A Multistage Deep Learning Algorithm for Detecting Arrhythmia

Gokhan ALTAN
Dept. of Computer Engineering
Iskenderun Technical University
Hatay, Turkey
gokhan_altan@hotmail.com

Novruz ALLAHVERDI
Dept. of Computer Engineering
KTO Karatay University
Konya, Turkey
novruz.allahverdi@karatay.edu.tr

Yakup KUTLU
Dept. of Computer Engineering
Iskenderun Technical University
Hatay, Turkey
yakupkutlu@gmail.com

***Abstract*— Deep Belief Networks (DBN) is a deep learning algorithm that has both greedy layer-wise unsupervised and supervised training. Arrhythmia is a cardiac irregularity caused by a problem of the heart. In this study, a multi-stage DBN classification is proposed for achieving the efficiency of the DBN on arrhythmia disorders. Heartbeats from the MIT-BIH Arrhythmia database are classified into five groups which are recommended by AAMI. The Wavelet packet decomposition, higher order statistics, morphology and Discrete Fourier transform techniques were utilized to extract features. The classification performances of the DBN are 94.15%, 92.64%, and 93.38%, for accuracy, sensitivity, and selectivity, respectively.**

Keywords*— *Deep learning, Deep Belief Network, Arrhythmia, ECG

I. Introduction

An electrocardiogram (ECG) is one of the biomedical signals, which shows the electrical activity of the heart. ECG reflects the distribution and reaction of heartbeats and whether the rhythm or the rate of the heart is steady or irregular [1]. ECG is one of the most important methods in the assessment of heart functionality and cardiac diseases such as arrhythmias, congestive heart diseases and more [2].

Arrhythmia is a cardiac irregularity of the heart caused by the problem of tachycardia, bradycardia or non-steady heartbeats [2]–[4]. Detecting different types of arrhythmia is a very important and vital subject [1], [3]. Many researchers have proposed various approaches to the classification of the arrhythmia beats. The MIT-BIH arrhythmia database (ADB) is the most widely used in ECG literature. Some techniques are based on the discrimination between two types of arrhythmias such as premature ventricular contraction (PVC) and non-PVC [5]–[8] and various types of arrhythmias [3], [9]–[17]. Most of the techniques have classified heartbeats into 5 classes that are defined by the Association for the Advancement of Medical Instruments (AAMI) [1], [18]–[27] and with different types of arrhythmias [4], [18], [28]–[30]. In these studies, a variety of features was extracted from ECGs and different type classifiers were utilized. The features have been based on the morphology of waveforms[1], [4], [6]–[8], [13], [15], [20]–[25], [31], temporal information [4], [8]–[12], [15], [17], [20], [21], [23]–[25], [27], [28], autoregressive modeling coefficients [32], Hidden Markov Modeling [5], Discrete Cosine Transform (DCT) coefficients [29], [33], high order spectral analysis [19], high order statistics (HOS) [3], [6], [7], [25], the Wavelet Transform [15], [21]–[24], [27], [29], [30], the Discrete Wavelet Transform (DWT) [7], [14], [19], [22], [29], QRS geometrical information [14], Principle Component Analysis (PCA) [16], integrate and fire sampler modeling [26], Deep belief network on waveforms features [17] and S transform [7]. Furthermore, PCA [16], [19], [22], [27], [34], Linear Discriminant Analysis (LDA) [19], [22], [34], Independent Component Analysis (ICA) [19], [27] and qualitative feature selection [4] are the methods that were used in feature dimensionality reduction. Finally, selected features are used to learn the discrimination of the arrhythmia heartbeats as a classifier such as artificial neural networks (ANN) [9], [13], [18], [19], [21], [28]–[30], [33], [34], support vector machines (SVM) [1], [5], [7], [16]–[19], [25], [27], [33] , binary classifiers [1], the k-Nearest Neighbor (k-NN) [3], [6], Linear model-based classifiers [20], [24], [26], the Gaussian mixture model [5], the Extreme Learning Machine [22], Hybrid Classifiers [8], [11], [14], [15], [28], the Self-Organization Map [23], Conditional Random Fields [25], Deep Belief Networks (DBN) [8], [12],and Cluster Analysis [4].

