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Classification of ECG Arrhythmia using Recurrent Neural Networks

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Abstract

In this paper, Recurrent Neural Networks (RNN) have been applied for classifying the normal and abnormal beats in an ECG. The primary aim of this paper was to enable automatic separation of regular and irregular beats. The MIT-BIH Arrhythmia database is being used to classify the beat classification performance. The methodology used is carried out using huge volume of standard data i.e. ECG time-series data as inputs to Long Short Term Memory Network . We divided the dataset as training and testing sub-data. The effectiveness, accuracy and capabilities of our methodology ECG arrhythmia detection is demonstrated and quantitative comparisons with different RNN models have also been carried out.

Keywords: Long Short Term Memory; Recurrent Neural Network ; Arrhythmia; Gated Recurrent unit;

1. Introduction

Electrocardiography (ECG) is an important and effective diagnosis in detecting the abnormal condition of the heart[1]. The electrocardiogram (ECG) signal is the recording of the bioelectrical activities of heart[2]. Early age detection of heart diseases (abnormalities) can prolong life and enhance the quality of living through appropriate treatment. Conventional methods[3-5] of detecting the heart diseases was the changes or abnormalities seen in the ECG signal by human observer. As a result, to increase the accuracy and the effectiveness of the signal automation and classification of the beats is necessary[6].

Electrocardiogram is a valuable indicator of the human health status. It contains a comprehensive information about physiological processes taking place in the human body and thus can be considered as a promising tool for health assessment [6]. However, at the present time it is primarily used in medicine to diagnose only heart and vessel diseases [3-4].

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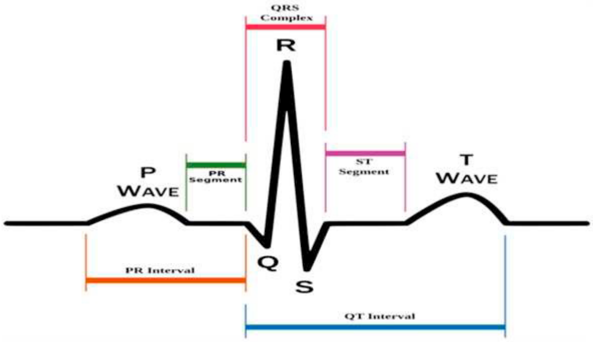

Fig. 1. ECG Signal Curve

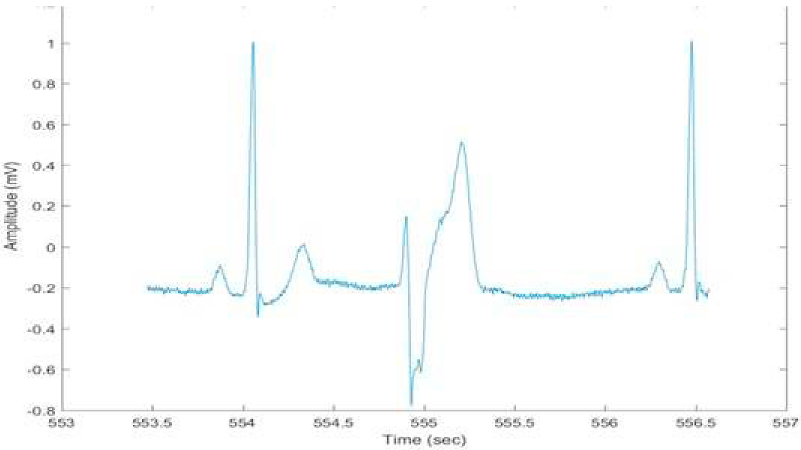

Fig. 2. ECG Curve Plotted using MIT-BIH Data

The objective of this paper is to apply RNN Long Short-term Memory network for the effective detection of arrhythmia from ECG signals. The ECG signal consists of sixteen type of heartbeats these are divided into two groups Normal and Arrhythmia heartbeats. The arrhythmia heartbeats are Left bundle branch block beat, Right bundle branch block beat, Atrial escape beat, Nodal (junctional) escape beat, Atrial Premature Beat, Aberrated atrial premature beat, Nodal (junctional) premature beat, Supraventricular premature beat, Premature Ventricular Contraction, Ventricular Escape beat, Fusion of Ventricular and Normal beat, Paced beat, Fusion of paced beat and normal beat, Unclassified beat.

