

Article

# Direct Assessment of Alcohol Consumption in Mental State Using Brain Computer Interfaces and Grammatical Evolution

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**Abstract:** Alcohol consumption affects the function of the brain and long-term excessive alcohol intake can lead to severe brain disorders. Wearable electroencephalogram (EEG) recording devices combined with Brain Computer Interface (BCI) software may serve as a tool for alcohol-related brain wave assessment. In this paper, a method for mental state assessment from alcohol-related EEG recordings is proposed. EEG recordings are acquired with the Emotiv EPOC+, after consumption of three separate doses of alcohol. Data from the four stages (alcohol-free and three levels of doses) are processed using the OpenViBE platform. Spectral and statistical features are calculated, and Grammatical Evolution is employed for discrimination across four classes. Obtained results in terms of accuracy reached high levels (89.95%), which renders the proposed approach suitable for direct assessment of the driver's mental state for road safety and accident avoidance in a potential in-vehicle smart system.

**Keywords:** alcohol; consumption; EEG; BCI; Emotiv; OpenViBE; Grammatical Evolution

## 1. Introduction

The electroencephalogram (EEG) is a clinical tool for detection and monitoring various neurological conditions, such as epilepsy, Alzheimer's, head trauma and assessing cognitive states. Undoubtedly, alcohol consumption affects mental state, decision-making, response and accuracy, and can cause impairments in memory, even in small concentrations [1]. Alcoholism and the consumption of large amounts of alcohol within a limited period (binge drinking) could cause toxicity and alter the human brain structure [2]. Usually, the alcohol level is measured through blood alcohol concentration and breath alcohol testers. However, the study of EEG recordings has proven to be a good technique for alcoholism identification [2].

Usually EEG is performed in a well-equipped clinical environment, operated from an experienced neurologist under certain conditions. Recently, sophisticated wearable EEG recording devices in combination with user-friendly, direct electronic systems that can communicate with the user's brain in real-time without any movement (Brain Computer Interfaces—BCI), have paved the way for autonomous recordings outside a clinical setting. These commercial EEG recording devices are usually offered for lifestyle (like meditation, gaming or wellness), to be utilized sufficiently for medical purposes. On the other hand, a typical BCI system consists of a signal acquisition device and a signal processing device. Different software tools (such as OpenViBE, OpenEEG, BCI2000 and MuLES) have

been developed over the last few years to provide an interface for portable EEG devices. BCI systems have been widely spread in many application fields and marvelous breakthroughs have emerged. Research attention is focusing on these platforms and their advantage along with lightweight, low-cost EEG recording devices for monitoring, assessing, tracking, and warning of different brain states and disorders.

Alcohol consumption is related to impaired driving, even in low doses [3,4]. Moreover, driver authentication from brain waves can be integrated into a driver's authentication system [5,6] and thus BCI systems for road safety have been into consideration [7–9]. Recently, automotive industries are oriented towards smart BCI systems that can capture drivers' brain waves for several purposes. In light of this, Volkswagen AG has partnered with Emotiv and presented the "Intuitive Car Finder" [10], which uses the EEG signals to recommend to a customer a suitable car (model and color) for them, according to their subconscious preferences. Also, Renault has used another headset provided by Emotiv (Emotiv Insight) in its customized car to read the driver's brain waves and control the vehicle [11]. Each person was responsible for a different task. One person controlled left turns, the other controlled right turns and the third handled the car's acceleration. According to the above, an alcohol-related BCI system offers tremendous potential for future applications.

In this paper, a method for discrimination of mental states related to alcohol consumption from brain waves is proposed. Multi-channel EEG data are acquired from the commercial wearable EEG recording device Emotiv EPOC+ during resting state with eyes closed. The analysis is performed in the BCI platform OpenViBE and the use of Grammatical Evaluation against standard classification algorithms is examined.

## 2. Related Work

During the last decades, brain waves related to alcohol consumption have gained the research interest. Most of the studies [12–15] focused on alcoholic patients and the subtle EEG changes, which can differentiate normal individuals from alcoholic patients. Other groups of researchers employed normal subjects which consumed alcohol either performing a task [16–20] or staying passive in resting state [21].

According to previous studies, individuals who consumed alcohol during a task indicated differences in theta power (4–8 Hz) [16,19,20] and fast-beta (20–35 Hz) bands as the alcohol consumption increased [17]. Also, increased relative power in low-alpha (8–10 Hz) and decrease in the correlation between right frontal-parietal have been reported [19]. On the other hand, research studies [21], from subjects who stayed passive during EEG recording, have related the power drop of the EEG signals acquired from the frontal lobe to extensive alcohol intake [21], as well as the increase in central occipital region [21]. These findings may serve as biomarkers for extensive alcohol consumption or potential alcoholism identification.

