Classification Of Alcoholic and Control Subjects using Spiking Neural Network

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Abstract

This study explores the application of Spiking Neural Networks (SNNs) within the NeuCube computational tool for classifying subjects with alcohol use disorders and control subjects based on EEG data. Leveraging cross-validation with three folds, robust classification was achieved. Visualizing SNN models provided tangible representations of distinctive neural activity patterns. Network analysis unveiled notable differences in interconnectivity, suggesting heightened cognitive function in the control group. Feature extraction through network analysis significantly enhanced classification accuracy. Comparing our findings with prior work, we assessed Naïve Bayes, logistic regression, and Multilayer Perceptron (MLP) algorithms, achieving the highest accuracy of 74.95% with MLP. In contrast, our current SNN approach within NeuCube surpasses previous results, particularly post-feature extraction with 80.20% accuracy, showcasing SNNs' effectiveness in handling complex neuroinformatic data. These results offer promising implications for the accurate classification of alcohol use disorders through advanced machine learning techniques.

Keyword- Classification, Alcoholism, Neuroinformatic, Brain Data Analysis, SNN, Neural Network.

1 Introduction

For thousands of years, men and women have struggled with alcoholism. For far too long, drinking was regarded as a sign of "personal weakness"; alcoholics were blamed for their condition, and little true hope or cure was provided. Researchers can now examine biological impacts on alcoholism, some of which are most certainly inborn and handed down from generation to generation, as a result of enormous advances in scientific research. (Henri Begleiter Neurodynamics Laboratory| SUNY Downstate Health Sciences University, n.d.)[1]. According to research, alcoholism runs in families. For example, if you are the kid of an alcoholic parent, especially the son of an alcoholic father, you are considerably more likely than your peers to acquire alcohol issues. In fact, if you are the kid of an alcoholic, you are four to nine times more likely to become an alcoholic than someone who comes from a non-alcoholic household. Children born to parents who abuse alcohol but are adopted and raised by non-alcoholics have an extremely high chance of developing alcoholism. Alcohol intake is linked to over 200 health problems and is one of the top five risk factors for illness worldwide(Lim et al., 2012) [2].

In recent years, the field of neuroinformatic has experienced rapid growth, with the aim of understanding the brain and its functions through the use of computational tools. One of the key applications of neuroinformatic is the classification of brain data using artificial intelligence and machine learning techniques. The utilization of spiking neural networks (SNNs) represents a cutting-edge approach to classification tasks. Unlike traditional artificial neural networks, SNNs mimic the behaviour of biological neurons, processing information in discrete spikes rather than continuous values. This unique characteristic allows SNNs to capture complex temporal patterns inherent in neural activity. When applied to the study of alcoholism, SNNs have ,the potential to discern subtle electrophysiological signatures associated with memory impairment, offering a level of granularity that conventional methods may overlook. By training these networks on comprehensive datasets, we can achieve remarkable accuracy in distinguishing between alcoholic and control drinkers. This not only advances our understanding of the neural underpinnings of alcoholism but also holds promise for early detection and personalized intervention strategies.

In this paper, We will explore the rationale behind this topic, present a brief literature review, describe the data, review previous research, do classification of alcoholic and control drinkers by using SNN method in NeuCube using a dataset previously used by (Zhang et al., 1997) [3], design an empirical study to analyse the data, visualize the data, apply the data modelling and analysis methods, summarize and compare the results of SNN with other ML methods used in Assignment 1 , and suggest further analysis. Through this paper, we aim to demonstrate the potential of artificial intelligence and machine learning in the field of neuroinformatic and its applications in the classification of brain data.

2 Literature Review

So far, there have been many research related to classification using electroencephalographic (EEG) data. For example, In the paper by Amin, H. U. et al they did classification of different cognitive tasks using EEG data with techniques like K-nearest neighbour (KNN), Support Vector Machine (SVM), Multi-layer Perceptron (MLP), and Naïve Bayes (NB). In this study, they did combination of DWT with FDA and PCA techniques make a robust feature extraction approach and in their conclusion they find highest accuracy of 93.33% with KNN (Amin et al., 2017) [4] .

