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Research Article

Automated Classification of Alcoholism Using Discrete Cosine Harmonic Wavelet-Packet Transform

Aradhana Manekar[1], Lochan Jolly[2]
[1] Research Scholar and Assistant Professor, E&TC department, Thakur College of Engineering and Technology. University of Mumbai, Maharashtra, India.*
aradhana.manekar@gmail.com
Orchid ID: https://orcid.org/0009-0004-2156-4646
[2] Professor, E&TC department, Thakur College of Engineering and Technology. University of Mumbai, Maharashtra, India.
lochan.jolly@thakureducation.org
Orchid ID: https://orcid.org/0000-0003-3038-7958

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ABSTRACT

Alcoholism, characterized by excessive alcohol consumption, leads to addiction and life-threatening health complications. This not only affects an individual's physical health but also their mental and social well-being. While traditional self-reported survey-based methods often lack reliability, neuroimaging studies provide more objective and accurate data. This study introduces the Discrete Cosine Harmonic Wavelet-Packet Transform (DCHW-PT) as an innovative method for automated alcoholism detection using EEG data. To the best of our knowledge, this is the first implementation of DCHW-PT in this domain. The framework leverages DCT's computational simplicity, producing precise real coefficients, unlike the DFT. It retains HWT's benefits, such as built-in decimation and interpolation, whereas DWT requires anti-aliasing and anti-imaging filters. WPT enhances multi-resolution analysis, and the shift-invariant nature of DCHW-PT provides an effective solution for detecting transient EEG signals associated with alcoholism. Extracted features—including Hjorth parameters (Activity, Mobility, Complexity), kurtosis, standard deviation, mean, energy, and skewness—offer a comprehensive statistical EEG description. Dimensionality reduction is achieved via a t-test, and model performance is assessed using accuracy, sensitivity, specificity, and F1-score, with 10-fold cross-validation. The Ensemble-Subspace classifier achieves 98.3% accuracy, with sensitivity (98.59%) and specificity (98.01%), surpassing traditional methods and aligning with leading EEG-based alcoholism detection algorithms. Ultimately, this study demonstrates the effectiveness of DCHW-PT in alcoholism detection, setting a foundation for future research in advanced alcoholism diagnostic applications.

Keywords: EEG, Alcoholism prediction, Machine learning, Hjorth Parameters, Discrete Cosine Harmonic Wavelet-Packet Transform DCHWPT

INTRODUCTION

Alcoholism, marked by chronic and excessive alcohol consumption, can cause severe physical and psychological dependence. Addiction of alcohol often results in serious health consequences, including liver damage, neurological disorders, and various other chronic diseases. As reported by the World Health Organization, Alcohol abuse is a major global health issue which contributes to approximately 2.6 million deaths annually and accounting for 4.7% of the global disease burden. Men particularly get affected, bearing a larger share of this burden (6.9%) compared to women (2.0%) (World Health Organization, 2025). Chronic alcohol consumption not only affects physical health but also impairs cognitive function. Alcohol use Disorder (AUD) lead to memory loss, decreased visuospatial abilities, and other cognitive deficits. (National Institute on Alcohol Abuse and Alcoholism, 2025).

Traditional methods for studying alcoholism, such as surveys and questionnaires, may not always provide reliable data due to their subjective nature. Neuroimaging techniques, particularly EEG, offer a more objective approach by directly measuring brain activity (Sunkara & Rajakumari, 2023; Anuragi & Sisodia, 2020). EEG is a valuable tool for