To the best of the authors' knowledge, only a few research studies have focused on the mental state discrimination of non-alcoholic individuals during alcohol consumption. Boha et al. studied the EEG changes caused by vodka mixed with orange juice (300 mL) in 32 subjects, during the performance of a mental arithmetic task [16]. The participants were examined before the alcohol consumption and after in three stages; (a) with a placebo; (b) with a low alcohol dose (0.2 g/kg alcohol); and (c) with a high alcohol dose (0.4 g/kg alcohol), each stage separated by one week. Each participant was asked to consume the alcohol in 5 min and the recordings were collected 30 min after, for 2.5 min (during the arithmetic task). Fast Fourier Transform is performed in the data, and the absolute frequency spectra were calculated in each EEG epoch. Moderate alcohol-related EEG changes were observed and power in theta band was decreased while participants performed the task. In study [17], the aforementioned group of researchers followed the same procedure. However, in this study Omega complexity and synchronization likelihood of the theta band is computed. Results showed decrease of the Omega complexity and increased synchrony in theta band, perhaps due to working memory effort.

In another alcohol-related study [18], Karungaru et al. analyzed EEG recordings obtained from 3 participants during alcohol consumption to quantify mental changes and investigate the effect of alcohol consumption in a monotonous task. A single-channel EEG recording device was used to collect the EEG signal from the FP1 channel (according to the 10–20 system) while the left-ear used as a ground reference. For the experiments, three subjects were used, and 2-min recordings were collected with eyes closed, while performing a certain task before and after alcohol consumption. The task was performed 6 times after the alcohol intake. The first subject consumed three 250 mL cans of beer (750 mL) and the other two, six 250 mL cans of beer (1500 mL) each. The Principal Component Analysis and the Linear Discriminant Analysis were used to extract several features, which trained a Neural Network classifier. Average classification accuracy among before and after state reached 92.3%. However, average accuracy for the 7-class problem (before and 6 tasks after alcohol consumption) did not exceed 59.2%.

A different approach was followed in study [19]. The authors examined the effect of alcohol on EEG changes while performing the task Tower of London and, whether these changes are related to their menstrual cycle. Thirty female participants were tested in two different phases of the menstrual cycle after consuming either red wine or a placebo in under 10 min. EEG recordings were performed 35 min after the consumption in resting state (5 min) and while participants performed the task of Tower of London (2 min). EEG recordings were analyzed with Fast Fourier Transform and absolute power, relative power and the degree of functional coupling between prefrontal and parietal cortices in each frequency band were extracted. Results indicated low power in theta band, increase of relative power in low frequencies of alpha band and decrease in the correlation between right frontal-parietal lobe.

Concerning the advantages of an alcohol-related EEG analysis, studies have employed EEG recording devices for in-vehicle systems [22,23]. Alcohol intake affects a driver's mental state resulting in fatigue and drowsiness [24], which increases dramatically the risk of a fatal car accident. In view of this, Sarraf et al. [21] performed an EEG analysis on 50 drunk and 50 non-drunk people. Their objective was to develop an intelligence system architecture that will enable/disable the car engine according to the abnormalities in EEG signal and not based on the driver's breath that could deceive the smart system. The proposed method employed Discrete Wavelet Transform (DWT) and an Artificial Neural Network (ANN) classifier and reached 95% accuracy. A 5-channel EEG recording cap was proposed for the intelligence system.

### 3. Materials and Methods

The OpenViBE BCI software (2.1.0, Rennes Cedex, France) [25] and the data acquired from the Emotiv EPOC+ device are used for the proposed approach. The EEG recordings are acquired, transmitted and stored to a local personal computer. Then, the OpenViBE platform is used for feature extraction. The signal is initially segmented in epochs of 1 s with 0.5 s overlap and 11 significant features are extracted from each signal epoch. The feature vector is fed to an innovative classification algorithm based on Grammatical Evaluation for the classification in 4 classes and its performance was compared with the performance of several classification algorithms. Linear Discriminant Analysis embedded in OpenViBE has also been employed under a whole case scenario. The proposed approach is depicted in Figure 1.

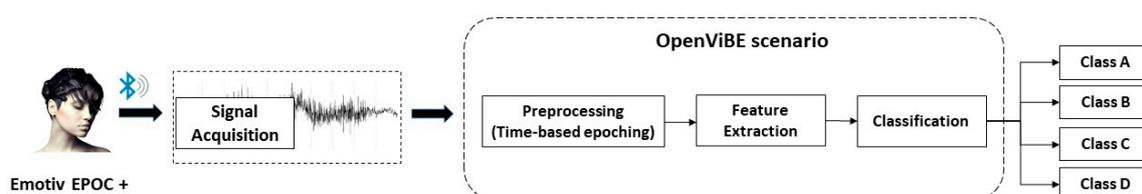


Figure 1. Flowchart of the proposed BCI system.

