A Novel Approach for the Identification of Chronic Alcoholics using ECG Signals

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***Abstract*—Several medical studies reveal alcohol consumption has pronounced effects on the heart rate variability (HRV) of the consumer. In this article, electrocardiogram (ECG) samples of chronically alcoholic subjects and normative subjects are collected for HRV analysis and feature extraction. The features extracted are then used by machine learning algorithms to classify subjects into chronically alcoholic or normative classes. For this classification problem, Support Vector Machines (SVM) and Extreme Learning Machines (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 being trained. An accuracy >80% was achieved by SVM and ELM without the use of ARX coefficients, while an accuracy >85% was achieved by both classifiers when ARX coefficients were included in the feature set.**

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) (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 alcoholic and normative subjects can be differentiated based purely on HRV. In this study, we define a chronic alcoholic to be an individual who consumes alcohol frequently and on a regular basis. {**How do you actually quantify large, regular and frequently?**} A teetotaler or very sparse drinker is considered a normative subject.

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. Another form of feature extraction on ECG signals is seen in [**11.5**], 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 [12] 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 [13] 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 previous studies, ~~in this study~~ here also HRV analysis has been used to extract time domain, non-linear and frequency domain features. However, in this study~~ here~~, 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 or pre-mature 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 that were followed to filter ECG signals, extract features, train the classifiers and validate their behavior (Fig. 1).

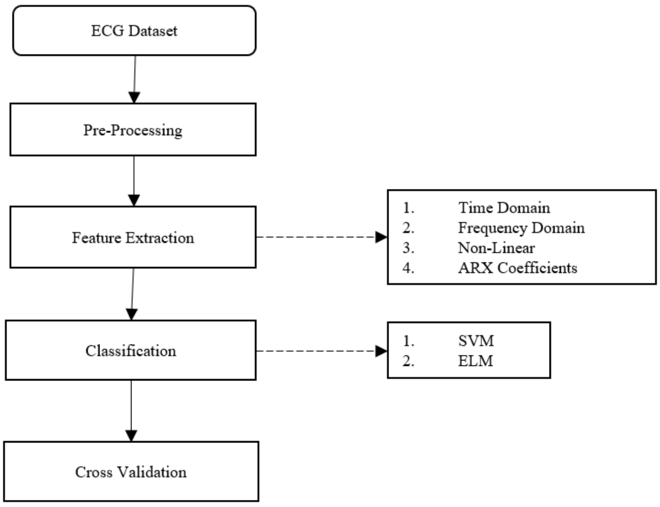

Fig. 1 Methodology

A. *Dataset Description*

To classify test subjects as chronic alcoholics 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 samples had a sampling frequency of 1kHz and each sample was recorded for approximately 5 minutes (300 seconds), to capture the activity of the autonomic nervous system (ANS) [14] which is primarily responsible in controlling the heartbeat. {**Patient age, Lead configuration, Instrument used for measurement**}

B. *Pre-processing*

The ECG dataset had disturbances like baseline wandering and power-line noise which needed to be removed to obtain clean ECG signals. Wavelet decomposition, a technique to break up a signal into shifted and scaled versions of itself [15], was used 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 [16]. Eight level wavelet decomposition was performed on the signal, and removal of the eighth components 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 [17, 19]. The four types of features that were extracted have been mentioned 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 heat is able to adapt to minor physiological changes in the body and thus, how much HRV is there in the subject. It was seen that HRV decreases in chronic alcoholics [18], 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 parasympathetic nervous system [14] which, as mentioned in previous sections, cause changes in the subject's heart rate. {**Repetitive?**}{**Tense mix up**}

TABLE I. TIME DOMAIN FEATURES

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

2) Non-Linear: Non-linear features (Table II) include the Poincare plot and approximate entropy [17]. The Poincare plot is a graphical method to visualize and measure the HRV of the subject, while the approximate entropy gives a measure of the inter-beat irregularity. Both these techniques help measure the amount of HRV in an individual.

TABLE II. NON-LINEAR FEATURES

Non-Linear Features	
1	$\boldsymbol{SD_1}$ – standard deviation of Poincare plot along x = y line.