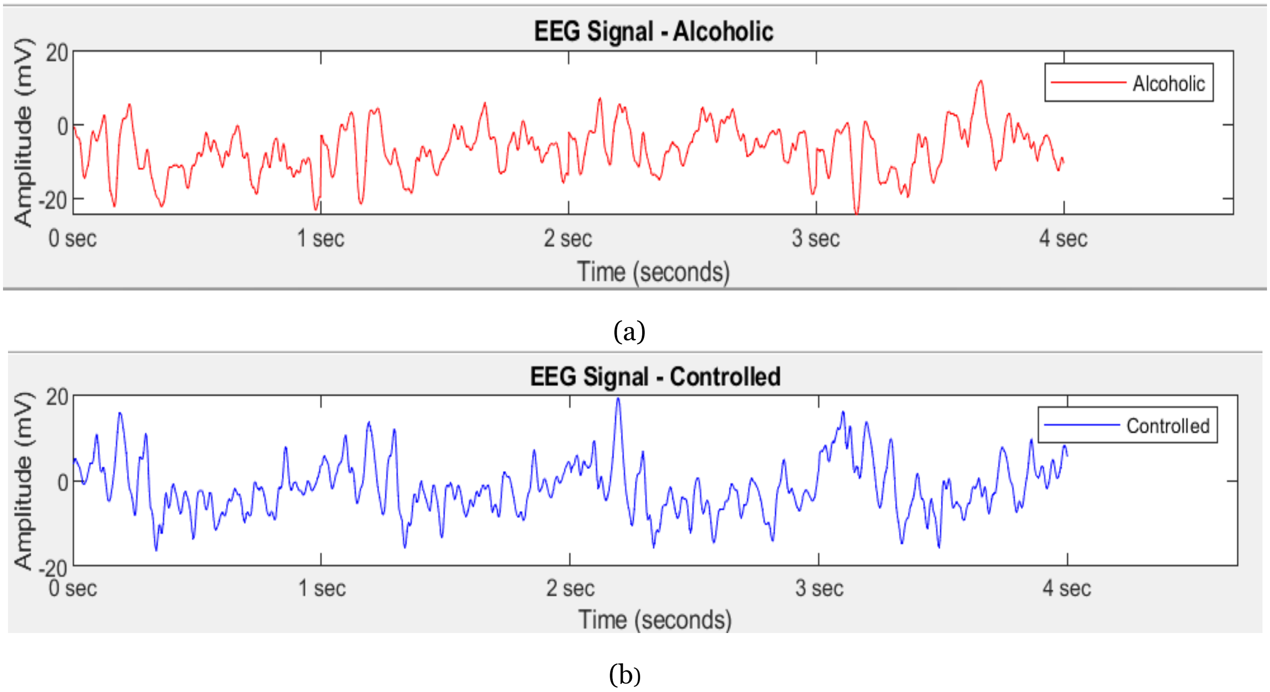


Figure 1. EEG signal samples for alcoholic and control subjects over 4 seconds (1024 samples). (a) EEG signal for an alcoholic subject. (b) EEG signal for a control subject.

monitoring brain function, but its complex, multi-channel data is often noisy, making manual analysis challenging even for experts (Manekar & Jolly, 2022; Sadiq et al., 2023). Figure 1 illustrates samples of EEG data for both alcoholic and control subjects across 1024 samples or 4 seconds. Based on the figure, it is difficult to distinguish between alcoholic and control signals only through visual observation. Here again, some automated framework is desired for accurate processing and characterization of the EEG to detect alcoholism. The proposed research addresses these above-mentioned issues by applying advanced techniques of signal processing to have better and more automated detection. For validation of our proposed method, we have made use of publicly available EEG database available in Irvine Knowledge Discovery in Database (UCI KDD) Archive.

EARLIER WORK

Various studies have employed wavelet-based approaches to extract EEG features for detecting alcoholism, with most utilizing the UCI alcoholic EEG dataset for validation. Shen et al. (2023) explored deep learning models to classify alcoholic EEG signals. Their approach utilized mutual information for connectivity analysis and Continuous Wavelet Transform (CWT).A different approach was proposed by Salankar et al. (2023), who combined Empirical Mode Decomposition (EMD), for feature extraction. Their model, tested on the UCI-KDD dataset, demonstrated high accuracy, particularly for EMD and VMD. Similarly, Bavkar et al. (2021) focused on optimizing EEG channels for alcoholism screening. Their method utilized EMD to extract features from Intrinsic Mode Functions (IMFs), followed by classification using an ensemble subspace K-NN model. The study employed the Harmony Search algorithm to identify optimal EEG channels based on accuracy and sensitivity, highlighting their biological relevance in alcoholic subjects. In a more recent study, Khandelwal et al. (2023) proposed an alternative methodology by applying oscillatory mode decomposition to EEG signal processing. The study tested multiple time window lengths to determine the optimal segment size for EEG analysis and evaluated classification performance using various machine learning models. Their results underscore the significance of signal decomposition techniques in enhancing classification accuracy. Further advancing this field, Sadiq et al. (2024) introduced a Fast Fractional Fourier Transform-Aided Graphical Approach for EEG-based alcoholism detection. Their framework incorporated multiscale principal component analysis to eliminate artifacts, followed by graphical visualization using Fast Fractional Fourier Transform coefficients. The study extracted 34 graphical features and refined them through ensembled feature selection. Among the classifiers tested, Recurrent Neural Networks (RNNs) demonstrated the potential of graph-based feature extraction and deep learning for EEG-based alcoholism detection. Application of decomposition techniques with machine learning classifiers have shown promising results so far.