### 3.1. Brain Computer Interface Devices and Software

The OpenViBE is a free and open-source software platform designed to run on any ordinary Personal Computer and so to be utilized by a broad range of users. The software includes a Scenario Designer for the development of the data flow in a tree-like view and an Acquisition Server for the direct communication between the software and most common BCI devices, through the provided drivers. At the Scenario Designer a list of existing algorithms is depicted as boxes, and the user adds, connects and arranges the boxes, creating a tree-like structure for signal analysis. In Figure 2, the training scenario of the OpenViBE for the 4-class problem and the Feature Extraction box is depicted in detail.

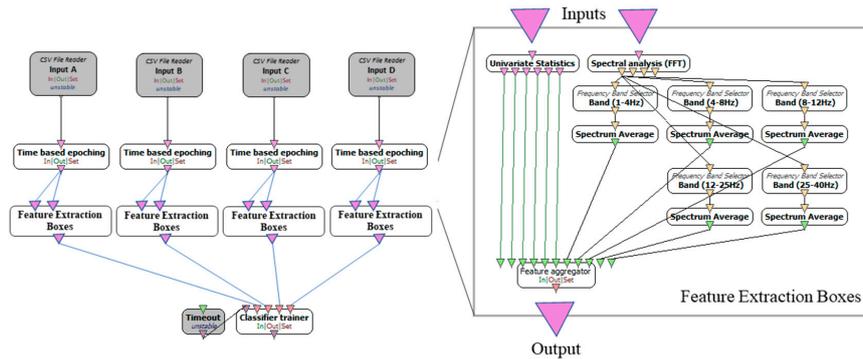


Figure 2. The OpenViBE training scenario of the analysis.

The Emotiv EPOC + EEG device is one of the most used sensory devices for EEG recording. It consists of fourteen contact points, located according to the International 10–20 system at AF3, AF4, F3, F4, F7, F8, FC5, FC6, P7, P8, T7, T8, O1, O2. Additionally, two more sensors one on the left and one on the right hemisphere of the head serve as reference channels. The sampling frequency is 128 Hz and the connection between the electrodes and the scalp is established using saline liquid solution, applied on all felt pads of each sensor. The manufacturer provides a list of software tools that implements the visualization of the quality of the connection of each sensor. The EEG data are transmitted to the computer over Bluetooth and the EmotivPRO software is the tool, wherein the quality of the connectivity is checked, and the recordings are monitored. The software interface is depicted in Figure 3.

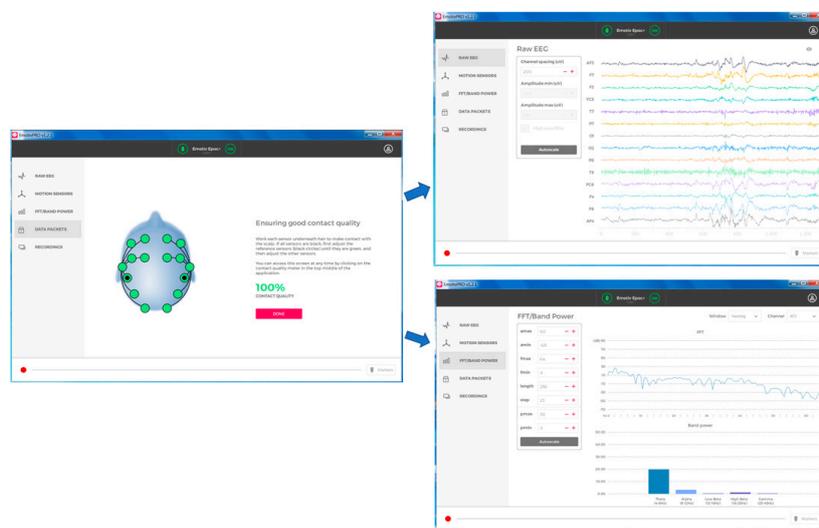


Figure 3. The EmotivPRO software for device set up and EEG monitoring.

### 3.2. Feature Extraction

A set of 11 time-based and spectral features was extracted in each epoch. Details of the features are presented in Table 1.

**Table 1.** Time and spectral features.

Features	Feature Details
Time-based features	Mean value
	Variance
	Range (max–min)
	Median value
	Inter-Quantile Range
Spectral features	Percentiles
	Spectrum average in gamma band (25–40 Hz)
	Spectrum average in beta band (12–25 Hz)
	Spectrum average in alpha band (8–12 Hz)
	Spectrum average in theta band (4–8 Hz)
	Spectrum average in delta band (1–4 Hz)

### 3.3. Classification Using Grammatical Evolution

Grammatical Evolution [26] is an Evolutionary Search Algorithm related to Genetic Programming that employs molecular biology principles in conjunction with the use of grammars. Nevertheless, in the Grammatical Evolution, the chromosomes are expressed as vectors of integers, wherein each element is a production rule from the particular Backus-Naur Form (BNF) grammar. According to the Grammatical Evolution, the procedure has two specific requirements; (a) the Context Free Grammar (CFG) of the target language, expressed in BNF format and (b) the associated fitness function.

