Automated method based on TQWT for the classification of alcoholism using EEG signals

M.Tech. Thesis

By

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DISCIPLINE OF ELECTRICAL ENGINEERING

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CANDIDATE'S DECLARATION

I hereby certify that the work which is being presented in the thesis entitled **Automated method based on TQWT for the classification of alcoholism using EEG signals** in the partial fulfilment of the requirements for the award of the degree of **MASTER OF TECHNOLOGY** and submitted in the **DISCIPLINE OF ELECTRICAL ENGINEERING Indian Institute of Technology Indore**, is an authentic record of my own work carried out during the time period from JUNE 2019 to JUNE 2020 under the supervision of Prof. Ram Bilas Pachori Professor at IIT Indore.

The matter presented in this thesis has not been submitted by me for the award of any other degree of this or any other institute.

Signature of the student with date
(BORRA JEEVAN TEJA)

This is to certify that the above statement made by the candidate is correct to the best of my/our knowledge.

12.07.2020

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Abstract

Alcoholism is a seriously addicted habit to most of the youth in the present days. It is very necessary to find and diagnosis the alcohol addicts as most of them did not realise that they are affected by the alcoholism. In old days it is very difficult to find the affected people by conducting manual question and answer sessions. But recent studies found that alcoholism have significant effects on EEG signals that can be extracted from using different computerised methods. In this thesis we have discussed one of the methods to find the alcoholism from electroencephalogram (EEG) signals. First, we have decomposed the EEG signals by using tunable Q factor wavelet transform (TQWT) in to different sub bands and determine the energy of each sub band. Then we extracted features from different sub bands using Hurst exponent, log energy, Shannon entropy, approximate entropy, threshold entropy, and normal entropy. Then we have used various classifiers to classify the effected and non-effected EEG signals from the extracted features. Then we compare different combination of features and classifiers to get the best results. In this method we have got an accuracy of 99.2% with and area under curve (AUC) of 0.99 for the Shannon entropy and logistic regression combination.

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LIST OF ABBREVATIONS

TQWT	Tunable Q factor wavelet transform
KNN	K nearest neighbour
SVM	Support vector machine
EEG	Electroencephalogram
LD	Linear discriminate
LR	Logistic regression
EML	Extreme machine learning
HE	Hurst exponent
SE	Shannon entropy
Log	Logarithmic
LE	Log energy entropy
NE	Norm entropy
TE	Threshold entropy

Chapter 1
Introduction

1.1 Alcoholism

Alcoholism is considered as mental sickness by the diagnostic and statistical mental disorder [1]. In recent day it is easy to addicted to alcoholism without knowing it. Generally, the person suffering from alcoholic addict have difficulty in controlling their desire to take alcohol. Most of them are fully aware of the harmful effects of alcohol but they are unable to control that habit and even they don't want others to know that they are having this addiction. In recent studies by world health organisation (WHO) alcoholism is declared as the fifth highest mortality rate among the deadliest diseases in the world [2]. And the early alcoholic deaths and moderate alcoholic deaths are more in recent days. Moreover, alcohol consumption reportedly increases the disability adjusted life year (DALY) and even lead to death. It is reported that 6% of deaths are due to alcoholism which is approximately around 3.3 million per year [30]. Addiction of alcohol may cause serious health issues like liver cancer, oesophagus cancer and oral cancer etc. And alcohol effects the personal life like relationships with work place and social gatherings. Excessive taking of alcohol causes physiological and behavioural changes in that person, and serious damage to the nervous system and may cause disability in learning and academic performances.

It is very hard to recognize the alcoholism cases by conventional methods. Normally, it is diagnosed in clinics and primary heath care centres by assessing responses to irritation by cutting down, first drink in the dawn, guilty feeling, and criticism. But it was found that it's rate of positive screening of alcoholic subjects is lower than 50% using these questions [3]. The reason for few patients not sharing the correct information might be due to anxiety of stigmatization and shame. In recent studies revealed that, electroencephalogram (EEG) signals can acquired non-invasively depict the state of brain and they can be effectively used for the detection, identification and treatment monitoring of the alcoholic patients [4].

1.2 EEG signals

From the research that has been conducted for establish and exploring the effect of alcoholism on EEG signals such that they will be used for the neurophysiological studies. These assessments have shown considerable clinical relation between EEG signals and alcohol usage. The alcoholic subjects have differences in the power spectrums of the delta (0–4 Hz), theta (4–7 Hz), alpha (8–12 Hz), gamma (>30 Hz) and beta (12–30 Hz) frequency sub bands in EEG signals [5]. In addition, with the above effects, the subject experiences changes in behaviour like seizures and hallucinations [6,7,8]. By finding out the variations in power level of the frequency sub bands in EEG signals, neurophysiological studies can be possible. Research on alcoholic subjects concludes that the EEG signals shows higher beta wave, delta wave and theta wave [60] power as compared to normal subjects. And increase in the beta 3 (20–28 Hz), beta 2 (16–20 Hz), and beta 1 (12–16 Hz) frequencies in EEG signals are the caused for parietal and frontal region of the alcoholic subjects. The results from Bauer's study on these subjects have showed a considerable change in beta activity within the frequency range of 19.5 to 39.8 Hz. The lower dose of alcohol which is below 0.5 g/kg can impact task related synchronization in theta frequency bands of EEG signals, and usage of alcohol in moderate dose may increase the power in alpha band (8–12 Hz). With the changes that are in EEG alpha topographic localization, activity, morphological nature and generalized cortical processes within our brain will get modified. And high dosage of alcohol which means exceeding 1.0 g/kg can increase activity of the EEG frequencies which are below 8 Hz. For this level of dosage, the lower delta spectral power and fast beta have been observed in low-binge and non-binge drinkers in contrast with the high-binge drinkers and added synchronization in gamma as well as theta frequency bands [9-10].

1.3 Overview of the existing techniques

In the process based on computer-aided diagnosis (CAD), signal processing techniques such as nonlinear dynamics, wavelet transforms, and chaos theory are dominantly used in feature extraction methods. More-over, artificial intelligence algorithms such as enhanced probabilistic networks, neural networks, support vector machine (SVM) and principal component analysis (PCA) are used to determine minute changes in given signal and the diseases can be automated diagnosis. The nonlinear and linear methods such as fractal dimension, entropies, correntropy [11] and largest Lyapunov exponent are extracted for detecting the deviation from the normal [12].

1.4 Objective

The main objective of this study is that to compare the different features that are extracted from the alcoholic and controlled EEG signals. And find the best accuracy possible using different kind of classifiers. The selected EEG signals are decomposed using TQWT, and from the selected sub bands we have to extract different features and then we have to compare them.

1.5 Organization of thesis

The arrangement of the remaining chapters in this thesis is as follows:

In chapter 2 firstly we have discussed about the TQWT and then we have explained theoretically about the features that are going to be extracted.

In chapter 3 the proposed methodology is shown and explained in detailed, along with various machine learning classifiers used, and also the performance merits are discussed.

In chapter 4 the experimental evaluated results are compared for various classifiers and the results are discussed by comparing performance indices.

In this final chapter 5 the thesis is concluded and the scopes for the future works are also discussed.

Chapter 2

Theory related to TQWT, feature extraction methods

2.1 Tuneable Q factor wavelet transform

The transform, that we denoted as the tunable-Q wavelet transform (TQWT) [13], is controlled by its oversampling rate (redundancy) and the Q-factor. The TQWT is developed using perfect reconstruction over-sampled filter banks with scaling factors that are real-valued. There are two forms in this transform. The first form is for the discrete-time signals having finite length and can be implemented effectively with fast Fourier transform (FFT). The second form is for the discrete-time signals which are defined on all of Z. Modest oversampling rates (e.g. 3-4 times over complete) are sufficient for the synthesis/analysis functions of the TQWT can be localized well [14].

The TQWT I mostly related to the rational dilation wavelet transform (RADWT). Similar to the RADWT, the TQWT is also fully discrete, and has the perfect reconstruction property, is developed in terms of iterated two-channel filter banks, is modestly overcomplete, and implemented using the discrete Fourier transform (DFT). In contrast to the RADWT, the TQWT is conceptually simpler, and can also be more effectively implemented by the radix-2 FFTs, and the parameters are easily controllable to the Q-factor of transform. The user can directly control the redundancy and Q-factor of the TQWT [15].

The filters, on which the TQWT is based, are specified directly in the frequency domain, they don't have rational transfer functions. Similar to the fractional spline wavelet transform that is also based on filters which are having non-rational transfer functions, the DFT provides 1) a means to define the transform for finite-length discrete data that preserves the perfect reconstruction property exactly and 2) an effective implementation of the signal using FFTs [16].

The high pass and low-pass sub-band signals created after J-stages having the frequency responses given by $H_1^{(J)}(\omega)$ and $H_0^{(J)}(\omega)$ respectively as follows:

$$H_0^{(J)}(\omega) = \begin{cases} \prod_{m=0}^{J-1} H_0\left(\frac{\omega}{\alpha^m}\right), & |\omega| \le \alpha^J \pi. \\ 0 & \alpha^J \pi < \omega \le \pi. \end{cases} \tag{1}$$

$$H_1^{(J)}(\omega) = \begin{cases} H_1(\omega/\alpha^{J-1}) \prod_{m=0}^{J-2} H_0\left(\frac{\omega}{\alpha^m}\right), & (1-\beta)\alpha^{J-1}\pi \le \omega \le \alpha^{J-1} \\ 0 & \text{otherwise.} \end{cases} \tag{2}$$

Where

$$H_0(\omega) = \theta\left(\frac{\omega+(\beta-1)\pi}{\alpha+\beta-1}\right), \tag{3}$$

$$H_1(\omega) = \theta\left(\frac{\alpha\pi-\omega}{\alpha+\beta-1}\right). \tag{4}$$

Here $\theta(\omega)$ is frequency response of Daubechies filter bank and can be given as follows

$$\theta(\omega) = 0.5(1 + \cos(\omega))\sqrt{2 - \cos(\omega)}, |\omega| \leq \pi. \quad (5)$$

The parameters Q and r are given as,

$$r = \frac{\beta}{1-\alpha}, \ (6) \ \ Q = \frac{2-\beta}{\beta}. \quad (7)$$

By selecting proper values of Q and r we can control the characteristics of filter by which we can also control the decomposition of the given EEG signal [17].

2.2 Features selection

2.2.1 Hurst exponent

To calculate long term memory of time series we generally use Hurst exponent [18]. It belongs to the autocorrelations of time series, and decrease rate when raising difference between value pairs lags. Theories which have this exponent are actually originally developed in hydrology sector for the practical matter of finding optimum dam size for the great Nile river (in Africa) volatile rain and droughty conditions that has been studied over a long period. The name "Hurst exponent", or "Hurst coefficient", was from Harold Edwin Hurst (1880–1978), he was a lead researcher in these studies; and the use of the standard notations H for the coefficient also related to his name.