Deep Learning (DL) is a new and powerful machine learning algorithm which has begun to be used widely in recent years. DL is used in the assessment of speech recognition, computer vision, natural language processing and biomedical signal applications. DL is a neural network model that aims to discover multiple and deeper levels of processes using multilayer hidden units for a better classification performance. The distinctive characteristics of DL from NN are having at least two hidden layers [35] and having a small number of neurons. Fewer neurons often provide convenience to the system by calculating the weights in the supervised learning stage of the algorithm [36]. These techniques have the ability to train deeper systems with many hidden layers.

In this study, the heartbeats from the ADB are classified into 5 arrhythmia classes recommended by AAMI standards. The moving window analysis technique is used to segment the ECG signals (ECGs) into short-term ECGs that have a length of 341 data points (the R peak is in the center of the data). The wavelet packet decomposition (WPD), waveform morphology, higher order statics and the discrete Fourier transform are used to extract features from segmented short-term ECGs. Features are classified using the multistage DBN classifier. The aims of this study are to determine the efficacy of the DBN classifier and to propose an alternative DBN based classification model on arrhythmia classification.

II. Materials and Methods

A. Database

In the literature, the most used database is the ADB [37] for arrhythmia classification. Therefore, ADB is used in this study. Data supplied to the ADB by the Beth Israel Hospital Arrhythmia Laboratory, contains 48 number of 2-lead ECGs from 25 men aged 32–89, and 22 women aged 23–89; each has 30min long with 360 Hz sampling frequency.

978-1-5386-4427-0/18/$31.00 ©2018 IEEE

The AAMI increased the understanding, safety, and effectiveness of medical techniques. Because of AAMI standardizations on arrhythmia heartbeats such as obtaining different subjects for training and testing, many supervised classifiers do not perform high classification accuracy rates. AAMI standards classify ECG beats into five classes: Normal (N), Ventricular (V), Supraventricular (S), Fusion (F) and Unknown (Q); beat distributions are explained in [3], [25] particularly.

B. Preprocessing

In ECG it is easy to have useless noise because of by skin-electrode changes or the other recording conditions. Noise on the ECGs causes the baseline wander effect. Two median filters are applied to ECGs to handle the baseline wander effect. Filtered ECGs are segmented into heartbeats by using a window which is R peak centered and almost 1 sec in length [3].

C. Feature Extraction

In this study, 6 morphological features, 8 from higher order statistics (HOS) of ECGs, 90 from HOS of WPD and 46 features from the Fourier transform are extracted. Feature extraction is described in [3], particularly.

1) High Order Statistics: The statistical features such as mean, median, minimum, and variance usually have an ability to characterize the signals and are frequently used in machine learning algorithms. But, some signals cannot be represented properly by first and second order statistical features. So, the main stream statistics such as 2nd, 3rd, and 4th order moments and cumulants are calculated as features.

2) Wavelet Packet Decomposition: The DWT decomposes the coefficients by analyzing low frequency sub-band (approximation) coefficients. However, the WPD decomposes both the low frequency sub-band (approximation) and the high frequency sub-band (detail) coefficients [3], [38]. Three features are extracted for each sub-band using HOS (2nd, 3rd, and 4th order) [3].

3) Morphological Features: QR and RS and slopes of right and left sides of R waves are extracted.

4) Discrete Fourier Transform (DFT): The DFT is a practical function that converts a finite sampled time domain into the list of coefficients of frequency domain. 46 energy values in the frequency band of 0–50 Hz are calculated [3].

III. CLASSIFIER

A. Deep Belief Networks

The aim of the DL is modeling complex, hierarchical and detailed features in data. DL algorithms are based on stochastic gradient descent, backpropagation and also new ideas such as the stacked denoising auto encoder, fine tuning and more. The DBN is one of the most used probabilistic generative DL algorithms which consists of stacked Restricted Boltzmann Machines (RBMs) [35], [39]. The DBN has multiple layers of hidden units. The top two layers have undirected connections between them. The lower layers have the top-down between adjacent units. The DBN has an ability to make deep assessments of the feature connections [36].

