Wavelet Decomposition based Automated Alcoholism Classification using EEG Signal

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***Abstract*—EEG signals convey information about a person's mental state, such as brain activity or degree of consciousness. Alcohol can also influence a person's degree of alertness. Long-term alcohol usage can cause certain patterns in EEG signals to emerge. Manual EEG signal analysis approach is difficult and time deterrent. As a result, neurologists make use of automated techniques to evaluate EEG data from their frequency sub-bands. The two separate brain states, alcoholism and normal, are identified in the current work utilizing Discrete Wavelet Transform technique for feature extraction from electroencephalogram (EEG) recordings. From the EEG signals under analysis, the sub-band coefficients using wavelet decomposition using Daubechies 7 basis wavelets are calculated. From the selected wavelet coefficients, statistical parameters including Minimum, Maximum, Average, Kurtosis, Mean square, and Standard-deviation are retrieved. In this research, this data is then sent to classifiers like Ensemble boosted trees, SVM, neural networks, and decision trees to distinguish between alcoholic and non-alcoholic EEG signals. While calculating accuracy ten-fold cross-validation is used to train the data. We discovered that the best results were provided by Ensemble boosted trees, with an Accuracy of 95.6 percent, Sensitivity of 91.3 percent, and FI score of 95.5 percent.**

***Keywords*— EEG, Alcohol, Wavelet transform, EEG features, DWT, Alpha, Beta, Gamma, Theta, Delta, Wavelet, decomposition, Alcoholism.**

I. INTRODUCTION

Alcoholism negatively impacts both a person's physical and social well-being. Alcohol intake has an impact on the overall well-being of humans and based on use patterns, these effects may be reversible or may even lead to fatal organ system collapse. Lack of coordination between the body and mind is the primary consequence of drinking, which suggests that alcoholism has an impact on brain function. Long-term impacts of alcohol misuse can alter the brain's structure causing brain shrinkage, loss of neural connections, and seizures[1]. Neuronal firing in the brain in electroencephalography (EEG) signal, offers a non-invasive way to assess brain activity. Since EEG can demonstrate alterations in brain function brought on by alcoholism, it is one of the methods that is frequently used to comprehend the effects of drinking on the brain. The example EEG sample of alcohol-subject and control-subject is shown in Figure 2 and Figure 3 respectively for 2000 samples.

Numerous research has been conducted recently for automatic alcoholism detection. Traditionally, various techniques utilizing wavelet transforms, including Continuous Wavelet Transform[2], Biorthogonal Wavelet filter banks, Empirical Decomposition[3], Dual-Tree Complex tuneable-Q Wavelet[4], and Flexible Analytical Wavelet Transform[5] are implemented. Additionally, other wavelet transforms like Stationary Wavelet Transform and Wavelet Packet Transform[6] are also utilized to extract features from EEG signals. Literature with intrinsic mode functions[7] for EEG rhythm separation is also available. To identify the Alcoholic person's EEG from normal, feature extraction is performed on the sub-bands derived. Since the wavelet transform provides greater time-frequency localization than the Fourier and Short time Fourier Transforms, it appears to be a more preferable method.

Most of the literature reviewed indicates many complex methods used for the extraction of the features and classification. Most of the work lacks clarity on the number of electrodes used and the number of samples needed. Most importantly they lack clarity in the calculations that are needed to separate frequency bands for feature extraction.

Presented below are our contributions to this paper:

1. Clear clarification on the separation of frequency bands is needed in electroencephalogram analysis with wavelet decomposition using Nyquist criteria along with levels required.
2. Only six features are used in the classification making the system simple to implement
3. The proposed methodology can be easily implemented using MATLAB for the classification
4. No Prepossessing is needed for the methods we are using thus making the system faster.

II. METHODOLOGY AND MATERIAL

This section provides a detailed explanation of the pre-processing, feature extraction, and automated alcoholism diagnosis methodology for the EEG signal which is shown in Fig. 1. The EEG signal datasets utilized for experimentation are described in the following subsections. The decomposition of the EEG signals into sub-bands using a Discrete Wavelet Transform is described. Dimensionality reduction utilizing feature extraction is performed on the EEG data. From the decomposed sub-bands, the statistical features like Mean Square, kurtosis, Minimum, Maximum, standard deviation, and Average are extracted. A quick overview of numerous classifiers, including Ensemble boosted trees, SVM, neural networks, and decision trees, which are used for testing and training from extracted features, as well as various performance evaluation measures for assessing the efficacy of learners is provided.

