EEG based classification for Alcoholism

Nishitha Lakshmi, Rani Adhaduk, , Nidarsh Nithyananda, S Rashwin Nonda and Pushpalatha K *
Department of Computer Science and Engineering, Sahyadri College of Engineering & Management, Mangaluru-575007

*E-mail:pushpalatha.cs@sahyadri.edu.in

ABSTRACT
Alcoholism is a tendency to continually rely on alcohol. Unchecked ingestion leads to gradual deteriorating mental health of the abusers. To study the changes in brain activity, Electroencephalography (EEG) is one of the acute and low cost methods. In this study, a sampling rate of 16 is experimented on the input EEG signals. The sampled data is extracted for features using mean. The best result obtained is an accuracy of 89.49% with Support Vector Machine (SVM) classifier using linear kernel.

Keywords:
Alcoholism, Artificial Neural Network, Cosine Similarity, EEG Signals, K-Nearest Neighbors, Mean, Support Vector Machine

1 INTRODUCTION

Alcohol is usually considered a `social beverage'. Unfortunately, the abuse of alcohol has caused societal rot. Alcoholism dulls brain activity and causes muddled physical reactions. Innumerable cases are recorded of liver cirrhosis deaths and many of the road traffic crash deaths caused by uncontrolled alcohol consumption. A healthy society refers to the perfect state of being wholly well in terms of the physical, emotional, spiritual aspects that surrounds the well-being of the existence of the society. This state of serenity of a society is disrupted when crime and diseases run rampant. As humans are social beings, these transgressions cause hindrance in the progress of a dynamic society and negatively affect mental health. Brain signal study is ideal to obtain the insights about mental health and activities as they are the blueprint of all nervous activity. Electroencephalography (EEG) is one of the most effective brain signal recording system that helps to study the brain activities.

EEG is a neuro-electricity activity that collects information in bulk that represents the psychological and physiological state of the human body by a conductive medium. Out of norm EEG signals represent irregular brain activities. By analyzing these EEG signals, we gain an understanding about occurrences of abnormal brain activity which plays an important role in diagnosis of different mental disorders like epilepsy, schizophrenia, addiction. EEG signals are also employed in criminal psychology studies where abnormal brain waves are significant in analyzing the violent crime patterns, lie detection and deception. In this paper, we provide performance analysis on various classification algorithms on our data set to diagnose abnormal brain activity and classify input EEG signals into control or alcoholic groups.

This paper is structured as follows. Section II recounts the related work published on EEG signal analysis. Section III illustrates our proposed work. Section IV shows experiments undertaken and results obtained. The concluding remarks for the proposed system are given in section V.

2 Related Work

Over the past few years, EEG has gained popularity in BCI or Brain-Computer Interface applications. EEG has been successfully used for diagnosis and treatment of mental abnormalities, brain-neuro-degenerative diseases and criminology studies. EEG can also be used to diagnose numerous neurological disorders such as dementia, brain tumors [15], Parkinson’s disease, Alzheimer’s and countless others.

With the advancement of technologies, the crime scenes also require a newer method wherein investigators can use modern ways to look for clues which might not be visible to the traditional method of collecting evidence. Based on the results that were published by the researchers on this topic, application of EEG significantly improves the accuracy of criminal identification to over 70%. This proves that EEG can also be used in the forensics discipline [1].

Yasmeen et.al., [21] suggested a model which analyzes EEG signal in seizure detection utilizing wavelet transform with statistical parameters. They took two different data sets, each having a different sampling rate. One had 128Hz whilst the other had 1024 Hz. Using discrete wavelet transformation, feature extraction was done, and a multi-layered neural network was used to differentiate between normal brain signals and brain signals indicating seizures.