The DBN is constructed from two stage learning algorithms. The first stage is known as pre-training of the network by greedy layer-wise unsupervised training. The number of the RBMs depends on the number of the hidden layers in the DBN [35]. Each RBM has a visible and a hidden unit and has a connection with the adjacent RBM. The visible unit of the first RBM is the input vector of the model which maps this vector to the representation of the hidden unit. The visible units (input vector) of the next RBMs are the represented hidden units of the previous adjacent RBMs [35]. The details on the DBN functions are given in [36], particularly.

RBMs have no visible-visible and hidden-hidden connections within units. In this way the parameters of the DBN such as weights, biases, are evaluated in the unsupervised stage by the aid of the probability of greedy layer-wise method. In the second stage, the obtained classification parameters of the DBN by unsupervised training are enhanced by the supervised fine-tuning within the Contrastive Divergence method [35], [40].

The performance of the arrhythmia classification model is measured by using statistical valuation functions: Specificity, Sensitivity, and Accuracy which are obtained from the confusion matrix of multistage classification [35]. The details on the calculation of performance measures are given in [3], [35], [36]. TP (True Positive) represents the truly classified heartbeats in the stages of proposed method.

IV. EXPERIMENTAL RESULTS

The detection of the arrhythmia type is fundamental for a quick and successful treatment. Nowadays, computer-based arrhythmia classification methods have a high accuracy rate in hard-to-detect arrhythmias and symptoms, as they are successful and steady in the diagnosis systems. In this study, a deep learning-based multi-stage classification model is proposed for achieving the efficiency of the DBN for automatic arrhythmia classification.

The dataset, which was used in the study, includes a total of 150 features: 8 from HOS of ECGs, 90 from 2nd, 3rd, and 4th order moments and cumulants of WPT, 6 morphological features, and 46 DFT coefficients. The feature vector is normalized to 0-1.

A multistage DBN classifier is proposed in this study. N, S, V, F, and Q types of arrhythmias are classified, respectively. 4 DBN structures are used in the proposed system. Fig. 1 depicts the structure of the proposed classifier.

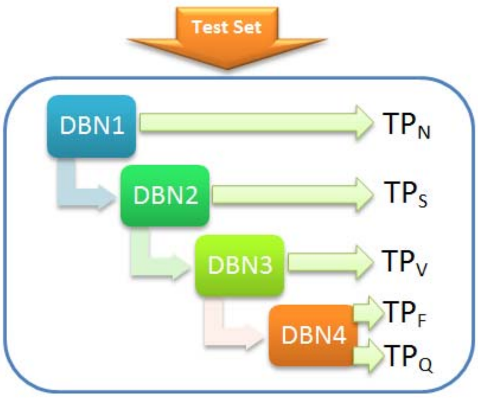

Fig. 1. Structure of the proposed multistage classification system

The DBN-based multi-stage automatic arrhythmia classification model consists of 4 stages. Greedy layer-wise pre-training is used in this model at the unsupervised learning stage of the DBN with 10 epochs. The activation function of the hidden layers on the supervised learning phase is the hyperbolic tangent function to avoid bias in the gradients and to have a stronger gradient. To unfold the DBN to a neural network for the supervised learning stage of the DBN, model parameters were selected by iterations. We experimented only with a limited number of parameters and the parameters in which the best classification performance achieved are given. In the first stage, DBN1 has separated N class heartbeats from V, S, F and Q arrhythmia heartbeats. The DBN1 has 2 hidden layers with 200-530 hidden units. The output layer has two outputs N and Others (S+V+F+Q). The learning rate is 4 and the softmax output function was utilized. In the second stage, DBN2 separated S class heartbeats from V, F and Q arrhythmia heartbeats. The DBN2 has 3 hidden layers with 260-420-120 hidden units. The output layer has two outputs: S and Others (V+F+Q). The learning rate is 4 and the softmax output function was utilized. In the third stage, DBN3 separated V class heartbeats from F and Q arrhythmia heartbeats. The DBN3 has 2 hidden layers with 50-60 hidden units. The output layer has two outputs V and Others (F+Q). The learning rate is 2 and the sigmoid output function was utilized. In the last stage, DBN4 separated F class heartbeats from Q arrhythmia heartbeats. The DBN4 has 3 hidden layers with 150-440-100 hidden units. The output layer has two outputs: V and F arrhythmia heartbeats. The learning rate is 3 and the softmax output function was utilized.