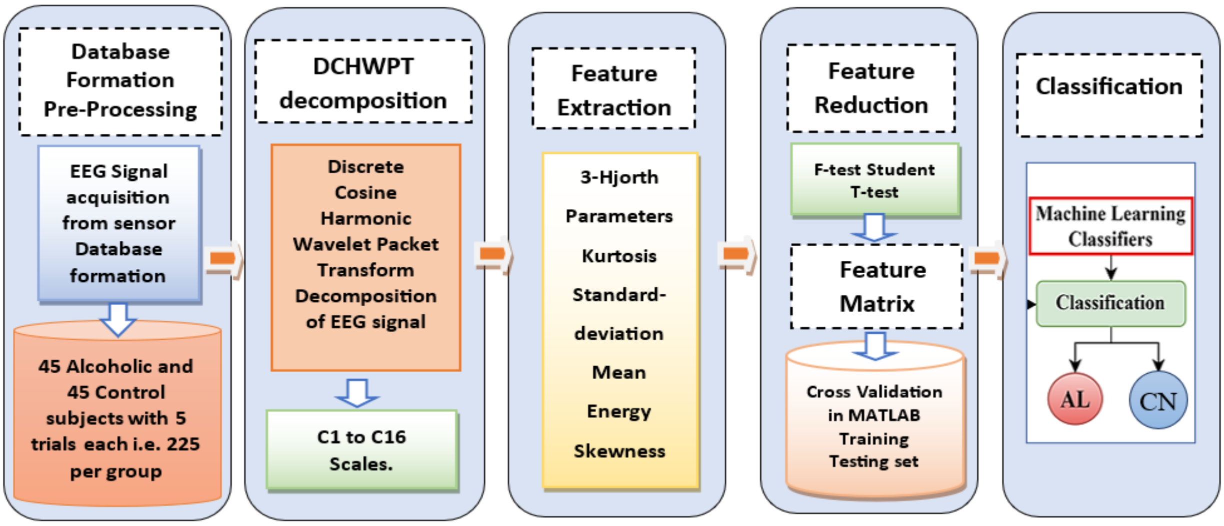


Figure 2. Methodology for DCHW-PT based automated alcoholism detection.

All these foregoing examples underscore the changing scenario of EEG-based alcoholism detection with powerful signal processing interface. Application of decomposition techniques with machine learning classifiers have shown promising results so far. Further advancements in signal processing and statistical feature selection will refine classification accuracy and robustness.

OBJECTIVES

Many methods have investigated wavelet-based and Fourier-based techniques for alcoholism detection. Though extensively used in EEG signal analysis, these methodologies pose numerous limitations, especially while dealing with sensitive applications such as alcoholism detection. The traditional schemes include Discrete Wavelet Transform (DWT) that requires decimation followed by interpolation in the sub-band decomposition; this involves band-limiting and image-rejection filters. Also, DWT suffers from a problem of shift variance, where small change in the input signal can cause significant changes in the wavelet coefficients. This has been seen as a limitation to the detection of fast-transient features in EEG signals. In addition, Fourier-based transform have leakage problems originating from abrupt data discontinuities in the Discrete Fourier Transform (DFT), that introduce additional complexity due to their coefficients being complex numbers. Additionally, many studies (Das et al., 2019; Sri, Rizal, & Fauzi, 2024; Cohen, Katz, Presil, Arbili, & Rokach, 2023; Kumari, Anwar, & Bhattacharjee, 2023).rely on complex attribute extraction and classification techniques, predominantly employing hand-crafted features and Machine Learning (ML) models, chosen based on researchers' expertise.

As a part of our contribution, we address the challenges in automated alcoholism detection by proposing a novel framework based on the Discrete Cosine Harmonic Wavelet-Packet Transform (DCHW-PT). Our approach eliminates the need for decimation and interpolation, effectively avoiding aliasing effects, while shift-invariance make it ideal for detecting fast, non-periodic EEG features. By utilizing the Discrete Cosine Transform (DCT) instead of the traditional Discrete Fourier Transform (DFT), we simplify and resolve complexity issues due to the real domain of DCT. This computational simplicity makes the DCHW-PT highly suitable for real-time EEG signal analysis. Furthermore, we introduce a straightforward and comprehensive framework that extracts seven statistical features, providing an efficient and accurate solution for Alcohol Use Disorder (AUD) detection

METHODS

The proposed DCHW-PT methodology for detecting alcoholism using EEG signals involves several well-defined steps as seen in Figure 2. Initially, EEG signals are acquired from sensors placed on the scalp of subjects, capturing the brain's electrical activity described in EEG dataset details. These signals are stored in a database containing 45 Alcoholic and 45 Control subjects, each with 5 trials, totaling 225 signals per group and 450 EEG signals overall. The EEG signals then undergo decomposition using the DCHW-PT. This implementation involves decomposition of both approximation and detail coefficients at each level. This results in a full binary tree of wavelet packet coefficients, which allows for more detailed analysis and synthesis of the signal. Post-decomposition, feature extraction is performed. The specific features extracted include the 3-Hjorth parameters, kurtosis, standard deviation, mean, energy, and skewness. These features provide a comprehensive statistical description of the EEG signals. To reduce the dimensionality of the feature space and retain only the most relevant features, the Student T test, a non-parametric statistical test, is applied. Classification was performed using the Classification Learner Application in MATLAB. For validation, 10-fold cross-validation was used to ensure the robustness and generalizability of the results. The classification stage employs various machine learning classifiers, including SVM, Neural Networks, and Ensemble methods, to classify the EEG signals into Alcoholic (AL) and controlled (CN) categories. The classifiers are trained to assess their performance in accurately distinguishing between the two categories. The comprehensive approach ensures that both the statistical properties of the signals and advanced machine learning techniques are leveraged to achieve high classification accuracy.