Cardiologists, after gaining years of experience to distinguish between normal and arrhythmic beats have also failed many times due to human nature, thereby opening the doors of exploration and innovation in this area of biotechnology. There are various machine learning and deep learning models deployed for detecting arrhythmia and some of them have outperformed the cardiologists. We henceforth discuss various machine learning models applied for arrhythmia detection to have a better intuition of the models and to gain insights of what should be and will be a suitable for this area of research.

To avoid the manual work of detecting arrhythmic beats in the ECG, we applied a machine learning algorithm to automatically detect the irregular beats and then the detected beats can be taken to the cardiologist for verification and further analysis.The classification accuracy can be considered to an extent and this paper can further simplify the work of Doctors and can be taken into consideration for further enhancement and development.

2. Literature Review

The papers written classify the beats using technologies with the changes in various parameters and using the non-linear dynamic tools[2] and as a result, this paper uses the recurrent neural networks with varying parameters and number of epochs where the accuracy changes as per the neurons in the hidden layer and number of epochs.

Distinctive methods have been available to develop robotized recognition and finding of ECG. Self Organizing Maps (SOM), Support Vector Machines (SVM), Multilayer Perceptron (MLP), Markov Models, Fuzzy or Neuro-fuzzy Systems and of various procedures have been recommended to enhance execution [26-28]. To date, a few analysts have made undertakings to apply SVM and distinctive another classifier to diagnosis cardiac beats. Various strategies have been introduced over before years for working up the motorized structures to absolutely order the ECG information. These include wavelet transform [29-30] direct vector quantization [31] and probabilistic neural network [32] and fuzzy crossover neural system algorithms [33]. Silipo et al. [34] proposed a differentiation task for characterization of ECG applying two arrangement strategies; one with administered learning strategy; and other learning with unlabeled information. Sugiura et al.[35] built up a fuzzy rationale based methodology for recognizing ECG arrhythmias and segregating ventricular arrhythmias. Acharya et al.[26] utilized cardiac rate changeability (HRV) as the base flag and executed ANN and fuzzy proportionality connection for the grouping of four ECG arrhythmias. Kohli et al. [35] suggest SVM based arrhythmia arrangement associated three strategies one against one, one against all and fuzzy choice capacity. In this paper one against all strategy gives the better exactness contrast with different techniques. Jadhav et al. [36] developed three diverse model of ANN for determination of heart arrhythmia. In this paper, RNN model is prepared to classify the arrhythmia in heart beats.

The majority of recent researches in this field are also focused on the detection of various cardiovascular illnesses. For instance, ECG signals are successfully applied for arrhythmia classification [5 -7] myocardial ischemia detection [8-10] coronary artery disease detection [11-13] etc. A wide and exhaustive overview of the current state in ECG signals processing and interpretation is given in book [14].

In [15], authors have shown that the ECG signals change their form for a number of non-cardiac disorders, such as pulmonary embolism, central nervous system (CNS) diseases, myasthenia gravis, muscular tremors, hypothermia and hypothyroidism. Another study [16] has pointed out that besides CNS diseases the changes are presented for some esophageal disorders. There was also shown that drugs, poisons and electrical injuries have a considerable impact on the waveform of ECG signals. In another paper [17] authors have presented a study where the connection between Friedreichs ataxia and electrocardiographic results was shown. These papers were very important for understanding the information function of the heart, but the proposed methods could not be expanded to detect other diseases while they rely on a specific form of the ECG abnormalities. The problem was largely solved by Uspenskiy in [1-2]. In his work, he has created a set of 216 features that were further extracted from the electrocardiograms and used for disease classification. The proposed solution was tested on the set of 30 diseases and has shown high performance. However, this method still has weaknesses. First, is does not answer the question whether the proposed features will perform well on new diseases. Another issue is that features were generated manually, and thus some information held in the source data can be lost.

