could be separated into two basic feature extraction methods such as fiducial and non-fiducial methods. The fiducial methods are based on measuring the local characteristics of ECG signals like temporal, morphological, amplitude, durational, interval and segment features of two selected waves on ECG waveforms. The fiducial methods are based on the time-domain features on the ECG [6]. The non-fiducial methods are the techniques that characterize the ECG waveforms with the frequency-domain features such as different decomposition methods. The non-fiducial methods extract new signal forms, sub-bands and coefficients from ECG waveforms using empirical and special wave functions [7].

Machine learning algorithms are frequently used classification methods in recent years. Evaluation of the machine learning algorithms provides high accurately and high performance classification problems. Deep learning (DL) is an adaptable learning algorithm that has a remarkable popularity with successful performance. The DL algorithms are commonly applied to image, speech and natural language processing techniques. In effect, the DL is an artificial neural network model that analyzes the detailed levels using more hidden layers and fully connection between them [8]. In this study, Deep Belief Networks (DBN) based heartbeats classification is applied to separate five types of arrhythmia heartbeats from different classes of using ECG waveform as input of the model.

The paper is organized into detailed information about the database, arrhythmia types that are defined by Association for the Advancement of Medical Instruments (AAMI) standards, pre-processing, and ECG waveform analysis and Second Order Difference Plot (SODP) feature extraction method, and classification process on arrhythmia waveforms. The proposed multistage classification system structure is expatiated. The experimental results that are obtained using the DBN classifier are presented and are discussed.

2. Material and Methods

Evaluation of computer based systems get advantage on managing and diagnostic medical treatment systems. The general purpose of diagnostic tools are gaining assessments on treatment processes and tracing the disorders with an effective and convenient analysis. The recent technological developments in integrated circuit systems and computer-aided intelligent monitoring and diagnosis systems are significantly substantial. In this section, information about the ECG structure and the classification models are revealed in depth.

2.1. Database

ECG is an inexpensive and potent method for detecting the arrhythmia types. The most of cardiology departments from various universities record their own data acquisitions. Hence there are numerous specified arrhythmia databases that are used in the literature. In this study, the MIT-BIH arrhythmia database (ADB) is utilized [9]. The ADB has been frequently used for enhancing detection and classification methods of the arrhythmia heartbeats. The ADB contains 48 long-term ECG signals from 25 men aged 32–89 years, and 22 women aged 23–89 years; each ECG record has 11-bit resolution with sampling rate of 360Hz. There are sixteen types of arrhythmias in the ADB. The AAMI standards define five main arrhythmia types from sixteen types of the

arrhythmia heartbeats. The AAMI standardizations are based on an objective and distinct processes in the assessments and monitoring of the disorders for clinical treatments and has an increased capability of learning phases for supervised machine learning algorithms [10]. The AAMI classifies sixteen types of arrhythmia into five classes regard as normal beats (N), supraventricular ectopic heartbeats (S), ventricular ectopic heartbeats (V), fusion heartbeats (F), and unknown heartbeats (Q). The numbers of testing and training sets of heartbeats in the ADB are indicated in

Table 1. Dispersion of ADB according to AAMI standards and quantities of test and training sets

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

(Table 1).

Long-term ECG signals may contain different types of noise that are occurred of according to environmental factors, metabolic factors (such as coughing) and activity of the patients, ECG recording device based noises (such as contact noise, probe problems, changing battery options, baseline wandering), electromyography noise, clinician artefact's, and position of patient. All ECG signals are filtered with two median filters to remove the baseline wander [11]. 6077 of ECG waveforms were segmented from long-term ECG signals to increase the data size using a moving window analyses technique with a length of 501 data points (R wave is located at the centre of window). All segmented waveforms are normalized to a [0, 1] range.