EEG dataset details

The publicly available EEG datasets of alcoholic and normal controlled subjects used in the present study have been taken from KDD UCI, University of California) archives (UCI Machine Learning Repository, 2017). All EEG signals are recorded according to a 10-20 electrode placement system from a total of 122 (77-alcoholic and 45-nonalcoholic) subjects with 120 trials, each with 64 channels (electrodes) forming the EEG full database. Each subject were shown standardized set of pictures from the 1980s Vanderwart and Snodgrass set. For each EEG signal measured sample length is one second and has a sampling rate of 256Hz. The artifacts, such as eye blinking muscle movements, are rejected. More details of this dataset are available at (https://kdd.ics.uci.edu/databases/eeg/eeg.data.html University of California). After data preprocessing, 225 data files from alcoholic subjects and 225 data files from control subjects were available.

Discrete Cosine Harmonic Wavelet Transform

The Harmonic Wavelet Transform (HWT), introduced by Newland (Newland, 1998).is a frequency domain signal decomposition technique. Use of rectangular window in the Discrete Fourier Transform (DFT) leads to leakage, which disperses energy across scales in the HWT, indirectly impacting neighboring scales. To address this issue, Narasimhan S.V and Shreyamsha Kumar et al. proposed the Discrete Cosine Transform (DCT) as a superior alternative to the DFT for spectral estimation within the HWT framework (Shivamurti & Narasimhan, 2011).Use of DCT (Ulicny, Krylov, & Dahyot, 2022). resolves the issue of DFT leakage. Thus, for efficient detection of alcoholism in non-stationary applications like EEG, the Discrete Cosine Harmonic Wavelet Transform (DCHWT) has been utilized (Narasimhan, Harish, Haripriya, et al., 2009).

For any signal x(t) the wavelet transform is defined as:

$$W_x(a,b) = \frac{1}{\sqrt{|a|}}\int_{-\infty}^{\infty} x(t)\Psi_s^*\left(\frac{t-b}{a}\right)dt \tag{1}$$

where b and a are translation and scaling factors and $*$ indicates the complex conjugate of ψ. These wavelets are compactly supported in time. However, there are various applications in signal analysis like EEG, where band-limited wavelet or scaling functions are more appropriate. The Mayer and Shannon wavelets are band limited wavelets and are supported compactly in frequency domain. The Shannon scaling function, i.e., the Sinc function, is given by

$$\phi(t) = \frac{sin(\pi x)}{\pi x} = \frac{e^{j\pi x} - e^{-j\pi x}}{2j\pi x} \tag{2}$$

According to Parcells Theorem the frequency domain representation of equation one can be given by

$$W_x(a,b) = \frac{\sqrt{|a|}}{2\pi}\int_{-\infty}^{\infty} X(\omega)\Psi^*(a\omega)e^{j\omega b}\, \mathrm{d}\omega \tag{3}$$

However, these functions are complex functions with limited bands. The practical computational edge of being real rather than complex in DCT renders it suitable for signal processing tasks and is thus preferred over FT. According to Parseval's theorem, the frequency domain representation of equation (3), for a real signal $x_S(t)$ and wavelet function $\psi_s(t)$, can thus be given by,

$$W_c(a,b) = \frac{\sqrt{|a|}}{2\pi} \int_{-\infty}^{\infty} X_s(\omega)\Psi_s(a\omega)\cos(b\omega)\, d\omega \tag{4}$$

The $W_c(a,b)$ is estimated from the (4) for given $X_s(\omega)$ and $\Psi_s(\omega)$ representing cosine transform of $x_s(t)$ and $\psi_s(t)$. $W_c(a,b)$ is thus the wavelet transform in the cosine domain rather than the Fourier domain. The cosine harmonic function exists only for a small set of frequencies, and it will have a null value for the rest of the frequency bands. It is given by,

$$\Psi_s(a\omega) = \begin{cases} 1, & \omega_c - \omega_o < \omega < \omega_c + \omega_o \\ 0, & -\omega_c - \omega_o < \omega < -\omega_c + \omega_o \\ 0, & elsewhere \end{cases} \tag{5}$$

Where ω_c *is* the translation parameters and ω_0 is the scaling parameter. The DCHWT decomposes the signal by grouping the coefficients of DCT [21] as depicted in Figure 3a. The Inverse Discrete Cosine Transform (IDCT) applied to the concatenated coefficients reconstructs the original signal, effectively reversing the transformation process. This ensures that the signal retains its original characteristics after transformation and processing. As depicted in Figure 3b, the IDCT successfully restores the time-domain representation of the signal, demonstrating the effectiveness of the transformation in preserving essential signal features.