The CFG grammar  $G$  is defined as  $G = (N, T, S, P)$ , where  $N$  is a set of non-terminal symbols,  $T$  is a finite set of terminal symbols with the constraint  $N \cap T = \emptyset$ . The terminal symbol  $S$  is named start symbol of the grammar and  $P$  is a finite set of production rules in the form  $A \rightarrow a$  or  $A \rightarrow aB$ ,  $A, B \in N, a \in T$ . The procedure initiates from the start symbol of the grammar and iteratively produces the program string, by replacing non-terminal symbols with the right hand of the selected production rule. The selection is performed in two steps:

- The next element from the vector is taken (denoted as  $V$ ).
- The production rule is selected using the scheme  $\text{Rule} = V \bmod R$ , where  $R$  is the number of production rules for the current non-terminal symbol.

The selection is executed iteratively until either a valid expression is produced, or the end of chromosome is reached. For the second case the chromosome is considered to be invalid and a large value assigned to the corresponding fitness. The main steps of the Algorithm 1 are [27]:

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**Algorithm 1**

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1. Initialization step
    - (a) Read the train data
    - (b) Set  $NG$  as the maximum number of generations
    - (c) Set  $NC$  as the number of chromosomes in the population
    - (d) Set  $PS$  as the selection rate
    - (e) Set  $PM$  as the mutation rate
    - (f) Initialize the chromosomes of the population
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## 2. Genetic step

### (a) For $i = 1$ to NG do

- (i) Create for every chromosome in the population a classification program using the previous procedure of grammatical evolution
- (ii) Calculate the fitness for every chromosome of the population
- (iii) Execute the genetic operators of selection and mutation

### (b) EndFor

## 3. Evaluation step

### (a) Create a classification program for the best chromosome in the population

### (b) Apply the previous program to test set and report the induced error

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## 4. Experimental Results

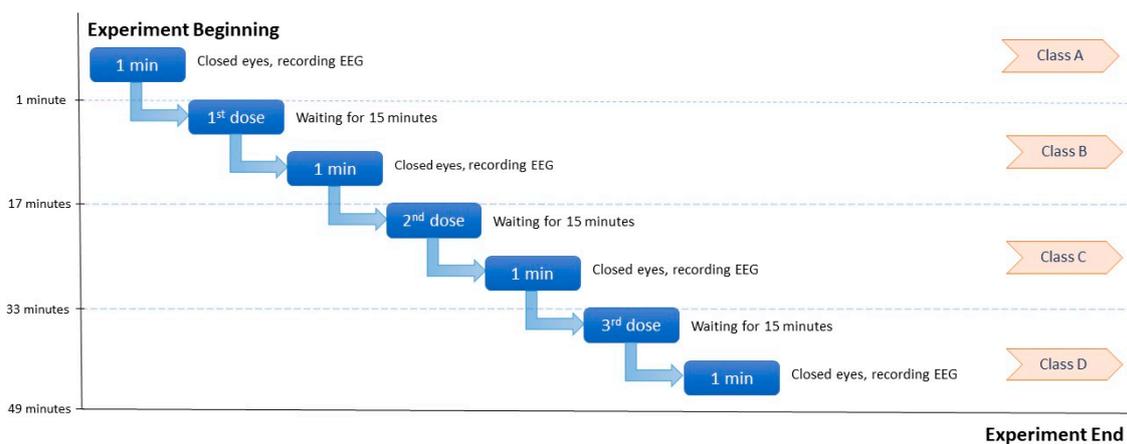
### 4.1. Dataset

Eight healthy, right-handed, normal-weight, non-smokers, drug-free men participated in the experiments to prove our concept. Participants were divided into moderate drinkers (up to 2 drinks per day) and heavy drinkers (5 or more drinks per occasion at least 5 days in month), according to the National Institute of Alcohol Abuse and Alcoholism (NIAAA) and the U.S. Department of Health and Human Services and U.S. Department of Agriculture [28].

The Alcohol Use Disorder Identification Test (AUDIT) developed by the World Health Organization was answered in accordance with the Administration Guidelines to identify and exclude excessive drinkers. The participants had negative history of alcoholism and their medical records were free of neurological and psychiatric disorders or metabolic syndromes. No alcohol, alcoholic drinks or caffeine were consumed for at least 16 h before the experiments and experiments were performed 2 h after participants had a standard full meal. Experiments were held in a control laboratory environment. After the experimental procedure, the subjects were advised not to leave the laboratory for at least 2–3 h for avoiding any possible side effects of the alcohol consumption.