3. Methodology Used

In this paper, we have used Recurrent Neural Networks to go ahead with the classification and diagnosis of the arrhythmic beats. The effectiveness of the heartbeat classification using RNN is carried out by the percentage of accuracy, specificity, and sensitivity. A detailed comparison with the work that has already been done in the field is also carried out and the important aspects are also taken into consideration. An important class of artificial neural networks came into existence when the need to work on sequential data came such as handwriting recognition and speech recognition. This class of artificial neural network is termed as Recurrent Neural Network as they can use their internal memory to process and classify the arbitrary sequences of inputs and these connections between the units form a directed cycle.

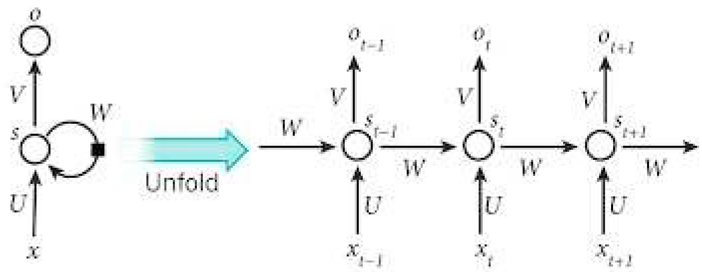

Fig. 3. Recurrent Neural Network

The field of deep learning is very exciting and so it has been used by various researchers to enhance and increase the performance and the accuracy measure. RNN and CNN are the two most exciting fields of Deep Learning and so they have also been applied to ECG Arrhythmia classification but CNN when applied to ECG, cuts the beats to pieces of fixed length that eventually reduces the performance of classification. RNN can turn to be better in aspect as the performance can be improved by providing handcrafted features to the classifier. Here, by using RNN we feed the present beat and the last beat i.e.T beat to learn the underlying important features of the beats accurately and automatically.

3.1. Recurrent Neural Network

Recurrent Neural Networks came into existence due to their highly dynamic behavior whereas multilayer feed-forward network has static mappings. RNNs have been used in multiple areas and have interesting applications in the field of associative memories, optimization and generalization. The time-series data is best classified using RNNs where the feedback and the present value is fed again into the network and as result, the output contains the traces of values present in the memory as well that increases the classification performance and provides better results than the conventional feed-forward networks. In this paper, three layers of RNN have been used with 128, 256 and 100 number of neurons in each layer respectively with 9 iterations. A dropout of rate 0.2 has been added after each layer. The activation used was linear with MSE as the loss function.

3.2. Gated Recurrent Unit

A Gated Recurrent Unit consists of two gates, a reset gate, and an update gate. The former gate determines how to combine the new input with the previous memory and the later one defines how much of that memory should be used to keep around.

In this paper, three layers of RNN-GRU have been used with 64, 128 and 100 number of neurons in each layer respectively with 5 iterations. A dropout of rate 0.2 has been added after each layer. The activation used was linear with MSE as the loss function.

3.3. Long Short Term Memory Network

Long Short-Term Memory (LSTM) is a specific type of recurrent neural network (RNN) architecture.LSTM was designed to model temporal sequences and the long-range dependencies and memory backup of RNN play a very important role and so they are turned to be more accurate and effective than conventional RNNs. The method is applied after pre-processing of the data where we remove the unwanted and missing and null signal values.

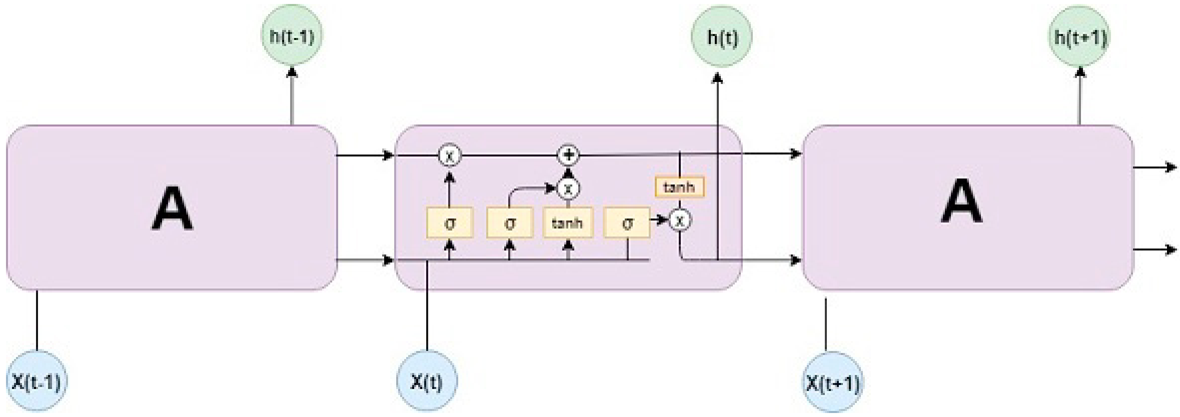

Fig. 4. Architecture of LSTM (A)