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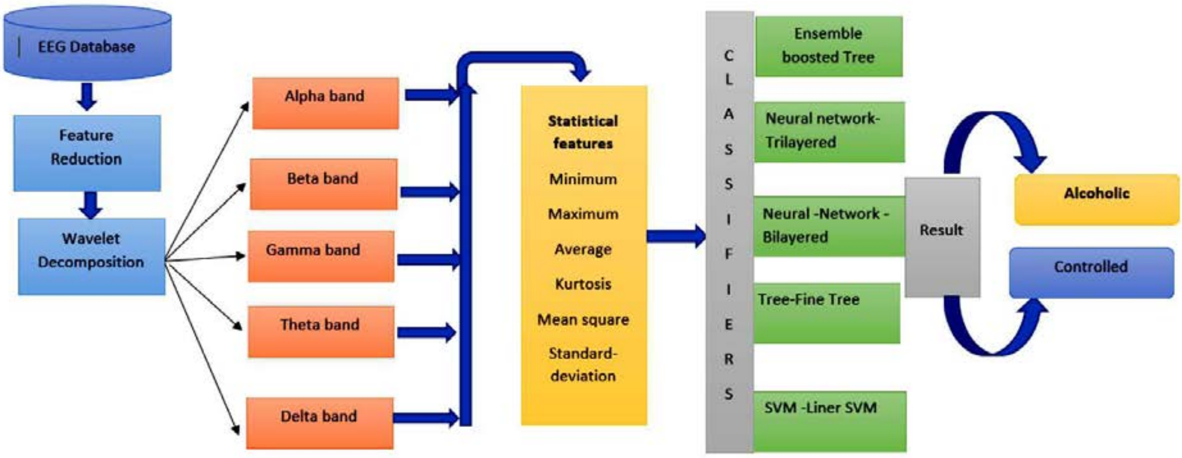

Fig. 1. Block diagram of the proposed system

A. Data set used

The UCI KDD online repository was used to get the experimental data, which is now accessible online for research https://kdd.ics.uci.edu/databases/eeg/eeg.data.html. This data comes from numerous studies looking at the correlations between genetic risk for addiction. It includes readings from 64 electrodes applied to subjects' scalps, and samples were taken at 256 Hz.

The experiment used 64-channel EEG data from the UCI Machine Learning Repository, which was captured at 256 Hz and included data from alcoholic and control subjects. Each electrode channel data contained 256 samples. A total of 450 subject data was used. 225 subjects were alcoholic and 225 were controlled.

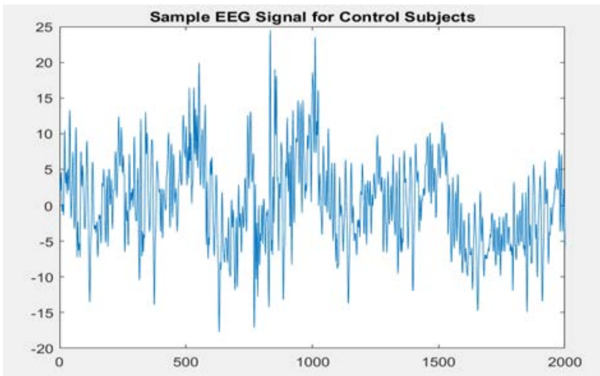

Fig. 3. Control Signal Sample for 2000 samples

B. Wavelet Decomposition

EEG signals are represented as time series data and are recorded in a microvolt. The derived frequency components of EEG signals are Delta, Theta, Alpha, Beta, and Gamma. Table 1 provides a quick overview of the EEG signals' sub-bands and their relation to the state of mind.

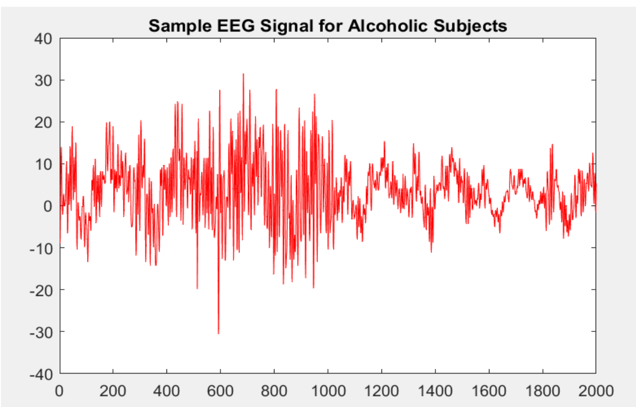

Fig. 2. Alcoholic Signal Sample for 2000 samples

With its ability to localize time and frequency, Wavelet Transform is an efficient tool for the analysis of EEG [8]. Short-time windows are used in Wavelet Transform (WT) to obtain high-frequency information whereas long-time windows are utilized to obtain a finer low-frequency resolution. Due to this, Wavelet transform offers accurate frequency information at low frequencies and accurate time information at high frequencies

TABLE 1. FREQUENCY BANDS FOR EEG SIGNAL WITH THEIR RANGE AND THEIR SUB-BAND LEVELS.