### 4.2. Experimental Procedure

The experimental procedure was performed according to a similar protocol of previous scientific studies [16,18]. For the experiments, each dose is a drink of 50 mL of 40% alc/vol spirit (whisky). The experimental procedure consists of four stages. The Emotiv EPOC+ was placed once on the first participant according to the 10–20 International System. The device was set up according to the instructions provided by the EmotivPRO Software and the quality of the connectivity was checked. The participant was asked to remain calm in a resting state. During the first stage, the participant did not consume any alcohol and the EEG signal was recorded with his eyes closed for 1 min. Afterwards, the participant was asked to consume one dose of the spirit and wait for 15 min. According to previous scientific studies [16,18,19] a 15-min interval is appropriate to capture the EEG changes of alcohol absorption and especially for 40% alcohol-by-volume spirits, which studies have shown [29,30] that a 20% *v/v* spirit is absorbed faster than beer and wine. After the 15-min interval, the EEG was recorded for 1 min with the participant's eyes closed. The same procedure was repeated in the third and the fourth stage until 150 mL of the spirit was consumed. Then, the same experiment was performed for the second participant. A schematic diagram of the experimental procedure is depicted in Figure 4.



**Figure 4.** The timeline of the experiment. Each dose is a 50 mL whisky (40% alc/vol). The total time in the end of each stage is shown in the orange box.

### 4.3. Classification Results

Each experimental stage corresponds to a different brain state and so to a different class. Thus, the alcohol-free EEG recordings acquired in the first stage formed the class A. Class B consists of the EEG recordings obtained during the second stage, meaning after the 1st dose and the 15-min interval. Accordingly, class C consists of the EEG signals of the third stage (after the 2nd dose and the 15-min interval) and class D contains the data acquired during the fourth stage (after the 3rd dose and the last 15-min interval). In Figure 4, each experimental stage is shown and each class is clearly distinguished.

Spectral features were used individually for the classification (Scenario 1) and then also in combination with time-based features (Scenario 2). Data from all the 14 electrodes of the Emotiv EPOC+ were used in both scenarios. Thus, in Scenario 1, which comprises 5 different spectral features as presented in Table 1, a total of 70 different features were extracted for all the 14 electrodes. Accordingly, in Scenario 2 that comprises both spectral and time-based features (11 features), a total of 154 different features were calculated from entire set of electrodes.

To examine the performance of the Grammatical Evolution, each scenario was also tested with 4 well-known classification algorithms (Decision Trees (DT), Linear Discriminant Analysis (LDA), MultiLayer Perceptron (MLP), and k-Nearest Neighbor (KNN)) combined with a dimensionality reduction stage. Principal Component Analysis (PCA) for dimensionality reduction and 3 feature selection techniques (Information Gain, Correlation Attribute Evaluation and Entropy-based) was initially applied in Scenario 1 and Scenario 2, and then each classifier was evaluated.

After applying Principal Component Analysis, 25 features were created for the moderate drinkers group and 37 features were created for the heavy drinkers of the Scenario 1. For Scenario 2, PCA resulted in 31 and 33 new features for moderate and heavy drinkers, respectively. For the application of the Information Gain, Correlation Attribute Evaluation and Entropy-based feature selection, the 10 best features were selected for each feature selection method for Scenario 1 and Scenario 2, according to their information gain, the correlation (Pearson's) and the entropy regarding the class. Thus, different feature vectors were used to train the 4 different classifiers. Grammatical Evolution can deal with the huge number of features since it contains a feature selection step and thus, no further dimensionality reduction stage is needed. To compare our approach with a combination of dimension reduction and classic classifiers, Waikato Weka Software and IBM SPSS Statistics Software have been employed, using the same set of features.

To train and test the classification algorithms, the 10-fold cross-validation technique was employed. According to this technique, the entire dataset is divided in 10 equal folds. In the first division 9 of these folds are used to train the classifier and the remaining 1 to test it. The procedure is repeated 10 times and each time a different fold is used as test set. In the final stage, the procedure is repeated

on the entire dataset for a last time and the reported results are an aggregation of the results of the 10 models.

To evaluate the performance of the Grammatical Evolution in discriminating 4 alcohol-related mental states, the four classifiers were statistically compared using the Paired-sample *t*-test [31], aiming to examine whether the classification accuracy differences are statistically significant. For this reason, a pairwise comparison of each of the four classifiers was conducted with the Grammatical Evolution. Results in terms of accuracy for the 5 classifiers for both Scenario 1 and Scenario 2 are presented in Tables 2 and 3. Furthermore, the statistical *t*-value and *p*-value are reported in the parenthesis.