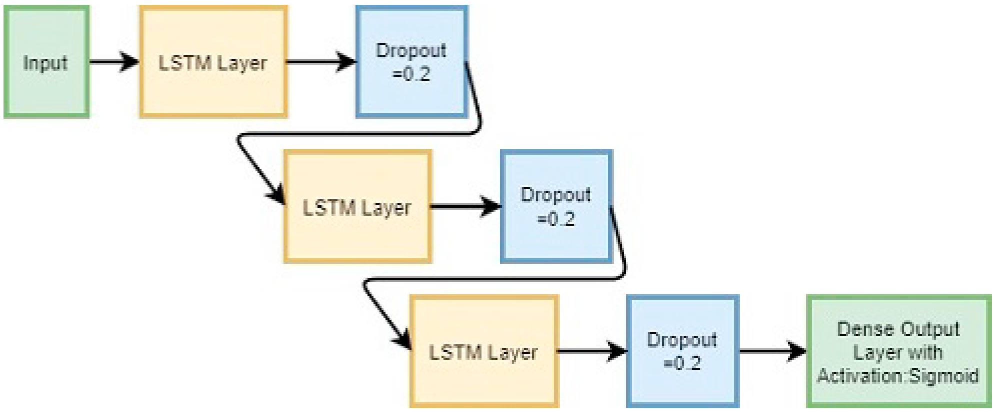

Fig. 5. Architecture of LSTM (B)

In this paper, three layers of RNN–LSTM have been used with 64, 256 and 100 number of neurons in each layer respectively with 5 iterations. A dropout of rate 0.2 has been added after each layer. The activation used was sigmoid with MSE as the loss function.

4. Simulation Results

4.1. Dataset Description

The MIT-BIH Arrhythmia Database is used for examining the beat classification performance. For training and testing purposes, one of the most popular, MIT-BIH Arrhythmia dataset was used. It contains 47 records of 30 minutes each and 40% of the records were those of cardiac patients. The records contained different types of signals based on different placement of leads: ML2, V1, V2, V4 and V5.[19]

Firstly, 70-30 splitting of data was done. ML2 signals were picked and for each record, the signal was segmented in 720-720 length chunks. Since the sampling rate was 360, 360 segments before the R-Peak value and 360 segments after the same ensured that almost 3 beats will be there in one chunk and the classification of the central beat was to be done against 15 possible arrhythmic labels.

