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Deep and Statistical Features Classification Model for Electroencephalography Signals

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ABSTRACT

People strive to make sense of the complex electroencephalography (EEG) data generated by the brain. This study uses a prepared dataset to examine how easily people with alcohol use disorder (AUD) could be distinguished from healthy people. The signals from each electrode are connected to one another and are first represented as a single signal. The signal is then denoised through variation mode decomposition (VMD) during the preprocessing stage. The statistical and deep feature extraction phases are the two subsequent phases. The crucial step in the suggested strategy is to classify data using a combination of these two unique qualities. Deep and statistical feature performance was evaluated independently. Then, using the eigenvectors created by merging all of the collected features, classification was carried out using our DSFC (Deep - Statistical Features Classification) model. Although the classification accuracy rate using only statistical features was 81.2 percent and the classification accuracy rate using only deep learning was 95.71 percent, the classification accuracy rate utilizing hybrid features created using the suggested DSFC technique was 99.2%. Therefore, it can be proven that combining statistical and deep features can produce beneficial results.

1. INTRODUCTION

Alcohol use disorder (AUD) is a medical illness characterized by an inability to regulate alcohol consumption despite negative effects on one's health and employment [1]. Although the frontal lobes are the area of the brain that are evaluated the most, AUD also seems to be linked to neurocognitive deficiencies brought on by the emergence of neurological disorders in other regions of the brain. Medical, neurological, psychological, and social issues might result from alcohol's damaging effects when it is consumed frequently and long-term [2, 3].

Although the negative impacts of screening and managing AUD patients have decreased, these policies are subjective and heavily rely on the opinions of the people who participated in the surveys. Due to unique conditions, screening mechanisms in individual notifications may result in incorrect and incomplete notifications as well as inaccurate outcomes. With the study of neurological data, it can be demonstrated that there are instances where AUD screening and evaluation are successful. For instance, it has been demonstrated that magnetic resonance imaging (MRI) can identify diseases such frontal atrophy brought on by AUD [3]. It is advised that this system be created with the understanding that the diagnosis of AUD will be aided by the use of EEG data to support these, as well as the findings generated by individual scanning, feedback, questionnaire, and MRI.

This study explores whether it is possible to distinguish between people with AUD and healthy people by analyzing EEG data. Consequently, the suggested method will be used in research on a pre-made EEG signal dataset that was recorded for these two groups. Both the problems to be solved and the steps for analysis are provided:

• To make EEG signals available to the technique, pre-processing is necessary.
• The features must be extracted from each signal packet, and an eigenvector must be created as well.
Every data packet needs to have a spectrogram produced.
• Extraction of deep eigenvectors from spectrograms using deep learning (DL).
• Generating and subjecting the hybrid eigenvector to classification.

1.1 Proposed approach

The alcoholic EEG dataset was used for this experiment [4]. The datasets include EEG signals from AUD and controls, two different groups of persons. The data from each group will be moved to files with the same name as the group names after being formed.

The signals from each electrode will first be combined and processed as a single signal. After the dataset has been rendered usable, the pre-processing approach ensures that the data are noise-free. Variation Mode Decomposition (VMD) is carried out in order to minimize possible noise in EEG recordings. EEG signal recordings lasting one second are examined for features. Mean, minimum, maximum, kurtosis, skewness, median, standard deviation, and energy are among the retrieved features. A statistical eigenvector will be produced from the features that need to be calculated. The spectrograms that will be used in the DL phase will be produced using the time-frequency values of each signal. The DL network classifies images of spectrograms. A deep eigenvector will be used to store the deep features that were obtained from the fully connected layer during the classification process. Both methods will produce features, which will then be combined to create a hybrid eigenvector. Utilizing classification algorithms, the generated hybrid eigenvectors are divided into categories.

1.2 Related works

P300 Event-dependent Brain Potential is hypothesized to represent neuroelectric activity related to cognitive processes like distraction and immediate memory activation when EEG data are evaluated. According to Sutton et al.'s research, humans develop a positive potential in their brains after concentrating on a stimulus for 300 milliseconds [5]. Recent research, however, has revealed that P300 is frequently impacted by biological processes, such as changes in subjects' levels of arousal [6]. A new convolutional neural network (CNN) model was proposed by Li et al., who primarily used the principal component analysis method to reduce noise and speed up the process. As a result, they claimed that their results were 95% accurate [7]. To generate EEG signal category-dependent representations, Zheng et al. proposed the use of Long Short-Term Memory networks (LSTMS-B) and integrated DL and collective learning. ResNet-based regression was trained to assess the application's meaning using the original image and the associated EEG representations that were previously learned. They achieved a classification accuracy of 90.16 percent overall [8]. In addition to addictions, in some conditions such as sleep disorders and seizure, EEG signals are used and applications are developed to ensure their detection [9, 10].