The mentioned Hurst exponent is referring as a "index of dependence" or the "index of long-range dependence". It classifies the relative tendency of the time series either to converge strongly to the mean or to cluster in a specific direction. The value H is usually in the range 0.5–1 which indicates a time series with long-term positive autocorrelation, which means both that a high value in a series shall probably be following by another high value and that values a very long time into future shall also tend to be high [19].

The values in the range of 0 – 0.5 indicates a time series with long-term switching between higher and lower values in aside by side pairs, which means that a single higher value will probably be following by a lower value and thus the value after that shall tend to be very high, with this tendency to change between higher and lower values lasting a longer time into future work [20].

The value H=0.5 will indicate a completely uncorrelated time series, but actually in facts it is the most value applicable to time series for which this autocorrelation at small time lags will be a positive or a negative value but where the absolute values of an autocorrelations decay exponentially quickly to zero [21-26].

Hurst expanded for variation range (R), standard deviation (S) the equation by Einstein which converts it to the more generic form as,

$$(R/S)n = c \times nH \tag{8}$$

Usually, the value R/S changes with the scale with an increase of a time increment according to this dependence degree equal to H which is otherwise the Hurst exponent.

2.2.2 Approximate entropy

Functions [27] which verify the additive-type property is well related for efficient finding of binary-tree structures and also the fundamental splitting property of wavelet packets decomposition. Classically the entropy-based criteria match these mentioned rules and describe data-related properties for a precise representation of a signal. Entropy is a common concept mentioned in many areas, mainly in field of signal processing. Many others are available and will be easily introduced. If the signal is given then the coefficients of signal are in an orthonormal basis [28].

In this subject like statistics, approximate entropy (ApEn) is a method used to measure the amount of regularity and ‘unpredictability’ of fluctuations over given time-series. Regularity is actually originally measured by precise regularity statistics, which has mainly focused on different entropy measures. But accurate entropy calculation needs large amounts of data, and found results shall be fully influenced by system noise, so it is not practical or preferable to apply these methods to experimental data. To find approximate entropy, the below algorithm steps must be used [29].

1: - Form the given time series data say “v(1), v(2)……v(N)”. These are raw data values from measurement equally spaced in time.

2: - keep the ’m’ constant and, an integer, and ‘r’, as a positive real number. The given value of ‘m’ must represent the length of compared run of given data, and ‘r’ also specifies a filtering level.

3: - From the above data make a sequence of vectors “x(1),x(2)……., x(N-M+1)” where x(i) = [v(i),v(i+1),……v(i+m-1)]

4: - Apply the above sequence to construct, for each of ‘i’ where

1< i< (N-m+1)

$$D_i^m(r) = \frac{number\ of\ x(j) such\ that\ c[x(i),x(j) \leq r]}{N-m+1} \tag{10}$$

$$c[x, x^*] = \max|u(a) - u^*(a)| \tag{11}$$

$$\phi^m(r) = (N-m+1)^{-1} \sum_{i=1}^{N-m+1} \log\left(D_i^m(r)\right) \tag{12}$$

$$\text{Approximate entropy} = \phi^m(r) - \phi^{m+1}(r) \tag{13}$$

2.2.3 Shannon entropy

Functions which are having an additive type property are well suited for efficient searching of the fundamental splitting. Classical entropy criteria will mostly match the conditions and describe about information-related properties for an accurate representation of the given signal. Entropy for any signal is common concept, mostly in signal processing techniques [30-34].

The (nonnormalized) Shannon entropy is given by,

$$E1(x_i) = X_i^2 \log (X_i^2) \qquad (14)$$

so

$$E1(x) = \sum_i X_i^2 \log (X_i^2) \qquad (15)$$

with the convention 0 log (0) = 0.

In the above expression X is the signal and (X_i) are the coefficients of X in an orthonormal basis [35].

2.2.4 Log energy entropy

This log energy implies the logarithmic energy, which is also a notable feature for EEG signals classification. This has its base in potential theory. The log energy for a signal is found using basic Parseval energy theorem [36].

Let x(t) is the signal and we need to find its log energy value LOEN then, for 'K' frequency bins and "l" frame indices

$$LOEN = \log E_x(l) \qquad (16)$$

$$E_x(l) = \sum_{k=1}^{K} |x(k,l)|^2 \qquad (17)$$

2.2.5 Threshold entropy

The threshold entropy is defined as,

E (X_i) = 1 if $|X_i| > p$ and 0 otherwise so

E (X) = #{ i if and only if $|X_i| > p$} is the number of time instants where signal magnitude is greater than the given threshold value p [37].

2.2.6 Norm entropy

The norm entropy with $1 \leq p$ is given as,

$$E(X_i) = |X_i|^p \text{ so} \tag{18}$$

$$E(X) = \sum_i |X|^2 = ||X||_p^p \tag{19}$$

In the above expression X is the signal and (X_i) are the coefficients of X in an orthonormal basis [38].

2.3 Summary

In this chapter we have discussed about TQWT, and different features that are going to be used in the proposed method theoretically. In the next chapter we are going to discuss about the proposed method with the required waveforms and graphs.

Chapter: 3

Datasets and proposed method

3.1 Introduction

In this chapter first we are going to discuss about the data set that we going to use. And then we are going to decompose the EEG signals using TQWT and we will calculate the energy of each sub band. Then we have to select the sub bands that are having significant energy. From that selected sub bands, we have extracted features that are discussed in the previous chapter. From the extracted features we have classified using different classification techniques.

3.2 Dataset

The EEG dataset used in this work was taken from the University of California, Irvine Knowledge Discovery in Databases (UCI KDD) archive. And it is available in online at the following http://kdd.ics.uci.edu/databases/eeg/eeg.data.html. This dataset is used to find relation between EEG signals and the correlation to alcoholism. This Dataset includes the EEG recordings of 124 alcoholic and normal patients captured from entire 10/20 standard sites or international montage in coordination with Standard

Electrode Position Nomenclature of American Electroencephalographic Association, 1990. The electrode attached to nose is used for ground. The electrode impedance is always less than 5k. All of these subjects have gone through 120 trials for different stimuli and that consists of 90 images of objects that were selected from the images from references [39-42]. These EEG signals have event related bio potentials obtained from 64 electrodes that are applied on scalp. The EEG signals are recorded for 32 s with cap (Electro cap Inter-national, ECI) having 61-lead electrode. The system was sampled at 12 bits resolution and 256 Hz. The EEG signals with undesired body and eye movements have been excluded and 30 recordings for each alcoholic and normal class are considered. This data uses 120 EEG signals of each normal and alcoholic class. All of these EEG signals have 2048 samples recorded for 8 s. The Figure 3.1 shows the example of the alcoholic and normal EEG signals respectively [43-46].

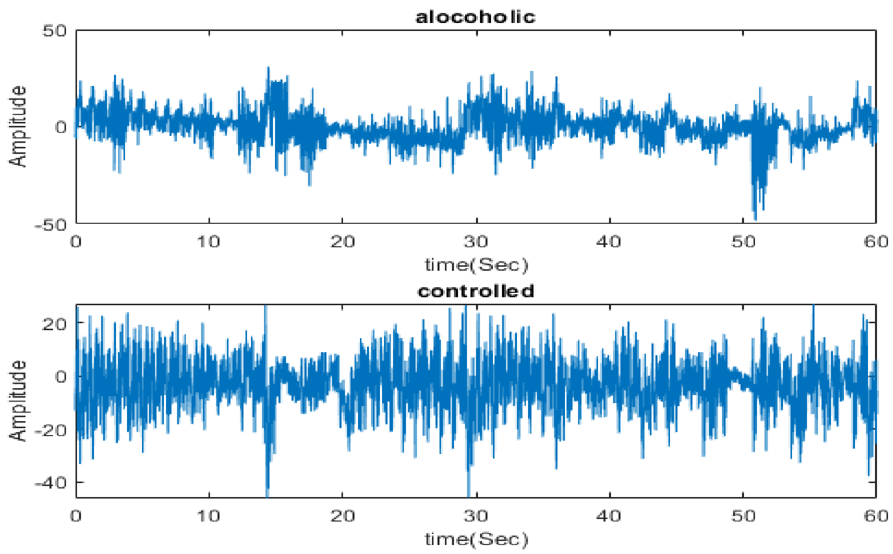
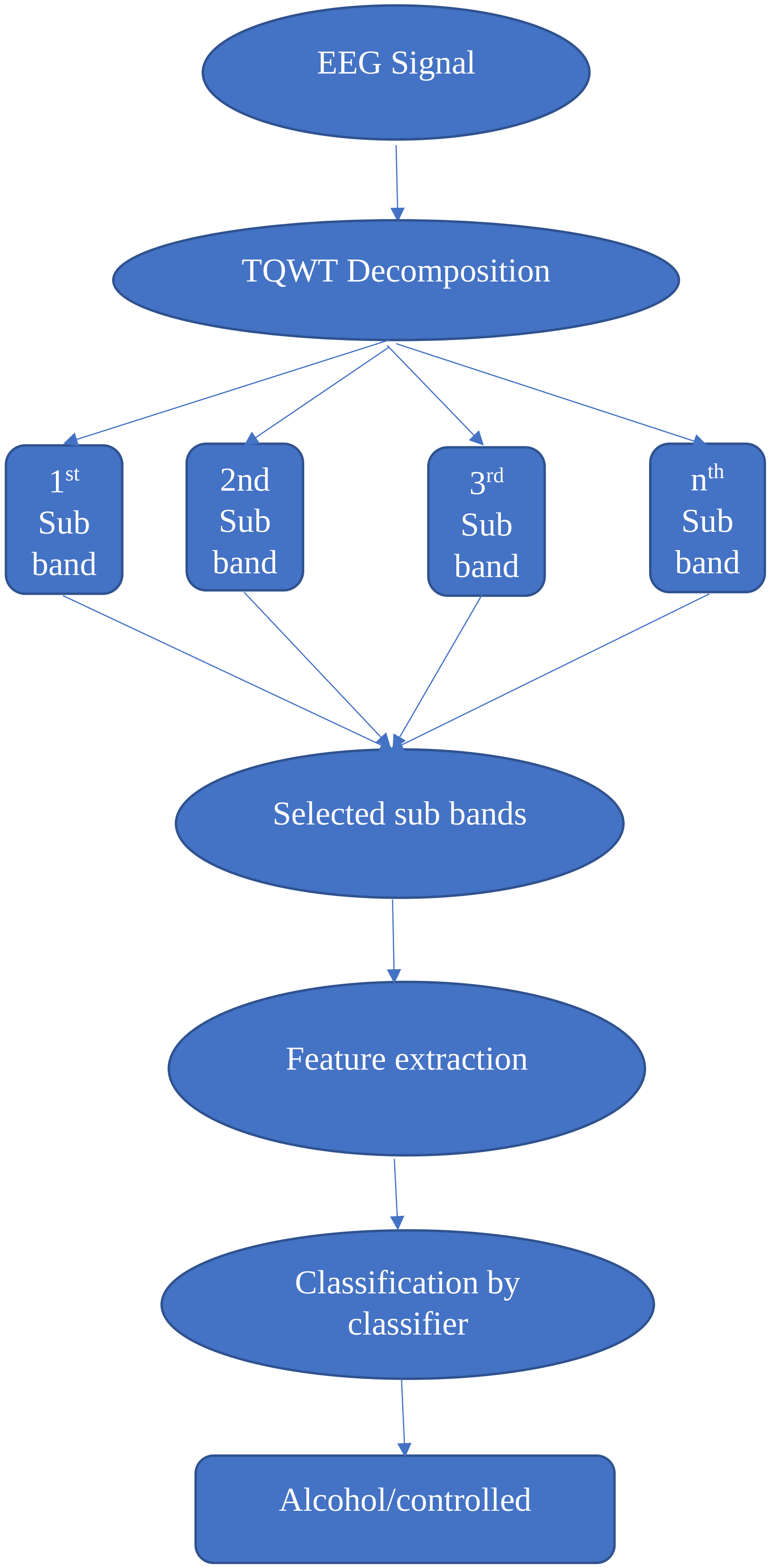


