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Discrete to Continuous Algorithm for Optimal Channel Selection to Detect Alcoholism through EEG Recordings

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Abstract: Alcoholism is a serious public health issue, and early diagnosis of this brain disease can be performed by analyzing Electroencephalogram (EEG) signals. However, the high dimensionality of EEG datasets requires significant computational time and resources for the automatic processing of EEG signals. This study proposes a novel method to reduce EEG dataset dimensionality using a Discrete to Continuous algorithm (DtC) by selecting optimal EEG channels. The DtC approach compares alcoholic and nonalcoholic EEG signals as two-time series in a two-dimensional space based on a distance measurement between the two-time series. The Dynamic Time Warping (DTW) algorithm is used to compare the performance of the DtC approach. Classification performance metrics were evaluated for both the DtC and DTW algorithms. The optimal selected channels by our approach are the C3, CP5, PO7, and F8 channels with accuracy values of 100, 100, 94 and 81%, respectively. These findings are consistent with previous research on statistical analysis and machine learning methods and with the DTW algorithm results. Our findings are also in line with scientific evidence from clinical research. The DtC approach was efficient in selecting the best channels to reduce the EEG dataset dimensionality, allowing us to select four out of the 64 EEG channels (C3, CP5, PO7, and F8) that retain essential information related to alcoholism, which is useful in reducing computational time and resources during the classification task of alcoholic EEG.

Keywords: Discrete to Continuous, Optimal Channel Selection, Alcoholism, Electroencephalography, Biological Time Series

Introduction

Alcoholism is a serious condition that is linked to substantial morbidity and mortality (CDCP, 2022; Dwivedi *et al*., 2017). Approximately 2.3 billion people drank alcohol regularly in 2016, with 237 million men and 46 million women experiencing health issues. The World Health Organization (WHO) estimates that alcoholism caused more than three million deaths in 2016. At the international level, alcohol abuse accounts for more than 5% of the morbidity burden (WHO, 2018). Alcoholism is defined as severe and persistent alcohol urges despite being aware of the many physical and mental issues that alcohol can cause (Liang and Olsen, 2014). Alcoholism affects a person's behaviour and impairs the functioning of vital organs. Most negative consequences concern the heart, immune system, liver, and brain. It has serious effects on memory and

cognitive function. Alcohol inhibits the production of new synapses, slows the development of the brain's functional areas, and can even result in cerebral death.

Developing an awareness of alcohol dependence relies on an early diagnosis of alcoholism that might be challenging to diagnose using traditional techniques. As part of standard alcohol disorder screening, clinicians might use, individually or together, questionnaires, interviews, or blood tests. Questionnaires and clinical interviews focus on drinking habits or the negative effects of alcohol consumption. These methods assess the quantity and frequency of drinks and evaluate patients' responses to criticism, the urge to drink, and feelings of guilt. Due to subjectivity, feelings of fear, and social stigma, alcoholic patients are less likely to provide relevant information. Furthermore, the blood test is often inaccurate in addition to being intrusive and uncomfortable (Buriro *et al*., 2021). These traditional methods suffer from subjectivity and a lack of accuracy. As a result, fewer alcoholics will test positive for alcoholism.

Neuroimaging technologies have demonstrated encouraging research findings in establishing objectivity and improving the accuracy of screening and diagnosis. Valuable information has been derived from the analysis of neurological data. Magnetic Resonance Imaging (MRI), Positron Emission Tomography (PET), Single Photon Emission Computed Tomography (SPECT) and Electroencephalography (EEG) techniques have been used to study changes in brain activity and discovered alterations related to alcohol consumption (Mumtaz *et al*., 2018). EEG is recognized as a significant approach to diagnosing alcoholism. It detects the brain's functioning states and records, at the scalp level, the electrical potentials generated by the brain's neurons. Due to its inherent features, such as noninvasiveness, high time resolution, and its evident association with alcoholism biomarkers (Enoch *et al*., 2002; Kayser and Tenke, 2015), EEG is deemed to be the appropriate method for studying electrical brain signals and early Alcohol Use Disorder (AUD) discrimination (Neeraj *et al*., 2021).

Traditional approaches to the analysis and interpretation of EEG recordings are extremely time-intensive processes involving highly skilled professionals. In addition, the reliability of EEG reports may be compromised due to the presence of noise and artifacts. Therefore, applying high-performance computerized techniques to analyze digital EEG signals can address the need for timely diagnosis and improve the reliability and efficiency of EEG reports supporting traditional approaches. Owing to the advancement of computer and digital technologies, automatic EEG analysis methods have been developed over the years as an effective advance toward their use in real-world applications.

The automatic classification of EEG signals has been the focus of recent research in various fields. This is either to provide automated decisions concerning a patient's disease or to assess brain activity. This includes studies on biometric authentication (Alariki *et al*., 2018), sleep stages (Prabhakar *et al*., 2022), epilepsy identification (Ren and Han, 2019), autism disease detection (Peya *et al*., 2022), etc. EEG-based alcoholism detection has also been investigated in the literature during the past few years through different approaches for early alcoholism diagnosis (Mumtaz *et al*., 2018).

Strengthening conventional methods for alcoholism screening, monitoring and treatment are essential. However, using traditional approaches for EEG interpretation at the level of Emergency Hospitals (EH) and Primary Health Care services (PHC) presents challenges to accurately identifying AUD patients. A combination of conventional methods and automatic EEG interpretation is required to ensure the quality and effectiveness of patient care, from screening through diagnosis and treatment to rehabilitation. The presence of noise and artifacts in EEG signals, in addition to their nonstationary and nonlinear nature, are key issues that can affect the performance of automatic identification methods. Hence, instead of using the entire EEG data, relevant and useful features need to be selected for AUD detection. The following are the main issues that can be addressed by preprocessing data to retain only relevant features: (1) Overfitting can have a negative impact on the performance of the method of identifying AUD patients. This is due to the presence of unneeded data and redundant features and (2) Handling high-dimensional datasets such as EEG recordings that can constrain memory and computing complexity and require substantial processing time.

The literature emphasizes the growing demand for accurate diagnosis and classification of neurological disorders (Khosla *et al*., 2020). The challenge lies in achieving high classification performance with less time complexity and fewer memory resources. Hence, preprocessing data is necessary to reduce data dimensionality (Adiwijaya *et al*., 2018). Dimensionality reduction techniques involve the selection of features after the extraction step has been performed from the raw EEG data and the selection of a subset of channels (Rabcan *et al*., 2020). According to studies in the fields of emotion recognition and mental fatigue detection, the use of a limited number of EEG channels can achieve similarly or even improved classification performances within a shorter time (Dura and Wosiak, 2021).

Thus, the purpose of the present work is to propose a subset of EEG signals that are reduced in dimensionality by selecting only pertinent and relevant EEG signals. The present paper pertains to the improvement of a point pattern matching method, namely, the Discrete to Continuous algorithm (DtC). The main aim and novelty of our research are to empirically investigate the effectiveness of the DtC algorithm to accurately select optimal EEG channels for alcoholism discrimination.

The main contributions of the present study are as follows:

- The DtC point pattern matching algorithm was applied for the first time to EEG channel selection
- The proposed approach was compared to the dynamic time-warping algorithm in terms of selecting optimal EEG channels. The feasibility of the DTW algorithm has been studied in the field of EEG data analysis since 1985 using simulated and actual EEG data
- The effectiveness of the proposed approach was demonstrated by running rigorous experiments on an open dataset
- In light of scientific evidence from clinical research regarding AUD's impact on the brain, the proposed approach results were discussed