**Table 2.** Results in terms of accuracy for the 5 classifiers. Scenario 1 corresponds to the feature vector that contains only spectral features. In the parenthesis the statistical *t*-value is reported as extracted from the Paired-sample *t*-test.

Feature Selection	Classifier	Scenario 1	
		Moderate Drinkers	Heavy Drinkers
Principal Component Analysis	Decision Tree	54.39%, ( <i>t</i> = 29.285) *	63.33%, ( <i>t</i> = 24.141) *
	Linear Discriminant Analysis	55.58%, ( <i>t</i> = 40,239) *	65.19%, ( <i>t</i> = 20.725) *
	MultiLayer Perceptron	66.53%, ( <i>t</i> = 14.567) *	80.06%, ( <i>t</i> = 8.398) *
	k-Nearest Neighbor	66.89%, ( <i>t</i> = 18.075) *	73.97%, ( <i>t</i> = 14.633) *
Information Gain	Decision Tree	58.99%, ( <i>t</i> = 28.769) *	59.51%, ( <i>t</i> = 20.057) *
	Linear Discriminant Analysis	53.15%, ( <i>t</i> = 35.698) *	50.27%, ( <i>t</i> = 22.019) *
	MultiLayer Perceptron	55.43%, ( <i>t</i> = 23.535) *	58.89%, ( <i>t</i> = 15.690) *
	k-Nearest Neighbor	62.92%, ( <i>t</i> = 26.112) *	60.33%, ( <i>t</i> = 32.457) *
Correlation Attribute Evaluation	Decision Tree	59.71%, ( <i>t</i> = 28.387) *	72.57%, ( <i>t</i> = 17.691) *
	Linear Discriminant Analysis	50.31%, ( <i>t</i> = 21.372) *	59.41%, ( <i>t</i> = 18.706) *
	MultiLayer Perceptron	56.77%, ( <i>t</i> = 31.751) *	69.79%, ( <i>t</i> = 10.324) *
	k-Nearest Neighbor	63.22%, ( <i>t</i> = 34.711) *	76.60%, ( <i>t</i> = 8.508) *
Entropy-based	Decision Tree	58.42%, ( <i>t</i> = 31.053) *	70.15%, ( <i>t</i> = 20.633) *
	Linear Discriminant Analysis	49.54%, ( <i>t</i> = 22.118) *	58.21%, ( <i>t</i> = 26.308) *
	MultiLayer Perceptron	60.07%, ( <i>t</i> = 30.640) *	71.49%, ( <i>t</i> = 11.294) *
	k-Nearest Neighbor	62.25%, ( <i>t</i> = 19.294) *	73.35%, ( <i>t</i> = 15.475) *
Grammatical Evolution		85.55	87.53

\* *p*-value < 0.001.

Classification accuracy for the group of moderate drinkers when applying the PCA feature reduction technique, ranges from 54.39–66.89% for the four classifiers. Heavy drinkers indicated better classification results for the PCA feature vector (63.33%, 65.19%, 80.06% and 73.97% for DT, LDA, MLP and KNN respectively). Concerning the feature selection methods, Information Gain did not show so promising results. LDA and MLP showed the worst classification accuracy (53.15% for moderate and 50.27% for heavy drinkers for LDA and 55.43% for moderate and 58.89% for MLP, respectively). DT and KNN performed slightly better with 58.99% for moderate drinkers and 59.51% for heavy drinkers when classified with DT and 62.92% for moderate and 60.33% for heavy drinkers when classified with MLP. The selected feature vector with the Correlation Attribute Evaluation obtained the best classification accuracy with KNN (63.22%) following by DT (58.99%), MLP (55.43%) and LDA (50.31%) for the moderate drinkers. For the same feature selection technique, heavy drinkers showed better classification accuracy reaching 76.60% with KNN and 72.57% with DT. LDA and MLP underperformed with 59.41% and 69.79% accuracy respectively. For the Entropy-based feature selection method, the group of heavy drinkers outperformed in the classification accuracy of all classifiers (70.15%, 58.21%, 71.49% and 73.35% for DT, LDA, MLP and KNN respectively), whereas the group of moderate drinkers did not show so good classification results (58.42%, 49.54%, 60.07% and 62.25% for DT, LDA, MLP and KNN respectively). Grammatical Evolution outperformed the previous

mentioned classifiers with classification accuracy reaching 85.55% for moderate drinkers and 87.53% for heavy drinkers.

**Table 3.** Results in terms of accuracy for the 5 classifiers. Scenario 2 corresponds to the feature vector that contains both spectral and time-based features. In the parenthesis is reporting the statistical *p*-value as extracted from the Paired-sample *t*-test.