Frequency Band	Range of Frequencies	Sub-Band Levels	State of Mind
Gamma	32-64Hz	D3	Concentration
Beta	16-32Hz	D4	Active mind
Alpha	8-16Hz	D5	Restful state
Theta	4-8 Hz	D6	Drowsy state
Delta	0-4 Hz	A6	Dreamy state

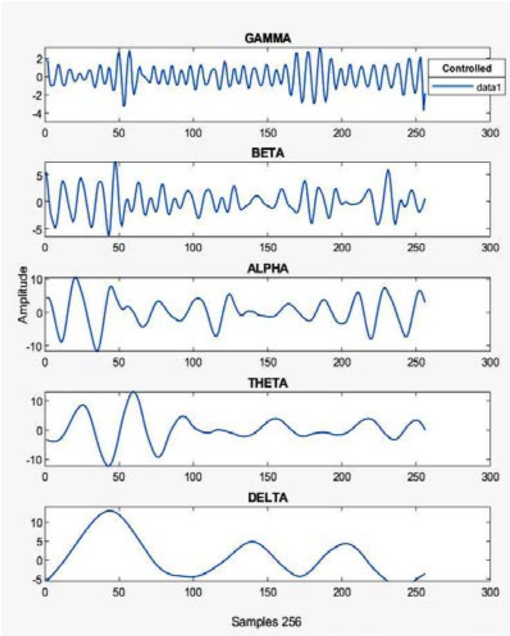

Fig. 4. Wavelet decomposition for 1 sec data for 256 samples of FP1 electrode for Control dataset

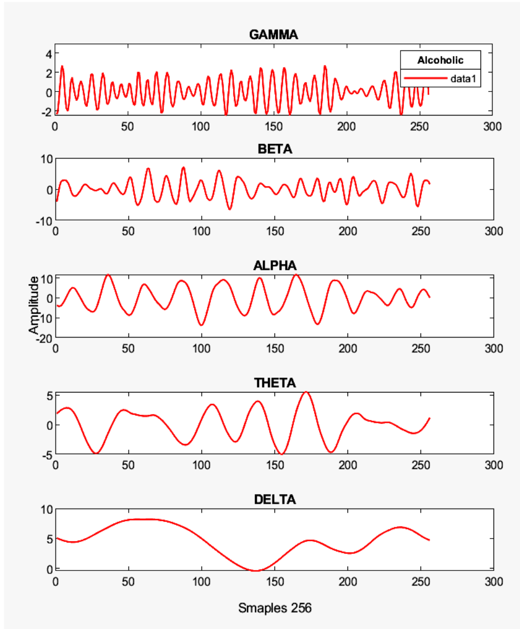

Fig. 5. Wavelet decomposition for 1 sec data for 256 samples of FP1electrode for Alcoholic dataset

C. Calculation of levels for decomposition

The number of decompositions needed to acquire the requisite frequency bands depends on how the EEG signals are divided into a set of wavelet coefficients, approximation coefficients as An, and detail coefficients as Dn, Where n is ranging from 1 to 5 in this case.

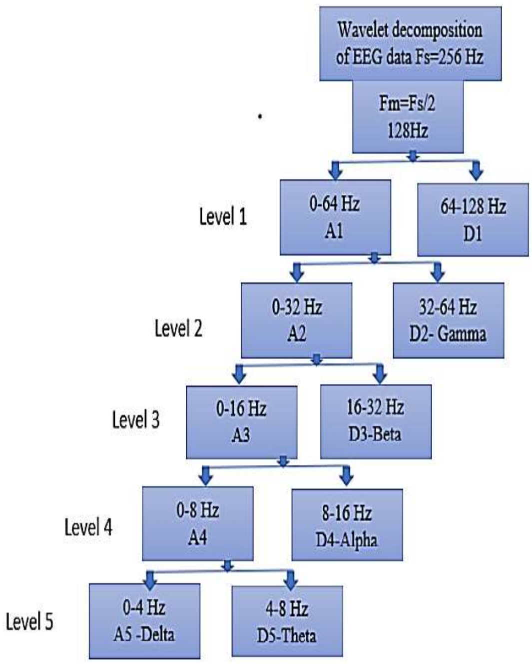

Fig. 6. Calculation of Wavelet Decomposition of EEG signal using DWT.

