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Machine Learning in Electrocardiogram Diagnosis

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***Abstract* — The electrocardiogram (ECG) is a measure of the electrical activity of the heart. Since its introduction in 1887 by Waller, it has been used as a clinical tool for evaluating heart function. A number of cardiovascular diseases (CVDs) (arrhythmia, atrial fibrillation, atrioventricular (AV) dysfunctions, and coronary arterial disease, etc.) can be detected non-invasively using ECG monitoring devices. With the advent of modern signal processing and machine learning techniques, the diagnostic power of the ECG has expanded exponentially. The principal reason for this is the expanded set of features that are typically extracted from the ECG time series. The enhanced feature space provides a wide range of attributes that can be employed in a variety of machine learning techniques, with the goal of providing tools to assist in CVD classification. This paper summarizes some of the principle machine learning approaches to ECG classification, evaluating them in terms of the features they employ, the type(s) of CVD(s) to which they are applied, and their classification accuracy.**

Indexd Terms—**Heart disease, Electrocardiogram, Classification, Machine learning.**

I. Introduction

CARDIOVASCULAR disease (CVD) is a label for a broad spectrum of disorders affecting both the vasculature (i.e. hypertension) and the heart muscle itself (i.e. myocardial infarction). Cardiovascular disease remains the number one cause of mortality in the western world, responsible for more than 16 million deaths annually worldwide [1]. In the United states alone, the prevalence of CVD was estimated to be approximately 80,000,000, attributed primarily to high blood pressure and coronary heart disease [2]. Approximately 30% of all patients with CVD ultimately die from the disease. Changes in life-style, such as reducing cholesterol intake and exercising regularly can reduce the chances of a fatal event associated with CVD. Therefore, early detection is a critical step in the prevention of death associated with CVD. Regular doctor visits, which includes an ECG, is a vital step towards early detection, results in large volumes of patient data that must be carefully scrutinised.

Computer based medical diagnostic systems are have been developed in order to assist medical professionals in the analysis of large volumes of patient data. The efficacy of these systems depends on the features that are used – which must of course be correlated with some disease state. With respect to ECG, a variety of signal processing techniques (FFT, wavelets, and related techniques) have been used successfully to extract a feature set that is subsequently used by a variety of machine learning classification tools. The efficacy of these systems is ultimately based on their ability to correctly classify a set of features. Typically, the classification efficiency is quantified by recording one or more of the following metrics: positive|negative predictive value (p|n pv), the overall classification accuracy, confidence interval (CI), or the area under the receiver operator characteristic (ROC) curve. These metrics allow different algorithms to be compared quantitatively.

In what follows is a discussion of various machine learning approaches that have been published with respect to their application to ECG signal analysis in patients with a variety of CVDs. The purpose of the review is to assess the evidence of healthcare benefits involving the application of machine learning to the clinical functions of diagnosis and analysis in ECG signals.

II. ECG Classification Aspects

An ECG is essentially a time series signal that reflects the electrical activity of the heart. The signal consists of a series of repetitive and stereotyped complex waveforms with an obvious frequency of approximately approximately 1 Hz. The heartbeat can vary across individuals and within individuals depending on a variety of conditions (i.e. emotional state, physical exertion, state of health, etc.). The first stage in developing an automated ECG classifier is to extract characteristic features from the waveform. Some features are considered first order – in that they can be derived directly from the data – such as the R-R time – the time between the largest peak that occurs in each heartbeat. Other features are derived from the base signal – these are extracted using signal processing techniques such as Fourier Transforms (FTs) and wavelets as examples. In a typical supervised classification scheme, the features are labelled with the decision outcome. Then the particular classifier is applied to the data –

via training and testing scenario. The performance is measured, and if successful (above some threshold), a classifier is born! As a meta-processing stage – the attributes are examined to determine their overall contribution to the classification accuracy – a manual credit assignment task. Those features/attributes that are found to be redundant are culled from the input space, distilling the feature space to a minimal set.

What follows is a description of a selection of machine learning techniques that have been applied successfully to a variety of ECG based datasets. A brief description of the technique, along with information regarding the features and the overall performance metrics are presented in tabular form – with citations to the original work. Lastly, a conclusion section summarises the principal results and highlights future areas of related research.