It is proven true that the emotions are affected by the alcohol intake and influence adverse effects on human abilities to think, act and behave. These progressions or harms appear in the brainwave recording of an EEG. The target behind this research [20] was to demonstrate the unfavorable impacts of alcohol on the brain. The EEG signals were denoised utilizing Independent Component Analysis and classified using Probability Neural Network to successfully recognize the brain signals influenced by alcohol.

Support vector machine [10]-[14], artificial neural networks [18,9,5,19], k-nearest neighbors [16,17] and many other machine learning methods [2]-[9] are a wide assortment of classification methods for seizure prediction and other disorders.

Therefore, from perusal of the related works we perceive that EEG recordings contain significant information regarding mental activities and are ideal in diagnosis of mental and chronic disorders. We also studied various feature classification algorithms suitable for EEG signals, which are employed in our experimental study. The goal of this paper is to obtain the most efficient classifier by comparing the accuracy rates resulted by experimental procedures undertaken.

3 Proposed Study

To analyze the performance of the classifiers, following phases are employed i.e. sampling, feature extraction with mean. Sampling allows the reduction in dimension of our large data set. The sampled data set with the optimal sampling rate is extracted for features using mean. These extracted features are fed as training data for various classifiers and their performance is analyzed.

3.1 EEG Data

Brain cells communicate with each other by sending messages as electrical impulses. Transportation of these impulses from one neuron to another, causes ionic drift between the two, which is recorded by the electrodes in electroencephalogram. Based on the frequency of EEG signals resulting due to conscious and sub-conscious brain activities, EEG signals are divided into four categorical wave forms i.e. alpha, beta, theta and delta. Delta(<4Hz) is found in the adults under slow-wave sleep. Theta (4 - 7 Hz) associated with weariness in teenagers and adults. Alpha (8 - 15Hz) wave form represents relaxed state in the adults and is associated with inhibition control. Beta (16 - 31Hz) is associated with state of high computation and alertness [22].

3.2 Feature Extraction

Feature extraction methods distill the sampled data for its characteristic attributes. Features are the representative parameters of input sampled patterns that facilitate differentiating between the samples of input feature patterns.

To analyze a representative subset of data points and identify the feature patterns, we employ the sampling method. In statistics, sampling is a process of selection of a subset of individuals from a group of observations (called population) to represent the whole population. Sampling also brings about reduction of the dimension of our data set, making it simpler for ease of interpretation.

***Mean*:** Mean is a scale of central tendency, which ascertains the feature around which central grouping occurs. We calculate the Mean value of a sample using the equation 1.

$$\mu = \frac{1}{n}\sum_{i=1}^{n} x_i \tag{1}$$

where x_i is sample value and n is the number of samples.

3.3 Classification

We aim to compare the performance of classifiers SVM, ANN, KNN and Cosine Similarity, thus obtain the most favorable classifier on our classifier. Extracted features are fed into classifiers to classify the abnormal EEG signals and finally sort, if the input EEG signals belong to the control group or alcoholic group.

3.3.1 *Support Vector Machine*

Collection of affiliated supervised learning techniques, proposed for classification. SVM maps input vector to a higher dimensional space where a maximal separating hyperplane is constructed. An SVM outputs a map of the sorted data with the margins between the two as far apart as possible using kernel functions. The function of kernel is to take data as input and transform it into the required form. SVM has many kernel functions and the ones used in our study are as follows:

Sigmoid Kernel:

$$K(x_i, x_j) = \tanh(\gamma x_i^T x_j + r)$$

RBF Kernel:

$$K(xi, xj) = \exp(-\gamma|x_i - xj|^2), \gamma > 0 \tag{3}$$

Linear kernel:

$$K(xi, xj) = x_i^T x_j \tag{4}$$

Polynomial Kernel:

$$K(x_i, x_j) = \left(\gamma x_i^T x_j + r\right)^d, \gamma > 0 \tag{5}$$

where x_i and x_j training vectors
x^T is the transpose of training vector, k (x_i, x_j) is a kernel function and γ, r, d are the kernel parameters.