Deep-learning neural networks is also popular in the area of classification. (Huang et al., 2020) [5] used a EEG classification methodology based on sparse representation enhanced deep learning networks. They used BCI Competition 2005 dataset to classify EEG waveforms of classes 1 and 2. Their methodology combines the advantages of sparse representation and fast compression residual convolutional neural networks to achieve an averaged accuracy of 98.82% in classifying EEG.

in a paper by (Wang et al., 2016)[6] he used a smaller version of the same dataset by (Zhang et al., 1997)[3] for his experiment and proposed three data selection strategies were used to retrieve representative data from drinkers' EEG signals. The approaches are principal component analysis with graph entropy (PCA-GE), channel selection with graph entropy (GE) difference, and channel selection using mathematical combinations. Three classifiers were used to classify the data from the three methods: the J48 decision tree, the K-nearest neighbour, and the Kstar. The authors discovered that the proposed techniques are successful in data selection while maintaining classification accuracy in identifying EEG signals from alcoholics and control subjects, with a classification accuracy of 94.5%.. He also observed by using only 19 most relevant electrodes instead of all 64 his accuracy and computation efficiency went up.

Ong et al. [7] proposes a method for selecting a subset of EEG channels using Principal Component Analysis (PCA) to improve classification accuracy of alcoholics and non-alcoholics based on their visual evoked potential (VEP) responses. The study found that the proposed method greatly reduced the number of channels needed for classification while preserving critical information, which could significantly reduce hardware requirements and classification time in future VEP recordings.

Fattah et al.[8] introduced a k-nearest neighbour classifier for distinguishing between alcoholic and non-alcoholic individuals, utilizing the reflection coefficient as a feature. Unlike autoregressive parameters, which exhibit a wide range of values, reflection coefficients are constrained between 0 and 1, rendering them highly robust against noise, especially when compared to AR coefficients. This suggests that the reflection coefficient provides superior accuracy in classification compared to spectral domain features. Initially, a high-pass filter is employed on the EEG data to retain the gamma band and all higher frequencies. Subsequently, the reflection coefficients are computed based on autocorrelation values. The KNN classifier is then employed with various k values to determine the most suitable one. It is observed that an increase in the number of reflection coefficients leads to an improvement in classification accuracy up to a certain point, resulting in enhanced overall classification accuracies.

So far there hasn't been many research on classification of alcoholics using SNN. In this paper, we want to apply Spiking Neural Network Method for classification and compare the performance to Naive bayes, logistic regression and Multilayer Perceptron (MLP) performed in assignment 1. By comparing the accuracy of these models we'd want to learn more about how these algorithms perf orm in tasks like EEG signal classification.

3 Method

3.1 Dataset Description

The dataset we use in this paper comes from H. Begleiter of Neurodynamics Laboratory of State University of NY Health Center (Begleiter,Henri.,1999)[9].This dataset has EEG recordings of 122 Control and alcoholic subjects each going through 120 trials. The Trial involved two groups: a control group of 48 male subjects recruited from hospital employees and an alcoholic group of 77 male alcoholics. Control subjects were carefully screened for alcohol and drug use, medical and psychiatric histories, and had no history of alcohol/drug abuse or neurological/psychiatric diseases. Both groups had normal vision or corrected normal vision. The control group had an average age of 25.81 years, while the alcoholic group had an average age of 35.83 years.

Alcoholics were diagnosed based on DSM-III criteria and confirmed by instruments developed by the COGA group. All alcoholic subjects had completed their detoxification and had no alcohol available to them during a 30-day hospitalization period. They had a history of heavy drinking for at least 15 years and started drinking around the age of 20. Patients with liver, metabolic, vascular, or neurological disorders were excluded from the study, as were those with a history of drug dependence or major psychiatric illness predating alcoholism.

The trial included a picture-based challenge comprising 90 distinct visual items displayed on a computer monitor. Subjects had to assess if the second picture (S2) matched the first stimulus (S1) and respond accordingly. The presentation of matching and nonmatching trials was randomized, and the task was sensitive to memory deficits.

In summary, the trial involved two groups, control and alcoholic, and used a picture-based task to investigate cognitive function related to memory in alcoholics compared to non-alcoholic controls. The alcoholic group had specific criteria for diagnosis and exclusion, and the task aimed to assess memory function (Zhang et al., 1997)[3].