Figure 3.1 EEG dataset alcoholic and controlled

3.3 Proposed method

The flow chart of the proposed methodology is as follows:



3.3.1 Decomposition of EEG signal using TQWT

The EEG signals are decomposed using TQWT with the values of r = 3, J = 8 and Q = 1. And the decomposed sub bands are as follows shown in Figure 3.2.

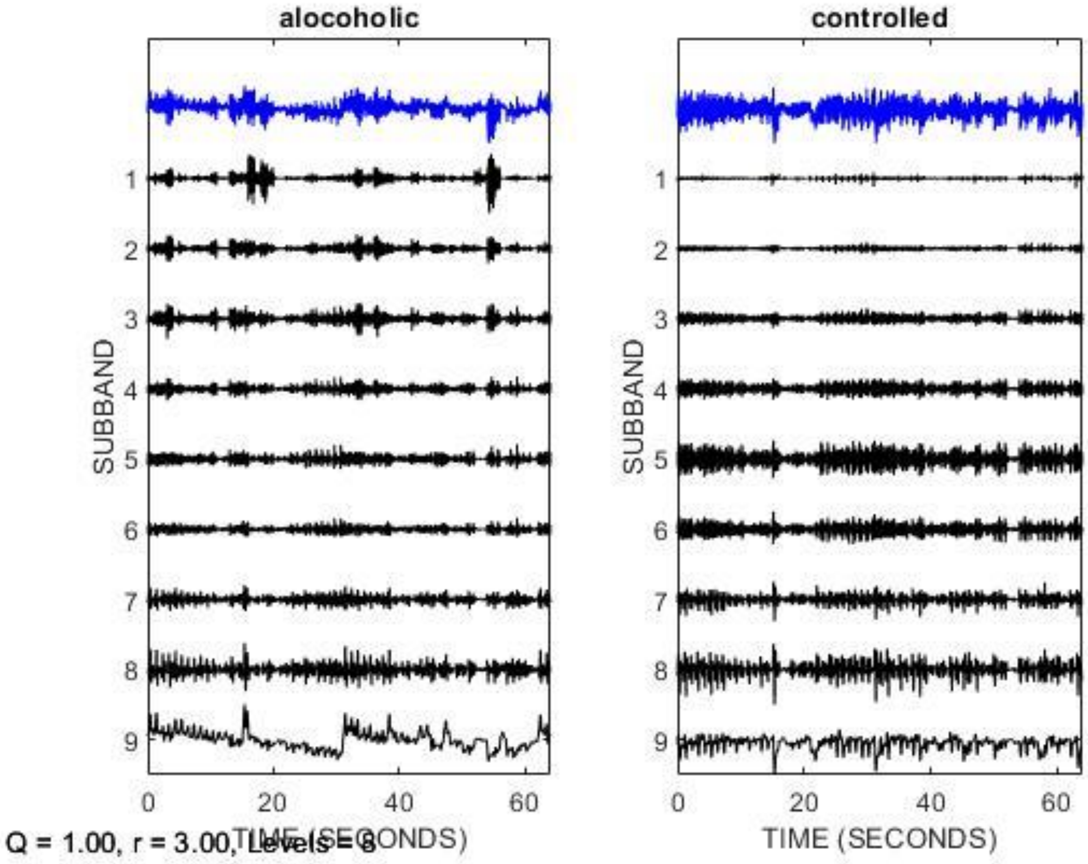


Figure 3.2 Decomposed sub bands using TQWT

3.3.2 Sub-band energy and selection

First, we have to calculate the energy of each sub band to understand which sub band has the maximum significant energy and then we have to select sub bands accordingly [47-49].

The energy of each sub band is shown in Fig 3.3.

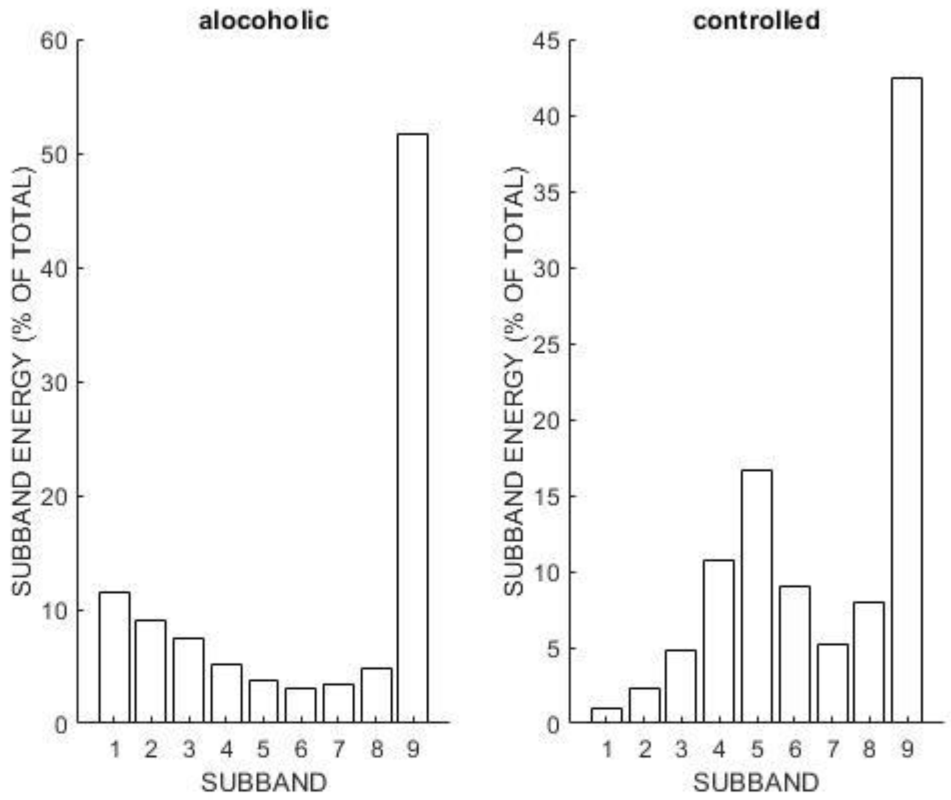


Figure 3.3 Energy of sub bands

From the energies that are calculated from the sub bands we have noticed that maximum change in energy is in lower sub bands as compared to higher sub bands so we can ignore the higher sub bands even though they contain more energy.

3.3.3 Extraction of features

Now from the selected sub bands we have to extract the features namely Hurst exponent, approximate entropy, Shannon entropy, log energy entropy, threshold entropy and norm entropy. The features that are acquired from the sub bands is shown in the chapter: 4 results and discussion.

3.4 Summary

In this chapter we have discussed about the dataset that is used in this method, the proposed methodology with the decomposed sub bands using TQWT, the energy of the sub bands and sub band selection based on the energy of sub band, and the features that are being used in this method. In the next chapter we will discuss about the results.

Chapter 4
Results and discussion

4.1 Tested values of all features

The following are the tested values of the features extracted from the sub bands using different entropy techniques namely Hurst exponent, log energy entropy, Shannon entropy, norm entropy and threshold entropy.

The following are the values of Hurst exponent. In the Table 4.1.1 and Table 4.1.2 we have shown the values of Hurst exponent for one controlled and one alcoholic respectively signal which is decomposed using TQWT.

Table 4.1.1 Tested values of Hurst exponent (alcoholic)

Hurst exponent	Tested values
HE 1	0.7908
HE 2	0.8326
HE 3	0.4932
HE 4	0.6545
HE 5	0.5136
HE 6	0.5997
HE 7	0.8892
HE 8	0.9470
HE 9	0.8672

Table 4.1.2 Hurst exponent tested values (controlled)

Hurst exponent	Tested values
HE 1	0.5632
HE 2	0.5854
HE 3	0.7686
HE 4	0.6652
HE 5	0.9553
HE 6	1.0373
HE 7	0.9016
HE 8	0.9505
HE 9	0.8292

In Table 4.1.3 we are going to show the values of Hurst exponent of different alcoholic signals.