III. Support Vector Machine in ECG Classification

Support vector machine technique was firstly proposed for classification and regression tasks by Vapnik [3]. SVM is a reliable classification technique, which is based on the statistical learning theory. The SVM originated from the idea of the structural risk minimization Support vector machines are primarily two class classifiers that have been shown to be attractive and more systematic to learning linear or non-linear class boundaries. The main idea of SVM is to construct a hyper-plane as a decision surface in such a way that the margin of separation between positive and negative examples is maximized (See Table 1).

Table I.
SVM methods for ECG classifications

Author(s)	**Feature extraction/reduction method**	**Accuracy (%)**
K. Polat et al. [4]	symptoms that are obtained from patients*	100
K. Polat et al. [5]	symptoms that are obtained from patients / PCA*	98
N. Acır et al. [6]	DWT and DCT	94.3 with DWT 96.4 with DCT
N. Ac ır et al. [7]	DCT*	95.2
S. S. Mehta et al. [8, 9]	slope at every sampling instant (T-waves and P-wave)	99.3
E. Derya et al. [10]	DWT	95.56
E. Derya et al. [11]	DWT	99.44
B. M. Zadeh et al. [12]	GDA	99.3
M. H. Song et al. [13]	DWT-LDA	99.5
L. Chengwei et al. [14]	8-lead ECG input	88.0

*Least Sqaure Support Vector Machine LS-SVM.

IV. Fuzzy Set Theory in ECG Classification

Fuzzy sets were introduced in 1965 by Zadeh [15] as a new way to represent vagueness in everyday life. They attempt to model human reasoning/thinking process. Fuzzy sets are generalization of crisp sets and have greater flexibility to capture faithfully various aspects of incompleteness or imperfection in information. For an ordinary set, an element either belongs to it or not; while for fuzzy sets, an element can partially belong to the multiple sets, with the proviso that the total membership values total one. Since fuzzy sets characterize imprecise properties, they can be effectively used to model vagueness associated with real-life systems. Fuzzy logic is based on the theory of fuzzy sets and approximate reasoning. It is much closer in spirit to human reasoning and natural language than the traditional logical system. Thus, fuzzy logic provides an effective means to model faithfully the approximate and inexact nature of the real world, such as is typically found in biological datasets. See Table 2.

Table II.
Fuzzy methods for ECG classifications

Author(s)	Feature extraction/reduction method	Accuracy (%)
W. K. LEI et al. [16]	DWT	98.1
U. R. Acharyaa et al. [17, 18]	certain parameters that extracted from the ECG signals	95-100

V. Artificail Neural Network in ECG Classification

ANN has been applied extensively to a wide range of classification problems within the healthcare domain. There are a variety of neural network approaches proposed in the literature that vary in terms of topology and operational mode. Each model can be specified by the following seven major concepts; (1) A set of processing units, (2) An activation function of each neuron, (3) Pattern of connectivity among neurons, that is, network topology, (4) Propagation method of activities of neurons through the network, (5) Rules to update the activities of each node, (6) External environment that feeds information to the network, (7) Learning method to modify the pattern of connectivity.

During learning, a neural network gradually modifies its weights and settles down to a set of weights capable of realizing the input-output mapping with either no error or a minimum error set by the user. The most common type of supervised learning is back-propagation (BB) learning (Multilayer-perceptron Feed-forward back-propagation MLPNN). Some other supervised learning includes: radial basis function (RBFNN), probabilistic neural network (PNN), generalized regression neural network (GRNN), cascade-correlation, and so forth. Some examples of unsupervised learning, for instance, self-organizing map (SOM-NN), adaptive resonance theory (ART), and so forth, are used when training sets with known outputs are not available. In the following, we describe the results of applying a variety of neural network algorithms. See Table 3.

