

A Novel Approach for the Identification of Chronic Alcohol Users from ECG Signals

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Abstract—Several medical studies reveal that alcohol consumption has pronounced effects on the heart rate variability (HRV) of the consumer. In this paper, machine learning algorithms use the features extracted through HRV analysis performed on ECG samples of chronic alcohol users and normative subjects, in order to classify them. To carry out the classification, a Support Vector Machine (SVM) and an Extreme Learning Machine (ELM) have been trained, and their performance has been compared. While time domain, frequency domain and non-linear features are generally extracted from ECG signals for HRV analysis, in this study a new set of features obtained from Autoregressive Modelling using Exogenous (ARX) Inputs have also been used to improve the accuracy of the algorithms. An accuracy of 80.36% and 89.29% was achieved by SVM and ELM respectively without the use of ARX coefficients, while an accuracy of 87.50% and 94.64% was achieved when ARX coefficients were included in the feature set. The use of ARX coefficients and the ELM classifier is the novelty of this paper, which helped in increasing the accuracy of the classification system.

Keywords— *Electrocardiogram, Heart Rate Variability, Support Vector Machine, Extreme Learning Machine, Autoregressive Modelling with Exogenous Input*

I. INTRODUCTION

The effects of consumption of alcohol by individuals in large amounts in a short period of time, or gradually for a prolonged period have been studied and documented extensively [1-3]. The Parasympathetic Nervous System (PNS) and Sympathetic Nervous System (SNS) are inputs to the Sino-Atrial (SA) Node of the heart, which initiates heartbeats and in turn controls the inter-beat-interval. The PNS lowers the heart rate, while the SNS increases it [4].

Alcohol consumption acts as a depressant on the brain and nervous tissue, which results in increased SNS activity and decreased PNS activity [5]. This causes an increase in the heart rate and decrease in the Heart Rate Variability (HRV), which is the variation or change in the inter-beat interval of the heart. Studies [6, 7] have detailed the correlation between the amount of alcohol consumed and the extent of change in the HRV, while accounting for factors like the subject's gender, weight, BMI, etc. From the results of these studies, it is possible to draw

conclusions that chronic alcohol users and normative subjects can be differentiated based purely on HRV.

Research conducted for the detection of drunk driving [8] utilized HRV analysis to extract time domain features for the classification problem using a support vector machine. Certain other studies [9-11] also used HRV analysis to extract another type of feature (non-linear features) for their classification algorithms. A third form of feature extraction on ECG signals is seen in [12], where spectrum analysis on ECG signals is performed to obtain frequency domain features for the classification of arrhythmia.

Auto Regressive (AR) modelling and AR model coefficients have been used as features for machine learning algorithms for quite a few applications. In [13] identification of individuals using ECG signals was performed by using SVM and K nearest neighbor (KNN) algorithms. One of the features used by the classifiers in that study were the coefficients of the AR model, which had been built to relate the QRS complexes of two successive heartbeats. Another study [14] applied AR modelling on half-second segments of six channel Electroencephalogram (EEG) data to obtain features for a Neural Network which classified the data into one of five cognitive tasks.

As done in the previous studies mentioned above, here also HRV analysis has been used to extract time domain, non-linear and frequency domain features. However, in this study, the features have been used to train the extreme learning machine (ELM) and compare its results with that of the support vector machine (SVM). Along with the above set of features, the use of a new set of features has been proposed in this study to improve the accuracy of the classifiers. An Autoregressive Model with Exogenous Inputs (ARX) has been developed using the ECG signals of alcoholic and normative subjects, and the model coefficients obtained have been used as additional features to the classifiers.

This study ensures that the test subjects were free from heart conditions such as cardiomyopathy, atrial fibrillation, premature ventricular contraction, etc. which can cause arrhythmia. Such a step is crucial to ensure that HRV measurements from the ECG dataset arise primarily due to the effect of alcohol on the subjects' heartbeat and not due to other pre-existing medical conditions.

II. METHODOLOGY

This section covers the steps followed to filter ECG signals, extract features, train the classifiers and validate their behavior (Fig. 1).