Related Works

In the last few years, many EEG based signal processing and analysis techniques have been investigated in the literature to identify brain changes related to alcoholism through computer-aided technologies (CAD). The major step in EEG signal processing involves using either statistical analysis or Machine Learning (ML) methods to discriminate between nonalcoholic and alcoholic EEG signals. Salankar *et al*. (2022) used four supervised learning techniques, namely, Random Forest (RF), K-Nearest Neighbors (KNN), Multilayer Perceptron Neural Network (ML-PNN), and Least Square Support Vector Machine (LS-SVM), to differentiate between alcoholic and nonalcoholic EEG recordings. Segmentation and decomposition of raw EEG data were initially performed and features were selected considering Second-Order Difference Plots (SODPs). Siuly *et al.* (2019) extracted statistical features from an optimum allocation-based sampling scheme. Supervised learning algorithms, including logistic regression, decision table, Support Vector Machine (SVM), and KNN, were utilized on the obtained vector set during the classification step to identify alcoholic EEG recordings. Correlation Dimension (CD)-based feature extraction was performed by Prabhakar and Rajaguru (2020) through four distance metrics: Chebyshev distance, city block distance, cosine distance, and correlation distance. To classify EEG signals as alcoholic or nonalcoholic subjects, the authors proposed and compared adaboost-based approach performances with various ML algorithms employing suitable extracted features. Buriro *et al.* (2021) investigated the utility of Wavelet Scattering Transform (WST)-based features using two Conventional Machine Learning (CML) tools, namely, SVM and Linear Discriminant Analysis (LDA). According to the authors, interesting results were produced by combining CML algorithms and WST-based features compared to the convolutional neural network. Padma Shri and Sriraam (2016) identified the optimal feature subset as having the least correlation and maximal class separation between a selected set of EEG channels based on variance measures. The classification was performed using Multilayer Perceptron-Back Propagation (MLP-BP) and KNN networks. Deep learning classification of EEG signals was performed (Neeraj *et al*., 2021) by processing both spatial and temporal features. First, spatial features were extracted based on the moving-window technique and Fast Fourier Transform (FFT) and combined with a Convolutional Neural Network (CNN). Then, temporal feature extraction was performed using Long Short-Term Memory (LSTM) and an attention mechanism. Khan *et al.* (2021) relied on the causal effects that are exchanged between various areas of a specific resting-state network known as the Default Mode Network (DMN). Using the Partial Directed Coherence (PDC) algorithm, the authors calculated the Effective Connectivity (EC) between the DMN brain regions that served as input to a 3D-CNN to identify alcoholic cases. Mukhtar *et al.* (2021), raw EEG time series data were fed into an optimized CNN. Both feature extraction and classification tasks were included in the optimized CNN to identify alcoholic and nonalcoholic subjects. Chaotic measures were employed by (Kannathal *et al*., 2005) to perform alcoholic and epileptic data analysis. These measures included entropies, Correlation Dimension (CD), the Largest Lyapunov Exponent (LyE), and Hurst Exponent (HE). Acharya *et al.* (2012) used an SVM classifier to identify alcoholic cases based on nonlinear features such as LyE, sample entropy, and approximate entropy. Feature selection consists of a statistical t-test performed on the nonlinear extracted parameters. Ren and Han (2019), the authors combined linear and nonlinear methods (wavelet transform, autoregression, and wavelet packet decomposition) to extract features. Then, they employed class separability techniques to eliminate redundant features. An LDA-based ensemble of extreme learning machines was then used to perform classification on two datasets related to alcoholism and epilepsy. The feature extraction methods considered in (Yazdani *et al*., 2007) include the second-order autoregressive model parameters, mean absolute value, the peak amplitude of the power spectrum, and variance of the signal. A Principal Component Analysis (PCA)-based dimensionality reduction was performed on the feature vector and then the reduced vector was fed to a fuzzy inference system for the classification of alcoholic and nonalcoholic cases. Rahman *et al*. (2020) assessed the effects of dimension reduction techniques on the classification performances of both traditional ML and Deep Learning (DL) methods in identifying alcoholic cases. The authors concluded that the PCA technique achieves interesting results when used with a DL method. The Wavelet Packet Decomposition (WPD) technique was applied (Saddam *et al*., 2017) to decompose the EEG signal, and features were extracted using descriptive statistical measures. The PCA technique was implemented in this research to reduce EEG signal dimensionality. Classification of alcoholic and nonalcoholic cases was performed based on an optimized Back Propagation Neural Network (BPNN). It has been shown that higher accuracy with shorter run times was achieved with PCA-selected features than without using the PCA technique.

Various approaches to reducing dimensionality have been proposed in the literature. Preprocessing and

postprocessing operations are typically performed on raw EEG recorded data, including feature extraction and selection steps before data are fed to ML models or statistically analyzed. Similar to feature selection techniques, EEG channel selection was also investigated in the health field as a dimension reduction guided by physiological considerations. Puri *et al*. (2022), identified relevant EEG channels for Alzheimer's disease detection as those having the maximum ratio of energy to entropy based on a wavelet packet analysis. The highest performance metrics were obtained with six EEG channels out of 16 channels using an SVM classifier. In the field of motor imagery classification, Tang *et al*. (2022) applied a modified Sequential Backward Floating Selection (SBFS) to discard irrelevant pairs of channels on a preprocessed EEG dataset. This was followed by a filtering method to extract features from selected channels based on the coefficients of the Common Spatial Pattern (CSP) filter. In the same field, a recent study (Ghorbanzadeh *et al*., 2023) employed the same SBFS approach to reduce the initial dimension of the feature space. Hardware limitations dictate the size of the selected subset of channels that may be prefixed or determined by classification performance metrics. The SBFS resultant features were improved based on a genetic algorithm before the final selection of channels.

The selection of optimal EEG channels has been the focus of research for the identification of many diseases. However, despite the AUD burden, it has been less common for researchers to study and analyze EEG signals to select optimal channels. To the best of the authors' knowledge, only a few studies have investigated dimensionality reduction by selecting optimal EEG channels to address AUD concerns (Bavkar *et al*., 2021; 2019; Ong *et al*., 2006; Palaniappan *et al*., 2002; Shooshtari and Setarehdan, 2010; Zhu *et al*., 2014). The aforementioned EEG analysis studies reduced the dimension of the EEG dataset either by applying feature extraction techniques alone or by performing features or channel selection based on extracted features. The selection of optimal EEG channels in most of the previously mentioned studies (Bavkar *et al*., 2019; Ong *et al*., 2006; Palaniappan *et al*., 2002; Shooshtari and Setarehdan, 2010; Zhu *et al*., 2014) is based on gamma band power being a major discriminating factor in AUD patients. An emphasis was placed on the gamma band power since visual stimulation is reported to invoke the gamma band spectra (Zhang *et al*., 1997). Bavkar *et al*. (2021) also depended on frequency band power to select optimal EEG signals; they decomposed the signal into different Intrinsic Mode Functions (IMFs) and derived only the first five IMFs with frequencies greater than 0.5 Hz. However, the novelty of our study's approach lies in broadening the focus outside the gamma frequency band. This is done by investigating any dissimilarities that may exist between alcoholic and nonalcoholic EEG signals. The DtC approach evaluates the relevance of data retained in each EEG channel by comparing raw data of a specific alcoholic EEG channel to the corresponding nonalcoholic EEG channel.

Our approach to reducing the dimensionality of the dataset to be analyzed relies on the concept that alcoholic patients' EEG readings display abnormal neuronal activity in specific areas of the brain (Gilman *et al*., 2010). By measuring the similarity degree between alcoholic and nonalcoholic EEG signals, it is possible to identify relevant electrode positions and, in turn, reduce the dimensions of the full EEG dataset to be analyzed to an optimal number of channels. Since EEG recordings can be seen as time series in 2-dimensional space, the correspondence degree of two EEG signals can be assessed by measuring similarity distances between two point sets.

Materials and Methods

EEG Data

Electroencephalogram is a noninvasive method to diagnose diseases and monitor brain function. EEG signals represent electrical brain impulses that are created by neural activity in the brain along the scalp. To measure electrical signals, electrodes are positioned to make contact with the surface of the scalp. The most widely known and globally recognized system for positioning these electrodes on the scalp is the international 10-20 system. These electrode signals are also known as channels. Each electrode is referred to by a letter ("F": Frontal, "T": Temporal, "C": Central, "P": Parietal, "O": Occipital) and by an even or an odd number, corresponding, respectively to the right or the left hemisphere, or by "z", corresponding to the midline between the two hemispheres. An EEG measures voltage differences (in microvolts) produced by nerve cells in the brain. Five main types of brain waves (delta, theta, alpha, beta, and gamma) may be differentiated according to their signal amplitude and frequency band (Luján *et al*., 2021).

The data analyzed in this study are retrieved from the ML repository archive (Begleiter and Porjesz, 1999) of the University of California at Irvine (UCI), USA. The data come from a study whose objective was to examine chronic alcoholics' deficiencies in knowledge encoding, retention, and retrieval. The task for the participants was to determine whether the displayed picture was the same as the precedent picture. EEG signals were recorded from 122 individuals, including 77 alcoholic subjects and 45 nonalcoholic subjects. Each of the 122 subjects completed 120 trials in which various stimuli were displayed. There are three different versions of the EEG dataset: Small, large, and full. Recording of EEG signals was taken from 64 electrodes placed on the scalp at a sampling frequency of 256 Hz. The EEG recordings were referenced using the Cz electrode. Two bipolar derivations were used to record the Electrooculograms (EOG) for both the horizontal and vertical axes.