Table 4.1.3 Hurst exponent values alcoholic

S.No	HS1	HS2	HS3	HS4	HS5	HS6	HS7	HS8	HS9
1	0.562	0.585	0.769	0.67	0.955	1.037	0.90161	0.9505	0.829173
2	0.759	0.563	0.654	0.51	0.834	0.909	0.96474	0.6343	0.925977
3	0.702	0.564	0.671	0.73	0.747	0.695	0.71223	0.9632	0.931343
4	0.631	0.577	0.677	0.84	0.952	0.861	0.66752	0.9628	0.91799
5	0.592	0.648	0.75	0.78	0.999	0.668	0.88425	0.904	0.883871
6	0.416	0.492	0.498	0.69	0.825	0.836	0.97317	0.9535	0.866933
7	0.546	0.612	0.626	0.76	1.04	0.91	1.01984	0.797	0.868586
8	0.646	0.652	0.676	0.84	0.932	0.724	0.8075	0.905	0.869683
9	0.527	0.635	0.758	0.75	0.98	0.849	0.89774	0.9548	0.852392
10	0.526	0.606	0.801	0.79	0.982	0.944	0.88757	0.8961	0.791601
11	0.791	0.684	0.733	0.78	0.919	0.933	0.93581	0.96	0.774086
12	0.539	0.555	0.649	0.92	0.849	0.956	0.80846	0.957	0.73029
13	0.559	0.528	0.716	0.92	0.92	0.915	0.71395	0.924	0.794174
14	0.758	0.73	0.749	0.92	0.722	0.802	0.82003	0.8825	0.825416
15	0.659	0.668	0.889	0.9	0.967	0.935	0.92946	0.9209	0.82396
16	0.631	0.632	0.503	0.6	0.946	0.933	1.0081	0.7687	0.801786
17	0.667	0.631	0.862	0.81	0.737	0.911	0.88763	0.8617	0.800452
18	0.502	0.52	0.902	0.87	0.605	0.848	0.80621	0.7088	0.822628
19	0.661	0.652	0.507	0.79	0.795	0.709	0.9386	0.8577	0.828946
20	0.59	0.629	0.813	0.79	0.691	0.875	0.92333	0.8609	0.81673

In Table 4.1.4 we are going to show the values of Hurst exponent of different controlled signals

Table 4.1.4 Hurst exponent values controlled

S.No.	HS1	HS2	HS3	HS4	HS5	HS6	HS7	HS8	HS9
1	0.732	0.869	0.982	0.782	1.048	1.002	0.976	0.969	0.693
2	0.763	0.831	0.863	0.896	0.524	0.924	0.885	0.886	0.829
3	0.791	0.833	0.493	0.655	0.514	0.6	0.889	0.947	0.867
4	0.709	0.715	0.979	0.846	0.757	0.614	0.858	0.946	0.856
5	0.838	0.84	0.905	0.907	0.986	0.657	0.962	0.898	0.902
6	1.002	1.007	0.651	0.845	0.702	0.881	0.954	0.894	0.877
7	1.06	1.038	0.835	0.861	0.961	0.854	0.866	0.906	0.882
8	0.996	1.002	0.688	1.001	0.946	0.632	0.744	0.884	0.861
9	0.955	0.945	0.929	1.051	0.786	0.91	0.93	0.916	0.819
10	0.483	0.522	1.039	1.078	1.005	0.982	0.869	0.91	0.757
11	0.869	0.797	1.118	0.981	0.991	0.975	0.773	0.818	0.712
12	0.876	0.804	0.729	0.882	0.93	0.884	0.909	0.918	0.753
13	0.672	0.661	1.093	1.113	0.924	0.879	0.921	0.691	0.81
14	0.81	0.82	1.068	1.115	1.013	1.005	0.898	0.948	0.843
15	0.915	0.911	1.079	1.044	0.97	1.021	0.849	1.09	0.889
16	0.902	0.914	0.645	0.903	0.99	0.854	0.792	0.927	0.932
17	0.643	0.612	0.781	0.799	0.957	0.945	0.901	0.91	0.9
18	0.871	0.915	0.898	1.027	0.922	0.975	0.972	0.934	0.728
19	0.993	1.022	1.09	1.131	0.629	0.919	0.939	0.89	0.819
20	1.09	1.119	1.1	1.095	0.962	0.671	0.938	0.882	0.819

In Table 4.1.5 we give the values of Shannon entropy for one alcoholic signal

Table 4.1.5 Shannon entropy tested values(alcoholic)

Shannon entropy	Tested values
SE 1	-5.1897 e+ 03
SE 2	-1.7173 e+ 03
SE 3	-3.6257 e+ 03
SE 4	-3.7080 e+ 03
SE 5	-6.1192 e+ 03
SE 6	-1.2548 e+ 04
SE 7	-7.4258 e+ 03
SE 8	-1.3609 e+ 04
SE 9	-1.3122 e+ 04

The Table 4.1.6 gives Shannon entropy for one example of controlled signal.

Table 4.1.6 Shannon entropy tested values (controlled)

Shannon entropy	Tested values
SE 1	-5.8939 e+ 03
SE 2	-2.8820 e+ 03
SE 3	-3.2221 e+ 03
SE 4	-1.6629 e+ 03
SE 5	-1.9600 e+ 03
SE 6	-0.8470 e+ 03
SE 7	-0.9704 e+ 03
SE 8	-1.8652 e+ 03
SE 9	-8.4417 e+ 03

In Table 4.1.7 we are going to show the values of Shannon entropy of different alcoholic signals.

Table 4.1.7 Shannon entropy values alcoholic

S.No	SE1	SE2	SE3	SE4	SE5	SE6	SE7	SE8	SE9
1	-5894	-2882	-3222	-1663	-1960	-847	-970	-1865	-8442
2	-5009	-2143	-1990	-1435	-2011	-859	-531	-826.2	-11216
3	-6993	-2701	-5853	-2583	-1963	-765	-344	-2039	-24806
4	-8564	-2624	-4348	-2380	-2165	-502	-379	-919.5	-32074
5	-9121	-3189	-4389	-2926	-969.5	-113	-1413	-1269	-33745
6	-4892	-4558	-5747	-3093	-883.8	-468	-2788	-572.6	-51331
7	-2605	-3921	-2280	-1590	-2205	-1502	-719	-4000	-84255
8	-4795	-3104	-2125	-1180	-698.5	-1410	-231	-8838	-87749
9	-3564	-3720	-2306	-1317	-1554	-1075	-1985	-541.4	-49048
10	-3248	-4681	-1697	-1111	-1468	-1712	-1101	-3574	-16963
11	-4712	-4382	-3258	-1039	-756.9	-2945	-115	-2518	-7300
12	-2310	-3690	-2089	-1086	-2392	-2846	-83.5	-221.3	-7381
13	-2529	-2746	-3223	-2295	-1038	-832	-1238	-60.29	-13965
14	-2704	-2035	-4398	-2846	-151.9	-67.5	-3943	-843.1	-20122
15	-4763	-2250	-2501	-1668	-1736	-719	-4607	-599.7	-16629
16	-2782	-3195	-3761	-1358	-1143	-1473	-1866	-1062	-7755
17	-4316	-3330	-2991	-2425	-98.45	-1021	-752	-2044	-4803
18	-2323	-1867	-3681	-2640	-224.3	-370	-1580	-1174	-17318
19	-6160	-2041	-2099	-2014	-182.6	-128	-2635	-5523	-38165
20	-4513	-3327	-2258	-1729	-659.1	-56.3	-1096	-1697	-41089

In Table 4.1.8 we are going to show the values of Shannon entropy of different controlled signals.

Table 4.1.8 Shannon entropy values controlled

S.No	SE1	SE2	SE3	SE4	SE5	SE6	SE7	SE8	SE9
1	-5190	-1717	-3626	-3708	-6119	-5671	-7426	-13609	-13122
2	-750	-2911	-3954	-5179	-4966	-5593	-5641	-3542	-6280
3	-19.7	-1094	-199.1	-3102	-3029	-3021	-6572	-17307	-32662
4	-67.6	-363.2	-2561	-2084	-4425	-7955	-4033	-18391	-46654
5	-11.2	-408.9	-1194	-1308	-12159	-8956	-5471	-3603	-33834
6	-71.7	-879.1	-1361	-2752	-8812	-7654	-4231	-8950	-70655
7	-332	-1726	-4291	-6611	-20244	-7997	-828	-28994	-1E+05
8	-311	-1548	-1868	-7720	-25238	-7314	-218	-5130	-82326
9	-24.1	-438.5	-1102	-6403	-23071	-5231	-2963	-2721	-31021
10	-8.64	-89.45	-3854	-5578	-42714	-8651	-7890	-3069	-13379
11	-90.1	-419.2	-3559	-4199	-67809	-5639	-6255	-236.2	-9613
12	-147	-815.7	-4553	-9005	-35785	-6741	-2513	-125.2	-6583
13	-109	-729.8	-13205	-23244	-19401	-6868	-1321	-494.9	-4598
14	-95.3	-563.6	-11479	-23624	-64310	-8641	-8786	-1331	-5278
15	-88.7	-522.9	-1642	-9982	-30572	-2145	-1799	-437.3	-10954
16	-84.7	-502.8	-2057	-4820	-9045	-1158	-1659	-6200	-17186
17	-66.4	-430.2	-2592	-11107	-35930	-8931	-2895	-10768	-9115
18	-124	-692.5	-6575	-21864	-29711	-7531	-1827	-4146	-12495
19	-169	-963.5	-9096	-23053	-1940	-4473	-592	-21609	-64990
20	-136	-818.3	-4213	-15118	-10505	-6124	-1018	-21765	-15605

The following are the tested values of log energy entropy. In the Table 4.1.9 and Table 4.1.10 below we have the values of log energy for one controlled and one alcoholic signal respectively.

Table 4.1.9 Log energy tested values (controlled)

Log energy	Tested values
LE 1	-206.14
LE 2	-145.49
LE 3	105.897
LE 4	79.3229
LE 5	136.1159
LE 6	185.9579
LE 7	105.6502
LE 8	69.0639
LE 9	44.6649

Table 4.1.10 log energy tested values (alcoholic)

Log energy	Tested values
LE 1	-180.6060
LE 2	-211.4023
LE 3	30.9622
LE 4	59.1910
LE 5	62.9901
LE 6	60.2892
LE 7	29.4430
LE 8	41.8466
LE 9	56.8049

In Table 4.1.11 we are going to show the values of log energy of different alcoholic signals.

Table 4.1.11 log energy tested values (alcoholic)

S.No	LE1	LE2	LE3	LE4	LE5	LE6	LE7	LE8	LE9
1	-180.6	-211.4	30.96	59.191	62.99	60.289	29.44	41.85	56.805
2	-189.5	-167	6.31	12.724	64.63	33.47	17.14	9.956	60.596
3	-218	-139.4	-6.28	-14.71	32.77	25.078	0.208	41.04	72.459
4	-264.9	-189.4	26.86	10.854	72.55	12.824	-5.44	16.12	73.152
5	-231.9	-148	-15.8	8.2628	37.01	-77.22	32.49	20.83	76.957
6	-156.5	-86.44	83.49	30.828	-21.2	-37.36	76.6	29.8	82.157
7	-201.6	-72.97	-21.3	-17.15	98.48	39.845	45.64	46.53	87.327
8	-235.3	-138.3	-0.97	-24.36	25.03	47.553	1.665	46.8	89.753
9	-227.2	-92.23	39.88	22.294	24.46	24.852	60.24	28.41	81.931
10	-270.9	-195.3	42.18	-62.99	14.02	69.288	36.4	38.38	67.647
11	-186.7	-51.11	40.46	-111.3	37.41	114.72	-23	40.81	54.872
12	-214.4	-69.39	-3.79	-17.42	78.14	100.73	-18.9	4.475	50.483
13	-205.6	-187.1	37.83	41.008	34.74	39.025	50.71	-0.92	58.063
14	-203.3	-180.6	93.5	110.97	-126	-137.6	91.23	21.92	60.38
15	-165.2	-86.96	96.75	15.632	68.03	29.129	47.98	28.49	61.293
16	-140.3	-23.35	86.9	40.011	37.14	64.1	70.03	24.24	42.646
17	-173.2	-61.44	102	53.122	-58.2	31.607	34.6	28.28	43.301
18	-239.2	-148.6	131.3	98.224	-76.7	-10.49	58.72	33.17	65.057
19	-189.6	-123.7	-20.8	20.893	-104	-86.7	41.9	57.07	77.164
20	-174.8	-62.18	1.701	-16.21	-30.8	-118.9	45.91	37.27	69.596

In Table 4.1.12 we are going to show the values of log energy of different controlled signals.