The Sampling Frequency of the used dataset is 256Hz. The Nyquist-Shannon theorem says that the output signals have a frequency bandwidth that is half that of the source signal, thus the level 5 Wavelet Decomposition would be needed to separate the Frequency band of the EEG signal into Alpha-band, Beta-band, Gamma-band, Theta-Band, and lastly Delta-band into the mentioned frequency bands in Table 2. For various frequency bands. Fig. 6 shows the decomposition of the EEG signal using DWT and Daubechies 7 (db7) wavelet into respective frequency bands.

D. Feature Extraction

Statistical features were obtained from each sub-band D2, D3, D4, D5 and A5 of the wavelet coefficients, i.e., minimum, maximum, Average, Kurtosis, Mean square, Standard-deviation. The EEG signal dataset's variations are described using the retrieved features. Kurtosis is a measure that shows how heavily or thinly the data are distributed in contrast to a normal distribution. In other words, high kurtosis sets of data are more likely to have huge outliers or heavy tails [9]. possess thin tails. A uniform distribution would be the worst-case scenario.

The standard deviation is computed by taking the square root of a number derived by comparing data points to the population's overall mean. The standard deviation is graphically represented as the breadth of a bell curve surrounding the mean of a data set[10]. The greater the width of the curve, the greater the standard deviation from the mean of a data collection. The standard definition of the mean square is the arithmetic mean of the squares of a collection of integers. Mean is another term for average. The sum of the column's values is divided by the sum of all values. Min and Max display the data's minimal (minimum) and maximum (maximum) values.

Feature vector for kurtosis, standard deviation, Mean square, minimum value, maximum value, and Average value are calculated. Table 3 represents the mean value for Alcoholics subjects while Table 4 represents the mean value for Control subjects. Dimensionality reduction utilizing feature extraction was performed on the time series data.

TABLE 2. Performance Metrices for Classifiers

Classifiers Used	Accuracy	Sensitivity	Specificity	Precision	FPR	Recall	F1 score
Ensemble boosted Tree	0.956	0.9130	1	1	0	0.9130	0.955
Neural network-Trilayered	0.911	0.913	0.909	0.9094	0.091	0.913	0.9112
Neural -Network -Bilayered	0.8885	0.913	0.864	0.8704	0.136	0.913	0.8912
Tree-Fine Tree	0.8895	0.87	0.909	0.9053	0.091	0.87	0.8873
SVM -Liner SVM	0.8675	0.826	0.909	0.9008	0.091	0.826	0.8618

Feature vectors are calculated for the Alpha, Beta, Gamma, Theta, and Delta bands i.e., D2, D3, D4, D5 and A5 sub-bands after the application of Discrete Wavelet Transform (DWT). Tables 3 and Tables 4 represent mean values of various statistical parameters namely: standard deviation, kurtosis, energy, maximum, and minimum extracted at fifth-level DWT decomposed sub-bands of either class.

TABLE 3. MEAN VALUES OF THE FEATURE VECTOR FOR CONTROLLED SUBJECTS

Controlled	kurtosis	Std dev	Mean square	Min	Max	Average
Gamma	13.58717	2.565716	7.316815	-20.2872	20.55391	-0.02145
Beta	9.851472	5.564213	33.0308	-32.2025	29.49914	0.029239
Alpha	6.031359	10.72552	130.2741	-46.2175	47.61374	-0.23886
Theta	7.692347	16.0849	332.3919	-78.0561	64.43793	-0.42616
Delta	8.657287	40.95055	2555.547	-175.646	186.2465	-10.5338

TABLE 4. MEAN VALUES OF THE FEATURE VECTOR FOR ALCOHOLIC SUBJECTS

Alcoholic	kurtosis	Std dev	Mean square	Min	Max	Average
Gamma	19.13139	4.643167	46.34027	-43.1044	43.727	-0.0204
Beta	10.52045	5.643983	34.55661	-36.2645	34.50659	0.041932
Alpha	9.39947	9.542795	101.7003	-45.5278	46.45925	-0.17118
Theta	6.358366	12.20709	184.3468	-50.4024	50.70601	0.539401
Delta	7.865563	34.65053	1991.01	-159.304	145.6052	-12.2986

These tables represent statistical parameters needed for classification. These features will comprise the feature vector that the classifier will use for the classification of Alcoholism.