Numerous studies have made use of the alcoholic dataset. Principal component analysis (PCA) was used by Sun et al. [11] to analyze the EEG data before using the Wavelet transform to divide the signals into five frequency bands. By comparing the power spectra of people with AUD with controls in the five primary frequency bands, it is evident that people with AUD have higher theta and delta power. Alcoholics have much lower alpha power, whereas controls have somewhat higher power in the gamma and beta bands. With the use of the power spectrum of the Haar mother wavelet and PCA, Nazari Kousarrizi et al. [12] retrieved features and reduced features. They were successful in classifying with 94.67 percent and 98.83 percent accuracy using support vector machines (SVM) and neural networks, respectively. They classified with 94.67 percent and 98.83 percent accuracy using SVM and NN, respectively. A system that uses nonlinear methods to separate AUD brain signals from regular signals has been proposed by Acharya et al. [13]. They demonstrated significant differences in the dynamic properties of the control and AUD EEG signals using nonlinear features such as Large Lyapunov Exponent (LLE), Approximate Entropy (ApEn), Sample Entropy (SampEn), and four other Higher Order Spectra (HOS), and they classified the signals with SVM, achieving an accuracy rate of 91.7 percent. An EEG signal categorization system with time-frequency representation, co-creation of histograms of Directed Guardians (CoHOG), and classifier-based Sparse Display (SRC) was proposed by Bajaj et al. [14]. They used the non-negative least square classifier (NNLS) as the classifier and got results that were 95.63% accurate. Zubair [15] created a way to use the Sliding Singular Spectrum Analysis approach to evaluate EEG signals. They isolated the EEG signals using this technique after first cleaning the signals of noise. Following these procedures, they used classification techniques to identify the AUD signals.

1.3 Contributions

The most crucial component of this strategy is the use of a hybrid eigenvector. In the deep learning (DL) model, a hybrid vector is produced by combining the values obtained from the statistical feature calculation with the deep features collected from the fully connected (FC) layer into a single vector. As a result, systems using simply statistical features or deep learning can reach higher accuracy levels. When running the application on the right data, the VMD utilized in the non-preprocessing stage adds a specific value. It makes sure that any noise that might be present in the EEG signals is eliminated and that only clean signal data is used for the operation.

The proposed method and the model's block diagram are provided in Section II. Here are the step-by-step theoretical details of the suggested approach. A designation of the scenario is also provided. The evolution of the selling performance function is then described. The experimental findings are provided in Section III in accordance with the data employed. Results are contrasted individually for each classification algorithm, and performance and error analyses are conducted. The conclusion is provided in Section IV, which also covers results and potential future advancements.

2. METHODOLOGY

The DSFC technique for classifying EEG signals was put out in this study. The block diagram in Figure 1 shows the current strategy, which consists of mixing and classifying eigenvectors derived from both DL and statistical methods. The recorded signals from each electrode in this method are first merged to create a single signal.

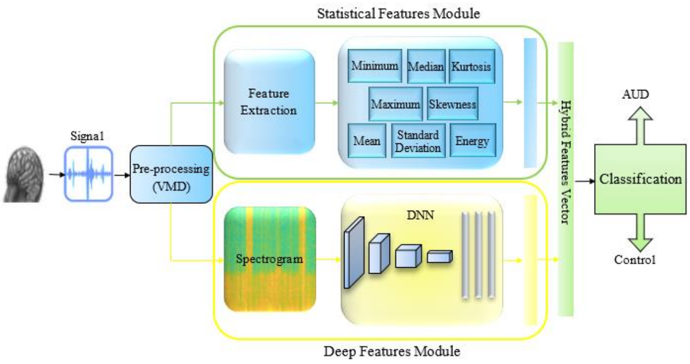

Figure 1. The block diagram for the new DSFC model

2.1 Signal denoising with VMD

In the pre-processing stage, VMD initially denoises the signals in the EEG dataset. A real-valued signal is divided into a small number of sub-signals and phases using the VMD method [16]. In this non-recursive signal separation technique, each sub-signal is generated around the center frequency. The bandwidth of each mode is evaluated in three steps. The Hilbert transform is used in the first stage to determine the frequency spectrum of each mode. In the second stage, each mode is shifted to the fundamental center frequency using its frequency spectrum feature. In the third step, the demodulated signal's Gaussian smoothness is used to calculate the mode's bandwidth [16]. the demand that outcomes be characterized as a variational problem. The following constrained optimization problem is addressed by VMD:

$$\underset{\{s_k\}\{w_k\}}{min}\left\{\sum_{k=1}^{K} \| \partial_t \left[\left(\partial(t)+\frac{j}{\pi t}\right) * s_k(t)\right] e^{-jw_k} \|_2^2\right\} \tag{1}$$

$$\sum_k u_k = f \tag{2}$$

where, u_k is the k-th decomposed mode; w_k is the k-th mode signal's center frequency; $f(t)$ is the input signal; $\left[\left(\partial(t)+\frac{j}{\pi t}\right) * M_k(t)\right]$ is the Hilbert transform of $u_k(t)$. The exponential term e^{-jw_k} pushes each mode's frequency spectrum to the center frequency [17, 18]. The augmented Lagrangian can be used to solve the constrained optimization problem.

$$\begin{aligned} L(\{u_k\},\{w_k\},\lambda) = \alpha &\sum_k \|\partial_t \left[\left(\partial(t)+\frac{j}{\pi t}\right)\right. \\ &\left. * M_k(t)\right] e^{-jw_k} \|_2^2 \\ &+ \left\| f(t) - \sum_k u_k(t) \right\| \\ &+ \langle \lambda(t), f(t) - \sum_k u_k(t) \rangle \end{aligned} \tag{3}$$

For the decomposition, initial parameters must be established. The parsing number w_k, the data fit constraint compensation parameter α are the parameters in question [17].