2.2. ECG Waveform

The ECG is a biomedical signal type that determines the normality and abnormality of heart beats using the electrical activity of the heart. The electrical activity changes on the heart are plotted as a waveform on the clinical treatments. The ECG waveforms may have different electrical charges according to the channel of the ECG [11], [12]. Channel during the recording ECG signals refers for leads. The leads are used for basic heart monitoring, checking for various arrhythmias and more. The use of the ECG in computer based medical diagnosis and decision support systems is very important and becoming popular application to detect the different waveforms and various cardiac disorders such as cardiovascular heart diseases, congestive heart failure, arrhythmia, etc.

The heart muscle is the only muscle group that has spontaneously muscle contraction in the whole body. Polarization is the discharging activity of electrical charge on heart. Depolarization is the charging activity of electrical activation on heart [13].

The amplitude of the ECG is between 0mV to 5mV and the

frequency range of the ECG is between 0.5Hz and 100Hz [2], [13]. P, Q, R, S and T waves are indicated on the baseline of the ECG waveform, respectively. If the amplitude value of Q, R and S waves is lower than 5mV, the name of the wave is indicated with lowercases (q, r, and s). The gap between the waves is entitled as a segment; the distance between the waves is entitled as an interval [12]. The ECG waveform is shown in (Figure 1).

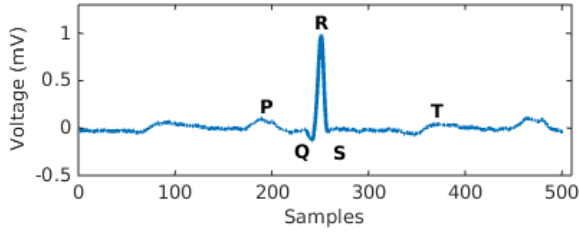


Figure 1. P, Q, R, S, and T waves on ECG waveform

A P wave is the electrical activity on the hearth during the depolarization of the atriums. In a normal cycle of the hearth, the right atrium and the left atrium depolarizes, respectively. Hence, the ascending tendency of the P wave come passes in the depolarization of the right side; descending tendency of the wave springs up during the depolarization of the left atrium. Although it is related with the physical activity and the environmental considerations, the duration of the P wave is about 0.10s; the amplitude value of the P wave is about 0.20mV in a normal derivation [2].

The Q, R and S waves are come up as the QRS complex. The complex is the electrical activity on the hearth on the depolarization of the ventricles. The R wave is positive electrical charge; Q and S waves are negative electrical charges in the complex. The Q wave is the first negative electrical charge following the P wave; the R wave is the first positive wave after the P wave and the S wave is the following negative electrical charge. The sighted QRS complex has different forms in various leads. The complexes point out the major differences even among normal individuals. An R and S wave occurs as a result of the contraction of the myocardium. The QRS complex dials the electrical activity arising out of ventricle contractions on the hearth [14]. The complex for the duration is about 0.11s and has an amplitude value up to 2-3 mV [2].

The T wave is the electrical charge on ventricular re-polarization. The T wave may be seen as a point or as a flat view. The wave may come out with positive, negative or biphasic electrical charges on different variations. The duration of the T wave is between 0.10s and 0.25s in a normal ECG derivation. It is usually seen following 300ms after the QRS complex. The electrical charges of T waves may be set to different loads considering to the heart rhythm. It comes closer to the QRS complex during the heart rhythm accelerates and otherwise moves away [14].

2.3. Second Order Difference Plot

The SODP is a mapping algorithm that has ability to extract meaningful and significant characteristics for heart rate variability, EEG and ECG waveforms [15]. If $x(t)$ signal represents for the ECG waveform, the SODP is the graphical presentation of $X(t)$ against $Y(t)$ functions which are defined as:

$$X(t) = x(t + 1) - x(t) \quad (1)$$

$$Y(t) = x(t + 2) - x(t + 1) \quad (2)$$

In other words, it consists of scattering of consecutive differences of the ECG signal. Thus, the statistical state of the values of

successive differences can be investigated. In the studies, the SODP is divided into sections using various sizes of radial circles, logarithmic grids, rectangles and squares based analysing methods. Elliptical area method, SD1 and SD2 features were extracted as additional features. The distribution of the ECG signals after SODP forms as an ellipse. The long diameter of the ellipse form SODP represents for SD1 and short diameter of the ellipse form SODP represents for SD2 [16]. The area of the ellipse, lengths of SD1 and SD2 are the practicable features of the SODP that are calculated in this study. The formulas of the features are seen in (Equations.3 to 9).