VI. ECG Classification Rough Set Theory and Hidden Markov Model

Rough set theory is a relatively new data-mining technique used in the discovery of patterns within data first formally introduced by Pawlak in 1982 [32]. Since its inception, the rough sets approach has been successfully applied to deal with vague or imprecise concepts, extract knowledge from data, and to reason about knowledge derived from the data. The basic philosophy of rough sets is to reduce the elements (attributes) in a DT based on the information content of each attribute or collection of attributes (objects) such that the there is a mapping between similar objects and a corresponding decision class. In general, not all of the information contained in a DT is required: many of the attributes may be redundant in the sense that they do not directly influence which decision class a particular object belongs to. One of the primary goals of rough sets is to eliminate attributes that are redundant. Rough sets use the notion of the lower and upper approximation of sets in order to generate decision boundaries that are employed to classify objects. Consider a decision table $A = (U, A \cup \{d\})$ and let and $X \subseteq U$. What we wish to do is to approximate X by the information contained in B by constructing the B-lower (B_L) and B-upper (B^U) approximation of X. The objects in B_L ($B_L X$) can be classified with certainty as members of X, while objects in B^U are not guaranteed to be members of X. The difference between the 2 approximations: $B^U - B_L$, determines whether the set is rough or not: if it is empty, the set is crisp otherwise it is a *rough set*. What we wish to do then is to partition the objects in the DT such that objects that are similar to one another (by virtue of their attribute values) are treated as a single entity. The rough set theory has been proved to be very useful in practice as clear from the record of many life applications; e.g. in medicine, pharmacology, engineering, banking, financial and market analysis. This theory provides a powerful foundation to reveal and discover important structures in data and to classify complex objects. One of the main advantages of rough set theory is it does not need any preliminary or additional information about data. For more details on the theory, software and applications of rough sets we refer the reader to the monograph by Pawlak [32] and several conference proceedings and collections of papers [33]-[35]. See Table 4.

Hidden Markov model is a statistical model in which the system being modelled is assumed to be a Markov process with unknown parameters, and the challenge is to determine the hidden parameters from the observable parameters.

In a regular Markov model, the state is directly visible to the observer, and therefore the state transition probabilities are the only parameters. In a hidden Markov model, the state is not directly visible, but variables influenced by the state are visible. Each state has a probability distribution over the possible output tokens. Therefore the sequence of tokens generated by an HMM gives some information about the sequence of states. The extracted model parameters can then be used to perform further analysis. Hidden Markov models are especially known for their application in temporal pattern recognition such as speech, handwriting, gesture recognition, part-of-speech tagging, musical score following, partial discharges and bioinformatics. See Table 4.

Table III.
ANN methods for ECG classifications

Author(s)	Feature extraction/reduction method	Classification model	Accuracy (%)
E. Derya et al. [19]	Eigenvector methods	RNN* MLPNN	98.06 for RNN 90.83 for MLPNN
I. Güler et al. [20]	DWT	ANN	96.94
S-N. Yu et al [21]	DWT	PNN	99.65
M. BEN MESSAOUD et al. [22]	The rate of heartbeat	RBFNN MLPNN	96 for MLP 85.2 for RBF
S. Meghriche, et al. [23]	Amplitudes, durations, and intervals of QRS, R, PP, RR, PR, and P waves.	CNN**	87.9
N. Belgacem et al. [24]	QRS complexes	MLPNN LVQ***	91.55 for MLP 89 for LVQ
G. K. Prasad et al. [25]	DWT	ANN	96.77
K. Lewenstein et al. [26]	Slope of an ST segment	RBFNN	97
N. Ouyang et al. [27]	Voltages of Q-, R-, S-, T-waveforms	FFANN	90.2 with anterior wall myocardial infarction (AI) 93.3 Without infarction.
Mozhiwen et al. [28]	Wavelet Transform	RBFNN	100 for trained samples 86.6 untrained samples
A. Rakotomamonjy [29]	DWT	ANN	79
B. Anuradha et al. [30]	Spectral entropy,	ANN	90
E. A. Fernandez et al. [31]	Attributes of the ECG	SOM-NN	90
U. R. Acharyaa et al. [17, 18]	Parameters that extracted from the ECG	ANN	85-100

*RNN: Recurrent Neural Network; **CNN: Compound Neural Network; ***LVQ: Learning Vector Quantization

TABLE IV.
RST AND HMM METHODS FOR ECG CLASSIFICATIONS

Author(s)	Feature extraction/reduction method	Accuracy (%)
Matthew C. Wiggins et al. [34]	Important coefficients: age, body surface area, and smoking history (RST).	87
S. Mitra et al. [35]	Time Plane Features Extraction (RST)	100 for trained samples 93 for untrained Samples
L. Clavier et al. [36]	Wavelet analysis method (HMM)	65% specificity 70%. sensitivity