2.2 Extracting signal features

The features of the denoised signal are calculated separately for each sample, producing an eigenvector. The mean feature of the signal can be calculated by:

$$\mathrm{a} = \frac{1}{n}\sum_{k=1}^{n} \mathcal{X}_k \tag{4}$$

where, a is the mean; n is the number of signal samples; x is the value of the sample in the signal; k is the sample number.

The median is the value that divides a signal in half when the values are sorted in ascending order. The middle value in the sorted array is the median value when the index number is odd, and the median value is the average of the two middle values when the index number is even. The steps in the calculation are as follows;

The index number is odd, the median value in the sorted array is the middle value; when the index number is even, the median value is the average of the two middle values. The calculation steps are as follows;

Calculate the signal's size, sort the signal in ascending order, and then locate the median value and designate it as the median.

Each signal's values are listed in ascending order from minimum to maximum, and the value in the first index is added to the eigenvector as the feature representing the minimum value. The value in the signal's last index, which is ranked from lowest to highest, represents the value of the feature. The eigenvector's maximum value field is expanded to include this determined value.

Skewness is the measurement of a non-symmetric probability distribution of a real-valued random variable in probability theory and statistics. Eq. (5) uses mathematical notation to determine the skewness, which is the third standardized moment [19].

$$s = \frac{E(x-a)^3}{\sigma^3} \tag{5}$$

The term "kurtosis" is used to describe the probability distribution's sharpness, or "kurtosis" quality, for real-valued random variables. It is derived from the distribution's visual representation. Kurtosis, the fourth standardized moment, is calculated using Eq. (6) [19].

$$ku = \frac{E(x-a)^4}{\sigma^4} \tag{6}$$

In Eqns. (5) and (6), $E(x)$ is the expected value; a is the mean; σ is the standard deviation; s is skewness; ku is kurtosis.

Eq. (7) calculates the standard deviation as the square root of the sum of the squares of the difference between the signal value and the mean.

$$\sigma = \sqrt{\frac{1}{n}\sum_{k=1}^{n}(x_k - a)^2} \tag{7}$$

where, σ is the standard deviation; a is the mean; n is the number of samples in the signal; x is the value of the sample in the signal; k is the sample number.

The signal is first subjected to a fast Fourier transform to calculate the energy feature. The new signal and its conjugate are then multiplied point by point, and the energy is computed by adding them together:

$$\mathrm{e} = \sum_{k=1}^{n} fft(\mathcal{X}_k).* conj(fft(\mathcal{X}_k)) \tag{8}$$

where, e is the energy; n is the number of samples in the signal; x is the value of the sample in the signal; k is the sample number.

2.3 Computing deep features

The spectrogram of the signal samples is first formed at this point. The time-frequency axis graph that is produced by figuring out the immediate signal's frequency serves as a representation of the spectrogram. Figure 2 is an example of a spectrogram.

In this case, the window $w(t)$ and the signal $x(t)$ to be evaluated. Preferably, the window should be an impulse in the time-frequency domain. In Figure 2, the signal is initially separated into windows, after which the fast Fourier transform is used to convert the signal to the frequency domain.

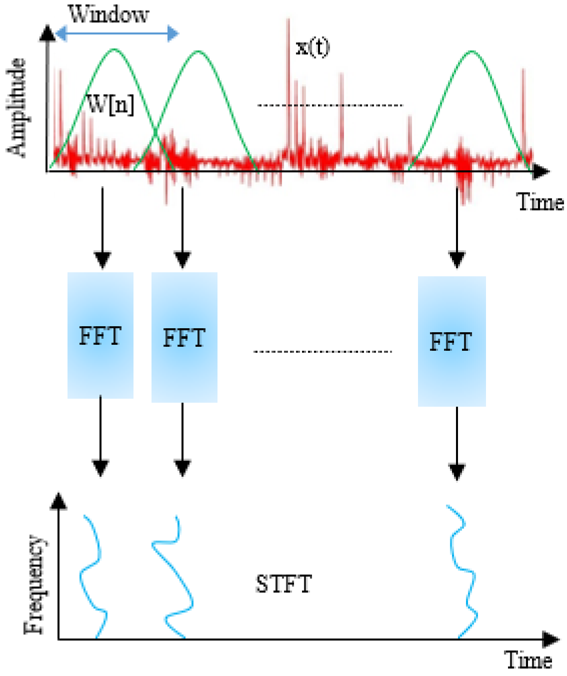

Figure 2. STFT representation for signal [20]