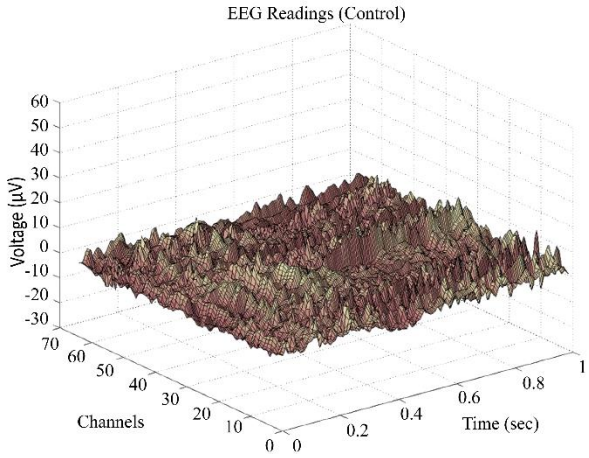

Fig. 1: Average nonalcoholic EEG signal amplitude (in μV) by time and channel over 10 trials in the case of a single stimulus

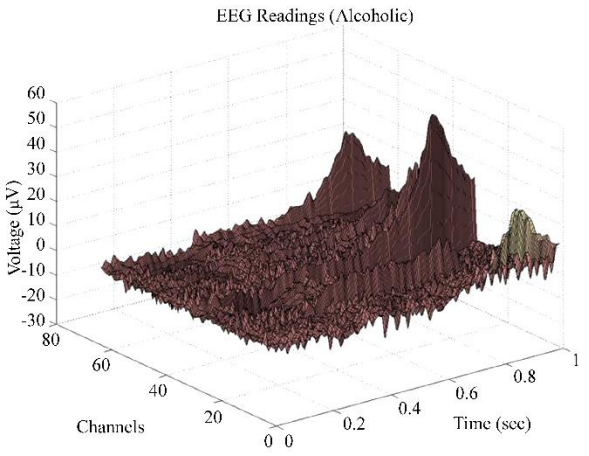

Fig. 2: Average alcoholic EEG signal amplitude (in μV) by time and channel over 10 trials in the case of a single stimulus

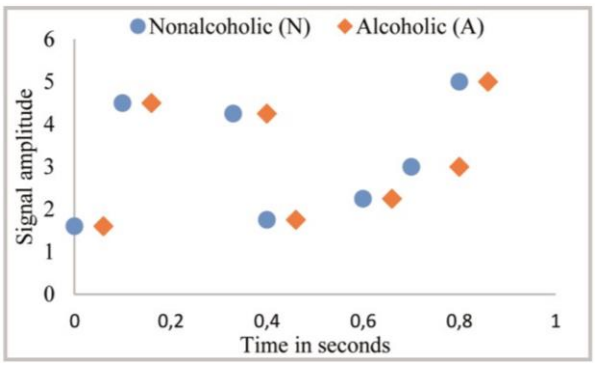

Fig. 3: Illustrative example of discrete alcoholic points (♦) and nonalcoholic points (*) EEG recording structures to be aligned. Each point represents an EEG signal amplitude over time

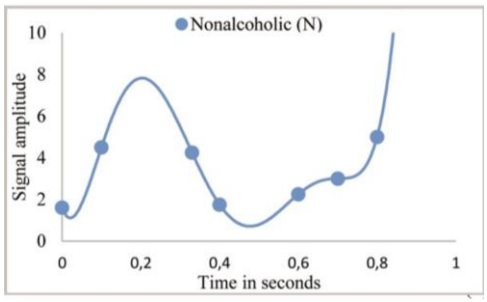

Fig. 4: Points of the nonalcoholic EEG recordings pattern interpolated by a continuous function. Points of the alcoholic signal are put aside

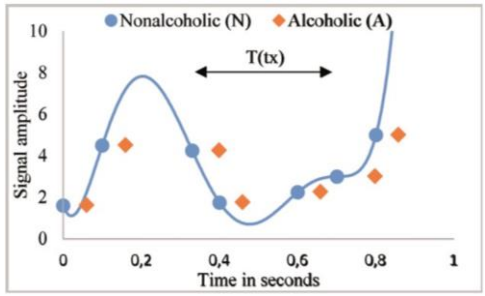

Fig. 5: The transformation T that would bring the alcoholic EEG signal points structure (points♦) back onto the nonalcoholic EEG signal points structure (points*)

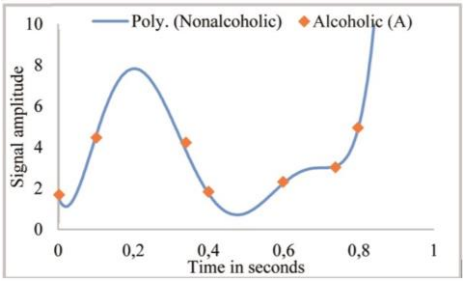

Fig. 6: The alcoholic EEG signal point structure (points♦) is fitted onto the polynomial interpolation of the nonalcoholic EEG signal point structure

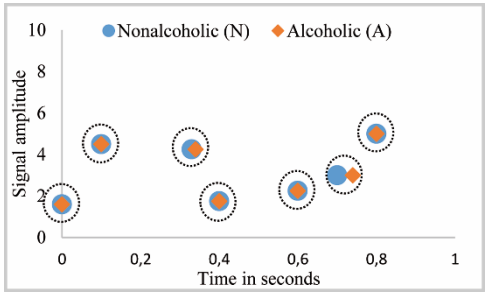

Fig. 7: Assignment of each point of the alcoholic EEG recording pattern (A) to its nearest neighbor in the nonalcoholic EEG recording pattern (N). The X-axis represents EEG recording time and the Y-axis corresponds to its amplitude

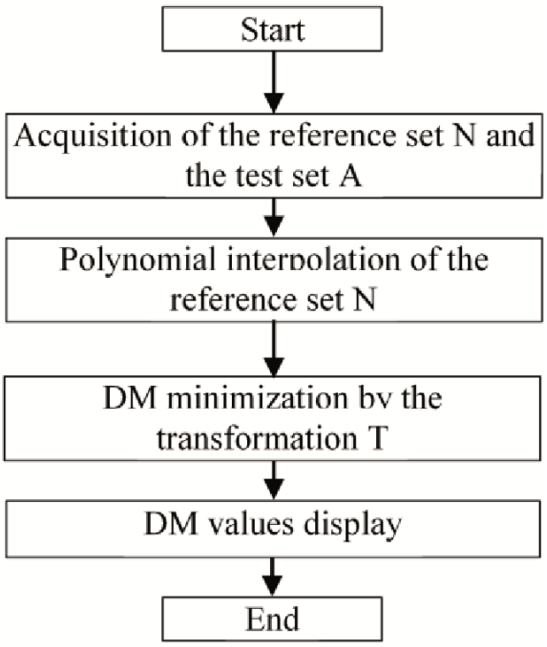

Fig. 8: Steps of the DtC algorithm

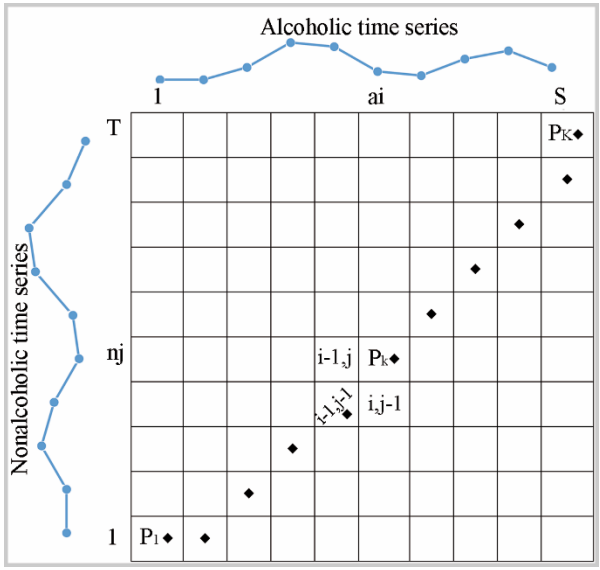

Fig. 9: A warping path referring to an alignment between alcoholic and nonalcoholic time series, where each point P_k of this warping path corresponds to a point (a_i, n_j)

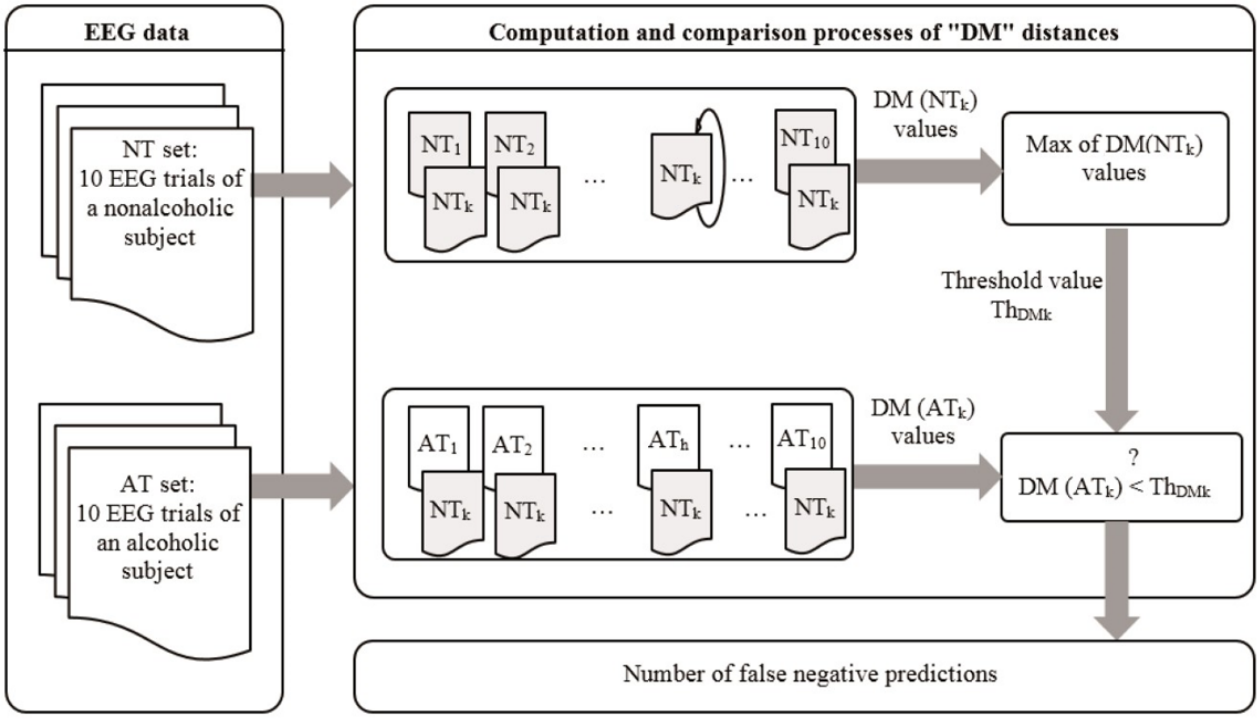

Fig. 10: Computation and comparison processes of distance measures between alcoholic EEG recordings (Alcoholic Trials (AT) set) and nonalcoholic EEG recordings (Nonalcoholic Trials (NT) set) illustrated for one channel and the k-index trial. DM (NT_k) are distance measure values calculated between two nonalcoholic signals (NT_k). DM (AT_k) are distance measure values calculated between an Alcoholic (AT_h) and a Nonalcoholic (NT_k) signal