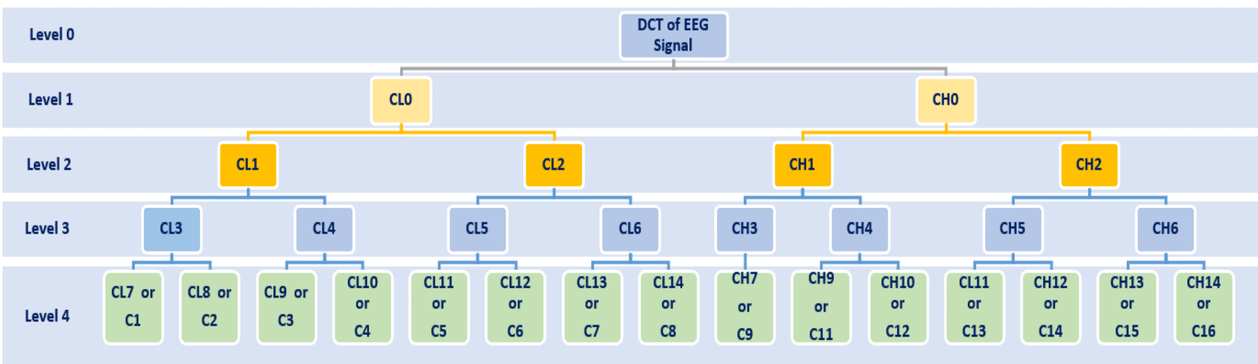
Discrete Cosine Harmonic Wavelet Packet Transform

Wavelet-Packet Transform (WPT) extends the traditional Wavelet Transform (WT) by decomposing both approximation and detail coefficients at each level. This results in a finer frequency resolution of the signal's components, making WPT particularly effective for analyzing complex, non-stationary signals like EEG.

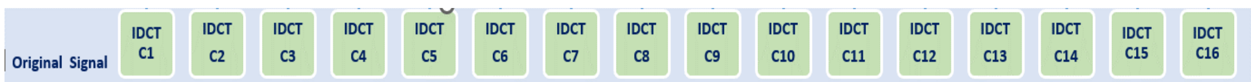
The Discrete Cosine Harmonic Wavelet-Packet Transform further enhances WPT by incorporating the Discrete Cosine Transform (DCT) and Harmonic Wavelet Transform (HWT). Leveraging DCT's computational efficiency and real-coefficient nature, DCHW-PT facilitates precise and efficient signal decomposition. Its hierarchical structure represents multi-level signal decomposition, with each node corresponding to a specific frequency band, allowing for detailed feature extraction and analysis.

Computation and Selection of Features

Features play a crucial role in pattern recognition. In the current work, various features were obtained for sixteen different sub-bands. The extracted features include the 3-Hjorth parameters: Activity, Mobility, and Complexity; kurtosis, which is indicative of the level of tailedness of the probability distribution; standard deviation, which gives

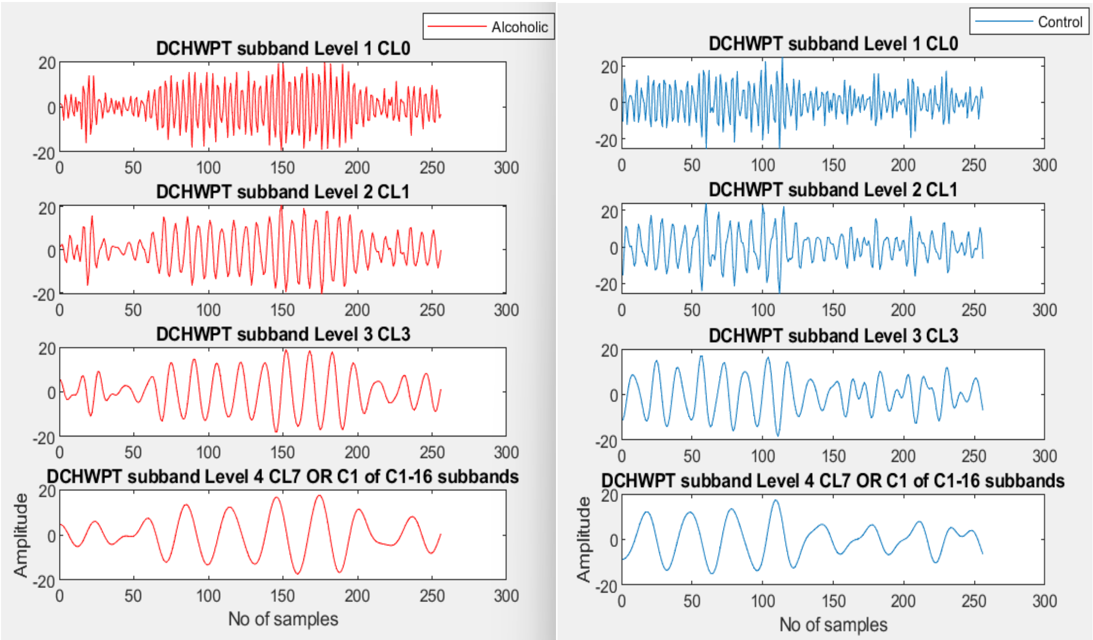


(a) DCHW-PT Signal Decomposition



(b)Reconstruction

Figure 3(a) DCHW-PT sub-band decomposition for level 4 and (b) DCHW-PT reconstruction of the signal by concatenation method.



(a) (b)

Figure 4: EEG Signal Sub-band Decomposition Using DCHWPT Across 4 Levels. (a) Shows the decomposition results for an alcoholic subject, while (b) represents the decomposition for a control subject. The approximation coefficients displayed are CL0 (Level 1), CL1 (Level 2), CL3 (Level 3), and CL7 or C1 (Level 4).

the variation or dispersion in the signals; mean energy, which represents the total energy of the signals; and skewness, which gives an indication of the level of asymmetry in the probability distribution.