Table 4.1.12 log energy tested values (controlled)

S.No	LE1	LE2	LE3	LE4	LE5	LE6	LE7	LE8	LE9
1	-206.1	-146	105.9	79.323	136.1	185.96	105.7	69.06	44.665
2	-285.6	-50.89	123.8	144.69	131.5	116.23	105.9	48.39	56.775
3	-426.6	-49.6	-95	176.08	89.83	86.617	95.41	69.79	78.595
4	-418	-148	26.12	55.017	83.36	146.49	92.15	72.97	73.908
5	-421.5	-193.4	-47.9	68.462	149.5	218.64	122.6	51.59	75.283
6	-504.7	-210.5	7.782	118.24	197.9	187.23	121.1	59.04	87.532
7	-375.3	-133.6	94.87	165.57	159.4	138.98	37.6	77.13	74.439
8	-385.2	-177	63.74	170.83	197.8	108.32	-2.68	55.62	71.097
9	-586.2	-361.9	12.49	220.22	228	157.81	67.86	41.27	64.787
10	-827.6	-552.3	192.1	235.69	241.7	248.93	102.1	40.58	49.822
11	-494.3	-349.3	96.67	162.32	289.3	270.97	90.5	-3.47	41.517
12	-537.6	-369.5	170.6	279.82	199	137.25	88.75	11.96	30.788
13	-621.3	-356.6	256.8	310.74	208.9	159.74	119.5	4.557	30.952
14	-512.9	-199.4	258.7	374.74	284.5	206.88	103.2	35.79	42.981
15	-387.8	-143.8	110.3	281.95	179.6	160.27	60.78	31.39	57.108
16	-431.7	-204	0.371	140.7	181.1	64.474	38.52	55.55	64.634
17	-452.1	-237.9	70.9	226.5	216.4	180.14	58.3	64.84	41.436
18	-504.7	-269.8	205.5	292.74	188.4	176.3	63.66	41.78	55.574
19	-355.9	-167.7	137.2	284.5	61.08	118.68	47.76	70.45	88.004
20	-435.3	-135.3	209.4	369.81	160.9	160.21	31.07	67.8	93.853

The following are the tested values of norm entropy with P = 1.5.

In the Table 4.1.13 and Table 4.1.14 below we have the values of norm entropy for one controlled and one alcoholic signal respectively

Table 4.1.13 Norm entropy tested values (controlled)

Norm entropy	Tested values
NE 1	692.2132
NE 2	526.1381
NE 3	441.1445
NE 4	363.6924
NE 5	307.3101
NE 6	215.7663
NE 7	147.5459
NE 8	185.2892
NE 9	422.5837

Table 4.1.14 Norm entropy tested values (alcoholic)

Norm entropy	Tested values
NE 1	664.3496
NE 2	489.2295
NE 3	592.9529
NE 4	568.5409
NE 5	641.8377
NE 6	1.0146 e+ 03
NE 7	576.2522
NE 8	634.4651
NE 9	506.7367

In Table 4.1.15 we are going to show the values of norm entropy of different controlled signals.

Table 4.1.15 Norm entropy tested values (controlled)

S.No	NE1	NE2	NE3	NE4	NE5	NE6	NE7	NE8	NE9
1	664.3	489.2	593	568.5	641.8	1015	576.3	634.5	506.7
2	296.4	614.2	593.6	733.9	566.4	589.4	757.5	269.8	373
3	150.6	438.8	141.8	602.4	407	387.4	740.3	756.7	1081
4	163.6	306	459.9	412.1	435.6	737.6	400.4	789.8	1209
5	146.1	303.9	274.9	356.7	915.7	1085	809	277.4	1039
6	154.2	372.9	319.1	524.9	873.2	929.2	764.9	474.6	1747
7	244.1	497	651.4	834.1	1233	695.6	149.4	1034	2280
8	235.3	462.9	409.9	924.1	1459	571.7	71.13	344.3	1755
9	127	256.2	312.8	908.6	1508	948	318.6	233.8	870.4
10	87.58	144.7	656.1	827	2064	1939	571.3	261	523.8
11	152.1	244.9	586.7	676.7	2982	2172	501.9	44.7	431.5
12	159.1	303.7	714.8	1094	1764	951.9	738.2	39.92	326
13	143.8	304.1	1258	1819	1318	693.5	913.7	72.41	254.1
14	156.5	323.8	1152	1936	2838	1373	641.7	155.8	296
15	182.9	344.7	422.4	1191	1543	895.5	239	86.56	491.4
16	165.2	312.1	384.7	671.6	853.7	253.7	196.3	383	687.6
17	150.5	289.2	468.8	1159	1822	1086	279.1	545	471.3
18	164.7	329.7	851.7	1736	1548	1245	234	293.1	516.9
19	209.3	401.9	942.8	1770	309.9	526.2	140.3	824.4	1663
20	183.6	383.1	724	1587	884.5	674.6	157.8	854.2	2685

In Table 4.1.16 we are going to show the values of norm entropy of different alcoholic signals.

Table 4.1.16 Norm entropy tested values (alcoholic)

S.No	NE1	NE2	NE3	NE4	NE5	NE6	NE7	NE8	NE9
1	692.2	526.1	441.1	363.7	307.3	215.8	147.5	185.3	422.6
2	591.5	513.2	379.7	331.7	308.4	198.8	110.9	100.3	528.7
3	686.1	550.2	553.5	401.3	292.3	185	81.13	192.3	899.6
4	742.8	510.7	536.7	433	329.4	156	83.99	100.9	1079
5	811.2	569.8	533.1	463.2	214.7	68.04	174.9	128.8	1140
6	624.6	677.2	671.7	491.7	176.5	126.9	314.8	93.52	1454
7	509.1	642.2	366.1	337.4	365.6	259.8	146.3	267.1	1961
8	646.1	600.1	381.6	296.3	182	273.3	76.3	434.1	2029
9	549.8	618	435.8	327.1	249.8	212.5	239.4	92.76	1403
10	518.2	657.3	365	274	238.1	295.2	162.2	246.1	707.3
11	661.1	740.5	430.7	250.7	187.9	440	51.54	220.7	397.8
12	500.3	680.2	376.1	301.3	349.9	408.3	44.08	54.2	383.9
13	508.3	561	448.8	439.5	215.2	194.1	193.8	27.13	585.9
14	509.5	492.8	523.9	491.4	64.86	48.96	385.2	113	764.3
15	564.3	560.2	487	372.2	302.7	196.4	379.7	96.99	673.8
16	541.8	660	513	345.3	236.9	276.8	253.7	118.3	388.1
17	607	631.7	496.6	439.5	72.85	217.8	142.2	177.2	295.3
18	481.5	484.7	570.3	490.2	82.92	121.5	219.7	134.7	694.5
19	636.7	509.6	382.1	392.4	65.26	64.48	266.1	355.6	1154
20	735.7	623.2	385.9	344.5	147.8	51.1	175.7	171.2	1224

The following are the tested values of threshold entropy with P = 0.6

In Table 4.1.17 and Table 4.1.18 below we have the values of Threshold entropy for one controlled and one alcoholic signal respectively.

Table 4.1.17 Threshold entropy tested values (alcoholic)

Threshold entropy	Tested values
TE 1	152
TE 2	164
TE 3	104
TE 4	102
TE 5	58
TE 6	60
TE 7	31
TE 8	16
TE 9	14

Table 4.1.18 Threshold entropy tested values (controlled)

Threshold entropy	Tested values
TE 1	148
TE 2	153
TE 3	94
TE 4	107
TE 5	55
TE 6	55
TE 7	26
TE 8	15
TE 9	16

In Table 4.1.19 we are going to show the values of threshold entropy of different alcoholic signals.

Table 4.1.19 Threshold entropy tested values (alcoholic)

S.No	TE1	TE2	TE3	TE4	TE5	TE6	TE7	TE8	TE9
1	148	153	94	107	55	55	26	15	16
2	154	161	94	96	56	51	22	13	16
3	153	167	84	87	49	53	21	15	15
4	150	157	87	91	52	47	20	13	15
5	141	160	84	94	50	34	25	13	15
6	155	177	101	97	39	43	31	16	15
7	154	173	90	92	58	50	29	16	15
8	147	162	95	89	52	51	24	15	16
9	142	174	99	96	49	53	30	15	16
10	132	153	104	85	50	55	28	15	16
11	163	173	99	72	51	57	22	14	16
12	150	160	92	94	56	60	22	13	16
13	149	154	96	102	52	54	30	10	15
14	154	161	104	109	28	23	32	15	14
15	162	173	107	95	52	53	26	15	15
16	155	185	104	106	50	57	31	14	15
17	158	179	111	101	38	52	28	14	15
18	160	164	115	106	33	46	30	15	15
19	161	167	87	95	25	29	25	16	16
20	168	175	90	87	41	31	29	15	15

In Table 4.1.20 we are going to show the values of Threshold entropy of different controlled signals.

Table 4.1.20 Threshold entropy tested values (controlled)

S.No	TE1	TE2	TE3	TE4	TE5	TE6	TE7	TE8	TE9
1	152	164	104	102	58	60	31	16	14
2	139	171	109	106	58	56	31	16	16
3	113	190	79	116	56	58	31	15	16
4	125	178	102	102	55	58	31	16	15
5	119	169	80	107	60	64	31	16	16
6	104	155	98	111	64	62	31	15	16
7	140	167	100	109	56	61	27	16	15
8	130	161	101	107	58	57	24	16	15
9	92	134	101	116	62	61	29	15	16
10	58	95	118	121	63	62	32	14	15
11	103	136	99	115	63	64	31	12	13
12	93	127	114	120	60	56	29	15	12
13	82	119	117	119	62	64	31	10	14
14	101	161	118	124	64	62	31	14	16
15	132	177	114	119	62	60	28	16	16
16	115	163	95	110	62	55	30	16	15
17	103	156	102	113	61	61	28	16	14
18	106	147	117	116	60	58	32	13	16
19	134	167	101	117	51	58	29	16	16
20	120	170	118	124	57	61	28	15	16

4.2 Accuracy using different classifiers

Table 4.2.1 shows the accuracy of Hurst exponent with receiver operatic characteristics (ROC) curve [54] in Fig 4.2.1.