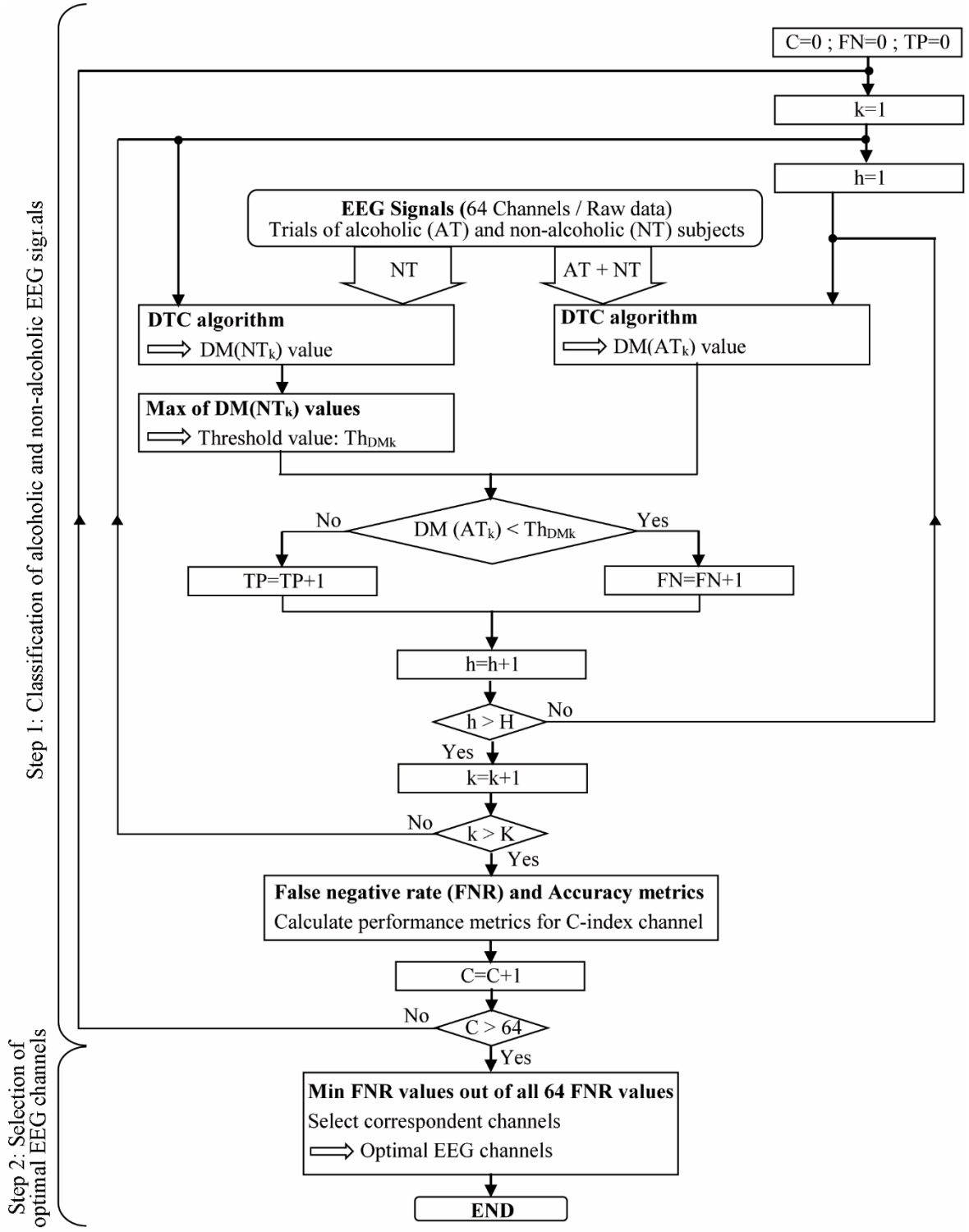

Fig. 11: Flowchart of the proposed methodology to select optimal EEG channels. C is a channel index out of 64 EEG channels. H and K are the total numbers of EEG signals in the alcoholic and the nonalcoholic EEG trial sets, respectively. DM (NT_k) are computed distance measures, for the C-index channel, between the k-index nonalcoholic EEG trial (NT_k) and all trials from the NT set (i.e., H trials) according to the NT_k trial. DM (AT_k) are computed distance measures for the C-index channel between an Alcoholic (AT_h) and an NT_k EEG signal. The threshold "Th_{DMk}" is the maximum Distance Measure (DM) out of all DM values within the nonalcoholic EEG trials set according to the k-index trial

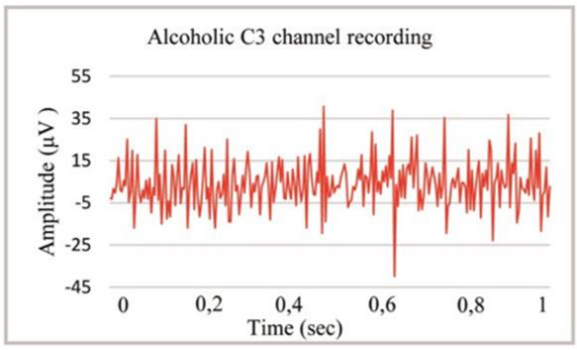

Fig. 12: The amplitude of the EEG signal (in µV) depicted by time for the alcoholic C3 channel recording

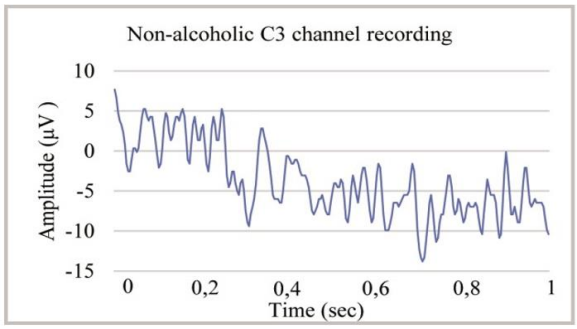

Fig. 13: The amplitude of the EEG signal (in µV) depicted by time for the nonalcoholic C3 channel recording

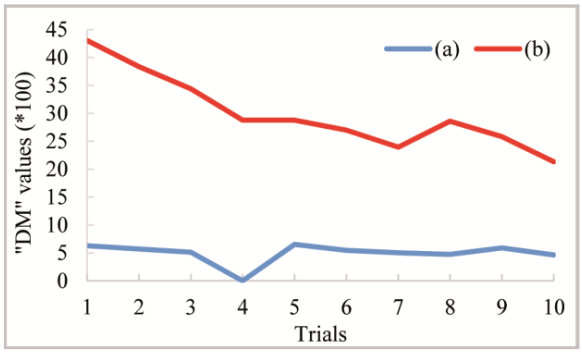

Fig. 14: Distance measures generated by the DtC algorithm at the C3 channel level, according to the 4-index trial. (a) Distance measures plot of the nonalcoholic EEG dataset between each other (DM (NT4)). (b) Distance measures plot of alcoholic EEG dataset compared to nonalcoholic EEG data (DM (AT4))

The subjects who were alcoholics had been sober for at least one month. The majority of alcoholics began drinking heavily when they were approximately 20 years old for at least 15 years. Criteria from the third edition of the Diagnostic and Statistical Manual of Mental Disorders (DSM-III) were used to make the initial diagnosis of alcohol abuse or dependence. Alcoholics with overt liver, metabolic, vascular, or neurological disorders were not selected (Zhang *et al*., 1997).

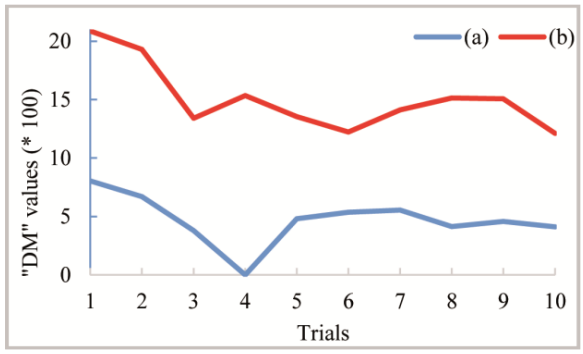

Fig. 15: Distance measures generated by the DTW algorithm at the C3 channel level, according to the 4-index trial. (a) Distance measures plot of the nonalcoholic EEG dataset compared between each other. (b) Distance measures plot of alcoholic EEG dataset compared to nonalcoholic EEG data

No history of mental or neurological disorders and no history of personal or family usage of psychoactive substances are key selection criteria for nonalcoholic subjects. Since the EEG signals of the dataset corresponded to the recordings of the brain's response to a visual stimulus, all subjects needed to have no vision issues.