III. MACHINE LEARNING TECHNIQUES

Classification in machine learning involves two stages: training and prediction. During the learning stage, the model is developed by utilizing the supplied training data. In the prediction phase, this model is put to use to speculate on the outcome based on the input data.

A. Ensemble Method:

In comparison to using a single decision tree, ensemble approaches integrate multiple decision trees to generate higher predicting performance. The key idea behind the ensemble model is that weak learners can be pooled together to form a strong learner.

B. Ensemble Boosted Trees:

Boosting is another ensemble method for developing a group of predictors. [11] This approach incorporates a sequential style of learning, in which learners first build simple models of the data and then go to examining the data for errors. We try to resolve the total error from the previous tree by fitting successive trees (random sample) until we get a satisfactory solution.

C. Neural Network:

A highly effective way for differentiating between alcoholics and non-alcoholics is the artificial neural network (ANN). It serves as a tool for automatic diagnosis[12]. The EEG signal is an example of extremely noisy data that can be classified using the ANN method due to the ANN's ability to generalize from a training set of samples[13].

D. Decision Tree

The decision tree is the most effective yet simple classification method [14]. We start at the root of the decision tree. The tree is built using an algorithmic method that specifies how to divide data into sections based on several criteria. Gini's index, which is the measure of impurity of a particular variable, is used as the split criteria. The lower the impurity the better it is considered. A Decision Tree is constructed to learn basic decision rules from existing data and then used to train a model that can predict the category of the target variable (training data).

E. Support vector machines

Support vector machines, work on the principle that a set of non linear data can be distinguished if mapped onto a higher dimensional feature space[15]. Searching for the best hyperplane to divide the data into two classes is done in the SVM binary classification algorithm.

IV. EXPERIMENTAL RESULTS AND DISCUSSIONS

A total of 450 subject data was used from the database. 225 subjects were alcoholic and 225 were controlled. Discrete Wavelet Transform of the samples was taken to get Alpha, Beta[16], Gamma [17], Theta, and Delta harmonics. Sub-band decomposition was done for five levels of DWT by doing calculations based on Nyquist criteria. It was concluded that D2, D3, D4, D5 and A5 would need to be calculated for extraction of Gamma[17], Theta, Beta, Alpha, and Delta wave bands. Various statistical features were derived from these sub-bands. Further, these values are given to Classifiers.The proposed classification models are shown in Table 2 are assessed against established matrices such as sensitivity, accuracy, precision, specificity, FPR, Recall, and F1 score as used in previous studies[18], The parameters set for the classifiers are shown in Table5. Comparative analysis of the proposed method with existing methodologies is presented in Table 6.

TABLE 5. CLASSIFIER PARAMETER VALUES SET IN EXPERIMENTATION

Ensemble	Ensemble type	Method	Number of learners	Number of Splits
	Boosted Tree	Ada-boost	30	20
Neural network-	Neural Network type	Activation	First layer size	Second layer size
	Bilayered	Relu	10	10
Neural Network	Neural Network type	Activation	First layer size	Second- and third-layer size
	Trilayered	Relu	10	10
Tree	Type	Max number of splits	Split criterion	Surrogate decision split
	Fine Tree	100	Gini's Diversity Index	Off
SVM	Variant -	Kernel Function-	Polynomial	Kernel Scale mode
	Liner SVM	Linear	-	Auto

Figures 7-11 represent the ROC for various classifiers used.in the current research for classification. It can be concluded that Linear SVM provide lowest result with a Accuracy of 86.7 percent, Sensitivity of 82.6 percent, and FI score of 86.18. The best results were provided by Ensemble boosted trees, with an Accuracy of 95.6 percent, sensitivity of 91.3 percent, and FI score of 95.5 percent.