$$S_X = \sqrt{\frac{1}{N} \sum_{n=0}^{N-1} X(n)^2} \quad (3)$$

$$S_Y = \sqrt{\frac{1}{N} \sum_{n=0}^{N-1} Y(n)^2} \quad (4)$$

$$S_{XY} = \frac{1}{N} \sum X(n)Y(n) \quad (5)$$

$$D = \sqrt{(S_X^2 + S_Y^2) - 4(S_X^2 S_Y^2 - S_{XY}^2)} \quad (6)$$

$$a = SD1 = 1.7321 \sqrt{(S_X^2 + S_Y^2 + D)} \quad (7)$$

$$b = SD2 = 1.7321 \sqrt{(S_X^2 + S_Y^2 - D)} \quad (8)$$

$$A_{ellipse} = \pi ab \quad (9)$$

where $A_{ellipse}$ represents for the area of the ellipse and a, b represent for the long and short diameter lengths, respectively.

2.4. 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 have a greedy layer wise training phase [17]. 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], [18]. 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 :

$$E(v, h) = -hWv - bv - ch \quad (10)$$

$$P(v, h) = \frac{e^{-E(v,h)}}{\sum e^{-E(v,h)}} \quad (11)$$

$P(v, h)$ represents for 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 [19].

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 [17]. 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 [17], [19].

3. Experimental Results

The morphological features are the most practicable features for computer based diagnosis and decision support systems for arrhythmia classification. The robust and responsible determination of arrhythmia is a prior necessity for diagnosing the cardiac diseases in clinical assessments. Each arrhythmia type may associate with different types of cardiac and pulmonary disorders. For this reason so, the detection and classification of the arrhythmia types have a so significant importance for cardiologists and treatment systems. In the early diagnosis and early treatment processes of the diseases, the assessment and analysis of the whole ECG signals after extracting ECG waveforms may cause time-loss for a successful and punctual treatment. Considering the importance of the classification of the arrhythmia types, a computer-aided classification of the 5 arrhythmia types is implemented extracting the SODP features and waveform with a DBN-based multistage machine learning algorithm. (Figure 2) depicts the structure of the multistage arrhythmia classification model.

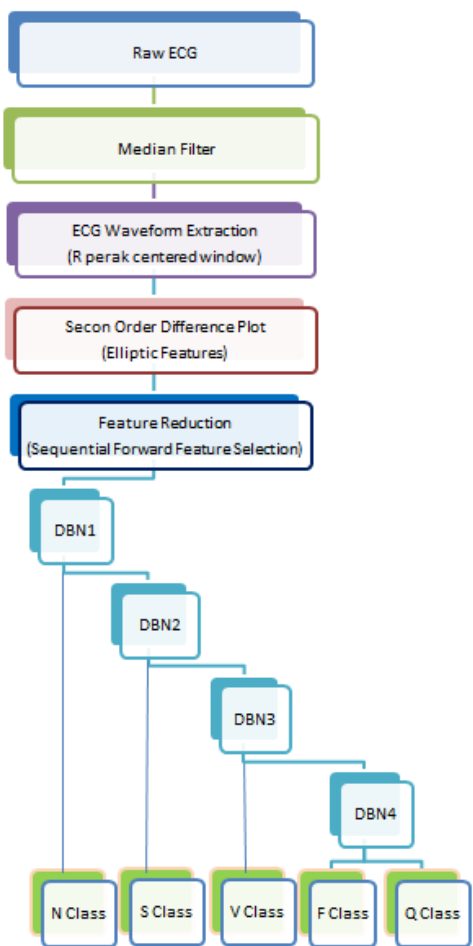


Figure 2. Structure of the proposed arrhythmia classification system

The lots of ECG signals that are obtained from the Physionet have ECG recording device-based, unknown noises and baseline wanders. Two median filters are applied to raw form of the ECG signals for filtering the noises and removing the baseline wanders. Assessment of the long-term ECG signals is a troublesome progression for cardiologists and also for computer-based analyses systems. In the view of the fact that situation, ECG waveforms were segmented from long-term ECG signals with a window analysis. The utilized analyzing window has 501 data points with