3.3.2 *K-Nearest Neighbors*

A non-parametric approach, which classifies the training data point according to majority of its nearest neighbors. Performance of KNN depends on the number of nearest neighbor values i.e. k = 2, 3, 4, 5. To classify the neighbor, we made use of Minkowski metric distance as given in equation 6.

$$D(X, Y) = \left(\sum_{i=1}^{n}|x_i - y_i|^p\right)^{1/p} \tag{6}$$

where $X = (x_1,x_2,...,x_n)$, $Y= (y_1,y_2,...y_n)$ and p is the parameter measure.

3.3.3 *Artificial Neural Network*

A framework of machine learning algorithms motivated by the working of biological neural networks. It consists of single or more layers to perform complex tasks. Each layer is made up of artificial neurons (nodes) and node connectors called edges. Artificial Neural Network comprises of three layers: input layer, hidden layer and the output layer. The inputs to the artificial neural network are stored in the artificial neurons of the input layer along with its respective weights, which is assigned based on its relative importance. The output of each artificial neurons is obtained only when a non-linear function called activation function is triggered by the weighted sum of its inputs, provides a result exceeding the threshold value.

Activation functions utilized in this experiment are:

ReLU: Rectified Linear Unit, takes a real-valued input and calculates a threshold at zero (replaces negative values with zero) using the equation 7.

$$f(x) = max(0, x) \qquad (7)$$

where x is a real sample value.

Tanh: It takes a real-valued input and transforms it into the range [-1, 1] by using the equation 8.

$$tanh\ (x) = \frac{2}{(1+exp(-2x))} - 1 \qquad (8)$$

where x is a real sample value.

Sigmoid: takes a real-valued input and transforms it into the range [0, -1] by using the equation 9.

$$\sigma(x) = \frac{1}{1+exp(-x)} \qquad (9)$$

where x is a real sample value.

3.3.4 *Cosine Similarity*

A similarity measure which is obtained by observing the cosine angle between the feature vectors. The outcome of the cosine similarity is bound in [0,1] where similarity score of 1 denotes vectors having same orientation and similarity score of 0 denoting vectors being relatively oriented at 90 degree. Cosine similarity then gives a useful measure of how similar two signals are likely to be in terms of their label i.e. alcohol or control using the following equation 10.

$$\cos\phi = \frac{A.B}{|A|.|B|} \qquad (10)$$

A and B are sample vectors of EEG data, |A| and |B| represent the cardinality of two vectors.

4 Experimental Results

We experimented using HP Pavilion 15-au007tx with the configurations of RAM - 8GB DDR4, CPU - Intel i5 6th generation. The coding for the experiment were done in Python2 language**.**

We have led our analyses by taking the data set from an open source, contributed by Henri Begleiter at the Neurodynamics Laboratory at the State University of New York Health Center at Brooklyn [23]. Placement of the electrodes was done in the internationally accepted 10-20 method. Data set comprises of EEG signal recordings from 64 electrodes from each subject which were sampled at the rate of 256 Hz for a second with 30 trials each. Each subject belonged to either one of the groups: control or alcoholic. Training and testing data comprise of 468 trials and 480 trials respectively. Training and testing trials were randomly combined in the ratio of 80:20.

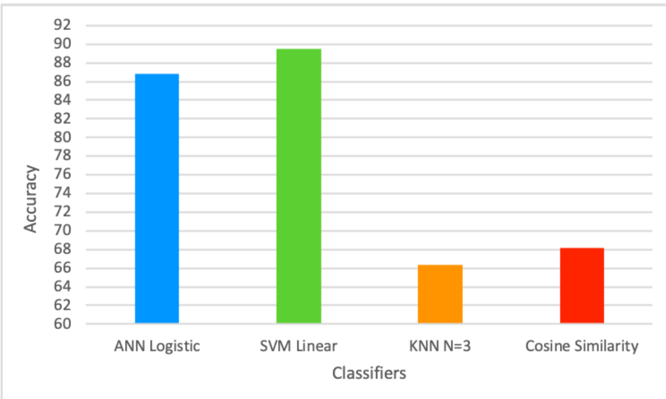
Table 1. Accuracy values of Classifiers with Mean