Hjorth parameters is a specific set of features, which delivers useful insight into the characteristics of time-series data, primarily EEG signals. They are particularly advantageous when used in the analysis of EEG since they help quantify the signal's temporal and frequency characteristics more accurately, making it useful for observing significant physiological or pathological conditions. Each of these features provides unique insights into the characteristics of the EEG signals. On the extracted features, the student's t-test method was performed in Microsoft Excel to select significant features and reduce complexity.

Classification

Various models have been applied to classify the EEG signals of alcoholics and non-alcoholics. The Ensemble Subspace Discriminant classifier combines multiple subspace discriminant classifiers operating on random feature subsets. This enhances the robustness and accuracy by leveraging the diversity among these classifiers for better generalization in high-dimensional and complex classification tasks. Quadratic SVM employs a polynomial kernel of degree two, which enables it to represent quadratic relationships and separate classes that are not separable in the feature space. By the number of neurons in its hidden layers, a Wide Neural Network is able to captures complex patterns.

RESULTS

The results of this study are discussed in three distinct parts: **Signal Processing,** where the EEG signals were decomposed using DCHWPT; **Statistical Inferences**, which validate the extracted features using significance tests; and the **Machine Learning Component**, where classifiers were applied to differentiate between alcoholic and control subjects based on the extracted features.

Signal Processing: Signal Decomposition using Discrete Cosine Harmonic Wavelet Transform

The EEG signal is decomposed using the Discrete Cosine Harmonic Wavelet Transform (DCHWT) to obtain 16 sub-bands across 4 levels, as shown in Figure 3. Decomposition of sub-bands for both alcoholic (left, in red) and control

Table 1: F-Test: A Preliminary Step to Assess Variance Equality Before a T-Test

Statistic	Group 1	Group 2
Average (Mean)	1.3788	1.3999
Variance	0.00486	0.00247
Sample Size	225	225
Degrees of Freedom (df)	224	224
F-Value	1.9711	
One-Tailed p-value (P(F≤f))	2.52E-07	
Critical F-Value (One-Tail)	1.2414	

(right, in blue) subjects is depicted in figure 4. Zero padding is done to make the scale size same. It is nearly impossible to differentiate visually between alcoholic and control signals based on these sub-bands, highlighting the need to rely on statistical methods like the t-test and machine learning algorithms for accurate classification

Statistical Inference: Significance of the extracted features

Before performing a t-test to compare means, an F-test was conducted to determine the equality of variances between the two samples. The F-test assesses whether the variances are statistically equal, with the null hypothesis (H0) assuming no difference in variances. If the F-test indicates equal variances (p>0.05) a Two-Sample Assuming Equal Variances T-test (pooled t-test) is appropriate. Conversely, if the F-test suggests unequal variances (p≤0.05), Welch's t-test is employed, as it does not assume equal variances and provides a more accurate analysis in such cases.

Statistical parameters for performance analysis (F-test and T-test)

After decomposing the EEG data into DCHWPT coefficients, a F-test was conducted to evaluate whether there is a statistically significant difference in the variance between the Alcoholic and Control groups. On sample basis, an F-test for the Hjorth Mobility feature performed prior to the t-test is shown in Table 1, to check whether the variances of the Alcoholic and Control groups are equal for the Hjorth Mobility feature. The Alcoholic group showed a variance of 0.0049, while the Control group had a variance of 0.0025. The test yielded an F-statistic of 1.9711 and a p-value of 2.52E-07. This extremely low p-value, well below the significance level of 0.05, indicates a statistically significant difference in the variances between the two groups. Additionally, the F-statistic exceeded the critical value of 1.2414, further supporting the rejection of the null hypothesis that the variances are equal. Therefore, the assumption of

Table2. T-test (Two-Sample Assuming Unequal Variances) in Microsoft Excel, performed on the Hjorth Mobility feature for two different groups of Alcoholic and Control

Statistic	Group 1	Group 2
Average (Mean)	1.3788	1.3999
Variance	0.00486	0.00247
Sample Size	225	225
Hypothesized Mean Difference	0	
Degrees of Freedom (df)	405	
t-Value	-3.6969	
One-Tailed p-value	0.000124	
Critical t-Value (One-Tail)	1.6486	
Two-Tailed p-value	0.000248	
Critical t-Value (Two-Tail)	1.9658	

Table 3a: P-values for all extracted features on scales D1 to D8 using DCHW-PT method for Alcoholic and Normal EEG signals using Student T Test

	Kurtosis	Std dev	Mean Energy	Skewness	Hjorth Activity	Hjorth Complex-ity	Hjorth Mobility
C1	0.160916	1.81E-05	0.001768	0.152425	0.001767	6.52E-07	0.00016
C2	0.194448	7.22E-05	0.000798	0.114822	0.000658	9.83E-13	1.07E-13
C3	0.444728	0.029438	0.002471	0.423115	0.001751	9.29E-10	5.38E-12
C4	0.058625	0.009027	0.004702	0.580411	0.002412	0.002599	0.000364
C5	0.274415	9.03E-10	3.91E-10	0.407548	7.29E-10	5.49E-08	8.98E-08
C6	0.080961	7.57E-10	9.73E-11	0.219139	1.02E-10	5.26E-10	8.78E-16
C7	0.284415	3.20E-08	1.75E-08	0.680646	1.75E-08	9.63E-09	8.56E-16
C8	0.294415	0.008027	0.003702	0.902501	0.001412	1.06E-15	1.70E-18

unequal variances was confirmed, and the subsequent t-test was conducted under the unequal variances assumption to ensure the validity of the analysis. Group Variable 1 being alcoholic and 2 being control.