R wave in the center point (256th data point) of the window. The analyzing window was moved and the whole ECG waveforms were extracted. The reason to choose the size of the window as 501 is extracting a whole ECG waveform with getting one sample from each P, Q, R, S and T waves. 6077 of ECG waveforms were extracted from 48 long-term ECG signals. Each extracted waveform is controlled if it has one sample from all waves. The SODP of the ECG waveforms were depicted and area of the ellipse, lengths of long diameter (SD1) and short diameter (SD2) of the ellipse were calculated using for 6077 of short-term ECG signals. The ECG waveforms with 501 data points and the 3 of elliptical features from the SODP were used as features in the classification model. The obtained feature vector is normalized to 0-1 range. Even if the computer based analyzing methods are robust, big size of the feature dimensionality leads long durational processes and deceptive learning processes for the supervised machine learning algorithms. Especially, the training time for the great number of feature size is improper for real-time and robust clinical treatment systems. Feature dimensionality reduction algorithms test the whole feature set with optimization techniques to reach the best classification performance for using minimum power in a minimum duration and getting maximum accuracy, specificity, sensitivity and selectivity values. The features reducing methods provide a more meaningful classification optimization, the weeding out the pointless or less meaningful feature vectors for concentrated supervised learning methods, the improving capacity of generalization with less parameters and features, optimizing the complexity during the analyses process and prediction of accuracy performance for supervised classifiers [20]. The sequential forward feature selection algorithm is implemented in the proposed multistage classification method to reduce feature size [21]. The optimization algorithm selects a subset of features which are not yet selected best feature between 501 data points and the SODP features and the best performance measurements for the arrhythmia classes by sequentially selecting and adding features previous best feature group until all improvements are done in the feature prediction list. The best classification performance for accuracy rate is achieved using 93 features, 90 from the ECG waveforms and 3 from elliptical features. The proposed DBN-based multistage arrhythmia classification model was re-trained using the best group of 93 features and system was tested with fixed model. The distribution of selected data points on the ECG waveform is plotted in (Figure 3) with the red asterisks.

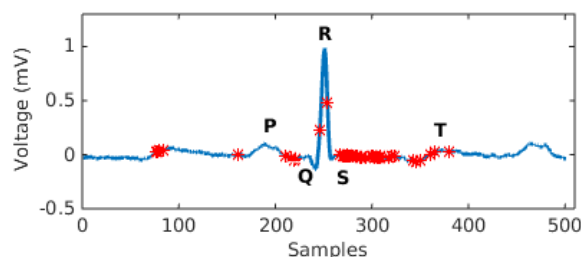


Figure 3. Selected data points from ECG waveforms after feature dimensionality reduction (Red asterisk)

The proposed DBN-based multistage model classifies N, S, V, F, and Q types of arrhythmias, respectively. The model consists of 4 of different structured DBN models. The DBN models use sparse auto-encoders and the RBM based unsupervised training phases. In this study, The RBM based greedy layer-wise pre-training is utilized at the unsupervised learning stages of all DBN structures with 5 epochs. The parameters of the RBM were fixed by