The signal's spectrum was then obtained by creating a time-frequency graph. It is crucial to frame the noise-free signals during the windowing stage in order to extract spectrograms from them. The frames for EEG signals split into 25 ms segments are programmed to overlap by 50%. The Hamming Window was used to highlight the core part of the signal and reduce unnecessary radiations in the end region in order to prioritize discontinuity at the start and end of each frame [21]. The signal is made available for rapid Fourier transform after this windowing procedure. These actions produce spectrogramics that should be analyzed in the DL phase. AlexNet is utilized for this task. The evolving neural network AlexNet took first place in the annual ImageNet competition in 2012 [22]. The architecture is pre-trained on the ImageNet database and is capable of differentiating 1000 different photos. This network's design primarily comprises of 3 FC layers that can serve as a function extractor and 5 convolutional layers. The FC layer of the AlexNet architecture is utilized for deep feature extraction, as seen in Figure 3. Spectrograms are used to categorize AlexNet into pre-trained networks. Deep features are acquired in the FC stage and used for the hybrid vector in addition to the classification results.

2.4 Classification

At this point, eigenvectors acquired by DL stages and statistical approaches are integrated. The EEG signal is classified using the newly discovered eigenvector. Four different classification techniques are being used at this time. These include SVM, k nearest neighbor (KNN), decision trees (DT) and linear discriminate analysis (LDA).

2.4.1 Support Vector Machines

SVMs are supervised learning methods for classification, regression, and outlier detection. The general classification method classifies the input field that the point defines into the output space. To classify anything, find the relationship between its y and x attributes, and then decide to which class it belongs [23]. SVM searches through all potential splitter planes in search of the best separation sub plane to categorize the data.

2.4.2 K Nearest Neighbor

When calculating distances, the KNN algorithm, a supervised learning technique used to solve classification and regression issues, can use Euclidean, Manhattan, or Minkowski distances. Which value belongs to which class is determined by computing the distance values between each vector and the Euclidean distance. The class to be included in the new value is decided upon as a result of the calculated distances, d [24].

2.4.3 Decision Trees

One of the supervised learning algorithms, tree-based approaches are frequently utilized in classification and regression issues. From the top, they have a structure that falls. Algorithms such as entropy, Gini, and least squares approach are employed to descend to sub nodes. It is initially determined from which feature the Gini index can be divided by taking a look at its value. The Gini value [25] depicts the distribution of variables in the dataset.

2.4.4 Linear Discriminate Analysis

With a predetermined n number of features, linear discriminate analysis (LDA), a multivariate statistical technique, aims to assign the closest assignment to the real classes of structures. Classes are selected and covariance is computed during the classification stage [26].

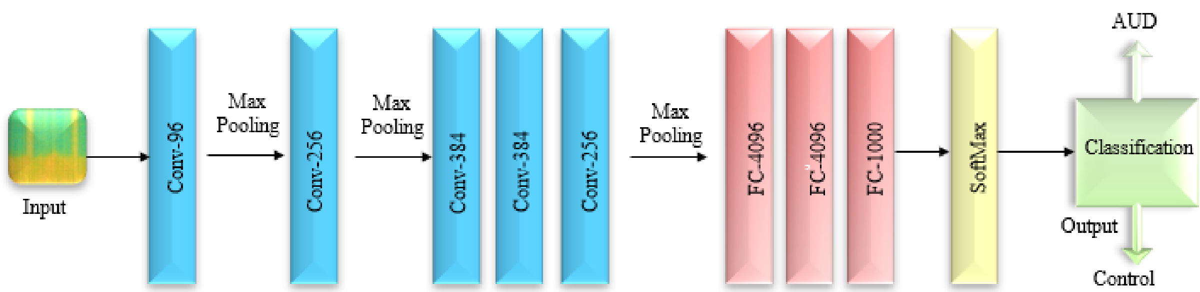

Figure 3. AlexNet basic architecture

3. EXPERIMENTAL RESULTS

The State University of New York Health Center's open EEG database was used in this investigation to get the EEG data [4]. These findings come from a significant investigation into the relationships between EEG and inherited propensities for drinking. The measurements are taken from 64 scalp electrodes sampled for one second at 256 Hz and included in a dataset of time series EEG recordings of control and alcoholic participants. There are 233 control signals and 235 alcoholic EEG signals in the dataset. These EEG signals were recorded by displaying images, and they came from 10 alcoholics and 10 non-drinkers [4].

These findings are based on a thorough investigation into the relationship between genetic vulnerability to EEG and AUD. Each electrode's 256 bits of information were combined together to create a signal that had 64 x 265 = 16384 bits of information. Later, this signal was used to conduct the transactions.