Classifier	Kernel/Activation Function	Accuracy
SVM	Linear	89.47
	RBF	62.45
	Sigmoid	52.11
	Polynomial	73.68
ANN	Logistic	86.84
	Relu	85.78
	Tanh	85.26
	Identity	84.36
KNN	K=2	64.09
	K=3	66.31
	K=4	59.47
	K=5	62.10
Cosine Similarity	-	68.21

4.1 Performance evaluation of classifiers with sampling rate 16

With sampling rate of 16 on an electrode, we get one feature from every 16 feature samples. Hence from 64 electrodes we get 16 X 64 = 1024 values, where the input data of size (948 X 1024) is fed to the classifiers SVM, ANN, KNN and Cosine Similarity. Following results are obtained.

We experiment with the SVM classifier and analyze the performance of four of its kernel functions. Therefore, from our analysis, we see in Table 1 that the linear kernel function on SVM gives an accuracy of 89.47%. Performance of ANN is analyzed with various activation functions where logistic function gives an accuracy of 86.84%, as seen in Table 1. When experimented with 2, 3, 4 and 5 neighbors of KNN classifier, it is evident that 3 nearest neighbors are suitable for our data set, giving an accuracy of 66.31۲۲%. The data set is lastly analyzed for the cosine similarity method, which gives an accuracy of 68.21%. Hence, we conclude that the best performance on our experimental input data is given by linear kernel of SVM with an accuracy of 89.47%.



4.2 **Comparison of computational time taken by EEG classifiers**

From the previous results obtained, as seen in figure 1, SVM gives the highest accuracy score of 89.47% and the second highest score i.e. 86.84% is given by ANN with logistic function. Hence, we compare the computational time for these two classifiers. From the Table 2, it is observed that SVM takes the minimal time of 0.74 seconds. Therefore, we conclude that SVM classifier is the most efficiently suited classifier for our data set.

Table 2. Computational Time taken by Classifiers in seconds

Classifiers	Time (s)
ANN	5.11
SVM	0.74

5 Conclusion

Alcoholism is an addiction risen with a need for reliance on a substance to make crucial decisions and to cope with events. Alcoholism predominantly dulls brain activity and triggers numerous societal illnesses. The aim of this paper is to analyze EEG signals and classify them as belonging to control or alcoholic group, efficiently. We conducted performance analysis of SVM, ANN, KNN, Cosine Similarity classifiers on our data set. Performance of the classifiers is checked for sampling rate of 16 and mean aids for feature extraction. Therefore, SVM classifier with linear kernel function, obtains the highest accuracy of 89.47%.

References

[1] Chan, Hsin-Te, et al. ``Applying EEG in criminal identification research." 2017 International Conference on Applied System Innovation (ICASI). IEEE, 2017.

[2] Adeli, Hojjat, Ziqin Zhou, and Nahid Dadmehr. ``Analysis of EEG records in an epileptic patient using wavelet transform." Journal of neuroscience methods 123.1 (2003): 69-87.

[3] Harikumar, R., and P. Sunil Kumar. ``Dimensionality reduction techniques for processing epileptic encephalographic signals." Biomedical and Pharmacology Journal 8.1 (2015): 103-106.

[4] Shahid, Arslan, et al. ``Epileptic seizure detection using the singular values of EEG signals." 2013 ICME International Conference on Complex Medical Engineering. IEEE, 2013.

[5] Ghosh-Dastidar, Samanwoy, Hojjat Adeli, and Nahid Dadmehr. ``Principal component analysis-enhanced cosine radial basis function neural network for robust epilepsy and seizure detection". IEEE Transactions on Biomedical Engineering 55.2 (2008): 512-518.