Data for this experiment were collected from 64 scalp-mounted electrodes for 1 second at 256 hertz (3.9 microsecond epoch). Electrode placements were made in accordance with Standard Electrode Position Nomenclature, which the American Electroencephalographic Association released in 1990 as shown in **Fig 1.** FP1 FP2 F7 F8 AF1 AF2 FZ F4 F3 FC6 FC5 FC2 FC1 T8 T7 CZ C3 C4 CP5 CP6 CP1 CP2 P3 P4 PZ P8 P7 PO2 PO1 O2 O1 X AF7 AF8 F5 F6 FT7 FT8 FPZ FC4 FC3 C6 C5 F2 F1 TP8 TP7 AFZ CP3 CP4 P5 P6 C1 C2 PO7 PO8 FCZ POZ OZ P2 P1 CPZ nd Y. "X" and "Y" are the electrodes that are used to record EOG signals, while "nd" is the reference electrode (Wang et al., 2016)[6].

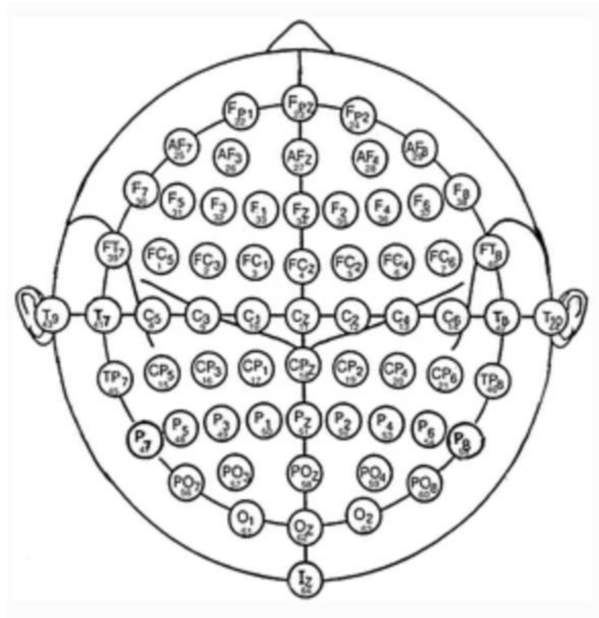

Fig 1. Electrode location according to American Electroencephalographic Association

In the original study by (Zhang et al., 1997)[10] that collected this dataset concluded that the event-related potential that the ERP method may be used to assess short-term memory, and the difference in ERP mnemonic effect between the control and alcoholic groups may represent a working memory deficiency produced by long-term alcohol misuse. The study discovered that alcoholics made more errors and took longer to complete the task than controls, and that In the sample and nonmatching trials, the greatest variations in evoked potentials between the two groups were identified in the temporo-occipital and frontal areas, with the right hemisphere being the most evident. The study gives information on the consequences of long-term alcohol misuse on short-term memory and demonstrates the utility of the ERP approach in evaluating memory.

3.2 Methodology

For our experiment we'll be using Spiking Neural Network in NeuCube. SNN is a type of artificial neural network that is inspired by the way neuron communicates in a human brain.

The NeuCube architecture is built upon a spiking neural network (SNN) designed to mimic the structural and functional aspects of specific brain regions involved in modeling spatio-temporal brain data (STBD). In NeuCube, the SNN takes the form of a three-dimensional evolving reservoir (SNNr). This reservoir learns from STBD and establishes connections between clusters of neurons that exhibit sequences (or pathways) of neural activity. The SNNr undergoes unsupervised training to understand the spike sequences representing individual input patterns. It also undergoes supervised training to differentiate and classify various dynamic patterns of SNNr activities that correspond to distinct input patterns from STBD, belonging to different categories. The output function (classification) module in NeuCube is responsible for categorizing the diverse dynamic patterns of SNNr activities(Kasabov, 2014) [11].

3.3 Data Analysis

For the data pre-processing of the dataset for the experiment we used python and bash script to convert the dataset into NeuCube format and separated the dataset into 2 class (Alcoholic and control) and we used 100 samples from each classes for our experiment.

For data analysis and visualization we used NeuCube 1.3. All experiments are performed AUT Computer Lab. We can see the EEG data mapping in **Fig 2.** With the yellow dots representing the EEG channels.