VII. HYBRID APPROACHES IN ECG CLASSIFICATION

Hybrid approaches in the current context employ multiple classifiers which are fused at some level to perform a classification task. Hybrid Systems are computational systems which are based mainly on the integration of different soft-Computing techniques (like Fuzzy Logic, Neurocomputing, Evolutionary Computing, Probabilistic Computing) but which also allow a “traditional” symbolic interpretation or interaction with symbolic components (Knowledge Based Systems / Expert Systems) to classify the ECG signals. There are many different possible combinations among the Symbolic systems and Soft-Computing techniques, and also different ways to integrate them. As for example, Neural Networks can be combined with Fuzzy Logic, Case-Based Reasoning (CBR) or Genetic Algorithms (GA) in order to obtain a unified model or even a co-processing scheme. Hybrid Intelligent Systems is based on the idea that most A.I. techniques are complementary. Hybrid Systems take advantage of their respective component strengths in order to increase the overall system performance and to eliminate the drawbacks of its components. See Table 5.

Case-based Reasoning means to use previous experience in form of cases to understand and solve new problems [6]. A case-based reasoner remembers former cases similar to the current problem and attempts to modify their solutions to fit for the current case. CBR consists of two main tasks [6]: The first is the retrieval, which is the search for or the calculation of most similar cases. The second task, the adaptation (reuse and revision) means a modification of solutions of former similar cases to fit for a current one. If there are no important differences between a current and a similar case, a simple solution transfer is sufficient. Sometimes only few substitutions are required, but sometimes the adaptation is a very complicated process. So far, no general adaptation methods or algorithms have been developed; the adaptation is still absolutely domain dependent.

One of the simplest classification techniques is the k-Nearest Neighbor (k-NN) classifier. Classification of an input feature vector X is done by determining the k closest training vectors according to a suitable distance metric. The vector X is then assigned to that class to which the majority of those k nearest neighbours belong to [5]. The k-NN algorithm is based on a distance function and a voting function in k nearest neighbors, the metric employed is the Euclidean distance. The k-nearest neighbor classifier is a conventional nonparametric supervised classifier that is said to yield good performance for optimal values of k [5]. Like most guided learning algorithms, k-NN algorithm consists of a training phase and a testing phase. In the training phase, data points are given in an n-dimensional space. These training data points have labels associated with them that designate their class. In the testing phase, unlabeled data are given and the algorithm generates the list of the k nearest (already classified) data points to the unlabeled point. The algorithm then returns the class of the majority of that list.

VIII. CONCLUSSION

This paper has presented a survey of the results of applying a variety machine learning techniques for the classifica-

TABLE V.
HYBRID METHODS FOR ECG CLASSIFICATIONS

Author(s)	Feature extraction/reduction method	Classification model	Accuracy (%)
Y. zbay et al. [37]	Segments of arrhythmia.	MLP-BB+FCNN*	98.9 for ANN 99.9for FCNN
A. Sengur et al.[38]	Wavelet transforms and short time Fourier transform	AIS based fuzzy k-NN**	95.9 sensitivity# 96specificity# #
Z. Dokur et al. [39]	Fourier and wavelet analyses	ANN+GAs	96
K. Lewenstein et al. [40]	Segment of QRS complex, P and T wave	ANN + Expert System	92.5 sensitivity 96.7specificity
C-W. CHU et al. [41]	Moving average and differential equation approach	ANN and CBR	very high clustering performance
R. Ceylan et al. [42]	Segments of arrhythmia	T2FCM+ANN***	99
R. U. Acharya et al. [17, 18]	Spectral entropy	ANN + Fuzzy	80-85

*FCNN: fuzzy clustering neural network; **AIS: Artificial Immune System; ***T2FCM: Type Two Fuzzy C-mean. # Sensitivity: (true positive fraction) is the probability that a diagnostic test is positive, given that the person has the disease [4]. # # Specificity: (true negative fraction) is the probability that a diagnostic test is negative, given that the person does not have the disease [4].

tion of ECG datasets. The data indicate that a variety of features have been utilised, yielding a range of classification accuracies which are within the range of 70-100% for the most part, depending on the exact metric used. Unfortunately, no systematic study has been performed which has examined the accuracy of a variety of classifiers on a single dataset – which would allow one to directly compare each method. One can state that machine learning algorithms are highly accurate – but are they useful within a clinical setting? This depends on the role of the classifier: if the results are to be sued to determine a course of treatment, then specificity and sensitivity issues must be taken into account. If these classifiers are to become part of the medical arsenal, then researchers must generate the required results that are considered important within the domain (medicine). Only then can these exciting results engender a multi-disciplined approach to medical research.

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