Subjects were shown either one stimulus or two stimuli; they underwent either a matched or a nonmatched condition of exposure in the case of two stimuli. The stimulus set consisted of 90 images of various items that were selected from a standardized set of pictures. A state is said to be matched when the two stimuli exposed are the same; otherwise, it is said to be nonmatched. The interval between trials was set at 3.2 s, with a 300 sec stimulus period for each trial. Trials containing noises and artifacts during signal recordings, such as excessive body movements, eye blinks, and power line noise, were rejected. The international 10-20 system was employed and extended with the following sites: "FPz", "AFz", "AF1", "AF2", "AFz", "AF8", "F1", "F2", "F5", "F6", "FCz", "FC2", "FC3", "FC4", "FC5", "FC6", "FC7","FC8", "C1", "C2", "C5", "C6", "CPz", "CP1", "CP2", "CP3", "CP4", "CP5", "CP6", "TP7", "TP8", "PI", "P2", "P5", "P6", "POz", "POI", "PO2", "PO7" and "PO8". Two EOG electrodes were added as bipolar deviations (Zhang *et al*., 1997).

The EEG data analyzed in the present study correspond to the small dataset in the case of a single Stimulus exposition (S1). Every subject underwent 10 trials, each lasting one second. Figures 1 and 2 show typical one-second EEG signals for nonalcoholic and alcoholic subjects, respectively. These plots show the 64-channel EEG signal power differences between alcoholic and nonalcoholic subjects.

Discrete to Continuous (DtC) Algorithm

The DtC method was first designed to measure chirality and recognize shapes (Raji and Cossé-Barbi, 1999). Point pattern matching is the key component of the DtC approach, aimed at finding similarities between two point sets. In this study, it is used to match EEG signals in

two-dimensional space. Most approaches perform this point-by-point comparison using matrices of distances between point sets. Therefore, such an approach may lead to long response times due to combinatorial problems, which come from the discrete nature of point sets to match. In contrast, the DtC method addresses the problem of searching for correspondence in a comprehensive way rather than point-by-point matching.

The basic idea of the DtC algorithm is to map the discrete representation of a signal to the continuous representation of a reference signal to address the problem.

The DtC approach is employed in the present study to compare alcoholic and nonalcoholic EEG signals according to specific metrics.

Let A and N be two EEG signals of alcoholic and nonalcoholic individuals, respectively, with A being the test set and N the reference set:

$$A=\{a_i\}_{i=1}^{S\leq T} \quad (1)$$

$$N=\{n_j\}_{j=1}^{T} \quad (2)$$

where, S and T denote A and N lengths and i and j are the time series indexes, respectively.

Alcoholic and nonalcoholic EEG recording patterns are depicted in Fig. 3 in the case of the same length time series ($S = T$), which are seven fictitious points used to illustrate the DtC algorithm concept. The key challenge is determining whether a discrete alcoholic EEG recording pattern (points♦) corresponds to a pattern of nonalcoholic EEG recordings (points ⁕). In other words, check for the existence of an allowed transformation T such as:

$$T(A)\subset N \quad (3)$$

As stated before, without knowing the correspondence particularities between point sets A and N, searching directly for the T transformation inevitably leads to long response times. This leads to the risk of a combinatorial explosion. The DtC approach first converts the discrete form of the N set to a continuous representation by polynomial interpolation while retaining the discrete form of point set A (Fig. 4). The problem of determining whether A is included in N then becomes a matter of determining if there exists a transformation T that would bring A back onto N.

The EEG signal is a time series plot with measurements of amplitude as the ordinate and time as the abscissa. Points of the reference set N (nonalcoholic) and the test set A (alcoholic) are examined in a 2-Dimensional (2D) space, i.e., the O_{xy} plane.

Considering the polynomial interpolation P in the O_{xy} plane, for each point n_j that, belongs to N, we have:

$$P(x_{nj})= y_{nj} \quad (4)$$

where, (x_{nj}, y_{nj}) refers to the n_j point coordinate.

Various interpolation methods are available to express P. The interpolation approach adopted in this study relies on the "cubic spline" technique. This polynomial interpolation technique prevents the polynomial's degree from being influenced by the size of the set of N points. Continuity and differentiability are also ensured throughout the interpolation interval (Fig. 4).

As explained previously, determining the correspondence between A and N is a matter of identifying whether a transformation T exists. Given the polynomial interpolation P, the transformation T aims to bring the points set A back onto the continuous representation of the points set N along the plane O_{xy}.

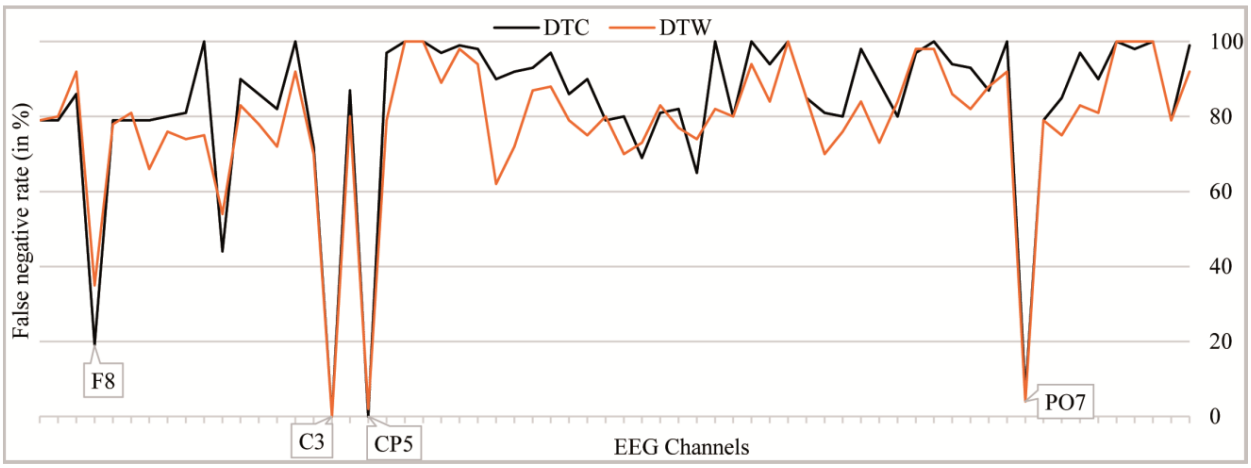

Fig. 16: False Negative Rate (FNR) values of all channels where FNR values of C3, CP5, PO7, and F8 tend to zero

As depicted in Fig. 6, this is done by translating points of the test set (*A*) along the time axis (*x*-axis) and computing the distance between the polynomial interpolation of the reference set and the points of set *A* (points of the test set). This is repeated until a minimal distance is obtained.

The converted points of *A* by the transformation *T* must also satisfy *P*, specifically:

$$p(x'_{ai}) = y'_{ai} \tag{5}$$

where, (x'_{ai}, y'_{ai}) refers to the a'_i point coordinates and a'_i refers to the transformation by *T* of a point $a_i \in A$.

The present paper aims to align EEG signals that are time series; hence, alignment of *A* and *N* signals is performed along the time axis O_x (Fig. 5 and 6). Therefore, the transformation *T* is transformed into a function with a single argument (Eq. 6 and 7), i.e., the translation t_x along the axis O_x:

$$x'_{ai} = x_{ai} + t_x \tag{6}$$

$$y'_{ai} = y_{ai} \tag{7}$$

Consequently, the polynomial interpolation *P* may be expressed as:

$$P(x'_{ai}) - y'_{ai} = 0 \tag{8}$$

$$\left(P\left(x'_{ai}\right) - y'_{ai}\right)^2 = 0 \tag{9}$$

Extended to all points of dataset *A*:

$$\sum_{i=1}^{S} \sqrt{\left(P\left(x'_{ai}\right) - y'_{ai}\right)^2} = 0 \tag{10}$$

where, *S* is the number of points in time series *A* (i.e., 256 points). Let *DM* denote the following function:

$$DM_{(t_x)} = \sum_{i=1}^{S} \sqrt{\left(P\left(x'_{ai}\right) - y'_{ai}\right)^2} \tag{11}$$

DM is a distance measure related to the "Euclidean distance" between the discrete reference set and the continuous polynomial interpolation *P*.

The parameters of the transformation *T* that minimize the *DM* distance measure must now be determined based on this formulation. The distance measure *DM* thus obtained is a nonlinear equation that can be solved using a variety of numerical techniques. The DtC algorithm uses the Nelder-Mead simplex method to minimize the distance measure *DM*.