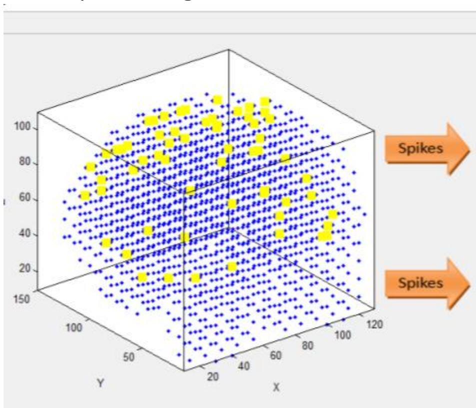

Fig 2. EEG mapping showing EEG channels in the dataset in yellow

To visualize both the classes in our dataset we used network analysis in NueCube as shown in Fig. 3 and 4. From this we can see that the Controlled subject have high level of interconnectivity in their brain compare to the alcoholic subjects. Also from from Fig 3. We can see that which part of the brain is active most during the experiment and which was least.

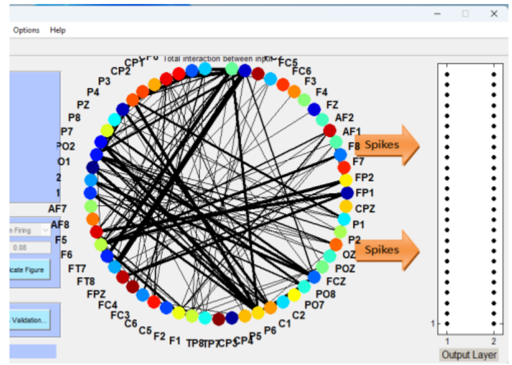

Fig 3. Control class network Analysis

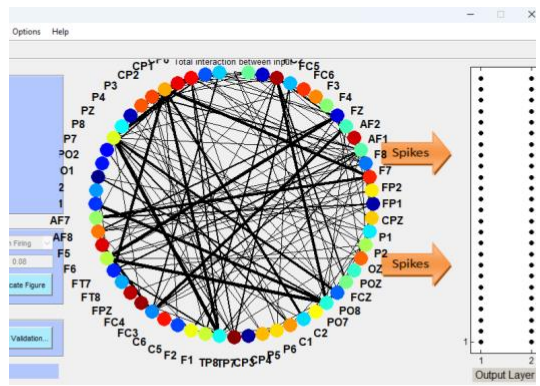

Fig 4. Alcoholic class Network Analysis

To Test the classification we performed the experiment in 4 different configurations and did cross validation with 3 folds.

I. Training the cube 1 time and no feature extraction
II. Training the cube 3 time and no feature extraction
III. Training the cube 1 time and with feature extraction
IV. Training the cube 3 time and with feature extraction

We observed there wasn't much difference in accuracy without feature extraction as shown in Fig 5 & 6 the accuracy for training the cube 1 or 3 times