Table 2 presents the results of a t-test (Two-Sample Assuming Unequal Variances) conducted using Excel, aimed at comparing the Hjorth Mobility feature between two distinct groups—Alcoholic and Control. The analysis reveals a statistically significant difference in the means of Hjorth Mobility between these groups. The Alcoholic group shows a mean value of 1.3788 with a variance of 0.0049, while the Control group has a slightly higher mean of 1.3999 and a smaller variance of 0.0025. Both groups have 225 observations. The two-tailed p-value is 0.000248, which is far below the conventional significance threshold of 0.05, indicating that the difference between the two groups is statistically significant. Therefore, the null hypothesis, that there is no difference between the Hjorth Mobility of Alcoholic and Control groups can be rejected. This finding underscores the distinct difference in Hjorth Mobility between the two categories, suggesting that this feature could play a crucial role in distinguishing Alcoholic from Control subjects based on EEG analysis.

Feature Analysis and Selection for EEG-Based Alcoholism Detection

As noted from table 3a and table 3b, Hjorth parameters demonstrated strong discriminative capability between the alcoholic and normal EEG signals. Other features also showed very low p-values, suggesting their effectiveness in distinguishing the two classes. These metrics, such as Hjorth parameters, standard deviation, and mean energy, consistently exhibit significant differences and play a crucial role in classification, making them valuable for identifying alcoholism through EEG signal analysis. Features with p-values below 0.05 were selected for further classification.

Table 3b: P-values for all extracted features on scales D9 to D16 using DCHW-PT method for Alcoholic and Normal EEG signals using Student T Test

	Kurtosis	Std dev	Mean Energy	Skewness	Hjorth Activity	Hjorth Complex-ity	Hjorth Mobility
C9	0.211718	0.007027	0.026189	0.109066	0.000412	1.27E-16	9.44E-20
C10	0.080441	6.57E-10	0.002702	0.115619	0.000597	7.51E-26	2.57E-28
C11	0.115418	0.005027	0.005067	0.393124	0.006202	1.08E-24	3.43E-23
C12	0.299625	0.001060	0.001633	0.143234	0.001873	7.70E-26	1.94E-24
C13	0.068366	0.009664	0.000179	0.403124	0.000179	2.07E-24	4.50E-23
C14	0.591533	0.028566	0.000538	0.113124	0.000552	8.69E-25	2.67E-23
C15	0.392571	0.006872	6.90E-05	0.868979	6.97E-05	2.78E-25	1.79E-24
C16	0.348287	0.015693	0.000164	0.423124	0.000164	1.41E-24	3.33E-23

Table 4 Various classifiers Parameters set for the experiment

Classifier	Parameters	Values	Settings
Medium Gaussian SVM	Kernel Function	Gaussian	Box Constraint: 1
	Kernel Scale Mode	Auto	Multiclass Method: OVO
Wide Neural Network	Network Type	Medium	Activation: ReLU
	Layer Size	First Layer: 100	Subsequent Layers: 10
Quadratic SVM	Kernel Function	Quadratic	Box Constraint: 1
	Kernel Scale Mode	Auto	Multiclass Method: OVO
Ensemble -subspace discriminant	Ensemble Method	Subspace	Learner Type: Discriminant
	Max Splits	20	Learners: 30
Narrow neural network	Network Type	Advanced	Activation: ReLU
	Layer Size	First Layer: 10	Subsequent Layers: 10

Machine Learning: Performance Metrics and Hyperparameter Optimization of Classifiers

An overview of the performance metrics across different classifiers is offered by Figure 5. The Ensemble-subspace discriminant classifier stands out as the most effective model with an accuracy of 98.3%, surpassing all other classifiers in overall performance. Notably, it exhibits the highest sensitivity (True Positive Rate) at 98.59% and specificity (True Negative Rate) at 98.01%, indicating its proficiency in accurately identifying both positive and negative cases. On the other hand, the Wide Neural Network (ANN-. Wide) also performs admirably, achieving an accuracy of 97.2%. It strikes a good balance between sensitivity (98.07%) and specificity (96.37%), showcasing its robustness in handling a wide range of cases.