The training set of the automatic arrhythmia classification model includes 3,345 heartbeats from various types of heartbeat classes and the trained DBN model is tested using 2,542 heartbeat classes which are defined by AAMI standards. The confusion matrix of the classifier is seen in Table 1.

TABLE I. CONFUSION MATRIX OF MULTISTAGE CLASSIFIER

Labels		*Predicted heartbeats*				
		N	***S***	***V***	***F***	***Q***
True heartbeats	***N***	**477**	2	8	16	4
	S	0	**288**	10	3	6
	V	3	0	**467**	2	3
	F	12	8	12	**173**	9
	Q	8	2	3	6	**478**

Melin et al. used ANN and a learning vector quantization multistage system to classify fifteen types of arrhythmias using fiducial points, segmentation of cycles and transformation of cardiac cycles with an accuracy rate of 97.64% to 99.16% [9]. Castillo et al. have presented ANN with gradient descent and a fuzzy k-NN hybrid intelligent system to classify five types of arrhythmias using heartbeat segmentation with an accuracy rate of 98% [28]. Chang et al. used the Gaussian mixture model with hidden Markov model features. Sensitivity, specificity, and accuracy are reported as 85.71%, 79.82%, and 82.50%, respectively, for six classes of arrhythmias [5]. Martis et al. have reported high classification performances using higher order spectral analysis and PCA with ANN and least square SVM [18]. Leutheuser et al. compared the real-time classification systems for arrhythmia detection on mobile devices using statistical features, heartbeat features and temporal features to classify 2 types of arrhythmias [6]. They reported their best accuracy rate of 93.30% using k-NN on android-based mobile devices. Alajlan et al. classified two arrhythmia types with the SVM system using morphological features, DWT, higher order statistics and S transform features. Sensitivity and accuracy are reported as 93.14%, and 93.49%, respectively [7]. Yeh et al. have reported an accuracy rate of 94.30% using a multistage cluster analysis model with morphological and shape features to classify five types of arrhythmias [4]. Yan et al. have reported an accuracy rate of 98.82% with morphological features, heartbeat features and raw two-lead ECGs to classify twelve types of arrhythmias using the DBN [12]. Rahhal et al. fed raw ECG waveforms, temporal features and the weights and biases that are trained by the DBN as features to the SVM training and classification [8]. An accuracy rate of 98.49% is reported for two types of arrhythmia heartbeats. It is hard to compare the classification performances of the studies, because of the different numbers and different types of classified arrhythmia heartbeats belonging to different patients. The purposed multistage DBN classification is based on the arrhythmia types which are defined by the AAMI. The comparison of the studies using the AAMI is seen in Table 2.

TABLE II. COMPARISON OF THE RELATED WORKS ON 5 TYPES OF ARRHYTHMIAS (N, S, V, F, Q) ACCEPTED BY ANSI/AAMI

Related Works	**Features**	**Classifier**	**Accuracy**
Martis et al. [33]	DCT, PCA	ANN LS-SVM PNN	99.12% 89.30%-98.17% 99.52%
Martis et al. [19]	DWT, ICA, LDA, PCA	LS-SVM ANN PNN	87.52%-97.40% 98.78% 99.28%
Kim et al. [22]	CWT, Morphological feature, DWT, PCA, LDA	ELM	97.94%
Chazal et al. [20]	Morphological features	LD	85.83%
Tadejko et al. [23]	Morphological features, Wavelet Transform	SOM/LVQ SVM	92.95% 97.82%
Llamedo et al. [24]	Wavelet Transform, Morphological features	LD	78.00%
Lannoy et al. [25]	Morphological features, HBF coefficients, HOS	W-CRF	85.39%
Alvarado et al. [26]	Integrate and Fire Sampler Model, Pulse based features	LD	93.60%
Ye et al. [27]	Interval Features, Wavelet Transform, ICA, PCA	SVM	86.40%
Proposed	Morphological features, HOS, WPD, DFT	DBN	94.15%