Table 4.2.1 Accuracy of Hurst exponent

Type of classifier	Accuracy
Coarse Gaussian SVM [55]	89.8%
Logistic regression [56]	84.2%
Linear discriminant [56]	83.1%
Medium KNN [57]	86.4%
Linear SVM [57]	89.2%

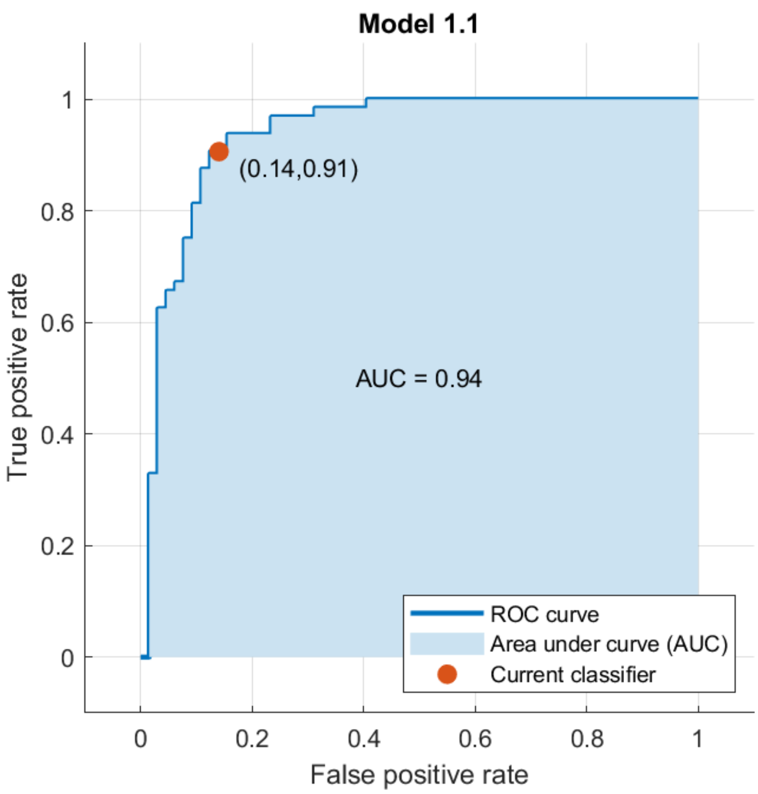


Figure 4.2.1 ROC of Hurst exponent

The following Table 4.2.2 shows the accuracy using Shannon entropy and ROC curve in Fig 4.2.2.

Table 4.2.2 Accuracy of Shannon entropy

Type of classifier	**Accuracy**
Coarse Gaussian SVM	91.8%
Logistic regression	99.2%
Linear discriminant	95.1%
Medium KNN	96.4%
Linear SVM	92.2%

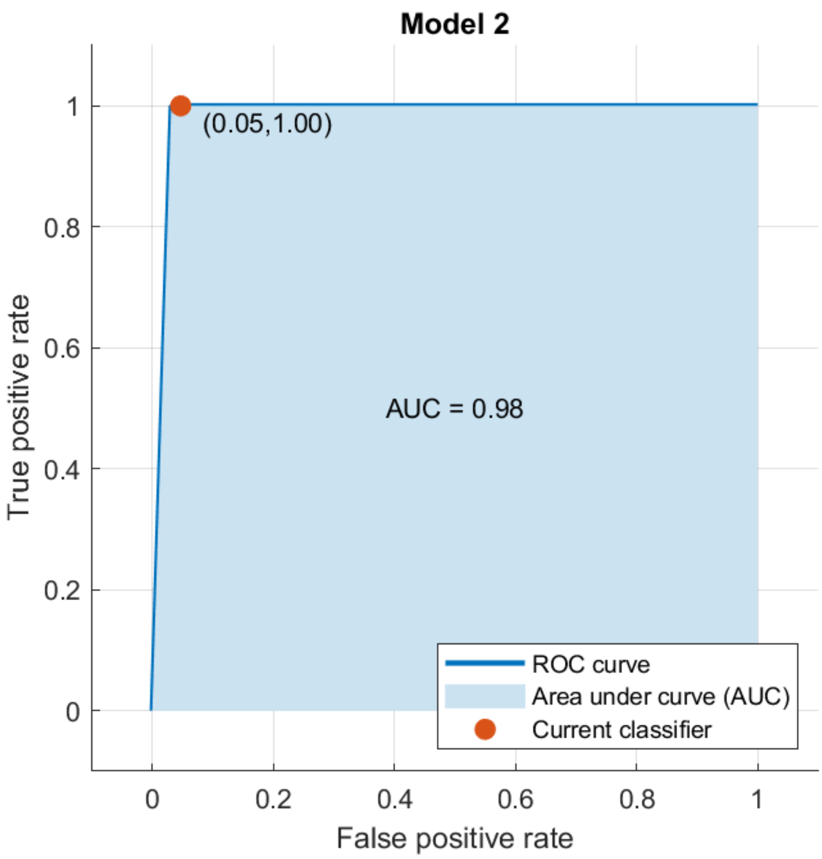


Figure 4.2.2 ROC of Shannon entropy

The following Table 4.2.3 shows the accuracy of log energy entropy and ROC curve in Fig 4.2.3.

Table 4.2.3 accuracy of log energy entropy

Type of classifier	**Accuracy**
Coarse Gaussian SVM	91.8%
Logistic regression	94.2%
Linear discriminant	98.4%
Medium KNN	96.8%
Linear SVM	98.2%

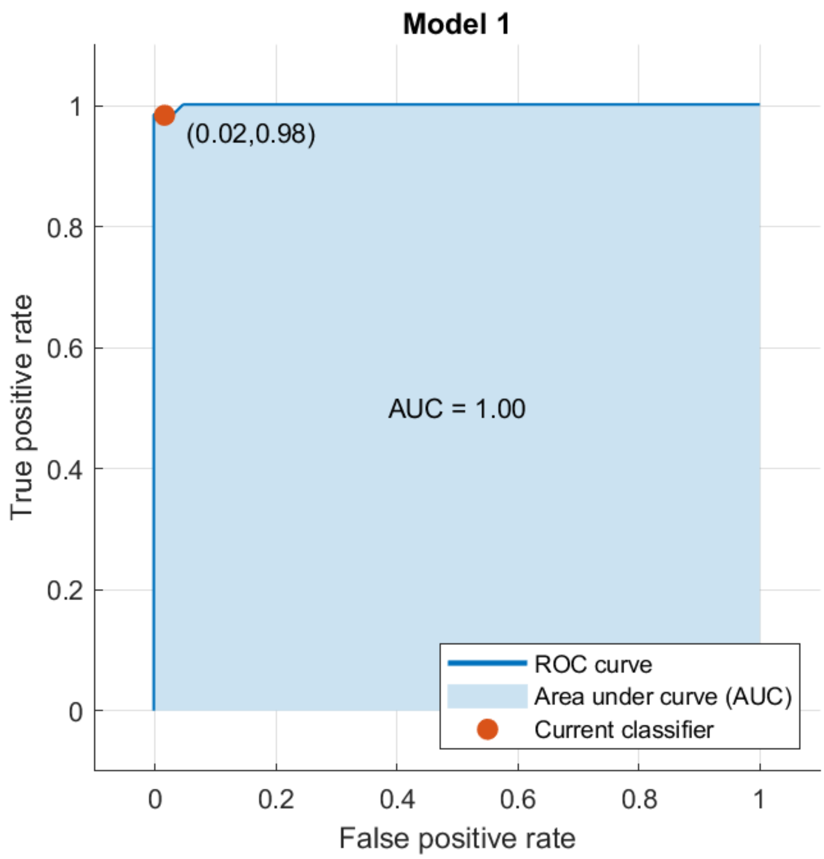


Figure 4.2.3 ROC of log energy entropy

The following Table 4.2.4 shows the accuracy of norm entropy with ROC curve in Fig 4.2.4.

Table 4.2.4 accuracy of norm entropy

Type of classifier	**Accuracy**
Coarse Gaussian SVM	93.8%
Logistic regression	94.5%
Linear discriminant	93.1%
Medium KNN	99%
Linear SVM	90.2%

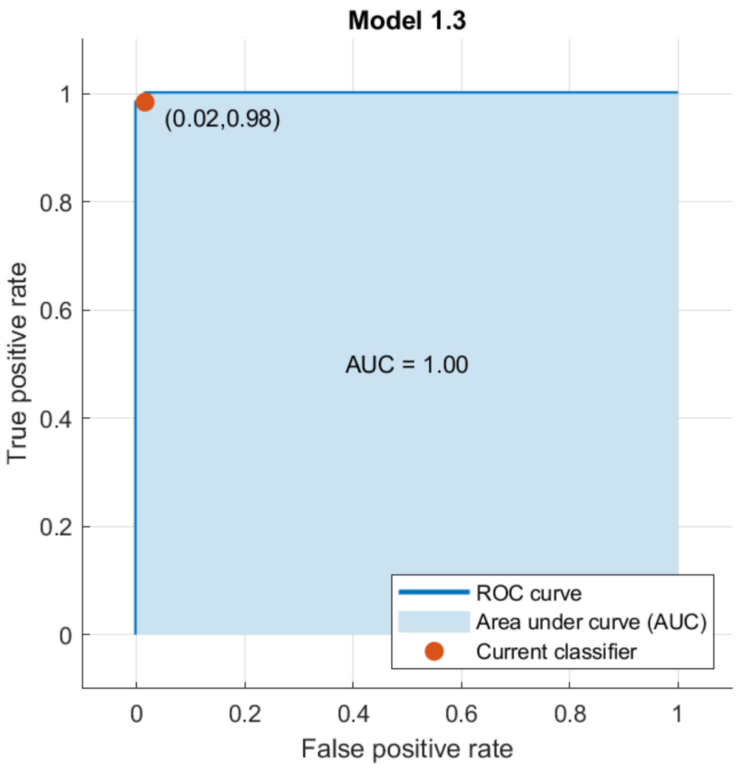


Figure 4.2.4 ROC of norm entropy

The following Table 4.2.5 shows the accuracy of threshold entropy with ROC curve in Fig 4.2.5

Table 4.2.5 Accuracy of threshold entropy

Type of classifier	Accuracy
Coarse Gaussian SVM	91.8%
Logistic regression	94.2%
Linear discriminant	97.7%
Medium KNN	96.1%
Linear SVM	92.2%