	Accuracy	Sensitivity	Specificity	Precision	F1 Score
Ensemble -subspace	0.983	0.9859	0.9801	0.98	0.9722
ANN-Wide	0.972	0.9807	0.9637	0.963	0.9717
SVM -quadratic	0.963	0.9584	0.9667	0.967	0.9627
Ensemble- Bagged	0.958	0.9584	0.958	0.958	0.9582
ANN-Narrow	0.954	0.948	0.9495	0.949	0.9485
SVM-medieum	0.947	0.9408	0.9524	0.953	0.9469

Ensemble -subspace ANN-Wide
SVM -quadratic Ensemble- Bagged
ANN-Narrow SVM-medieum

Figure 5 Performance Metrics of DCHW-PT-Based Classification Using Various Classifiers

Table 5. Comparison table with the latest state of the art Implementation

	Contributors	State of the art technology used	Accuracy
1	Subrata Pain, Saurav Roy, Monalisa Sarma, Debasis Samanta (2023)	Combined EEG features and brain connectivity in a graph and classified using a Graph Neural Network (GNN) and Phase Lag Index (PLI).	93.28%
2	Koliqi, R., Fathima, A., Tripathi, A.K., et al. (2024)	Nonlinear dynamics theory to EEG signals with CEHOC optimization and various entropy features for SVM classification.	95.89%
3	Rajaguru, H., Vigneshkumar, A., & Gowri Shankar (2023)	Heuristic Classifiers with Stochastic Gradient Descent Technique for Tuning the Hyperparameters	96.31%
4	M. T. Sadiq, A. Yousaf, S. Siuly, and A. Almogren (2024)	Multiscale principal component analysis and ensembled feature selection with n0eural network for EEG Alcoholism Detection	97.50%
5	Proposed Method: Aradhana Maneker & Lochan Jolly (2025)	Discrete Cosine Harmonic Wavelet-Packet Transform with kurtosis, standard deviation, mean energy, skewness, Hjorth activity, complexity, and mobility features and Student T test with Ensemble subspace classifier	98.3%

Hyperparameter settings for various machine learning models, including SVM and neural networks are illustrated in Table 4. Key parameters include kernel functions (Gaussian and quadratic for SVM), box constraint levels, activation functions (ReLU), layer sizes, and multiclass classification methods (One-vs-On and Second-and-Third-layer size for neural networks), as well as learner types and the number of learners for ensemble methods

Comparative Analysis of State-of-the-Art EEG-Based Alcoholism Detection Techniques

Comparative analysis of the latest state-of-the-art techniques for EEG-based alcoholism detection is offered by Table 5. It highlights various advanced methodologies that have been developed, utilizing a wide range of approaches including Empirical Mode Decomposition, nonlinear dynamics theory, graph-based neural networks, and multiscale principal component analysis. Each of these methods focuses on feature extraction, optimization, and classification, achieving high classification accuracy in distinguishing between alcoholic and non-alcoholic EEG signals. Our proposed Discrete Cosine Harmonic Wavelet Packet Transform methodology stands out in the comparison table, demonstrating superior performance with an accuracy of 98.3%.

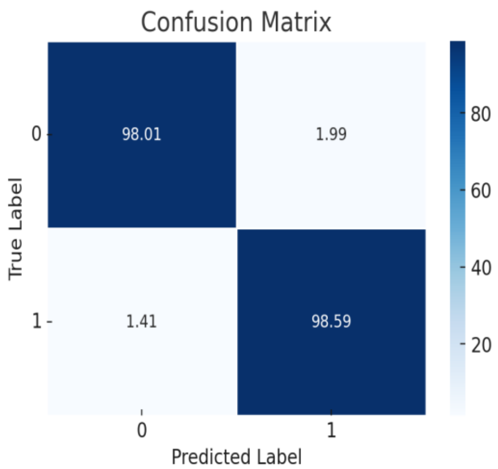


Figure 5 Confusion metrics for Ensemble subspace classifier giving accuracy of 98.3%.

CONCLUSION AND FUTURE WORK

Alcoholism is a serious societal issue, affecting individuals and communities by straining healthcare systems, disrupting families, and reducing economic productivity. Our method aims for high accuracy and unbiased classification, using neuroimaging techniques that offer significant advantages over traditional survey methods. The Discrete Cosine Harmonic Wavelet Packet Transform method stands out by effectively capturing transient features in EEG signals. This application marks the first instance, to our knowledge, of utilizing DCHW-PT for EEG based Alcoholism detection. The proposed framework yields outstanding classification accuracy with Ensemble subspace classifier. Extraction of features such as kurtosis, standard deviation, mean energy, skewness, and Hjorth activity, complexity, and mobility parameters and feature selection by Student's T-test improves and cross-validation (10-fold) strengthens the approach. Moreover, the DCHWPT framework provides computational advantages in terms of shift invariance and lower complexity due to which it is more computationally efficient for real-time applications than traditional wavelet- or Fourier-based methods. This study introduces a promising EEG-based framework to detect alcoholism and the approach can be of use in future for many other neurological disorders like Epilepsy and Alzheimer's disease. In improving outcomes for individuals suffering from neurological and psychological conditions with particular emphasis on addressing the global challenge of alcoholism, our research advances the available EEG analysis techniques

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