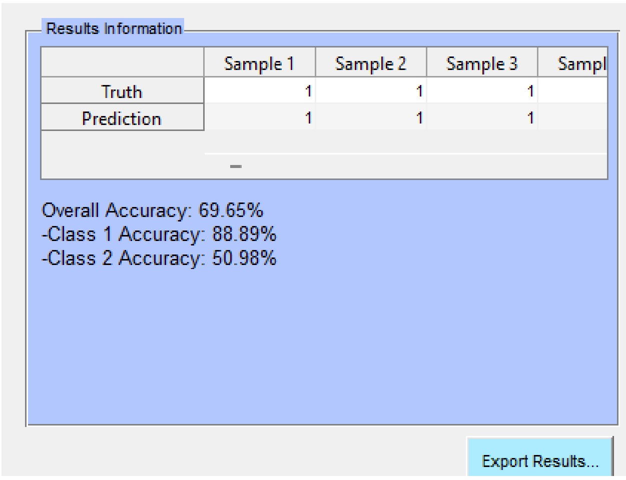

Fig 5. Result after Training the cube 3 time and no feature extraction

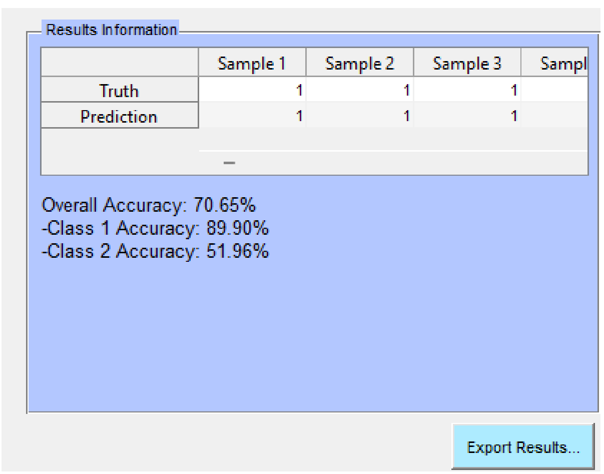

Fig 6. Result after Training the cube 1 time and no feature extraction

For feature extraction we used Network Analysis and remove the channels FC5,FC2,FC6,F4,C1,C2,CPZ. Which have no relations that can be seen in Fig 7.

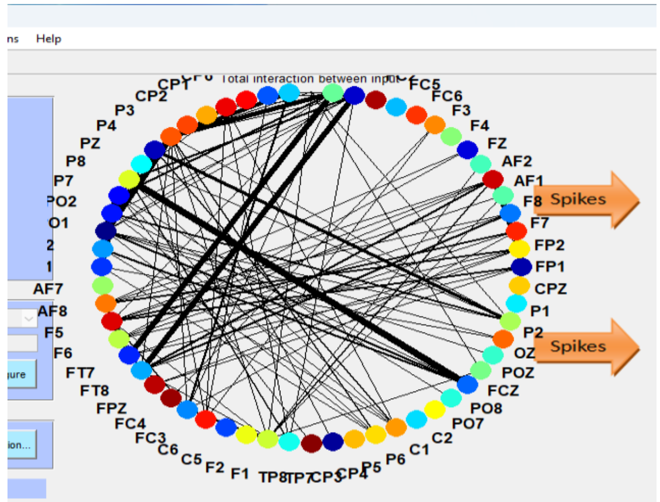

Fig 7. Network analysis of Alcoholic and control class

After feature we observed increase in the accuracy. We got 80.20% accuracy compared to 69.65% and 75.25% compared to 70.65% in cube trained 1and 3 times respectively as shown in Fig. 8 and 9.

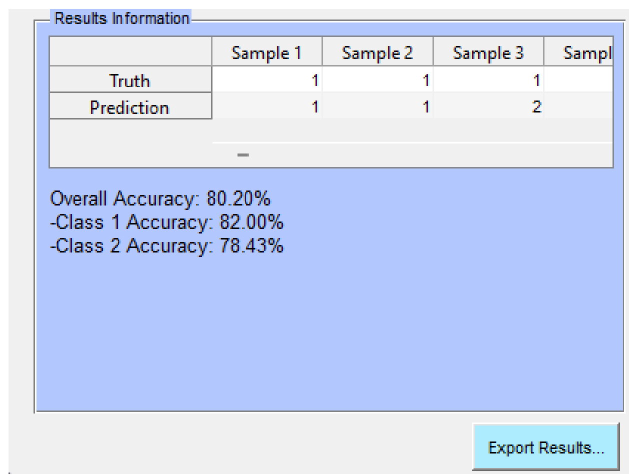

Fig 8. Result after Training the cube 1 time and post feature extraction

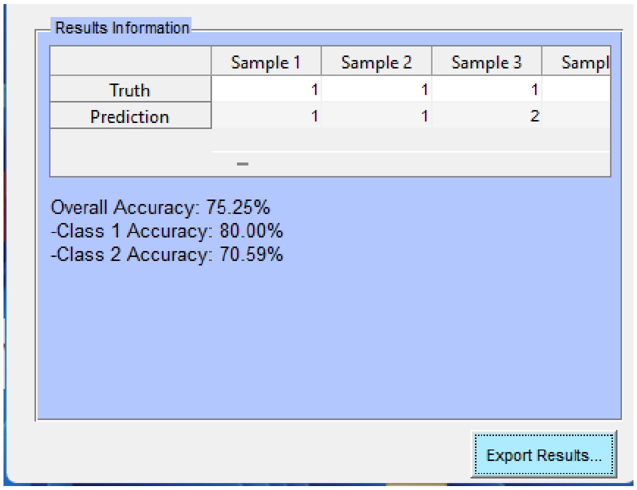

Fig 9. Result after Training the cube 3 time and post feature extraction

4 Results and Discussion

4.1 Results

We employed the NeuCube computational tool to analyse and classify the EEG data. The classification process involved utilizing a cross-validation method with three folds. This approach ensures robustness and reliability in evaluating the model's performance.