iterations. The DBN-based classification models were iterated with a limited number of the parameters and the highest achieved classification performances are presented. The learning rate parameter of the structure is 3 and the softmax output function was approved stationary for all DBN models. The proposed multistage arrhythmia classification model has 4 DBN models with various sizes of hidden units and various latent layers. The first model DBN1 has 3 hidden layers with 120-260-240 hidden units and separates N type of arrhythmia from others (S, V, F, and Q types of arrhythmia); the second model DBN2 has 3 hidden layers with 200-330-210 hidden units and separates S type of arrhythmia from others (V, F, and Q types of arrhythmia); the third model DBN3 has 2 hidden layers with 130-90 hidden units and separates V type of arrhythmia from others (F and Q types of arrhythmia); and the last model DBN4 has 2 hidden layers with 80-110 hidden units and separates F type of arrhythmia type from Q type of arrhythmia. The four DBN models are blocked as sequentially to the next one and have the ability to classify five types of ANSI/AAMI arrhythmias. The DBN-based automatic arrhythmia classification model was pre-trained using 4077 of samples from all types of arrhythmia that are distributed homogeneously in the train set. The unsupervised calculated weights are updated using supervised training neural network model. The model was tested with 2000 of samples. The confusion matrix of the test performance is seen in (Table 2).

Table 2. Confusion matrix of multistage classifier

Labels		Predicted heartbeats				
		N	S	V	F	Q
True heartbeats	N	492	2	7	6	2
	S	0	291	4	3	8
	V	2	0	481	1	6
	F	3	4	3	184	10
	Q	3	3	5	6	474

In the literature, different numbers of arrhythmia types are classified with machine learning algorithms. Most of the study used the morphological features to detect the significant

characteristics from ECG waveforms. Non-fiducial features are the created new form of the signals using transformation packages. Different machine learning algorithms are utilized in the classification and detection applications of arrhythmia types. In the studies that use Support Vector Machines (SVM) classification algorithm, (Zhang et al., 2014) utilized inter-beat features, morphological features from amplitude and distances of the waveforms for classifying 4 types of arrhythmia with an accuracy rate of 86.66%, a sensitivity rate of 93.81%, and a selectivity rate of 98.98% [22]; (Alajlan et al., 2014) extracted morphological features, high order statistical features and wavelet band features applying the Discrete wavelet transform, S transform and classified arrhythmia types into 2 classes with high performances such as an accuracy rate of 93.49%, and a sensitivity rate of 93.14% [23]; (Batra et al., 2016) extracted fixed features and Principle Component Analysis feature reduction algorithm for separating 11 classes of arrhythmia with an accuracy rate of 84.82% [24]. In the studies that use Artificial Neural Network (ANN) classification algorithm, (Melin et al., 2014) utilized cycle features and fiducial features and integrated with a multistage Learning Vector Quantization classification approach and separated 15 classes of arrhythmia with an accuracy rate of 99.16% [25]; (Thomas et al., 2015) extracted wavelet band coefficients using different orders of Wavelet transform, high order statistics and fiducial features from QRS complex for separating 5 classes of arrhythmia with an accuracy rate of 94.64% and a sensitivity rate of 94.60% [26]. In the study that used the Naive Bayes and k-NN algorithms, (Leutheuser et al., 2014) extracted statistical and high order statistical features, and template based features from segmented ECG signals on real-time working android application for 2 classes of arrhythmias and reported k-NN classifier is more successful with an accuracy of 93.30% [27]. The SODP is a becoming popular significant characteristics extraction mapping algorithm on ECG signals. (Yayik et al., 2014) used the SODP together with Empirical Mode Decomposition for diagnosis of congestive heart failure with an accuracy rate of 94.73% [28]. (Altan and Kutlu, 2015) proposed a logarithmic grid analyzing algorithm on the SODP for human identification and achieved an accuracy of 91.52% for 90 subjects [16]. The DL algorithms, especially the DBN, are being intensely applied to applications on

Table 3. Comparison of the related works focused on arrhythmia detection defined by AAMI