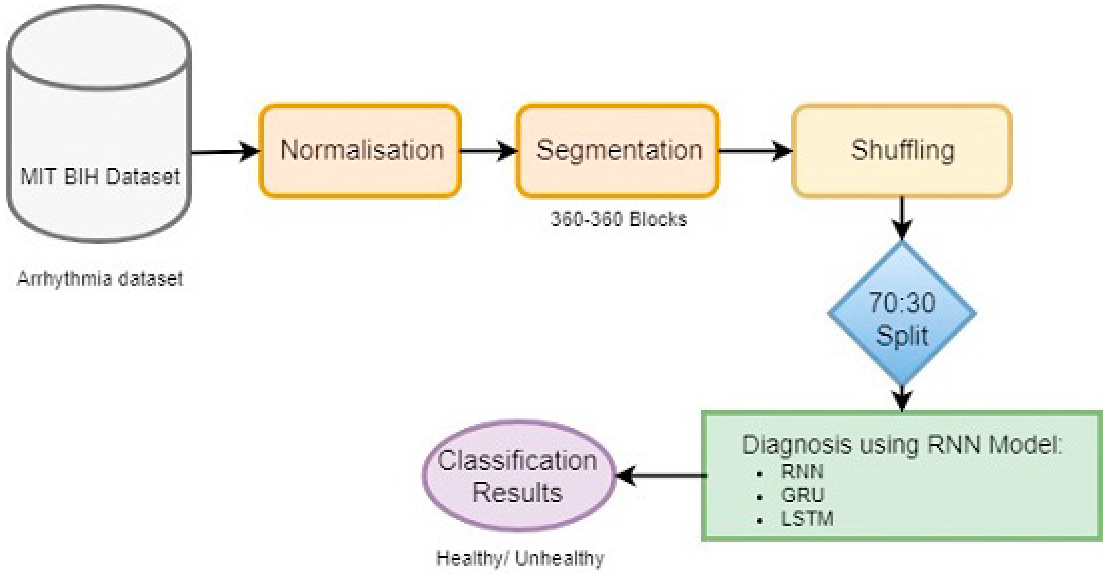

Fig. 6. The proposed ECG arrhythmia detection steps

Table 1. Confusion Matrix

	True(N)	False(A)
True(N)	15824	1294
False(A)	1831	9182

Table 2. ECG Arrhythmia Classification Results

	Algorithm	**Accuracy**	**Sensitivity**	**Specificity**
ECG Classification	RNN	85.4	80.6	85.7
ECG Classification	RNN GRU	82.5	78.9	81.5
LSTM ECG Classification	RNN LSTM	88.1	92.4	83.35

4.2. Performance Measurement using Confusion Matrix

The performance was evaluated on the basis of three main measurement performance on RNN models that are accuracy, specificity and sensitivity of the classification. These measurements are described by using confusion matrix . True Positive is exists when there is Arrhythmia and it was detected correctly and so for the algorithm to work correctly and for the accuracy the percentage of True positive should be high as compared to other values. Accuracy of the classification refers to the total number of beats that are correctly classified whether it was a Normal Beat or Arrhythmia. For binary classification, Accuracy = (True Positive +True Negative)/(True Positive + True Negative + False Positive + False Negative).
Sensitivity of the classification can be referred as :
Sensitivity = True Positive/(True Positive + False Negative)
Specificity of the classification can be referred as :
Specificity = True Negative/(False Positive + True Negative)

5. Conclusion and Future Work

The RNN LSTM showed accuracy of 88.1% when we take the number of iterations to be 5 and hidden layers to be 3 and there are 64, 256 and 100 neurons per hidden layer respectively which shows better