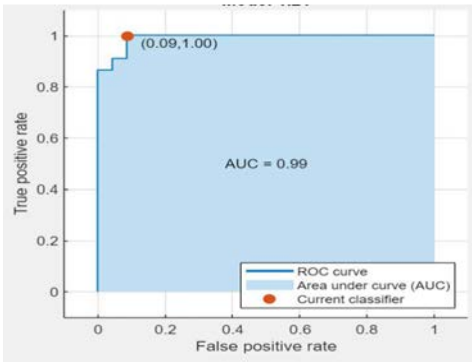

Fig. 7. Ensemble boosted Tree

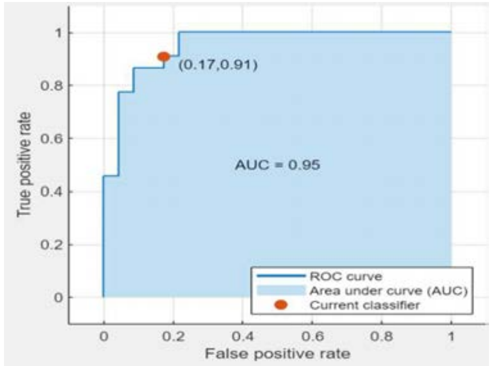

Fig. 8. Neural network-bilayered

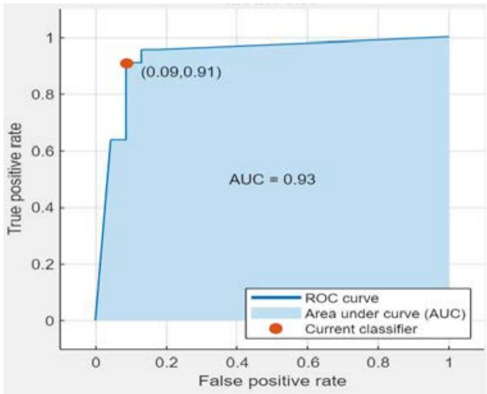

Fig. 9. Neural network-Trilayered

TABLE 6 .COMPARATIVE ANALYSIS OF THE PROPOSED METHOD.

Author	Features	Classifiers	Accuracy
U.R. Acharya et al.[19]	SPE, LLE, HOS and APE features	SVM	91.7%
O. Faust et al. [20]	Higher Order Spectra	DT, KNN,GMM, PNN , FSC, NBC	92.4%
Taran and Bajaj[7]	COV, Negentropy , AD ,entropy and IQR	LS-SVM ELM	93.75%
Gopika et al.[21]	Spectral entropy features	MLP classifier and KNN	93.08%
S. Shah et al[22]	LE features	LS-SVM,KNN	94.2%
Zhu et al[23]	Horizontal visibility graph entropy	SVM KNN	94.5%
Proposed Method	Min, Max, Average, Kurtosis, Mean square, Standard-deviation	Ensemble boosted trees, SVM, neural networks, and decision trees	**95.6%**

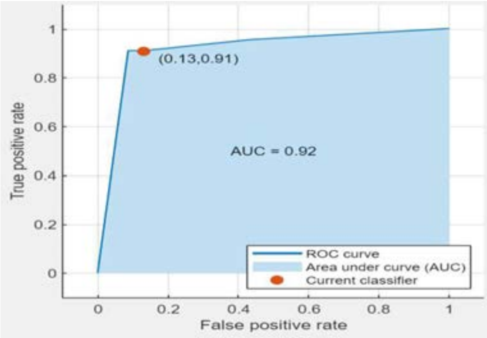

Fig. 10. SVM -Liner SVM

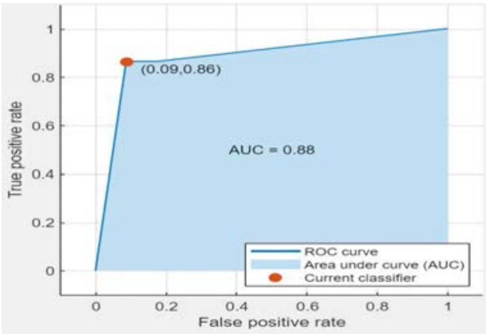

Fig. 11. Tree-Fine Tree

V. CONCLUSION

Electroencephalography signals can reveal the effects of alcohol on the brain to a significant extent. Wavelet decomposition method is used effectively to separate Wavelet Sub-bands. Using Nyquist criteria which sub-band will separate into Alpha, Beta, Gamma, Theta, and Delta bands is calculated. Six features only have been used for classification, making the system efficient. There was no pre-processing technique applied, making the system simple to implement. The difference in EEG waves as biomarker can be used to differentiate between alcoholics and non-alcoholics. The best results were provided by Ensemble boosted trees, with an Accuracy of 95.6 percent. Future works can be using methods to reduce data dimensionality for larger datasets. Also, statistical methods for feature selection can be applied to get better results.

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