[a] CWT: Continuous Wavelet Transform, LD: Linear Discriminant, W-CRF: Weighted Conditional Random Fields, ELM: Extreme Learning Machines, PNN: Probabilistic Neural Network, LS-SVM: Least Square-SVM, SOM/LVQ: Self-Organization Map/Learning Vector Quantization

Martis et al. and Kim et al. have reported high accuracy rates in the classification of AAMI types of arrhythmia. Each study is based on a different number of heartbeats from different subjects. So it is hard to compare the results in an objective way. Enhancing the classification accuracy of arrhythmia types is not the first object; the aims of this study are determining the efficiency of the DBN classifier for arrhythmia classification and proposing a multistage classifier system that is an alternative to other machine learning models. The classification performances of the proposed system are 94.15%, 92.64%, and 93.38%, for overall accuracy, average sensitivity, and average selectivity, respectively. The results are higher than in most of the related works and this case identifies the success of the DL in the classification of arrhythmia.

V. Conclusion

Various feature extraction methods that characterize the irregularity on ECGs, several popular classification methods have been investigated for various types of automatic arrhythmia recognition. The DBN is becoming a popular machine learning algorithm for the classification of automatic arrhythmia. Therefore a DBN based multi-stage classification system is constructed.

Features are based on a combination of a set of derived morphological, WPD, Fourier and HOS. A 4 stage DBN based system is utilized in classification of heartbeats. This paper presented an attempt to develop a computerized classifier, which can detect arrhythmia types in an efficient and reliable way. The results show that the proposed multi-stage classifier for discriminating a broad range of heartbeats performs good with average sensitivity, average selectivity, and overall accuracy rates of 92.64%, 93.38%, and 94.15%, respectively.

Acknowledgment

N.Allahverdi thanks the KTO Karatay University for its support of this work.

References

[1] Z. Zhang, J. Dong, X. Luo, K. S. Choi, and X. Wu, "Heartbeat classification using disease-specific feature selection," *Comput. Biol. Med.*, vol. 46, no. 1, pp. 79–89, 2014.

[2] M. Gabriel Khan, *Rapid ECG Interpretation(Contemporary Cardiology)*, 3rd editio. Humana Press, 2007.

[3] Y. Kutlu and D. Kuntalp, "A multi-stage automatic arrhythmia recognition and classification system," *Comput. Biol. Med.*, vol. 41, no. 1, pp. 37–45, 2011.

[4] Y. C. Yeh, C. W. Chiou, and H. J. Lin, "Analyzing ECG for cardiac arrhythmia using cluster analysis," *Expert Syst. Appl.*, vol. 39, no. 1, pp. 1000–1010, 2012.

[5] P.-C. Chang, J.-J. Lin, J.-C. Hsieh, and J. Weng, "Myocardial infarction classification with multi-lead ECG using hidden Markov models and Gaussian mixture models," *Appl. Soft Comput.*, vol. 12, no. 10, pp. 3165–3175, 2012.

[6] H. Leutheuser, S. Gradl, P. Kugler, L. Anneken, M. Arnold, S. Achenbach, and B. M. Eskofier, "Comparison of real-time classification systems for arrhythmia detection on Android-based mobile devices," *IEEE Eng. Med. Biol. Soc. Annu. Conf.*, vol. 2014, pp. 2690–2693, 2014.

[7] N. Alajlan, Y. Bazi, F. Melgani, S. Malek, and M. A. Bencherif, "Detection of premature ventricular contraction arrhythmias in electrocardiogram signals with kernel methods," *Signal, Image Video Process.*, vol. 8, no. 5, pp. 931–942, Jul. 2014.

[8] M. M. Al Rahhal, Y. Bazi, H. AlHichri, N. Alajlan, F. Melgani, and R. R. Yager, "Deep Learning Approach for Active Classification of Electrocardiogram Signals," *Inf. Sci. (Ny).*, vol. 345, pp. 340–354, Feb. 2016.