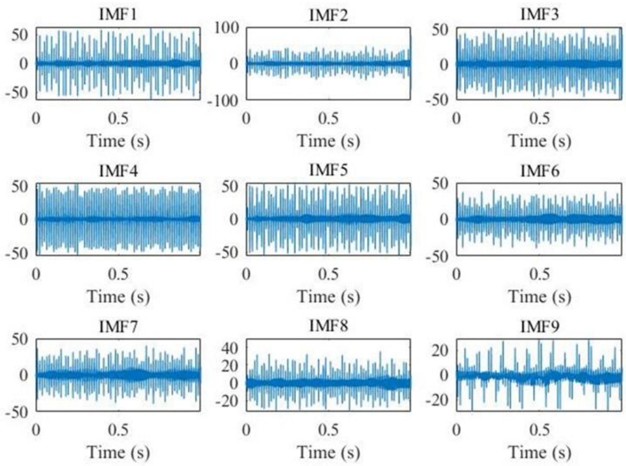

Figure 4. VMD of EEG signal for 9 modes

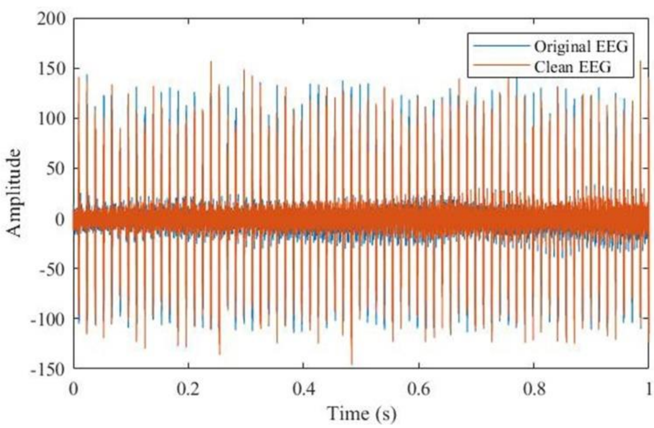

Figure 5. Original and denoised EEG signal

All calculation results in our DSFC model were achieved by Matlab R2020a. In the first stage, the signal is denoised using VMD with the selected parameters w_k=5, α=120 and tol=10^{-7}. For efficient signal decomposition, the above parameters are kept constant in many investigations [17]. Figure 4 shows 9 mode decomposed EEG signals. Figure 5 displays the original EEG signal and the noise removed by applying VMD.

The statistical features are calculated separately for each signal sample. The graphic in Figure 6 was obtained for the mean feature. It can be seen that the shift ranges between -12 and 15 when the graph is analyzed. These values are the calculated mean results to be used for classification.

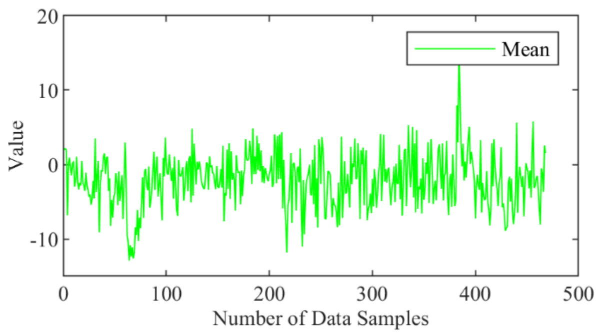

Figure 6. Computed data for the mean feature

The median feature detected has values that range from -13 to 10. The standard deviation is computed, and some of the outcomes are displayed in Table 1. Similar to all other features, the energy feature is determined for each EEG signal sample. The minimum value is another feature that is determined for each signal. The value change range for this feature is between -10 and -150. Variable maximum feature values range from 2 to 450.

The calculated results for all data are shown in Figure 7 as a result of the calculation performed in the skewness feature, which revealed a change between -6 and 8. Another feature is the kurtosis value, which has a value range of 1 to 140 values.

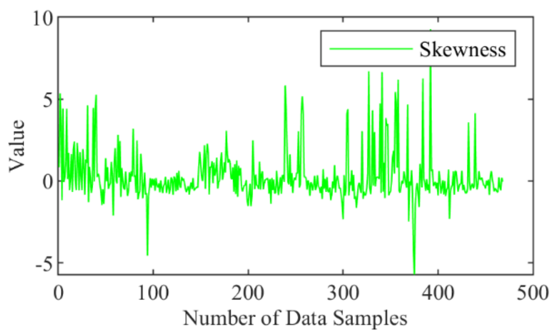

Figure 7. Data calculated for the skewness feature

Table 1. Sample values calculated for statistical features

Sample	Mean (a)	Median (m)	Standard deviation (σ)	Energy (e)	Kurtosis (ku)	Skewness (s)	Maximum (ma)	Minimum (mi)
1	1.98	1.22	7.50	16.18×10^9	6.46	0.84	51.90	-39.82
2	1.89	1.17	10.90	32.88×10^9	34.13	3.36	146.26	-63.37
3	-6.83	-5.43	8.39	31.46×10^9	6.32	-1.16	28.07	-90.62
4	0.20	-1.77	15.69	66.12×10^9	38.13	4.42	202.25	-64.35
5	-0.32	-0.29	6.73	12.19×10^9	6.57	0.19	35.84	-56.44
6	-1.45	-1.2	8.61	20.50×10^9	20.99	1.15	98.63	-78.30