Feature Selection	Classifier	Scenario 2	
		Moderate Drinkers	Heavy Drinkers
Principal Component Analysis	Decision Tree	54.96%, ( <i>t</i> = 36.905) *	60.90%, ( <i>t</i> = 23.464) *
	Linear Discriminant Analysis	55.07%, ( <i>t</i> = 20.997) *	67.98%, ( <i>t</i> = 13.365) *
	MultiLayer Perceptron	68.28%, ( <i>t</i> = 14.641) *	80.89%, ( <i>t</i> = 8.469) *
	k-Nearest Neighbor	76.35%, ( <i>t</i> = 3.451) ***	84.04%, ( <i>t</i> = 4.335) **
Information Gain	Decision Tree	50.31%, ( <i>t</i> = 20.493) *	58.73%, ( <i>t</i> = 17.948) *
	Linear Discriminant Analysis	44.68%, ( <i>t</i> = 26.378) *	51.92%, ( <i>t</i> = 18.690) *
	MultiLayer Perceptron	48.91%, ( <i>t</i> = 21.261) *	61.00%, ( <i>t</i> = 22.797) *
	k-Nearest Neighbor	57.08%, ( <i>t</i> = 22.712) *	62.91%, ( <i>t</i> = 20.325) *
Correlation Attribute Evaluation	Decision Tree	52.07%, ( <i>t</i> = 18.237) *	75.83%, ( <i>t</i> = 8.038) *
	Linear Discriminant Analysis	40.24%, ( <i>t</i> = 27.991) *	59.35%, ( <i>t</i> = 25.952) *
	MultiLayer Perceptron	48.35%, ( <i>t</i> = 25.775) *	68.24%, ( <i>t</i> = 18.666) *
	k-Nearest Neighbor	56.30%, ( <i>t</i> = 16.395) *	75.57%, ( <i>t</i> = 11.341) *
Entropy-based	Decision Tree	50.98%, ( <i>t</i> = 18.085) *	51.91%, ( <i>t</i> = 31.298) *
	Linear Discriminant Analysis	49.28%, ( <i>t</i> = 29.809) *	52.33%, ( <i>t</i> = 28.626) *
	MultiLayer Perceptron	53.98%, ( <i>t</i> = 23.165) *	49.12%, ( <i>t</i> = 22.302) *
	k-Nearest Neighbor	53.61%, ( <i>t</i> = 14.929) *	50.01%, ( <i>t</i> = 31.960) *
Grammatical Evolution		80.52%	88.70%

\* *p*-value < 0.001, \*\* *p*-value < 0.005, \*\*\* *p*-value < 0.01.

Regarding Scenario 2, which contains spectral and time-based features, features extracted with PCA for the group of moderate drinkers combined with DT, LDA, MLP and KNN showed good classification accuracy (54.96%, 55.07%, 68.28% and 76.35% respectively). Among feature selection methods and PCA, the best accuracy of Scenario 2 was obtained with this PCA, for heavy drinkers with KNN (84.04%) followed by MLP (80.89%), LDA (67.98%) and DT (60.90%). For the feature vector of Information Gain and the moderate drinkers the best accuracy was given by KNN (57.08%), whereas DT, MLP and LDA did not perform so well (50.31%, 48.91% and 44.68% respectively). Classification accuracy for the same feature selection method and the group of heavy drinkers, was slightly better (58.73%, 51.92%, 61% and 62.91% for DT, MLP, LDA and KNN, respectively). Moreover, not great classification results were obtained with the selected feature vector with the Correlation Attribute Evaluation combined with KNN (52.07%) following by DT (40.24%), MLP (48.35%) and LDA (56.30%) for the moderate drinkers. However, Correlation Attribute Evaluation in combination with DT and KNN outperformed for this technique (75.83% and 75.57% respectively) followed by MLP (68.24%) and LDA (59.35%). The Entropy-based feature selection showed the worst classification for both moderate and heavy drinkers. For moderate drinkers the best accuracy was given with MLP (53.98%) followed by KNN (53.61%), DT (50.98%) and LDA (49.28%). Likewise, for the group of heavy drinkers, accuracy values did not show great alterations (52.33%, 51.91%, 50.01% and 49.12% for LDA, DT, KNN and MLP, respectively). Nevertheless, Grammatical Evolution indicated the best classification accuracy for both groups (80.52% and 88.70% for moderate and heavy drinkers).

### 5. Discussion

This experimental procedure contains EEG recordings from two groups of drinkers, moderate and heavy. Four alcohol-related mental states are discriminated with the Grammatical Evolution and compared with standard classifiers combined with feature selection methods and PCA. The obtained

results show that Grammatical Evolution outperforms the PCA method and the three feature selection techniques combined with several typical classifiers in both scenarios for both groups of moderate and heavy drinkers. The above results indicate that the classification performance is not necessarily improved by the dimensionality reduction of the feature vector.