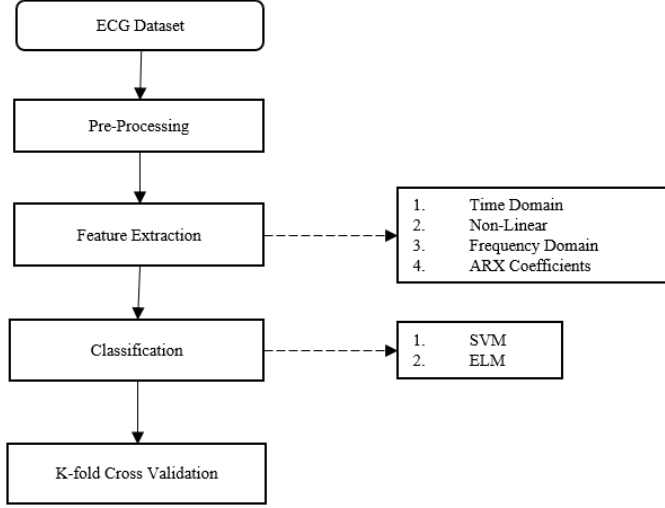


Fig. 1 Methodology

A. Dataset Description

To classify subjects as individuals with chronic alcohol dependence or normative, the classifier was trained with ECG data recorded at the Autonomic Lab, Department of Neurophysiology, NIMHANS, Bengaluru on ensuring informed consent adhering to the Declaration of Helsinki. The dataset consisted of 56 ECG samples, of which 28 samples were of chronically alcoholic subjects and the other 28 samples were that of normative individuals. The ECG signals were sampled at a frequency of 1kHz and each was recorded for approximately 5 minutes (300 seconds), to capture the activity of the autonomic nervous system (ANS) [15] which is primarily responsible in controlling the heartbeat.

Lead II ECG recording was done with Power Lab, 16 channel data acquisition system. Modified Chest Lead (MCL) three electrodes monitoring system (right 2nd inter-costal space mid clavicular line, left 2nd inter-costal space mid clavicular line (neutral) and left 5th inter-costal space mid clavicular line) was used and parameters were analyzed using Lab Chart 7 v1.1 software, given by AD Instruments, Bella Vista, Australia.

B. Pre-processing

The ECG dataset had disturbances like baseline wandering and power-line noise, which required removal to obtain clean ECG signals. Wavelet decomposition, a technique to break up a signal into shifted and scaled versions of itself [16], was utilized to remove such sections of the signal.

Here, discrete wavelet transform with Daubechies wavelet was used. The Daubechies wavelet worked well for the ECG dataset because the shape of the QRS complex in the ECG signal and the Daubechies wavelet resembled one another closely [17]. Eight level wavelet decomposition was performed, and removal of the eighth component from the original signal rid the ECG signal of baseline wandering. The power-line noise

had a much smaller amplitude than the total swing of the ECG signal, and was left unfiltered.

C. Feature Extraction

Features were extracted from the filtered signal using some of the techniques mentioned in [18, 20]. The four types of features that were extracted have been elaborated in this section.

1) *Time Domain*: Time domain features (Table I) utilize inter-beat intervals (RR interval series) to obtain a measure of the variability in the subject's heart rate. Measurements like the standard deviation of the RR interval series shows how quickly the heart is able to adapt to minor physiological changes in the body and hence, how much HRV is there in the subject. It was seen that HRV decreases in chronic alcoholics [19], and this change was captured by some of the time domain features. Other measurements like the root mean square of the RR interval sequence gave information about the subject's PNS [15] which, as mentioned in previous sections, causes changes in the subject's heart rate.

TABLE I. TIME DOMAIN FEATURES

Time Domain Features	
1	$RR_{mean} = \frac{1}{n} (\sum_{i=0}^n RR_i)$ The mean of the RR interval sequence in milliseconds.
2	$RR_{std} = \sqrt{\frac{1}{n-1} \sum_{i=0}^n (RR_i - RR_{mean})^2}$ The standard deviation of the RR interval sequence in milliseconds.
3	$HR_{mean} = \frac{60 \times 1000}{RR_{mean}}$ The mean heart rate in beats per minute.
4	$HR_{std} = \frac{60 \times 1000}{RR_{std}}$ The standard deviation of the heart rate in beats per minute.
5	$RR_{rms} = \sqrt{\frac{1}{n-1} \sum_{i=0}^{n-1} (RR_{i+1} - RR_i)^2}$ The RMS of the RR interval series in milliseconds.
6	RR_{50} Number of RR intervals that are larger than 50 milliseconds.
7	$RR_{r50} = \frac{RR_{50}}{n-1}$ Normalized number of RR intervals that are larger than 50 milliseconds.