[9] P. Melin, J. Amezcua, F. Valdez, and O. Castillo, "A new neural network model based on the LVQ algorithm for multi-class classification of arrhythmias," *Inf. Sci. (Ny).*, vol. 279, pp. 483–497, Sep. 2014.

[10] J.-S. Wang, W.-C. Chiang, Y.-L. Hsu, and Y.-T. C. Yang, "ECG arrhythmia classification using a probabilistic neural network with a feature reduction method," *Neurocomputing*, vol. 116, pp. 38–45, 2013.

[11] H. H. Haseena, A. T. Mathew, and J. K. Paul, "Fuzzy clustered probabilistic and multi layered feed forward neural networks for electrocardiogram arrhythmia classification," *J. Med. Syst.*, vol. 35, no. 2, pp. 179–188, 2011.

[12] Y. Yan, X. Qin, Y. Wu, N. Zhang, J. Fan, and L. Wang, "A restricted Boltzmann machine based two-lead electrocardiography classification," *2015 IEEE 12th International Conference on Wearable and Implantable Body Sensor Networks (BSN)*. pp. 1–9, 2015.

[13] M. Moavenian and H. Khorrami, "A qualitative comparison of Artificial Neural Networks and Support Vector Machines in ECG arrhythmias classification," *Expert Syst. Appl.*, vol. 37, no. 4, pp. 3088–3093, 2010.

[14] M. R. Homaeinezhad, S. A. Atyabi, E. Tavakkoli, H. N. Toosi, A. Ghaffari, and R. Ebrahimpour, "ECG arrhythmia recognition via a neuro-SVM-KNN hybrid classifier with virtual QRS image-based geometrical features," in *Expert Systems with Applications*, 2012, vol. 39, no. 2, pp. 2047–2058.

[15] M. Javadi, S. A. A. A. Arani, A. Sajedin, and R. Ebrahimpour, "Classification of ECG arrhythmia by a modular neural network based on Mixture of Experts and Negatively Correlated Learning," *Biomed. Signal Process. Control*, vol. 8, no. 3, pp. 289–296, 2013.

[16] A. Batra and V. Jawa, "Classification of Arrhythmia Using Conjunction of Machine Learning Algorithms and ECG Diagnostic Criteria," *Int. J. Biol. Biomed.*, vol. 1, pp. 1–7, 2016.

[17] M. Huanhuan and Z. Yue, "Classification of Electrocardiogram Signals with Deep Belief Networks," *Computational Science and Engineering (CSE), 2014 IEEE 17th International Conference on*. pp. 7–12, 2014.

[18] R. J. Martis, U. R. Acharya, K. M. Mandana, a. K. Ray, and C. Chakraborty, "Cardiac decision making using higher order spectra," *Biomed. Signal Process. Control*, vol. 8, no. 2, pp. 193–203, 2013.

[19] R. J. Martis, U. R. Acharya, and L. C. Min, "ECG beat classification using PCA, LDA, ICA and Discrete Wavelet Transform," *Biomed. Signal Process. Control*, vol. 8, no. 5, pp. 437–448, 2013.

[20] P. De Chazal and R. B. Reilly, "A patient-adapting heartbeat classifier using ECG morphology and heartbeat interval features," *IEEE Trans. Biomed. Eng.*, vol. 53, no. 12, pp. 2535–2543, 2006.

[21] T. Ince, S. Kiranyaz, and M. Gabbou, "A generic and

robust system for automated patient-specific classification of ECG signals," *IEEE Trans. Biomed. Eng.*, vol. 56, no. 5, pp. 1415–1426, 2009.

[22] J. Kim, S. D. Min, and M. Lee, "An arrhythmia classification algorithm using a dedicated wavelet adapted to different subjects.," *Biomed. Eng. Online*, vol. 10, no. 1, p. 56, 2011.

[23] P. Tadejko and W. Rakowski, "Hybrid wavelet-mathematical morphology feature extraction for heartbeat classification," in *EUROCON 2007 - The International Conference on Computer as a Tool*, 2007, pp. 127–132.