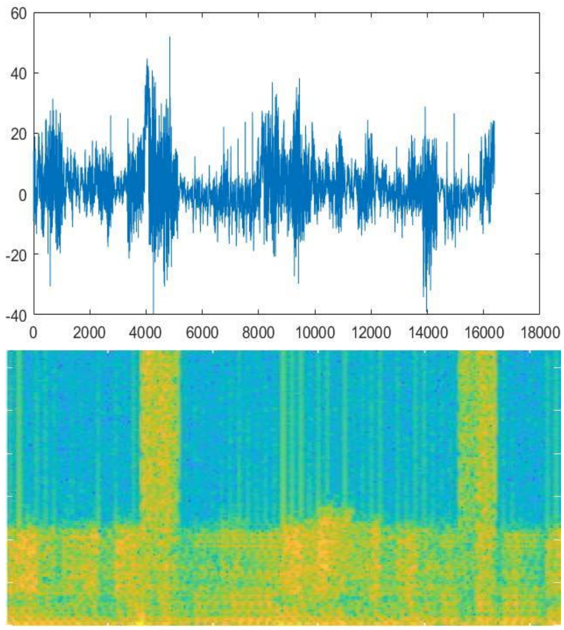

Figure 8. All electrodes combined EEG signal graph and spectrogram response

The statistical features calculation is already complete. Table 1 shows the statistical features calculated for six different sample signals.

Prior to performing calculations for the extraction of deep features, spectrograms for each EEG data sample are first built. By matching the signal's value in the frequency domain to its value in the time domain, visual graphs known as spectrograms are produced. A spectrogram created for a sample EEG input is shown in Figure 8. Figure 9 and Figure 10 are the randomly chosen spectrograms for the control group and all individuals with AUD, respectively.

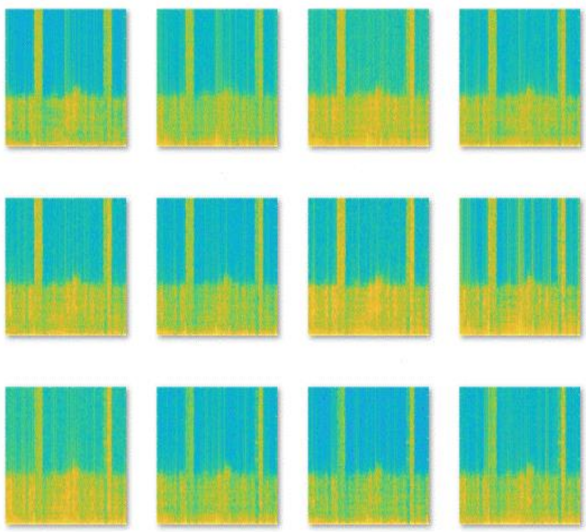

Figure 9. Examples of individuals with AUD spectrograms

At this phase, deep features must be estimated. For this reason, spectrograms are classified using AlexNet. The AlexNet FC layer's 4096 output values will be applied as deep features. These in-depth properties are noted for each signal spectrogram. The accuracy and loss graph produced following the training and validation phases of AlexNet is shown in Figure 11. The remaining 30% of the spectrograms from the 70% training stage are used for validation in the DL step. For each network, the program has advanced through 1000 iterations.