2	$\boldsymbol{SD_2}$ – standard deviation of Poincare plot along x = – y line.
3	$\boldsymbol{ApEn}$ – 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 [17]. These features reflect the activity of the sympathetic nervous system (SNS) and the parasympathetic nervous system (PNS) [14] which are two portions of the autonomic nervous system that controls the heartbeat [4].

TABLE III. FREQUENCY DOMAIN FEATURES

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

4) Coefficients of Autoregressive Model with Exogenous Input: The autoregressive (AR) model establishes a connection between a particular output variable and its previous values [19]. In this study, an expanded version of the AR model called the Auto-regressive exogenous (ARX) input model has been used. The ARX model tries to build a relationship between the input sequence and expected output sequence provided to it [19] as given by (1).

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

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 hales were loaded into the System Identification Toolbox in MATLAB to develop an ARX model. The coefficients of the ARX model ~~developed~~ were used as additional features to train the classifier.

An overview of the array of features (including ~~the coefficients of the polynomial~~ those of the five parameter ARX model) are as follows:

RR_{mean}, RR_{std}, HR_{mean}, HR_{std}, RR_{rms}, RR_{50}, RR_{r50}, SD_1, SD_2, $pk_{freq_{vlf}}$, $pk_{freq_{lf}}$, $pk_{freq_{hf}}$, $ab_{pow_{vlf}}$, $ab_{pow_{lf}}$, $ab_{pow_{hf}}$, pw_{ttl}, rp_{vlf}, rp_{lf}, rp_{hf}, $norm_{lf}$, $norm_{hf}$, $ratio$, $ApEn$, ARX_{coeff1}, ARX_{coeff2}, ARX_{coeff3}, ARX_{coeff4}, ARX_{coeff5}

RR_{mean},	RR_{std},	HR_{mean},
HR_{std},	RR_{rms},	RR_{50},
RR_{r50},	SD_1,	SD_2,
$pk_{freq_{vlf}}$,	$pk_{freq_{lf}}$,	$pk_{freq_{hf}}$,
$ab_{pow_{vlf}}$,	$ab_{pow_{lf}}$,	$ab_{pow_{hf}}$,
pw_{ttl},	rp_{vlf},	rp_{lf},
rp_{hf},	$norm_{lf}$,	$norm_{hf}$,
$ratio$,	$ApEn$,	ARX_{coeff1},
ARX_{coeff2},	ARX_{coeff3},	ARX_{coeff4},
ARX_{coeff5}		

{**Single line array?**}

D. Classifiers

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

1) Support Vector Machine: An SVM with regularization [20] 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 SMO algorithm [21] 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 (Section 2.5).

2) Extreme Learning Machine: The ELM was also trained on the same dataset as the SVM, and again, an RBF kernel was applied to the dataset before feeding it to the ELM algorithm. In the ELM algorithm [22, 23], the input weights are set randomly and the values to which they are set can affect the accuracy of the classifier significantly. Variations up-to and sometimes beyond ten percent can be seen due to changes in the random assignment of the input weights. To increase the probability of obtaining the most accurate classifier for the given dataset, the ELM algorithm was trained several times (1000 times) for different randomly generated input weights and the input weights yielding the highest 7-fold cross validation accuracy were used.

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 peaked when the number of hidden neurons used was five to twenty. (Fig. 2).

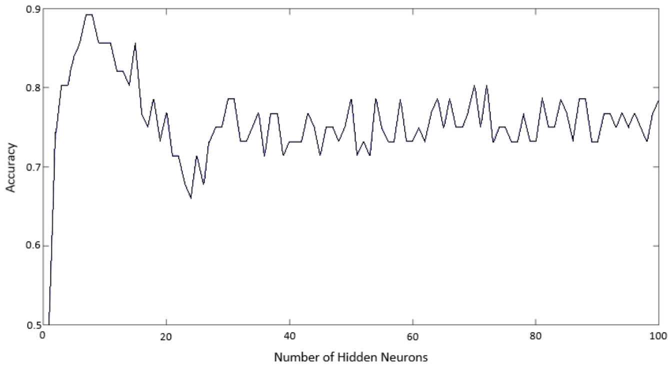

Fig. 2 Accuracy v/s hidden number of neurons

For the case where ARX coefficients were not included in the features set to train the ELM, six neurons were sufficient while fifteen neurons were required when ARX coefficients were also included.