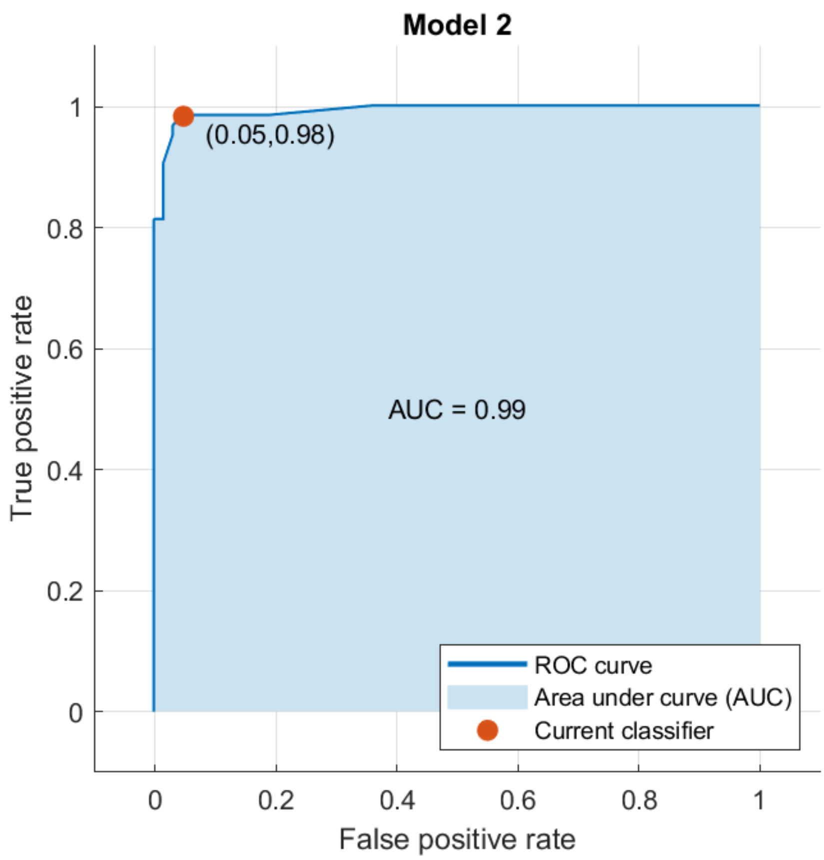


Figure 4.2.5 ROC of threshold entropy

4.3 Scatter plot and Confusion matrix

The following Figure 4.3.1 and Figure 4.3.2 are the Scatter plot and Confusion matrix of Hurst exponent respectively.

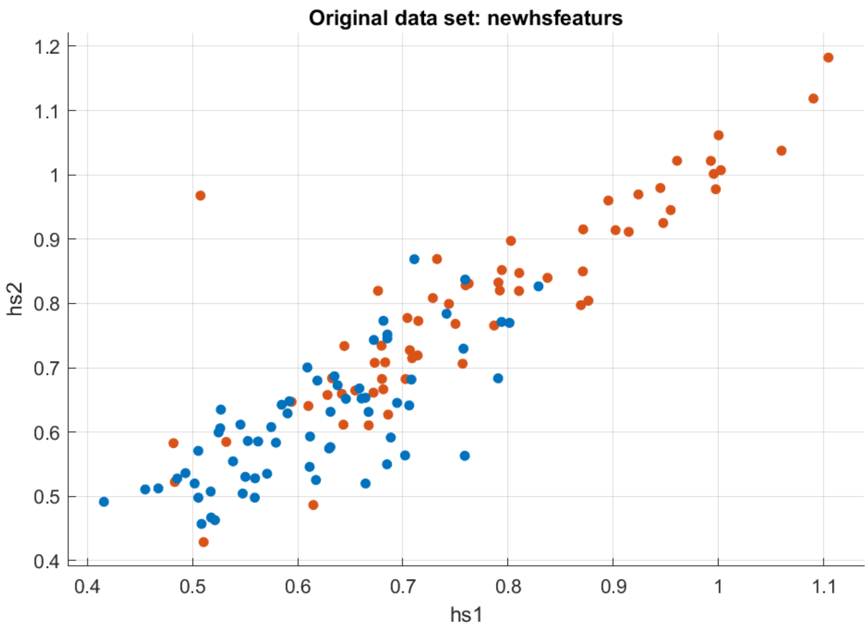


Figure 4.3.1 scatter plot of Hurst exponent

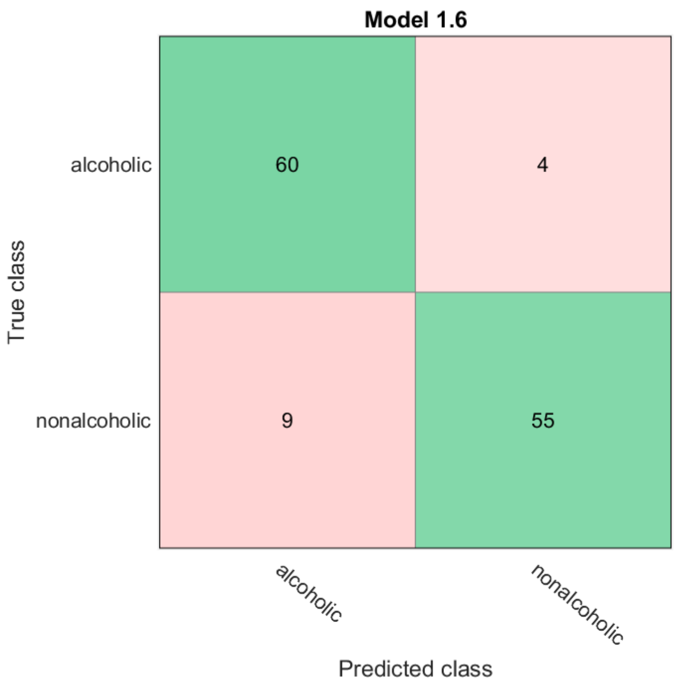


Figure 4.3.2 Confusion matrix of Hurst exponent

The following Figure 4.3.3 and Figure 4.3.4 are the scatter plot and confusion matrix of Shannon entropy respectively.

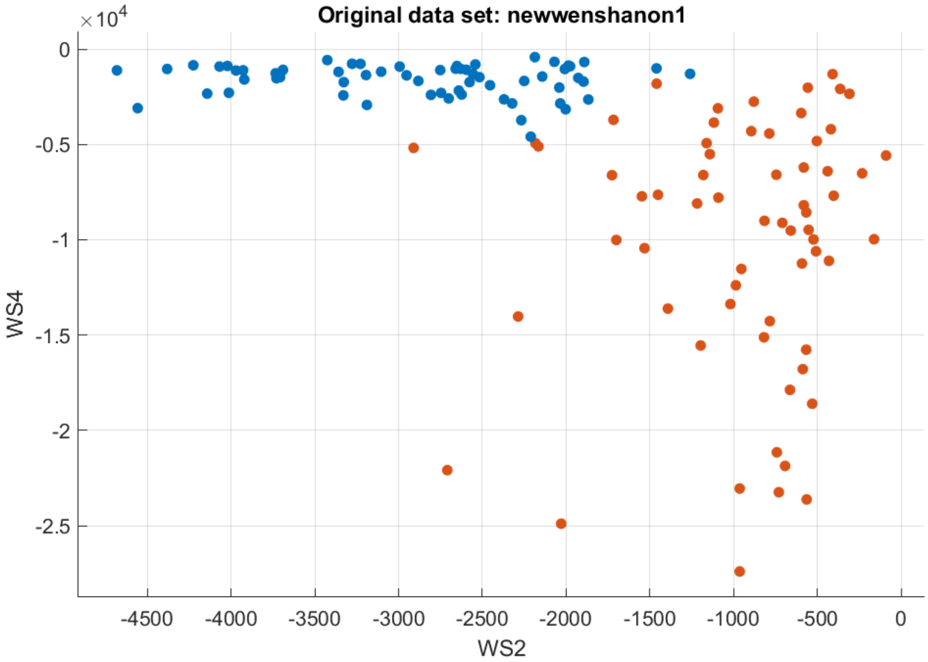


Figure 4.3.3 Scatter plot of Shannon entropy

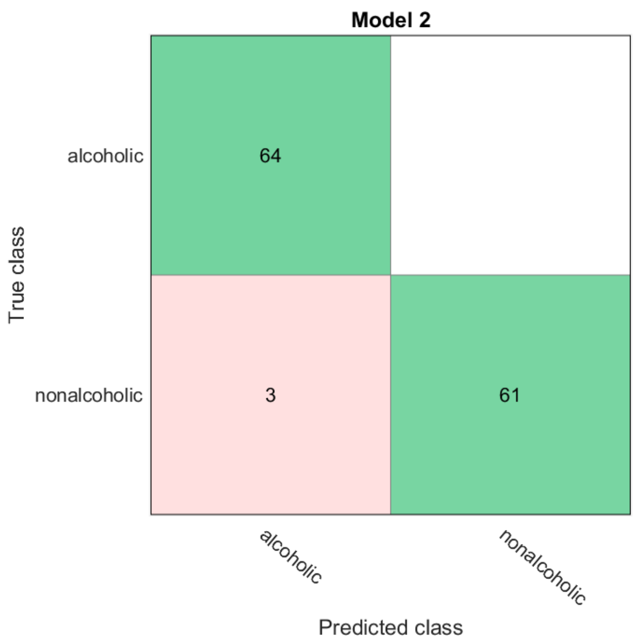


Figure 4.3.4 Confusion matrix of Shannon entropy

The following Figure 4.3.5 and Figure 4.3.6 are the scatter plot and confusion matrix of log energy entropy respectively.