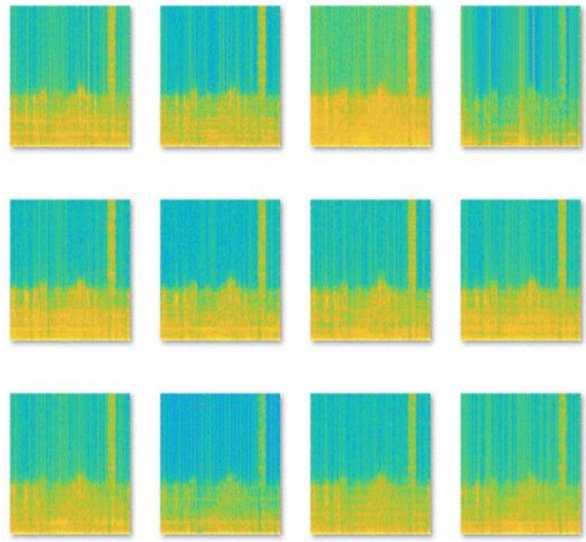

Figure 10. Examples of control spectrograms

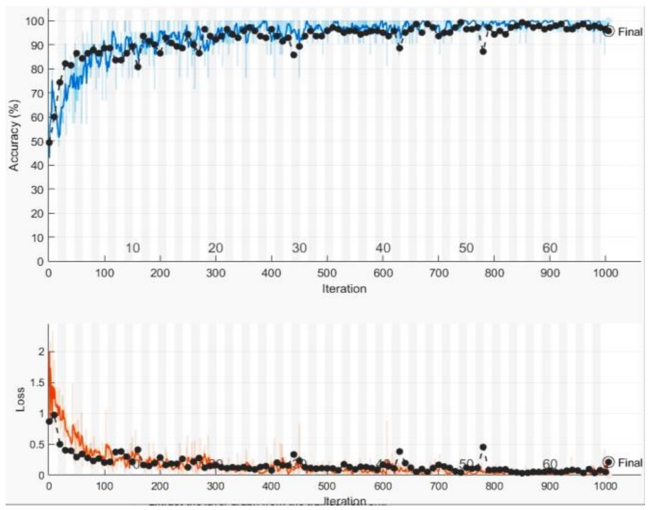

Figure 11. AlexNet accuracy and loss graphics

The results of classification using only statistical features are displayed in Table 2 when each feature is used independently. It is evident from Table 2 that SVM yields the best outcomes. The most useful feature for LDA classification, according to Table 2, is Energy, which accounts for 55.8% of the classification algorithm. The Minimum has a 65.6 percent share of the market for DT. The Minimum feature is the one with the highest weight in KNN, at 61.1 percent. When compared to all other SVM classifier methods, it can be shown that the best results are obtained for all features with the exception of the skewness feature. The smallest value feature, which yielded a result of 66.0 percent, produced the best results using this strategy. In light of this circumstance, it is evident that the statistical traits with the least value stand out as the most useful.

Table 2. Classification results according to separate statistical features

Classification Algorithm	Mean	Median	Minimum	Maximum	Skewness	Kurtosis	Energy	Standard Deviation
LDA	45.9%	48.9%	50.0%	48.3%	45.9%	55.3%	55.8%	45.7%
DT	58.1%	60.5%	65.6%	57.3%	**57.7%**	56.2%	62.0%	56.6%
KNN	57.7%	57.5%	61.1%	57.5%	54.9%	59.2%	60.3%	56.2%
SVM	**58.3%**	**60.7%**	**66.0%**	**59.6%**	57.5%	**60.7%**	**62.4%**	**59.4%**

Table 3. Different classification algorithm results of statistical features

Classification algorithm	Result
LDA	66.5%
DT	68.4%
KNN	76.3%
SVM	81.2%

Table 3 shows a classification that was generated by combining all statistical variables and attempting to predict the signals from the control group and the individuals with AUD. At this point, it can be observed that Table 3's results are superior to Table 2's results.

At this time, it has been concluded that assessing all traits jointly is preferable to assessing them singly. Despite the fact that SVM delivers the best classification results using only statistical data, the 18.8% error rate indicates poor performance and needs to be decreased.

The AlexNet DL model is shown to have a 95.71 percent accuracy rate when only spectrogram data is used to create DL results.

Table 4. DL results obtained with spectrogram images

Model	Learning type	Train and test images	Classes / Image number	Iteration	Accuracy (%)	Elapsed time (min)
AlexNet	Deep Learning	Train 70% Test 30%	Alcoholic / 235 image Control / 233 image	1000	95.71	14.25

The results of the DL approach are shown in Table 4. These results are considered insufficient even though they are superior to the accuracy rate determined from statistical features. As can be seen, the error rate is 4.29 percent.

The confusion matrix for the AlexNet model's 30% validation procedure results is displayed in Figure 12. The suggested hybrid DSFC technique is anticipated to improve the accuracy attained thus far and deliver more precise results.

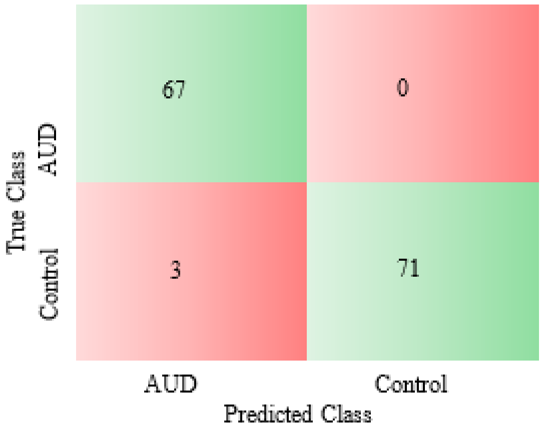

Figure 12. Confusion matrix of AlexNet DL algorithm

4104 features in hybrid eigenvectors have been created and categorized. Using features from two separate deep learning techniques, distinct hybrid eigenvectors were built, classified, and the outcomes were compared.

Table 5 shows that the accuracy rates have increased, and the result—which is a better value than the earlier findings—was obtained using the SVM classifier, even though other classification techniques also gave results that were superior to those of the earlier applications. At the end, the mistake rate dropped to 0.8 percent, which was a lower error rate than in the initial case.