E. Validation

K-fold cross validation was used to validate the accuracy of the model that was trained. For both classifiers, seven folds ($k = 7$) with eight samples in each fold was used, such that four samples from alcoholic and normative class would be a part of every fold.

The dataset was divided randomly into 7-folds. One fold was used as the validation set, while the remaining folds were used to train the system. The first fold was returned to the training set and a different fold (2^{nd} fold) was used to test the algorithm's accuracy. Such a process was carried out cyclically to yield 7 accuracies, the average of which resulted in the 7-fold cross validation accuracy.

The sensitivity and specificity of the classifiers was also calculated to ensure the system was not biased and the classification accuracy remained high for the alcoholic and normative classes.

III. RESULTS AND DISCUSSION

Results pertaining to the pre-processing of ECG signals using wavelet decomposition, selection of the ARX model with the most optimal number of parameters, and cross validation accuracies obtained for the SVM and ELM have been provided in this section.

The output of applying wavelet decomposition in the pre-processing stage can be seen in (Fig. 3). 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.

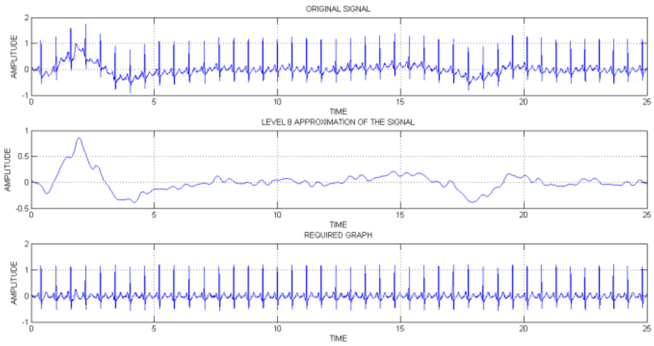

Fig. 3 Wavelet decomposition for baseline wandering removal

ARX models using different number of parameters in the $A(q)$ and $B(q)$ polynomials provide different signal approximation accuracies and misfit. 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 parameters ($A(q)$ being a second order polynomial and $B(q)$ being a third order polynomial) was consistently small ($< 20\%$) for all the samples. Increasing the total number of parameters used in the ARX system to a value beyond five, only showed a small insignificant decrease in misfit (Fig. 4).

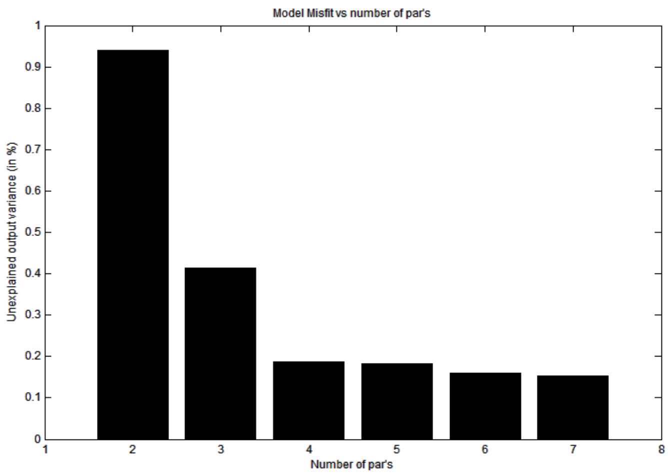

Fig. 4 Misfit versus total number of ARX model parameters

It was also observed that the use of the ARX model with the least misfit percentage also yielded the highest cross validation accuracy for the classifiers. Thus, to get good results from the classifier without adding too many new features to the feature set, coefficients of the ARX model with five parameters ($n_a = 2$ and $n_b = 3$) have been used as features. **ADD or APPEND to table to support this claim.**

What ARX seems to be capturing in its model is the long term variations in the ECG that occur over the two halves of the 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 link the first half of the signal to the second half of the signal. 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 of the ECG signal. In essence, such a model seems to be another form of capturing/measuring variations in the heart rate using larger/longer sections of ECG signal ~~at a time~~.