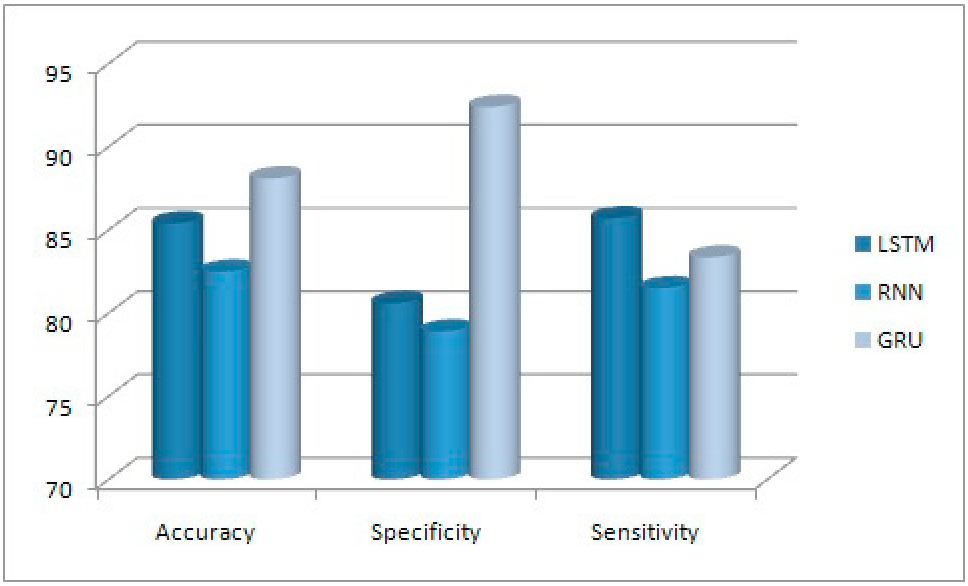

Fig. 7. Classification results

detection of arrhythmia than RNN and GRU as the accuracy of RNN is 85.4% and GRU is 82.5% which is less than LSTM accuracy. The model is implemented directly using the signals from the MIT BIH database and no pre-processing has been done. Therefore, the complexity of our implemented model is much lesser than traditional machine learning algorithms. In this paper, binary classification of arrhythmia has been done and the results can be improved by extending it to multi-class classification. Since not much significant work has been done in this field of binary classification (Arrhythmia detection) our proposed model accomplishes the same and provides the scope for further work in this area. The classification accuracy can be increased further by increasing the number of epochs. The paper shows that long short-term memory gives the best result in the binary classification of the ECG Arrhythmia and further work can be done on the classification by using Convolution Neural Networks on the dataset MIT BIH for the classification process. The number of epochs and the number of neurons in the hidden layer could be increased further for the classification process.

References

[1] V.M. Uspenskiy. Information function of the heart. a measurement model. MEASUREMENT 2011, 1:383-386, 2011.

[2] V.M. Uspenskiy. Diagnostic system based on the information analysis of electrocardiograph. In Embedded Computing (MECO), 2012 Mediterranean Conference on, pages 74-76, June 2012.

[3] Wagner Galen and Strauss David. Marriotts Practical Electrocardiography. LWW, 2013.

[4] K. Perloff Joseph and J. Marelli Ariane. Clinical Recognition of Congenital Heart Disease. Elsevier, 2012.

[5] Babak Mohammadzadeh Asl, Seyed Kamaledin Setarehdan, and Maryam Mohebbi. Support vector machine-based arrhythmia classification using reduced features of heart rate variability signal. Artificial Intelligence in Medicine, 44(1):51- 64, 2008.

[6] Mi Hye Song, Jeon Lee, Sung Pil Cho, Kyoung Joung Lee, and Sun Kook Yoo.Support vector machine based arrhythmia classification using reduced features. International Journal of Control, Automation, and Systems, 3:571-579, 2005.

[7] A.J. Joshi, S. Chandran, V.K. Jayaraman, and B.D. Kulkarni. Hybrid svm for multiclass arrhythmia classification. In Bioinformatics and Biomedicine, 2009. BIBM 09. IEEE International Conference on, pages 287-290, Nov 2009.

[8] V.Ahanathapillai and J.J. Soraghan. Myocardial ischemia detection algorithm(mida): Automated echocardiography sequence analysis for diagnosis of heart muscle damage. In Computing in Cardiology, 2010, pages 405-408, Sept 2010.

[9] T. Konttila, M. Stenroos, H. Vaananen, H. Hanninen, M. Lindholm, I. Tierala, and T. Katila. Support vector classification of acute myocardial ischemia with reduced sets of body surface potential map electrodes. In Computers in Cardiology, 2005,pages 869-872, Sept 2005.