Related Works	Feature Extraction Methods	Classifier	Accuracy
(Owis et al.,2002) [32]	Correlation dimension, Lyapunov exponents	k-NN	86.67%
(Martis et al., 2013) [33]	DWT, LDA, PCA	ANN	99.28%
(Kim et al., 2011) [34]	CWT, Morphological feature, DWT, PCA, LDA	ELM	97.94%
(Tadejko et al., 2007) [35]	Morphological features, Wavelet Transform	SVM	97.82%
(Llamedo et al., 2011) [36]	Wavelet Transform, Morphological features	LD	78.00%
(Alvarado et al., 2012) [37]	Pulse based features	LD	93.60%
(Ye et al., 2012) [38]	Interval Features, Wavelet Transform, ICA, PCA	SVM	86.40%
(Kutlu et al., 2016) [39]	ECG Waveform	DBN	95.05%
Proposed	ECG Waveform + SODP	DBN	96.10%

*CWT: Continuous Wavelet Transform, LD: Linear Discriminant, ELM: Extreme Learning Machines, PNN: Probabilistic Neural Network, DWT: Discrete Wavelet Transform, ICA: Independent Component Analyse, PCA: Principle Component Analyse

ECG signals. The DBN may adopt for both feature extraction [29], [30] and classification [18], [31]. (Huanhuan et al., 2014) extracted the DBN-based layer weights and other system parameters as features from complete waveforms and calculated R-R timing interval features. The extracted DBN features are unfolded to a multi-stage SVM classifier model for classifying 6 types of arrhythmia defined by ANSI/AAMI standard. They reported an accuracy rate of 98.82% [30]. (Rahhal et al., 2016) extracted temporal features, morphological features and DBN-based layer weights and system parameters. In the unsupervised pre-training phase they used stacked denoising autoencoders. They fed the all features to the SVM classifier. They performed a separation for 2 classes of arrhythmia types defined by ANSI/AAMI with an overall accuracy rate of 98.49% [29]. (Yan et al., 2015) handled R-R interval features, heartbeat features and raw ECG signal as the input of the DBN classification model and reached an accuracy rate of 98.82% for performing the classification of 12 classes of arrhythmias [18]. Classification of the various numbers of arrhythmia types were studied in literature. We focused on the five classes of arrhythmia types defined by ANSI/AAMI (N, S, V, Q, and F). The achievements on the experimental studies are shared in this study. The works related with the classification of the arrhythmia types defined by ANSI/AAMI are compared in (Table 3).

It is hard to compare the classification performances in a stable way, because of the various numbers of ECG signals, various types of the arrhythmia classes, various patients, different databases and different machine learning algorithms in the classification stage. High classification performances are reported in the literature. In the previous 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. The SODP features are added to the feature set and all feature selection and training algorithms were re-applied using the new feature set. The system was renewed with fixed neuron sizes and training parameters. The high system performance that was investigated in our previous work with 106 features is exceeded with an accuracy rate of 96.10%, a sensitivity rate of 95.33%, and selectivity rate of 95.68% using 93 features including three elliptical features from the SODP.

4. Conclusion

The P, Q, R, S and T waves plot with a constant pattern in normal sinus rhythm. Any in-probable changes consisted in the ECG waveforms cause suspicion about the irregularity or arrhythmia for clinicians and computer-aided assessment systems. Since the extraction of the interval features, segmental features, heart rate, frequency of different waves on ECG waveform and popularly non-fiducial features obtained from various transformation applications revealed a big fabulous utilization for cardiologists to diagnose the various cardiac disorders included arrhythmias and more, the morphological features from the ECG waveforms have frequently been a common method in clinical trials and computer-aided assessment systems [12], [14]. The experimental results has proven that, the most of the revealing data points on the ECG waveform for the classifying the arrhythmia types are more often between P-Q waves and especially between for the proposed DBN-based multistage classification model. The elliptical SODP features contribute positively and are benefit as additional features for proposed arrhythmia classification.

The proposed DBN-based multistage arrhythmia classification model has detected the ANSI/AAMI defined 5 classes of

heartbeats with a high accuracy rate of 96.10%. The classification results have verified the prosperity and impression of the DL algorithm when used with ECG waveforms and the elliptical features from the SODP.

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