Once the alignment of the points in set *A* on the continuous representation of *N* is performed as defined by *T*, it is then possible for the DtC algorithm to assign each point in set *A* to its nearest neighbor in *N*, i.e., its isomorph. As shown in Fig. 7, dashed circles refer to the assignment between points of the reference set and the test set; only discrete points of the reference set are considered, while polynomial interpolation is ignored. The accuracy of this assignment is assessed by computing the Root Mean Square (RMS). Since the present paper aims to calculate the distance between the *A* and *N* time series (i.e., *DM* values) and does not focus on computing the number of common points between the *A* and *N* time series, the RMS computation is omitted in this study.

Figure 8 illustrates the operating steps of the DtC algorithm.

Dynamic Time Warping Algorithm

The Dynamic Time Warping algorithm (DTW) enables the comparison of two sets of time series signals that may have shifts or distortions concerning each other. In this method, time series signals are locally compressed or stretched until an optimum distance (i.e., the shortest) is found between the warped sequences to determine the degree of similarity between them. The first applications of the DTW algorithm were in the area of speech recognition in the 1970s (Sakoe and Chiba, 1978). In the field of EEG data analysis, DTW feasibility has been investigated since 1985 to cluster EEG waveforms using simulated and actual EEG data (Bavkar *et al*., 2021). DTW proved its effectiveness in detecting Alzheimer's disease by monitoring gait and physiological signals (Varatharajan *et al*., 2018).

Using the DTW algorithm, EEG signals of alcoholic and nonalcoholic individuals are compared to each other as two-time series, *A* (Eq. 1) and *N* (Eq. 2), of length S and *T* by measuring the distance between these time series with a similarity function *f* (Eq. 12).

DTW allows comparing a point from the alcoholic series (i.e., *A*) with several other points of the other series (i.e., *N*) and determines where and how many points from the first series can be aligned to points of the second series. In this study, alcoholic and nonalcoholic EEG time series are of the same length (*S* = *T*):

$$d(i, j) = f\left(a_i, n_j\right) \tag{12}$$

where, *d* (*i*, *j*) denotes the distance between points a_i and n_j.

Nonlinear adjustment of *A* and *N* is represented by a path *P* (Fig. 9) in the matrix [1, *S*]*[1, *T*]:

$$\{P(k) = (u(k), v(k)) \mid k = 1 to K\} \tag{13}$$

where the functions *u*(*k*) and *v*(*k*) of an admissible path *P* should satisfy specific conditions:

- Boundary condition: The first and last indexes from the first series must match the first and last indexes from the second series, respectively, without requiring their unique match
- Continuity condition: This prevents the alignment path from jumping in "time" axes, ensuring that useful features are not skipped during alignment
- Monotonicity condition: This prevents the alignment path from going back in the time axes, which ensures that no features are repeated

As illustrated in Fig. 9, the only paths leading to point $P_k(i, j)$ have to originate from points (i-1,j), (i-1,j-1), or (i, j-1). Various warping paths are possible through the grid in Fig. 9. The DTW approach involves choosing the path with the smallest distances $d(i, j)$ so that the sum of the distances along the path is minimal.

The main goal of the DTW technique is to calculate the similarity distance between two-time series datasets by using warping functions (Eq. 13). Considering P, the algorithm calculates the distance between time series A and N as follows, where weight coefficient $m_P(k)$ is applied to the k^{th} segment of the path P and M_P is a normalization coefficient depending on the function m_P:

$$dp(A,N)=\min_p\left[\sum_{k=1}^{K} d(P(k))*mp(k)/M_p\right] \quad (14)$$

Selection of Optimal EEG Channels

The proposed approach uses the DtC algorithm to select the optimal channel. The DTW algorithm is used to compare the performance of the DtC technique. As outlined earlier, to select the most significant and optimal EEG channels, it is a matter of finding a subset of channels that allows the classification of a given subject into its appropriate category (alcoholic or nonalcoholic). To test the applicability of our approach, the data employed correspond to EEG recordings from one alcoholic and one nonalcoholic subject in the case of a single stimulus exposition. Recordings of EEG signals were taken from 64 channels with 256 points per channel lasting one second per trial. Each subject performed 10 trials.

The DTC-based approach compares two EEG recordings, which are two-time series. The DtC aims to identify similarities or dissimilarities between these two-time series using the Distance Measure (DM). When "DM" tends to zero, as minimized by the parameters of the transformation T in Eq. 11 shows that the two-time series are similar; otherwise, they are dissimilar.

Figure 10 describes key elements of EEG signal classification, namely, the computation and comparison procedures of DM values. Figure 11 depicts the overall flowchart of the proposed methodology, which illustrates the steps of the EEG signal classification and optimal EEG channel selection procedures. To assess the performance of our approach, the same flowchart in Fig. 11 was adopted using the DTW method to generate DM values. A detailed description of these processes is provided below:

1- Let NT denote the set of trials performed by the nonalcoholic subject. For each channel, the distance measure DM is computed according to a specific element of the NT set. That is, for a given k-index trial from the NT set (NT_k), DM is calculated between NT_k and itself (where $DM = 0$) and between NT_k and the nine remaining trials in the same set. This step is repeated for $k = 1$ to 10 (10 is the number of trials performed by the nonalcoholic subject). Let us refer to $DM(NT_k)$ as DM values calculated in this way (i.e., according to the k-index trial performed by the nonalcoholic subject)
2- Let AT denotes the set of trials performed by the alcoholic subject. For the same channel, DM is computed between each element of the AT set and a specific trial NT_k from the NT set. This step is repeated for $h = 1$ to 10. Let us refer to $DM(AT_k)$ as DM values calculated in this step according to the k-index trial performed by the nonalcoholic subject
3- Next, the maximum value from the DM (NT_k) set is selected as a threshold DM value Th_{DMk} according to the k-index trial, with which elements from the DM (AT_k) set are compared. The Th_{DMk} value represents the greatest dissimilarity between nonalcoholic trials. Each time the DM (AT_k) value is less than the reference Th_{DMk}, this is counted as a false negative prediction of an EEG signal. This step is also repeated for $h = 1$ to 10
4- Finally, considering that TP, FN, FP, and TN are true positive, false negative, false positive, and true negative predictions, respectively, by the same channel, where FP and TN values equal zero since the AT set contains only alcoholic cases, the False Negative Rate (FNR) and Accuracy (Acc) metrics are calculated for each channel as follows:

$$FNR(in\%)=\frac{FN}{TP+FN}*100 \quad (15)$$

$$ACC(in\%)=\frac{TP+TN}{TP+FN+FP+TN}*100 \quad (16)$$

Equation 15 and 16 are used to determine the performance measures, which are employed in the selection of the most representative channels.

Experimental Results

The EEG signal dataset was downloaded from the UCI ML repository (Begleiter and Porjesz, 1999). In this experimental step, EEG readings from one alcoholic and one control (nonalcoholic) subject were used. Ten trials per person were performed and one stimulus was

presented to each individual in each trial. The DtC and DTW algorithms were coded in the Java programming language. They were implemented on a computer with a 2.30 GHz AMD Ryzen 3700 U processor and 8 GB of RAM. The experiments were conducted in two stages: (a) Classification of alcoholic EEG signals in comparison to nonalcoholic signals and (b) Selection of optimal channels for alcoholism screening and diagnosis (Fig. 11).

Discrimination between alcoholic and nonalcoholic subjects is a matter of finding whether there is a correspondence between two EEG recordings, which are two-time series. The DtC algorithm targets checking for the existence or absence of such correspondence between these two-time series. Alcoholic EEG signals were classified in comparison to nonalcoholic signals by calculating the distance measure between two-time series using the DtC and DTW algorithms. Nonalcoholic EEG signals were compared, and the maximum distance measure value was adopted as a threshold value in the classification process.

Table 1 summarizes the optimal channel selection results of the proposed approach compared to the DTW method. It reports false negative rates and accuracy percentages by channel. Four channels were selected as the best channels, namely, C3, CP5, PO7, and F8, with accuracy values of 100, 100, 94, and 81%, respectively. For the same channels, the DTW algorithm achieves 100, 98, 96, and 65% accuracy values.

As demonstrated by these results, the DtC and DTW algorithms produce almost similar results for C3, CP5, and PO7 channels. False negative rates for the DtC algorithm are similar to those for the DTW algorithm, except for the F8 channel, where FNR is 19 and 35%, respectively.

Figure 12 reveals that the alcoholic EEG signal recorded from the C3 channel has faster wave oscillations and higher amplitude (nearly six times) than the nonalcoholic EEG signal (Fig. 13) at the same channel.

As depicted in Table 1, the highest accuracy (100%) and the lowest FNR (0%) values were obtained at the C3 and CP5 channel levels using the DtC algorithm and at the C3 channel level using the DTW algorithm, followed by PO7 and F8 channels in decreasing order of performance using both algorithms.

Figure 14 and 15 display the distance measures generated by the DtC and DTW algorithms, respectively, at the C3 channel level. As shown, no correspondence exists between A and N EEG signals according to the 4-index trial. The x-axis refers to trials and the y-axis indicates DM values. Plot (a) depicts distance measures within the nonalcoholic trial set based on the 4-index trial (DM(NT4)). Plot (b) refers to DM values computed between the set of trials performed by the alcoholic subject and the 4-index trial performed by the nonalcoholic subject (DM(AT4)). The DM plot cancels at the 4-index point on the x-axis since it compares the nonalcoholic EEG signal with itself.