[10] P Ranjith, P.C Baby, and P Joseph. ECG analysis using wavelet transform: application to myocardial ischemia detection. ITBM-RBM, 24(1):44 - 47, 2003.
[11] Ismail Babaoglu, Mustafa Servet Kiran, Erkan Ulker, and Mesut Gunduz. Diagnosis of coronary artery disease using artificial bee colony and k-nearest neighbor algorithms. International Journal of Computer and Communication Engineering, 2:56-59, 2013.
[12] R. Alizadehsani, M.J. Hosseini, Z.A. Sani, A. Ghandeharioun, and R. Boghrati. Diagnosis of coronary artery disease using cost-sensitive algorithms. In Data Mining Workshops (ICDMW), 2012 IEEE 12th International Conference on, pages 9-16, Dec 2012.
[13] A. Kampouraki, G. Manis, and C. Nikou. Heartbeat time series classification with support vector machines. Information Technology in Biomedicine, IEEE Transactions on, 13(4):512-518, July 2009.
[14] Adam Gacek and Witold Pedrycz. ECG Signal Processing, Classification and Interpretation. Springer-Verlag London, 2012.
[15] L. Yash, L. Pallavi, and A. Sameer. Ecg in non cardiac disorders.
[16] Mieghem Carlos, Sabbe Marc, and Knockaert Daniel. The clinical value of the ecg in noncardiac conditions. Chest, 125:1561-1576, 2004.
[17] John S. Child, Joseph K. Perloff, Philip M. Bach, Allan D. Wolfe, Susan Perlman, and R.A. Pieter Kark. Cardiac involvement in friedreichâĂŹs ataxia: A clinical study of 75 patients. Journal of the American College of Cardiology, 7(6):1370-1378, 1986.
[18] Mikael Henaff, Kevin Jarrett, Koray Kavukcuoglu, and Yann Lecun. Unsupervised learning of sparse features for scalable audio classification.
[19] Honglak Lee, Roger Grosse, Rajesh Ranganath, and Andrew Y. Ng. Convolutional deep belief networks for scalable unsupervised learning of hierarchical representations.
[20] Hoo-Chang Shin, M.R. Orton, D.J. Collins, S.J. Doran, and M.O. Leach. Stacked autoencoders for unsupervised feature learning and multiple organ detection in a pilot study using 4d patient data. Pattern Analysis and Machine Intelligence, IEEE Transactions on, 35(8):1930-1943, Aug 2013.
[21] S. Osowski, L. T. Hoai, and T. Markiewicz, Support vector machine-based expert system for reliable heartbeat recognition, IEEE Trans.BiomedEng., 51(4), 2004, 582-589.
[22] P. de Chazal, M. O'Dwyer, and R. B. Reilly, Automatic classification of heartbeats using ECG morphology and heartbeat interval features, IEEE Trans.BiomedEng., 51(7), 2004, 1196-1206.
[23] E. J. da S.Luz, T. M. Nunes, V. H. C. de Albuquerque, J. P. Papa, and D. Menotti, ECG arrhythmia classification based on optimum-path forest, Expert Systems with Applications, 40(9),2013,3561-3573.
[24] O. T. Inan, L. Giovangrandi, and G. T. A. Kovacs, Robust neural-network-based classification of premature ventricular contractions using wavelet transform and timing interval features, IEEE Trans.BiomedEng., 53(12), 2006, 2507-2515.
[25] i. GUIer and E. D. Obeyli, ECG beat classifier designed by combined neural network model, Pattern Recognition, 38(2),2005, 199-208.
[26] Predicting the severity of Breast Cancer masses with ensemble of Bayesian Classifiers Journal of Computer Science 2010.
[27] R. D. Raut and S. V. Dudul, Arrhythmias classification with MLP neural network and statistical analysis, Proc. - 1st Int. Conf. Emerg. Trends Eng. Technol. ICETET 2008, pp. 553-558, 2008.
[28] B. M. Asl, S. K. Setarehdan, and M. Mohebbi, Support vector machine-based arrhythmia classification using reduced features of heart rate variability signal, Artif. Intell. Med., vol. 44, no. 1, pp. 5164, 2008.
[29] G. Selvakumar, K. B. Bagan, and B. Chidambararajan, Wavelet Decomposition for Detection and Classification of Critical ECG Arrhythmias, pp. 8084, 2007.
[30] L. Khadra, A. Fraiwan, and W. Shahab, Neural-wavelet analysis of cardiac arrhythmias.
[31] 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, 2014.
[32] S. Yu and Y. Chen, Electrocardiogram beat classification based on wavelet transformation and probabilistic neural network, vol. 28, pp. 1142-1150, 2007.
[33] M. Engin, ECG beat classification using neuro-fuzzy network, vol. 25, pp. 1715-1722, 2004.
[34] R. Silipo, G. Bortolant, and C. Marchesi, Supervised and unsupervised learning for ciiagnostic E, Evaluation, pp. 931-934, 1996.
[35] T. K. Toshifumi Sugiural, Hisashi Hiratal, Yukio Harada2, AUTOMATIC DISCRIMINATION OF ARRHYTHMIA, vol. 20, no. I, pp. 108-111, 1998.
[36] N. Kohli, N. K. Verma, and A. Roy, SVM based Methods for Arrhythmia Classification in ECG, pp. 486-490, 2010.
[37] S. M. Jadhav, S. L. Nalbalwar, and A. A. Ghatol, Artificial Neural Network Based Cardiac Arrhythmia Disease Diagnosis, 2011 Int. Conf. Process Autom. Control Comput., pp. 16, 2011.