The SVM and ELM algorithms provided 7-fold accuracies of 80% or greater when only time domain, frequency domain and non-linear features were used to train them. However, the inclusion of ARX coefficients in the feature set increased the 7-fold accuracy of both algorithms by 5% or greater (Table IV). The ELM used six hidden neurons to provide the highest accuracy in the case where ARX coefficients were not included, while fifteen hidden neurons provided the highest accuracy when ARX features were included in the dataset. Thus, only a small number of additional neurons were necessary to obtain a significant increase in accuracy for the case with ARX features.

TABLE IV. COMPARATIVE RESULTS OF SVM AND ELM WITH AND WITHOUT (FIVE PARAMETER) ARX FEATURES

Feature Used	SVM	ELM
Without ARX Coefficients	80%	89%
With Five Parameter ARX Model's Coefficients	86%	94%

The sensitivity and specificity of both algorithms was well above 80% percent and this verified that neither algorithms was biased toward either of the two classes (Table V).

TABLE V. COMPARATIVE RESULTS OF SENSITIVITY AND SPECIFICITY OF SVM AND ELM

Parameter	SVM	ELM
Sensitivity	89%	92.86%
Specificity	82%	85.71%

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. Even the sensitivity and specificity of the ELM classifier is superior to that of the SVM. 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 5% or greater in their accuracy.

In the current study, the input weights and number of hidden neurons ~~and hidden neuron weights~~ for the ELM algorithm have been optimized by 'brute force' through multiple trial-error steps. The plan ahead, is to prevent this randomness and utilize a technique called Meta-Cognitive Learning on ELM to make it learn more intelligently and accurately the first time around itself. Another point that can be worked on which might further improve the accuracy of the classifiers, is the use of non-linear ARX (NL-ARX) model coefficients as features. It has been seen thus far that ARX coefficients clearly supplement the classifiers and increase their accuracy. However, in this study, only an intuitive guess/suggestion has been made about the correlation between the ARX model and the physiological changes occurring in the subject's body on consuming alcohol. Research to find the actual ~~significance~~ relation of ARX models ~~on~~ to physiological changes in the human body needs to be explored in detail. Finally, 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. {**compare with other works also? AGAIN?**}

ACKNOWLEDGMENT

This study would not be possible without the dataset obtained from The Automic Lab, NIMHANS, Bangalore. For this, we would like to thank the staff of NIMHANS for all their help, patience and cooperation. We would also like to thank the staff of PES University for their continued support and encouragement to pursue this work of applying machine learning algorithms to classify chronic alcoholic and normative subjects from their ECG signals.

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~~APPENDIX~~

Stuff to verify/ask:

1. **Verify all tense in paper is the same**
2. **Verify Table, Figure nos, reference numbers**
3. **Age of patients and leads of electrodes**
4. ~~**Keep it as chronic alc and normative OR chronic alc and non-alc OR alcoholic and normative, etc**~~
5. ~~****Results Discussion too brief?? But it seems to cover everything**~~
6. ~~**** Change RR_mean to NN_mean??**~~
7. ~~**ADD in futrure work: Finding phisiological signinficance of ARX meodelling**~~
8. **Ensure abreviations have been used with full form before hand**
9. **Use of “>” 80% okay in abstract?**
10. **Constant re-use of references (eg.) ref 19 used twice in same paragraph**

~~Three~~ One MAIN changes:

1. ~~**Is the ARX “order” correct? Na=3, nb=2**~~
2. **Reasoning of what ARX is doing … (i) shift it’s position to results or conclusion … better not only, (ii) mention there itself or in conclusion or both places that in-depth analysis is required to figure out what is actually happening**
3. ~~**Explanation for how best random input weights of ELM are selected**~~

Other notes:

Part of the introduction:

*1*We have used ARX
*2*We have applied to both SVM and ELM to show it generalizes over all classifiers
*3*Note that ELM outperforms

ARX model of five parameters OR five parameter ARX model

Tables must come at the end of each page

Make new copy and edit…formatting may get messed up