2) *Non-Linear*: Non-linear feature (Table II) extraction methods include the Poincare plot and the calculation of the approximate entropy [18]. The Poincare plot is a graphical method to visualize and gauge the HRV of the subject, while the approximate entropy gives a measure of the inter-beat irregularity. Both these techniques help quantify the amount of HRV in an individual.

TABLE II. NON-LINEAR FEATURES

Non-Linear Features	
1	SD_1 – standard deviation of Poincare plot along $x = y$ line.
2	SD_2 – standard deviation of Poincare plot along $x = -y$ line.
3	$ApEn$ – Approximate entropy of RR interval sequence.

3) *Frequency Domain*: Frequency domain features (Table III) take the power spectral density of the RR interval sequence and utilize power contained in different frequency bands as features for the classifiers [18]. These features reflect the activity of the SNS and the PNS [15] which are two portions of the ANS that controls the heartbeat [4].

TABLE III. FREQUENCY DOMAIN FEATURES

Frequency Domain Features	
1	$pk_{freq_{vlf}}, pk_{freq_{lf}}, pk_{freq_{hf}}$
2	Frequency at which the peak of PSD occurs for the very low frequency (VLF), low frequency (LF) and high frequency (HF) bands.
3	
4	
5	$abs_{pow_{vlf}}, abs_{pow_{lf}}, abs_{pow_{hf}}$
6	
7	
8	pw_{ttl} Total power contained in the signal.
9	
10	
11	$rp_{vlf} = \frac{abs_{pow_{vlf}}}{pw_{ttl}}$ Ratio of the power in a particular band (VLF, LF or HF) to the total power in the signal.
12	
13	
14	$norm_{lf} = \frac{abs_{pow_{lf}}}{pw_{ttl} - abs_{pow_{vlf}}}$ Ratio of power in a particular band (LF or HF) to the power of the signal without considering contribution of power due to VLF band.
15	
16	
17	$abs_{ratio} = \frac{abs_{pow_{lf}}}{abs_{pow_{hf}}}$ Ratio of the absolute power in the LF band to the absolute power of the HF band.
18	
19	

4) *Coefficients of Autoregressive Model with Exogenous Input*: The autoregressive (AR) model establishes a connection between a particular output variable and its previous values [20]. In this study, an expanded version of the AR model called the ARX input model has been used. The ARX model tries to build a relationship between the input sequence and an expected output sequence provided to it as given by (1).

$$A(q)y(t) = \sum_{t=1}^{n_u} B_t(q)u_t(t - nk_t) + e(t) \quad (1)$$

Where $u(t)$ is the input sequence, $y(t)$ is the output sequence, $e(t)$ represents noise, q is the time shift operator and $A(q)$ and $B(q)$ are polynomials in q [20].

After the baseline wandering was removed from the ECG signal, it was divided into two halves. One half of the signal was provided as the input to the ARX system and the other half served as the expected output. These two halves were loaded into the System Identification Toolbox in MATLAB to develop an ARX model. The coefficients of the ARX model were used as additional features to train the classifier.

ARX models using different number of parameters provided different signal approximation accuracies and misfit percentages. For the ECG dataset used, it was seen that the ARX model's misfit percentage decreased with increase in the total number of parameters used by the model. The misfit observed for a total of five or greater parameters was less than 20%. Increasing the total number of parameters used in the ARX system to a value beyond five, showed insignificant change in misfit and that the seven parameter ARX model had the best fit (Fig. 2).