As stated earlier, the DtC approach consists of comparing patterns of EEG signals and searching for the degree of similarity or dissimilarity. This is done to investigate the ability of the DtC algorithm to select optimal EEG channels that retain the most significant information for alcoholism detection. The dissimilarity degree is assessed using performance metrics (FNR and accuracy). The lower the FNR value, the higher the similarity between EEG signals. Figure 11. illustrates the bloc diagram of the DtC methodology. To further explain the selection process of the aforementioned channels, the DtC and DTW plots in Fig. 16 provide FNR values predicted for all 64 EEG channels. The x-coordinate represents EEG channels and the FNR values are reported on the y-coordinate. When compared to the DTW algorithm, DtC displays similar results. As illustrated, the minimum points that correspond to channels C3, CP5, PO7, and F8 are quite distinctive on both plots, where the y-coordinate value (i.e., FNR value) is smaller and decreases toward zero compared to the other y-coordinates on the plots. Out of 64 EEG channels, C3, CP5, PO7, and F8 are selected as relevant and optimal EEG channels based on their classification Accuracy (Acc) in detecting AUD patients.

Discussion

In this study, the DtC algorithm was adapted and improved to provide a novel method for selecting the most significant and optimal EEG channels. This method may assist in patient classification for alcoholism screening or diagnosis. It is worth mentioning that the main objective of this study is not to propose an EEG signal classification model. It is intended to demonstrate a novel approach to reducing the multichannel EEG database's dimensionality. Hence, this section discusses the effectiveness of the proposed optimal channel selection approach.

According to the classification performances shown in Table 1, similar channels were selected by both the DtC and DTW approaches (Fig. 16). This shows that the C3, PO7, CP5, and F8 electrode sites retain essential information for alcoholism discrimination and correspond to the brain area that alcohol consumption affects the most.

Hu and Prado (2023) computed the beta-band squared coherence between EEG channels for alcoholic and nonalcoholic subjects. The C3 channel exhibits a high squared coherence with the C1 channel in the alcoholic EEG data, while in the control (nonalcoholic) data, the C3-C1 squared coherence was essentially nil. When comparing the coherence values of actively associated channel pairs in the alcoholic EEG data, the authors demonstrated that C3-C1 was the unique channel pair presenting a high coherence in the alcoholic data, while it was zero for the nonalcoholic data. These findings indicate the presence of representative characteristics and abnormal activity at the placement site of the C3 electrode for the alcoholic subject, which confirms our results.

Table 1: Performance comparison of the DtC and DTW algorithms by optimal selected channels

	Performances (in %) by optimal selected channels		
The algorithm	Channel	Accuracy	False negative rate
Discrete to continuous	C3	100	0
	CP5	100	0
	PO7	94	6
	F8	81	19
Dynamic time warping	C3	100	0
	CP5	98	2
	PO7	96	4
	F8	65	35

Table 2: Comparison of the DtC approach with existing channel selection methods

	Selection approach characteristics		Classification approach characteristics		
Existing channel selection methods	Channel selection methods	Number/{localizations} of electrodes	Accuracy (in %)	Feature selection	Classification
Bavkar *et al*. (2021)	Harmony search algorithm	61/{The entire EEG dataset except three reference electrodes.}	96.50	Amplitude and frequency modulated bandwidth features	Ensemble subspace KNN
		19/{FP2, F7, F8, FC5, T7, C3, O2, O1, AF7, AF8, F6, FT7, FPz, C6, P6, PO7, PO8, Oz, and P1}	91.50		
		12/{FP1, FC6, FC5, T7, Cz, O1, AF7, AF8, FC4, PO7, PO8, Oz}	93.87		
Bavkar *et al*. (2019)	Improved Binary Gravitational Search Algorithm (IBGSA)	13/{FP1, FPz, FP2, AF7, AF8, FC5, FC6, T7, TP7, TP8, Cz, PO8 and PO7}	92.50	Gamma band power	Ensemble subspace KNN
Zhu *et al*. (2014)	Statistical test (nonparametric wilcoxon tests)	1/{CP6}	79.4(with SVM)	Horizontal Visibility Graph Entropy (HVGE)	KNN or SVM
		3/{C1, C3 and FC5}	87.6(with SVM)		
		13/{AF8, C1, C2, C3, C4, CP1, CP5, CP6, FC5, FT7, P8, PO8 and PZ}	95.8(with SVM)		
		63/{The entire EEG dataset except the "nd" reference electrode}	98.2(with KNN)		
Shooshtari and Setarehdan (2010)	Absolute gamma band power and correlation analysis	2/{F8, AF8}	82.98	Absolute gamma Band power	Least Squares Support Vector Machine (LS-SVM)
		4/{F8, F6, AF8, FT8}	82.27		
		1/{AF8}	81.56		
		2/{AF8, F8}	81.56		
		3/{F6, AF8, FT8}	81.56		
		2/{AF8, FT8}	80.85		
		3/{F8, F6, AF8}	80.85		
Ong *et al*. (2006)	Principal Componen Analysis (PCA)	61/{The entire EEG dataset except for three reference electrodes}	95.83	Gamma band power	MLP NN
		16/{FP1, AF7, F7, AF8, F8, FT8, T8, PO8, O2, O1, PO7, TP7, T7, CZ, F1, FC2}	94.06		
		8/Not available	86.01		
		4/Not available	75.13		
Palaniappan *et al*. (2002)	Genetic Algorithm (GA) with Fuzzy Artmap (FA) Classifier	61/{The entire EEG dataset except three reference electrodes}	95.90	Spectral power ratios	FA or MLP-BP
		7/{CP5, AF8, FT8, FPZ, F1, TP8 and C2}	94.30		
Our proposed Approach	DtC algorithm	1/{C3}	100.00	Raw data	Based on DM Values computed with the DTC algorithm in the channel selection step
		1/{CP5}	100.00		
		1/{PO7}	94.00		
		1/{F8}	81.00		

A comparison of our approach with previous studies on optimal EEG channel selection of alcoholic subjects from the dataset introduced in (Begleiter and Porjesz, 1999) is summarized in Table 2. The findings of the DtC optimal selection channel approach were in line with previous studies' results. As shown in Table 2, all the channels that were selected by the DtC algorithm, i.e., the C3, PO7, CP5, and F8 channels, were also selected in previous studies. Classification performances in these studies showed that the optimal selected subsets of channels retain significant information in comparison to the entire EEG dataset.

By using WST-based features, Buriro *et al*. (2021) concluded that the occipital and parietal areas generate the most informative signals, which correspond to the CP5 and PO7 electrode positions selected by our approach. Bavkar *et al*. (2021), the authors recommend 19 channels as the most appropriate for classifying EEG data, including three electrode locations selected by our approach, namely, the C3, PO7, and F8 channels. The ensemble subspace KNN classifier achieved accuracies of 96.5 and 91.5 by using the entire data and the 19-channel subset, respectively. The selection process utilized the binary harmony search algorithm. Bavkar *et al*. (2019), several classifiers were employed to assess their accuracies in the classification of EEG data for the discrimination of alcoholic cases. Without using optimization, i.e., with the 61 EEG channels, the ensemble subspace KNN classifier achieved a higher accuracy rate (95.1%). By evaluating four optimization methods, a reduced dataset containing 13 EEG channels was selected based on the improved binary gravitational search algorithm with less accuracy (92.5%) for the same. Zhu *et al*. (2014) proposed three subsets of optimal channels that include C3 and CP5 electrode sites. The authors used the Horizontal Visibility Graph Entropy (HVGE) method to extract features and selected channels based on the Wilcoxon statistical test. By analyzing the entire EEG data and the 13 EEG channel data, the SVM classifier achieved accuracies with a minor difference (98.2 and 95.8). The selection method employed by Ong *et al*. (2006) focuses on the PCA technique. The authors propose a reduced EEG dataset dimensionality with 16 EEG channel sites, including F8 and PO7 electrodes. The CP5 electrode location was also identified in (Palaniappan *et al*., 2002); it is part of an optimal subset composed of seven EEG channels that were deemed to retain enough information to be used in the classification of alcoholic cases. The MLP-BP classifier achieved almost similar performance (95.9 and 94.3) on the entire dataset and the optimal selected subset of channels, respectively. Studies (Bavkar *et al*., 2021; 2019; Ong *et al*., 2006; Palaniappan *et al*., 2002; Shooshtari and Setarehdan, 2010; Zhu *et al*., 2014) present findings from research on the discrimination of alcoholic EEG signal cases using the same EEG dataset. These studies propose a higher number of channels compared to the DtC approach. However, optimally reducing the EEG dataset dimensionality helps enhance memory performance and computing complexity, resulting in improved classification performance and accuracy.

Most of the research in Table 2 looks for the subset of channels that achieve the closest classification performance to the entire dataset performance to reduce the database's dimensionality. To the same end, the proposed approach in this study is focused on comparing the performance of EEG channels with each other. In this way, only EEG channels retaining the most significant information would be involved in the classification process and irrelevant channels should be discarded. Shooshtari and Setarehdan (2010) substantially reduced the number of channels to be fed into the classification model. Based on absolute gamma-band power and correlation analysis, the authors selected combination sets of one or a maximum of four channels located essentially in the frontal lobe of the brain. The common optimal selected EEG channel between this study and the DtC approach is the F8 electrode.