[24] M. Llamedo and J. P. Martinez, "Heartbeat classification using feature selection driven by database generalization criteria," *IEEE Trans. Biomed. Eng.*, vol. 58, no. 3 PART 1, pp. 616–625, 2011.

[25] G. De Lannoy, D. François, J. Delbeke, and M. Verleysen, "Weighted conditional random fields for supervised interpatient heartbeat classification," *IEEE Trans. Biomed. Eng.*, vol. 59, no. 1, pp. 241–247, 2012.

[26] A. S. Alvarado, C. Lakshminarayan, and J. C. Príncipe, "Time-based compression and classification of heartbeats," *IEEE Trans. Biomed. Eng.*, vol. 59, no. 6, pp. 1641–1648, 2012.

[27] C. Ye, B. V. K. Vijaya Kumar, and M. T. Coimbra, "Heartbeat classification using morphological and dynamic features of ECG signals," *IEEE Trans. Biomed. Eng.*, vol. 59, no. 10, pp. 2930–2941, 2012.

[28] O. Castillo, P. Melin, E. Ramírez, and J. Soria, "Hybrid intelligent system for cardiac arrhythmia classification with Fuzzy K-Nearest Neighbors and neural networks combined with a fuzzy system," *Expert Syst. Appl.*, vol. 39, no. 3, pp. 2947–2955, 2012.

[29] H. Khorrami and M. Moavenian, "A comparative study of DWT, CWT and DCT transformations in ECG arrhythmias classification," *Expert Syst. Appl.*, vol. 37, no. 8, pp. 5751–5757, 2010.

[30] M. Thomas, M. K. Das, and S. Ari, "Automatic ECG arrhythmia classification using dual tree complex wavelet based features," *AEU - Int. J. Electron. Commun.*, vol. 69, no. 4, pp. 715–721, 2015.

[31] P. D. C. P. De Chazal, M. O'Dwyer, and R. B. Reilly, "Automatic classification of heartbeats using ECG morphology and heartbeat interval features," *IEEE Trans. Biomed. Eng.*, vol. 51, no. 7, pp. 1196–1206, 2004.

[32] D. Ge, N. Srinivasan, and S. M. Krishnan, "Cardiac arrhythmia classification using autoregressive modeling.," *Biomed. Eng. Online*, vol. 1, p. 5, 2002.

[33] R. J. Martis, U. R. Acharya, C. M. Lim, and J. S. Suri, "Characterization of ECG beats from cardiac arrhythmia using discrete cosine transform in PCA framework," *Knowledge-Based Syst.*, vol. 45, pp. 76–82, 2013.

[34] D. Wang and Y. Shang, "Modeling Physiological Data with Deep Belief Networks.," *Int. J. Inf. Educ. Technol.*, vol. 3, no. 5, pp. 505–511, 2013.

[35] Y. Bengio, P. Lamblin, D. Popovici, and H. Larochelle, "Greedy Layer-Wise Training of Deep Networks," *Adv. Neural Inf. Process. Syst.*, vol. 19, no. 1, p. 153, 2007.

[36] N. Allahverdi, G. Altan, and Y. Kutlu, "Diagnosis of Coronary Artery Disease Using Deep Belief Networks," *2. Int. Conf. Eng. Nat. Sci.*, p. in press, 2016.

[37] A. L. Goldberger and coworkers, "PhysioNet: a research resource for studies of complex physiologic and biomedical signals.," *Comput. Cardiol.*, vol. 27, pp. 179–182, 2000.

[38] M. Y. Gokhale, "Time Domain Signal Analysis Using Wavelet Packet Decomposition Approach," *Int'l J. Commun. Netw. Syst. Sci.*, vol. 03, no. 03, pp. 321–329, 2010.

[39] G. E. Hinton, S. Osindero, and Y.-W. Teh, "A fast learning algorithm for deep belief nets.," *Neural Comput.*, vol. 18, no. 7, pp. 1527–54, 2006.

[40] Y. Bengio and O. Delalleau, "Justifying and generalizing contrastive divergence," *Neural Comput.*, vol. 21, no. 6, pp. 1601–1621, 2009.