Our approach showed the best classification accuracy without the need of a feature selection technique and is certainly preferred, since it can handle a big set of attributes and avoids possible overtraining phenomena. Among the 4 classification algorithms and PCA and the 3 feature selection methods, KNN indicated the best classification accuracy in conjunction with the feature vector that were selected with Correlation Attribute Evaluation for heavy drinkers of Scenario 1. Furthermore, in Scenario 1 KNN indicated classification accuracy above 70% when combined with features from PCA (73.97%) and features selected based on their entropy (73.35%) for heavy drinkers. In Scenario 2, PCA and KNN gave the best accuracy (76.35%), following by Correlation Attribute Evaluation with DT (75.83%) and KNN (75.57%).

Generally, classification accuracy is better for the group of heavy drinkers in comparison with the moderate drinkers in almost all cases of both Scenario 1 and Scenario 2. Moderate drinkers showed better classification accuracy only in the case of the spectral feature vector (Scenario 1) as obtained with Information Gain and with LDA and KNN; however, the difference in accuracy values arise from 2% to 3%. On the other hand, moderate drinkers outperformed in Scenario 2 with the set of features as created with PCA and classified with MLP and KNN. All things considered, the four classification algorithms and the Grammatical Evolution discriminated the alcohol-related mental state of heavy drinkers better than the mental state of moderate drinkers.

The obtained  $t$ -values and the  $p$ -values of the Paired-sample  $t$ -test confirms the differences in the classification results. The  $t$ -values are generally large, indicating the big differences between classifiers. Low  $t$ -values are obtained only with KNN combined with Correlation Attribute Evaluation for heavy drinkers (Scenario1) and in combination with PCA for both moderate and heavy drinkers (Scenario 2). Another case with low  $t$ -value is for MLP combined with PCA for heavy drinkers (both scenarios) and for DT in combination with Correlation Attribute Evaluation for heavy drinkers (Scenario 2). Concerning the  $p$ -values, in almost all cases the probability is less than 0.001, excluding the case of KNN combined with PCA for Scenario 2 (both moderate and heavy drinkers).

To the best of the authors' knowledge, this is the first attempt of discriminating the mental state related to different alcohol doses. Owing to the different, consecutive alcohol doses of our method, the proposed approach has more potentials than a simple discrimination between drunk and no-drunk people as have previously presented in [12–15]. Our approach introduces a 4-class classification problem, wherein each class represents the different mental state as depicted from EEG recordings obtained while participants consumed different alcohol doses. Undoubtedly, the proposed approach is more advantageous, since automotive industries are increasingly focusing on in-vehicle smart BCI systems [10,11] and can provide information for the different alcohol-related brain states, offering the chance to avoid a possible fatal car accident due to alcohol consumption. Furthermore, the Emotiv EPOC+ is a lightweight, wearable EEG device that consists of 14 channels and is more suitable, instead of a single-channel [18] or a 5-channel device [21], providing more spatial information, and hence accurate assessment of the driver's mental state after alcohol intake.

## 6. Conclusions

Alcohol consumption causes alterations in stages of mind and is related to serious and sometimes persistent changes in the brain structure and functionality. Wearable EEG recording devices in BCI systems can provide direct assessment of the alcohol-related brain waves. The proposed approach introduces a method for direct assessment of the mental state from alcohol-related EEG recordings. Eight physiological individuals, grouped as moderate or heavy drinkers depending on their alcohol consumption, participated in the experiments. Participants were asked to consume 3 doses of 40% alc/vol whisky in specific intervals in a control laboratory environment, while EEG was recorded

with the wearable EEG recording device Emotiv EPOC+. The EEG recordings were acquired before and after alcohol consumption in 3 stages. The data were processed in the OpenViBE platform and the Grammatical Evolution was used to differentiate the 4 different mental states. Results show that this approach finds potential use in smart car systems for reducing the frequency of car accidents. Advanced BCI systems can be integrated into smart cars and brain waves can serve as a biomarker for automatically slow acceleration when a driver's alcohol concentration is between driving limits and even prevent engine starting, when alcohol concentration exceeds drink-driving limits.

Future work will focus on recruiting more participants of different age, weight, in different states (sleep restricted, binge drinkers, etc.), different spirits, doses and dilutions to encompass all possible alcohol-related mental states and present a more comprehensive system. Also, the ability of the proposed BCI system for real-time classification will be evaluated.

**Author Contributions:** N.G., M.G.T., A.T.T. and T.B. conceived of the idea. N.G., T.B. and K.D.T. recorded the EEG signals. I.T. performed the classification experiments employing the grammatical evolution algorithm. N.G. and A.T.T. processed the signals and extracted the features using the OpenViBE system. K.D.T. and M.G.T. provided the comparative experiments using features selection and Classification. K.D.T. and all the others prepared the manuscript. N.G. organized the research team and had the general supervision of the project.

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