Table 5. Classification of EEG signals with hybrid feature values

Classification algorithm	DSFC results (%)
	AlexNet +Statistic Feature
LDA	93.60
DT	76.10
KNN	92.30
SVM	99.20

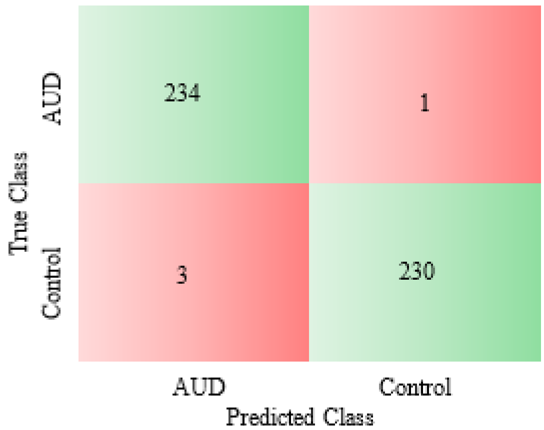

Figure 13. Confusion matrix of SVM algorithm for DSFC

Judging by the SVM's confusion matrix in Figure 13, it can be seen that the individuals with AUD group received 234 correct results, while the control group received 230 correct predictions.

Table 6. Literature comparison

Literature	Dataset	Method	Classifier	Accuracy
[11]	Alcoholic	PCA+Wavelet Transform	-	-
[12]	Alcoholic	PCA+Wavelet Transform	SVM-NN	94.67% - 98.83%
[13]	Alcoholic	LLE, ApEn, SampEn, and four HOS	SVM	91.70%
[14]	Alcoholic	CoHOG and Eig(Hess)-CoHOG	NNLS	95.83%
[15]	Alcoholic	SSA-ICA - PCA	XGBoost	98.97%
Proposed Method (DSFC)	Alcoholic	Deep Feature + Statistical Feature	SVM	96.80%
		VMD + Deep Feature + Statistical Feature	SVM	99.20%

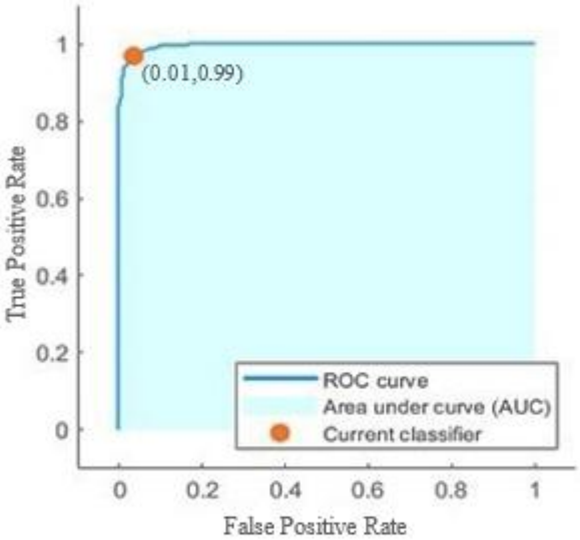

Figure 14. ROC plot of SVM algorithm

The ROC chart for the SVM technique that yields the best results is displayed in Figure 14. At this stage, it is clear from a comparison of the methods that the proposed hybrid method performs more accurately than the others. As seen by the hybrid vector classification's greater valid accuracy rate when compared to the prior test results, the approach in this instance is unquestionably more successful. The results of the DSFC methodology were found to be 3.49 percent better than the DL method and 18 percent better than statistical feature classification. A comparison of studies that made use of the same dataset is presented in Table 6.

4. CONCLUSIONS

Human motions, thoughts, mood swings, sleeping, and resting are known to cause EEG signals in the brain, which also vary based on the circumstance. This study sought to determine whether EEG signals might be used to identify addictions while accounting for alterations in people's moods. The study used a pre-made alcoholic data collection with two groups: AUD sufferers and controls. In order to appropriately separate the EEG signals of the two groups, statistical features were first extracted and categorized, and 81.2 percent, which was deemed insufficient, was achieved. The hybrid model was chosen in order to achieve a better result, even though AlexNet, which is used for the classification method of spectrograms with the DL model, achieved a 95.71 percent accuracy rate. The primary approach used in this work, referred known as DSFC, combines statistical and in-depth data to create and categorize a hybrid eigenvector. A 99.2 percent accuracy rate is attained when hybrid eigenvectors are classified using SVM, which is better than the prior tested methods.

In order to interpret EEG signals more precisely and create decision support systems that can help experts, we will keep researching EEG signals captured in various addiction and disease states.

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NOMENCLATURE

AUD	Alcohol Use Disorder
EEG	Electroencephalography
VMD	Variation Mode Decomposition
DSFC	Deep - Statistical Features Classification
DL	Deep Learning
SVM	Support Vector Machines
KNN	k Nearest Neighbor
CNN	Convolutional Neural Networks
LSTM	Long Short Term Memory networks
PCA	Principal Component Analysis
NN	Neural Network
LLE	Large Lyapunov Exponent
ApEn	Approximate Entropy
SampEn	Sample Entropy
HOS	Higher Order Spectra
SRC	Sparse Display
NNLS	Non-Negative Least Square Classifier
FC	Fully Connected
DNN	Deep Neural Network
FFT	Fast Fourier Transform
STFT	Short-Time Fourier Transform
DT	Decision Trees
LDA	Linear Discriminate Analysis
CoHOG	Co-creation of Histograms of Directed Guardians