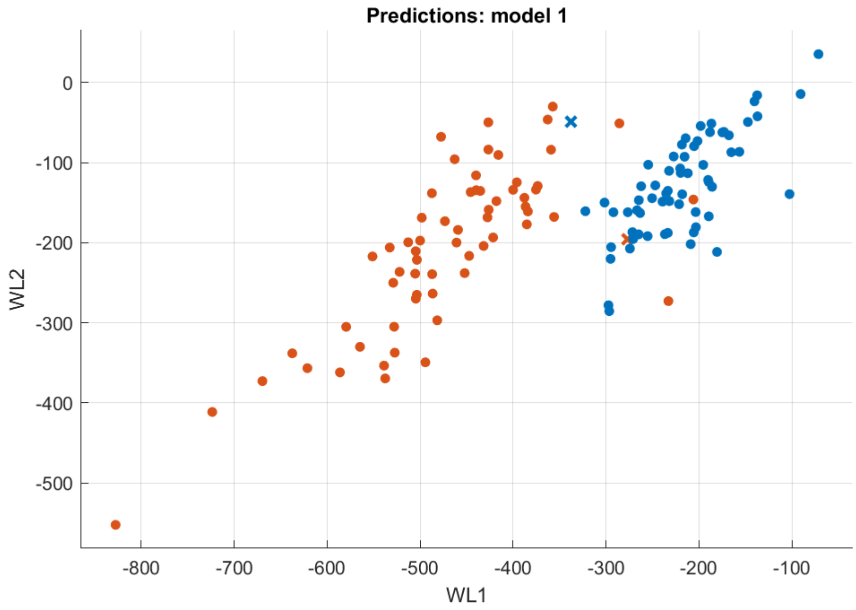


Figure 4.3.5 Scatter plot of log energy entropy

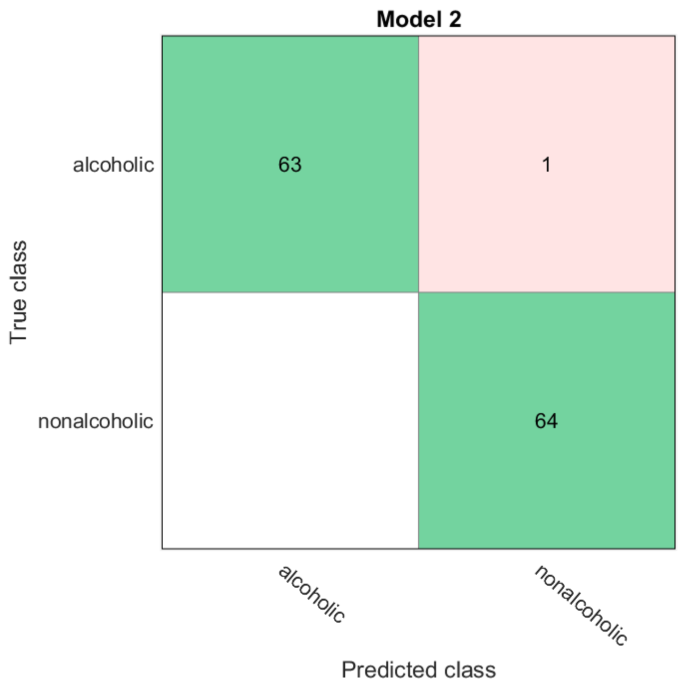


Figure 4.3.6 Confusion matrix of log energy entropy

The following Figure 4.3.7 and Figure 4.3.8 are the scatter plot and confusion matrix of norm entropy respectively.

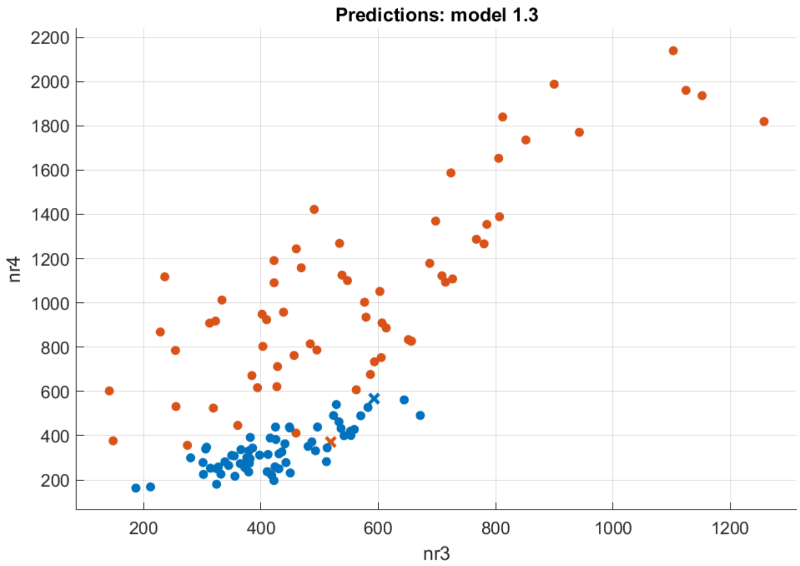


Figure 4.3.7 Scatter plot of norm entropy

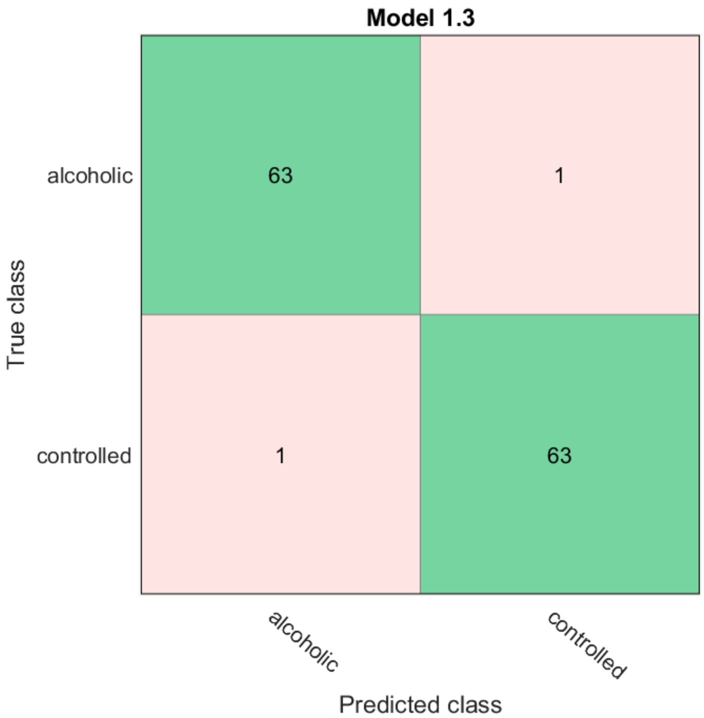


Figure 4.3.8 Confusion matrix of norm entropy

The following Figure 4.3.9 and Figure 4.3.10 are the scatter plot and Confusion matrix of threshold entropy respectively.

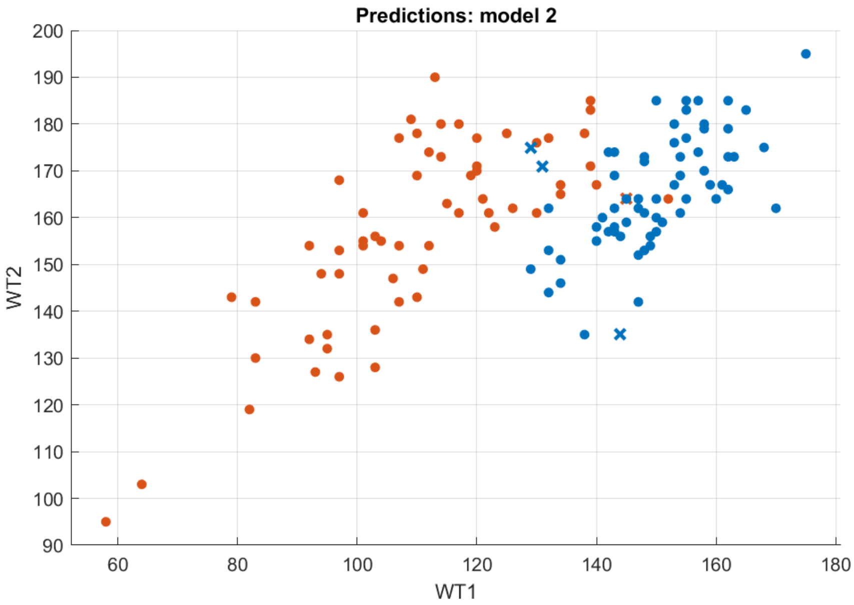


Figure 4.3.9 Scatter plot of threshold entropy

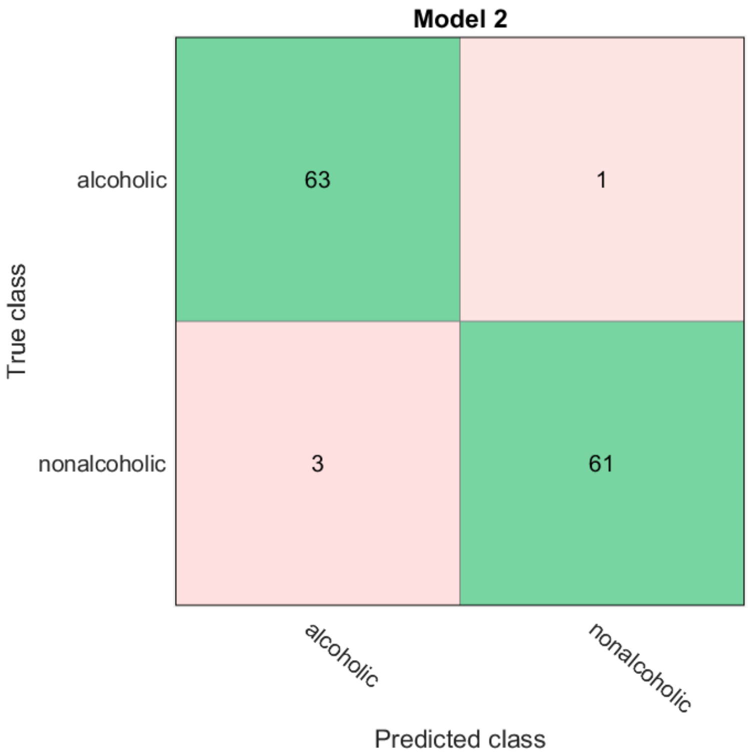


Figure 4.3.10 Confusion matrix of threshold entropy

From the above accuracy, ROC, scatter plot and confusion matrix we are getting the results as follows shown in Table 4.3.1.

Table 4.3.1 accuracy of features and classifiers

Name of the feature	**Type of classifier used**	**accuracy**
Hurst exponent	Coarse Gaussian SVM	89.8%
Shannon entropy	Logistic regression	99.2%
Log energy entropy	Linear discriminant	98.4%
Norm entropy	Medium KNN	99%
Threshold entropy	Linear discriminant	97.7%

Chapter 5

Conclusion and future scope

5.1 Conclusion

Finally, we have compared and proposed a new approach to identify the alcoholic and controlled EEG signals using TQWT and different feature extraction techniques and classifiers.

And from the above results we have got an accuracy of around 99.2% from Shannon entropy using logistic regression.

5.2 Future scope

In this study we have used the data which is collected in 1990 using old technology we can record new data using present technology and with new classifier techniques we can achieve more accurate results.

And other features like fuzzy entropy and correntropy and PCA analysis can be used from getting more knowledge about classifying alcoholic and controlled.

Hardware can be designed for the proposed method and this method can be studied for various kinds of biomedical signals.

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