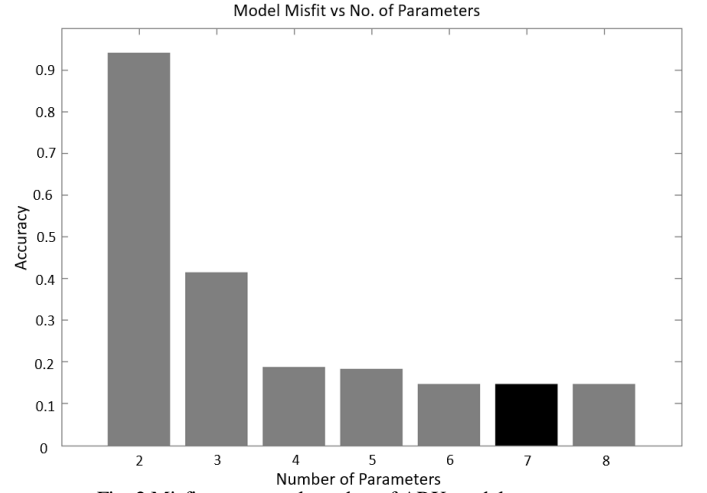


Fig. 2 Misfit versus total number of ARX model parameters

D. Classifiers

Two classifier algorithms, each having a different ideology have been trained on the dataset. One of the classifiers is the SVM, which uses the idea of hyperplanes and decision boundaries, while the other is based off neural network concepts and is the ELM.

1) *Support Vector Machine*: An SVM with regularization [21] has been implemented on the dataset of 28 alcoholic and 28 normative samples. An RBF kernel was used in order to better separate the data points in a higher dimension. The SVM makes use of the Simplified Sequential Minimal Optimization (SMO) algorithm [22] to solve the Lagrangian problem and obtain weights for the hyperplane. Finally, the SVM's performance was validated using k-fold ($k = 7$) cross validation (Sub-section E).

2) *Extreme Learning Machine*: The ELM [23, 24] was trained on the same dataset as the SVM and here also, an RBF kernel was applied to the dataset. The accuracy of the ELM varied based on the number of neurons used in the hidden layer.

A graphical plot of the accuracy of the algorithm versus the number of hidden neurons showed that the accuracy generally peaked when the number of hidden neurons used were between a small range of five and twenty (Fig. 3).

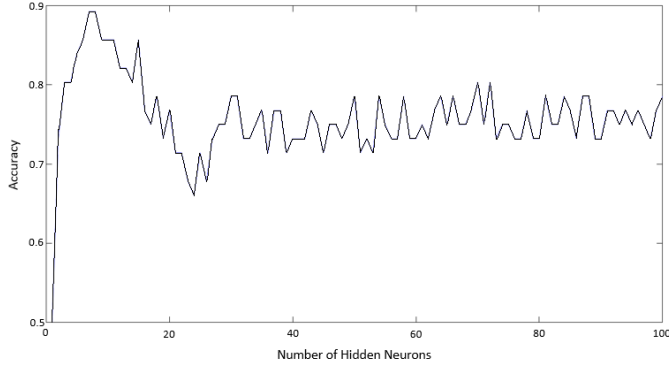


Fig. 3 Accuracy v/s hidden number of neurons

E. Validation

K-fold cross validation with $k = 7$ was used to validate the accuracy of the model that was trained. It was ensured that each fold had an equal number of chronic alcoholic and normative samples. Also, the sensitivity and specificity of the classifiers was calculated to ensure the system was able to identify chronic alcoholics with a high degree of accuracy.

III. RESULTS AND DISCUSSION

Results pertaining to the pre-processing of ECG signals using wavelet decomposition, the effect of using ARX model coefficients as features, and cross validation accuracies obtained for the SVM and ELM are provided in this section.

The output of applying wavelet decomposition in the pre-processing stage is seen in (Fig. 4). The first subplot shows the original ECG signal with baseline wandering, the second subplot shows the level-8 approximation of the baseline wandering, and the third subplot shows the filtered signal without baseline wandering.