Researchers define alcohol consumption from more than one perspective. A psychological perspective views alcohol consumption as deviant behavior that conflicts with social norms and values and is dependent on socioenvironmental factors (Dullas *et al*., 2021). Insights into brain structure and function in both normal and deviant behavior can be provided by state-of-the-art imaging (Pujol *et al*., 2019). Studies on risky deviant behavior reveal alterations in the frontal lobe and reduced gray matter in brain regions, which are linked to social cognition (Straiton and Lake, 2021; Yang and Raine, 2009). However, most correlations between behavior and brain function remain undiscovered (Marek *et al*., 2022). A medical perspective classifies alcohol consumption either as a health risk factor that includes hazardous and low-risk consumption or as a disorder (Saunders *et al*., 2019). The fifth version of the diagnostic and statistical manual of mental disorders code (DSM-5) distinguishes three severity degrees of alcohol use disorders, namely, mild, moderate, or severe, which are equivalent to “alcohol dependence” and “harmful pattern use of alcohol” in the latest revision of the International Classification of Diseases (ICD-11) (Saunders *et al*., 2019). Chronic and heavy alcohol use can cause permanent brain atrophy; indeed, drinking in this way alters brain size and shape and has a depressive effect on the central nervous system both in middle-aged and adults (Mukherjee, 2013; Sullivan and Pfefferbaum, 2019). Excessive alcohol use has been linked to numerous patterns of macro-and microstructural alterations especially changes in the frontal, diencephalon, hippocampus, and cerebellar regions (Daviet *et al*., 2022). Alcohol interferes

with neurotransmitter function by slowing it down and even blocking it from performing its essential functions so that these neurotransmitters are destroyed (Banerjee, 2014). Heavy alcohol consumption also leads to thiamine deficiency, which is known to cause brain injuries (Rao and Topiwala, 2020). While alcohol consumption has been largely documented to negatively impact brain health when consumed chronically and heavily, research findings regarding the effects of Low-to-Moderate (LtM) alcohol use on brain health have been inconsistent; indeed, it was found that consuming LtM amounts of alcohol improves brain function (Zhang *et al*., 2020). However, recent research revealed that the harmful effects of alcohol consumption on brain macro and microstructure are well perceptible in those who drink an average of one to two units per day (one unit is equivalent to ten milliliters or eight grams of ethanol), which is defined as LtM alcohol use (Daviet *et al*., 2022). In addition, research on sex-specific moderate alcohol use suggests that women are more susceptible than men to developing alcohol-induced brain dysfunction (Harper *et al*., 2018).

The DtC approach identified significant effects of alcoholism from a medical perspective. The EEG data analyzed in our study correspond to recordings of the brain's response to a visual stimulus. This is done to assess alcoholics' deficiencies in visual information encoding, retention, and retrieval. Functionally, more than one brain region is involved in visual information processing. Previous research has revealed visual processing abnormalities in the frontal area, particularly in the right hemisphere and in the temporal and occipital areas for alcoholics compared to nonalcoholic subjects (Gilman *et al*., 2010; Zhang *et al*., 1997). In the present study, the DtC approach findings are consistent with previous research since optimal selected channels F8, CP5, and PO7 are also located in these areas (Fig. 17). As mentioned in the results section, the highest classification performance achieved by the DtC approach was at the C3 channel level; the DTW algorithm also confirmed this. In addition, the C3 channel was selected as containing significant information in previous studies (Bavkar *et al*., 2021; Zhu *et al*., 2014) studies. Given these findings, it may be concluded that the C3 electrode site generates representative characteristics for the alcoholic subject. However, these characteristics are not related to visual processing deficiencies since the C3 channel corresponds to the left sensorimotor hand area. Indeed, during EEG recordings, all subjects were asked to handle a mouse key to accomplish tasks. These findings raise the question of whether EEG investigation of sensory-motor nerves may assist in identifying nerve deficiencies related to alcohol consumption.

Feature selection techniques involve removing redundant and irrelevant features from the initial set of data to enhance classification performance and reduce dataset dimensionality (Zhang, 2021). The qualitative comparison of the DtC approach with existing methods to select optimal EEG channels revealed that the feature selection that was used did not enhance classification accuracy (Table 2). It is possible that some relevant information was omitted since these studies' approaches focus on frequency band power as a discriminating marker of AUD. However, our approach is an exhaustive search of optimal EEG signals and performed a raw data-based AUD discrimination that gives the highest accuracy among all other EEG channel selection methods.

Furthermore, implementation of EEG analysis for early and objective diagnosis at the level of Emergency Hospitals (EH) and Primary Health Care services (PHC) requires professional assistance due to the high dimension of EEG signals and the complex processes needed for installation. Our approach proposes a subset of relevant EEG signals, which may assist in implementing practical EEG devices for AUD discrimination. In addition to accelerating the adaptive efforts that must be taken in the follow-up, monitoring, and managing recovery and withdrawal among AUD patients.

The main limitation of the present study is that the DTC-based classification task relies on the availability of an adequate reference for nonalcoholic EEG recordings. As explained earlier, DTC-based discrimination between alcoholic and nonalcoholic EEG signals was performed using the threshold value Th_{DMk}, which is the maximum distance measure between two nonalcoholic EEG recordings. The DtC algorithm was efficient in selecting optimal EEG signals, but its generalization as a classification model is not an appropriate approach for AUD discrimination. Another limitation is the paucity of information in the open EEG database, especially on the severity of alcohol-use disorder. As mentioned earlier, the provided description of the dataset indicates that a majority of the enrolled AUD patients for EEG recordings were Heavy Drinkers (HD) for at least 15 years, while the severity of AUD disease in the rest of the patients is not available. In addition, no information was given in the dataset about which EEG recordings pertained to heavily drinking individuals or if there was a mild or moderate degree of dependence.

To overcome the study's limitations, there is a need to create a dataset with labeled EEG recordings based on patients' age, gender, and severity of alcohol dependence. In the future, we could compensate for these limitations by generalizing the DtC approach to labeled EEG recordings. This would enable us to gain more insight into the similarity in the optimal channels between labeled EEG recordings. To determine the key points in preventing, treating, and recovering from alcohol dependency, a wide variety of solutions have been investigated. This includes the understanding of brain transition and evolution mechanisms from hazardous use to dependence.

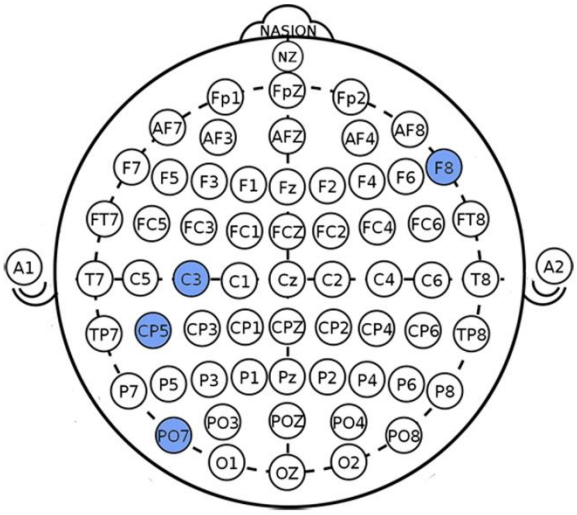

Fig. 17: EEG channel placement according to the international 10-20 system showing the positions of optimal channels selected by the DtC algorithm (positions C3, CP5, PO7 and F8 are marked with a different background color)

Conclusion

The DtC approach was efficient in selecting optimal EEG channels for AUD discrimination. Our approach findings reveal that the C3, CP5, PO7, and F8 electrode sites retain relevant information to discriminate alcoholism. Locations of the CP5, PO7, and F8 electrode sites correlate perfectly with the regions of the brain that alcohol use severely affects.

Those four locations maintain sufficient information for alcoholism discrimination. This is concordant with the scientific evidence currently available from clinical research that shows that three brain areas are affected by alcohol consumption as a response to visual stimuli. Thus, the amount of EEG data to be analyzed in alcoholism discrimination may be reduced to only three channels instead of 64 EEG channels. These three channels may be employed to propose a useful classification model, which could substantially decrease the computation time and hardware requirements. Moreover, the abnormal brain functioning detected by the DtC algorithm at the C3 electrode site suggests that the C3 channel may be a biomarker to predict alcoholism-related damage at the hand nerve level in an early stage before the first symptoms manifest.

Although the present work focused on reducing the dimensionality of an alcoholic EEG dataset, the proposed approach can also be used to decrease the dimensionality of EEG datasets from other diseases.

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Author's Contributions

Hayat Sedrati: Problem identification, conceptualization, data set identification, writing-original draft, methodology, development and algorithmic programming, results evaluation and interpretation.

Wajih Rhalem: Problem identification, conceptualization, methodology, development and algorithmic programming.

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Chakib Nejjari and Fatima El Omari: Results evaluation and interpretation.

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Ethics

This article is original and contains unpublished material. There are no ethical issues involved in this manuscript.

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