The SNN models were trained with different classes of data, namely alcoholic and control subjects. The resulting models were visualized to gain insights into the underlying neural activity patterns. These visualizations provided a clear representation of the distinct neural signatures associated with each class.

To further understand the neural dynamics, we conducted network analysis employing two distinct methods. The first method examined the interconnectivity within the control class, revealing a notably higher level of network connectivity compared to the alcoholic class. Additionally, the analysis identified specific brain regions exhibiting heightened activity during the experiment. These findings offer valuable insights into the functional disparities between the two subject groups.

In Assignment 1, we employed a range of machine learning tools including Naïve Bayes, logistic regression, and Multilayer Perceptron (MLP) using weka. Among these, MLP yielded the highest accuracy of 74.95%. In comparison, our current study utilizing Spiking Neural Networks (SNNs) within the NeuCube framework has demonstrated even more promising results. The accuracy achieved with SNNs, particularly after employing feature extraction techniques, surpassed the performance of previously utilized machine learning algorithms. This highlights the efficacy of SNNs in handling complex neuroinformatic data and suggests their potential as a superior tool for classification tasks involving EEG data.

One compelling practical application of our research lies in the realm of Brain-Computer Interfaces (BCIs). By leveraging Spiking Neural Networks (SNNs) within the NeuCube framework for classifying subjects with alcohol use disorders, we advance our understanding of the neural dynamics associated with addiction. This knowledge can be harnessed to develop more effective BCIs that interface directly with the brain's electrical activity. Such interfaces have transformative potential in the rehabilitation of individuals struggling with alcohol use disorders. BCIs can facilitate neurofeedback interventions, allowing individuals to gain real-time insight into their brain activity patterns and learn to self-regulate them. This technology opens new avenues for personalized and adaptive rehabilitation strategies, offering individuals greater agency in their recovery journey.

4.2 Discussion

While our study has performed decently into the classification of alcoholic and control drinkers based on EEG signals, there are several aspects of our analysis that warrant critical consideration.

1. **Dataset Size and Variability**: While the dataset used is from a reputable source, it's worth noting that having a larger and more diverse dataset could further strengthen the findings. Additionally, exploring datasets from different sources or demographic groups could provide a more comprehensive understanding of alcohol-related EEG patterns.

2. **Generalization to Clinical Settings**: It's important to acknowledge that the study primarily focuses on controlled experimental conditions. The findings may not fully capture the complexities of real-world clinical scenarios, where variables like comorbidities, medication, and varying levels of alcohol consumption might influence EEG patterns differently.

5 Conclusion and Future Work

In conclusion, this study delves into the classification of subjects with alcohol use disorders and control subjects using Spiking Neural Networks (SNNs) within the NeuCube computational tool. Leveraging EEG data, we achieved robust classification through cross-validation and visualized distinctive neural activity patterns. Network analysis unveiled notable differences in interconnectivity, highlighting heightened cognitive function in the control group. Feature extraction further enhanced classification accuracy, showcasing the effectiveness of SNNs in handling complex neuroinformatic data. Comparing our findings with prior work, our SNN approach within NeuCube outperforms previous results, marking a significant step forward in accurately classifying alcohol use disorders. These results hold promising implications for both neuroinformatics and clinical applications, particularly in the realm of Brain-Computer Interfaces. However, it's important to acknowledge areas for improvement, such as interpretability and generalization to clinical settings. Future research should explore ensemble approaches, transfer learning, online adaptation, and the integration of multimodal data to further advance the field. This work demonstrates the potential of advanced machine learning techniques in neuroinformatics, paving the way for innovative solutions in understanding and addressing neurological disorders.

6 References

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