[6] Gandhi, Tapan, et al. ``Expert model for detection of epileptic activity in EEG signature". Expert Systems with Applications 37.4 (2010): 3513-3520.

[7] Supriya, Supriya, et al. ``Weighted visibility graph with complex network features in the detection of epilepsy". IEEE Access 4 (2016): 6554-6566.

[8] Ahmadi, Amirmasoud, Vahid Shalchyan, and Mohammad Reza Daliri. ``A new method for epileptic seizure classification in EEG using adapted wavelet packets". 2017

[9] Srinivasan, Vairavan, Chikkannan Eswaran, and Natarajan Sriraam. ``Approximate entropy-based epileptic EEG detection using artificial neural networks". IEEE Transactions on information Technology in Biomedicine 11.3 (2007): 288-295.

[10] Bayram, K. Sercan, M. Ayyuce Kızrak, and Bulent Bolat. ``Classification of EEG signals by using support vector machines." 2013 IEEE INISTA. IEEE, 2013.

[11] Bhuvaneswari, P., and J. Satheesh Kumar. ``Support vector machine technique for EEG signals". International Journal of Computer Applications 63.13 (2013).

[12] Zavar, M., et al. ``Evolutionary model selection in a wavelet-based support vector machine for automated seizure detection". Expert Systems with Applications 38.9 (2011): 10751-10758.

[13] Guler, Inan, and Elif Derya Ubeyli. ``Multiclass support vector machines for EEG-signals classification". IEEE Transactions on Information Technology in Biomedicine 11.2 (2007): 117-126.

[14] Subasi, Abdulhamit, and M. Ismail Gursoy.

``EEG signal classification using PCA, ICA, LDA and support vector machines". Expert systems with applications 37.12 (2010): 8659-8666.

[15] Murugesan, M., and R. Sukanesh. ``Towards detection of brain tumor in electroencephalogram signals using support vector machines".International Journal of Computer Theory and Engineering 1.5 (2009): 622.

[16] Huang, Jie, et al. ``An Improved kNN Based on Class Contribution and Feature Weighting." 2018 10th International Conference on Measuring Technology and Mechatronics Automation (ICMTMA). IEEE, 2018.

[17] Bablani, Annushree, Damodar Reddy Edla, and Shubham Dodia. ``Classification of EEG Data using k-Nearest Neighbor approach for Concealed Information Test".Procedia computer science 143 (2018): 242-249.

[18] Guler, Nihal Fatma, Elif Derya Ubeyli, and Inan Guler. ``Recurrent neural networks employing Lyapunov exponents for EEG signals classification".Expert systems with applications 29.3 (2005): 506-514.

[19] Classification Technique Based on ANN for EEG Signals". IJCSIT (2014).

[20] Rachman, Nurindah Tiffani, Handayani Tjandrasa, and Chastine Fatichah. ``Alcoholism classification based on EEG data using Independent Component Analysis (ICA), Wavelet de-noising and Probabilistic Neural Network (PNN)".2016 International Seminar on Intelligent Technology and Its Applications (ISITIA). IEEE, 2016.

[21] Yasmeen, Shaguftha, and Maya V. Karki. ``Neural network classification of EEG signal for the detection of seizure". 2017 2nd IEEE International Conference on Recent Trends in Electronics, Information & Communication Technology (RTEICT). IEEE, 2017.

[22] Kirmizi-Alsan, Elif, et al.``Comparative analysis of event-related potentials during Go/NoGo and CPT: decomposition of electrophysiological markers of response inhibition and sustained attention." Brain research 1104.1 (2006): 114-128.

[23] S. U. O. N. Y. H. C. Neurodynamics Laboratory, ``UCI Machine Learning Repository," 13 October 1999. [Online]. Available: https://archive.ics.uci.edu/ml/datasets/EEG+Database.