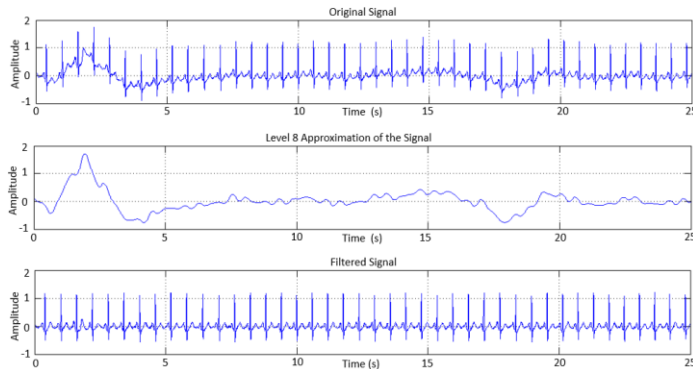


Fig. 4 Wavelet decomposition for baseline wandering removal

All feature extraction methods mentioned in previous sections were performed for the filtered signal shown in the third subplot of Fig. 4. An overview of the array of features (including those of the seven parameter ARX model) is as follows:

$$\text{Features} = \{ RR_{mean}, RR_{std}, HR_{mean}, HR_{std}, RR_{rms}, RR_{50}, RR_{r50}, SD_1, SD_2, ApEn, pk_{freq_{vlf}}, pk_{freq_{lf}}, pk_{freq_{hf}}, abs_{pow_{vlf}}, abs_{pow_{lf}}, abs_{pow_{hf}}, pw_{ttl}, rp_{vlf}, rp_{lf}, rp_{hf}, norm_{lf}, norm_{hf}, abs_{ratio}, ARX_{coeff1}, ARX_{coeff2}, ARX_{coeff3}, \dots, ARX_{coeff7} \}$$

What ARX seems to be capturing in its model is the long term changes occurring in the ECG signal. By splitting the signal into two sections and using one as the input and the other as the expected output, an ARX model is built to relate the first half of the signal to its second half. This we believe captures the gradual change that occurs through the span of the initial portion of the ECG signal and its latter portion. While time domain, frequency domain and non-linear features perform HRV analysis using short sections (RR intervals) of the ECG signal, the ARX model utilizes the entire first and second halves. In essence, such a model seems to be another form of capturing variations in the heart rate using longer sections of ECG signals.

As mentioned earlier, the seven parameter ARX model yielded the least mistfit (Fig. 2) and was therefore included in the feature set. Table IV shows that the SVM and ELM algorithms provided 7-fold accuracies of 80.36% and 89.29% respectively when only time domain, frequency domain and non-linear features were used to train them. However, the inclusion of the seven parameter ARX model coefficients in the feature set increased the 7-fold accuracy of the SVM to 87.50%. Similarly, features obtained from the seven parameter ARX model increased the ELM algorithm's accuracy to 94.64%.

TABLE IV. SEVEN FOLD ACCURACIES OF SVM AND ELM FOR DIFFERENT FEATURE SETS

Classifiers		without ARX Model	with 7 parameter ARX Model
SVM	Accuracy	80.36%	87.5%
	Sensitivity	82.14%	92.86%
	Specificity	78.57%	82.14%
ELM	Accuracy	89.29%	94.64%
	Sensitivity	83.93%	92.86%
	Specificity	94.64%	96.43%

IV. CONCLUSION

With the results that have been obtained, it is clear that HRV analysis is a very viable method to extract features from ECG signals for the application of classifying chronic alcoholic and normative subjects. A comparison made between the SVM and ELM classifiers shows that the ELM outperforms the SVM when trained with and without ARX features. The most significant observation was the effect that the ARX features had on the classifiers. The inclusion of ARX coefficients in the feature set worked well with both classifiers and yielded an improvement of around 7% and 5% in the SVM and ELM algorithms' accuracy, respectively.

In the current study, the input weights and number of hidden neurons for the ELM algorithm have been optimized by 'brute force' through multiple trial-error steps. The plan ahead would be to utilize a method that could reduce the computation required to obtain the best weights. It has been seen thus far that ARX coefficients clearly supplement the classifiers and increase their accuracy. However, the correlation between the ARX model and the physiological changes occurring in the subject's body on consuming alcohol needs to be established. An interesting way to broaden the scope of this study would be to convert this binary classification paradigm into one where the algorithm is able to classify subjects into multiple classes based on the level of alcohol intake. The proposed study also needs to be implemented on an extended dataset containing a larger number of samples.

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