Performance Analysis of different Machine Learning Algorithms for Detection of Sleepy Spindles from EEG signals

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***Abstract*:-- Now a days spindles caused by drowsiness and it has become a very serious issue to accidents. A constant and long driving makes the human brain to a transient state between sleepy and awake. In this BCI plays a major role, where the captured signals from brain neurons are transferred to a computer device. In this paper, I considered the data which are collected from single Electroencephalography (EEG) using Brain Computer Interface (BCI) from the electrodes C3-A1 and C4-A1.Generally these sleepy spindles are present in the theta waves, whose are slower and high amplitude when compared to Alpha and Beta waves and the frequency in ranges from 4 – 8 Hz.The aim of this paper to analyse the accuracy of different machine learning algorithms to identify the spindles.**

Keywords:- Electroencephalography (EEG), Brain Computer Interface (BCI), Wavelet Transform, Fast Fourier Transform (FFT), Support Vector Machines (SVM), Neural Networks (NN), Random Forest (RF), Gaussian Naïve Bayes (GNB), K-nearest neighbour (K-NN)

INTRODUCTION

Spindles are caused while the human is in sleeping or in drowsiness .This state of behaviour is identified by the physical activities of the human like rapid eye blinking or full eye closing. This will make big accidents in driving. So, our proposed work is we are analysing the mental activity of human brain by using Electroencephalography (EEG) signals based on Brain Computer Interface (BCI) technology. Here I am analysing performances of different classification technique on the EEG signal. The signal is extracted from single channel EEG from C3-A1 and C4-A1 electrodes.

LITERATURE SURVEY

Drowsiness can be detected from other technologies like image processing. But our proposed way of detection is very efficient because here we directly extracted the brain signals to examine the driver state of the emotion. Here the main challenge is how to identify the driver drowsiness state of emotion. EEG has various frequency bands called theta, delta,alpha, beta and gamma. Figure: 1 shows a few examples of the brain waves frequencies and corresponding human brain state of emotion.

In [12]M.Murali, Varun Pathak, Manish Sen proposed using of Level splitter section(LSS) to analyses the level of state of emotion of the driver and gives alert and keep the vehicle in self-controlled functioning mode until awaken state .

In [13] A. Garces Correa and E. Laciar Leber proposed a method by combining best features extracted from power Spectral Density (PSD) and Wavelet Transform (WT). He used NN for classifying the extracted features.

In 2009 A. Garcés Correa, P Diez , E Laciar proposed the work that the results obtained with the Central frequency, the first quartile frequency, the Maximum frequency, the power of Theta and Alpha bands and discriminate analysis were of 73.6 % of good drowsiness segment detection. Adding new features (ZC and IEEG) and classifying the data with NNs the results improved to 84.1 %.In [18] Pai-Yuan Tsai; Weichih Hu; Kuo, T.B.J.; Liang-Yu Shyu proposed a model of detection accuracy when the subjects were alert (79.1%) was much less than the accuracy when the subjects were drowsy (90.9%). Here my proposal produce accuracy 98.45% of detecting drowsiness by extracting brain signals from C3-A1 and C4-A1 using BCI. ANN – MLP (Multi-LayerPerceptron) with 2 layers of 100 neuron each and 10 epochs for forward pass and backward pass.

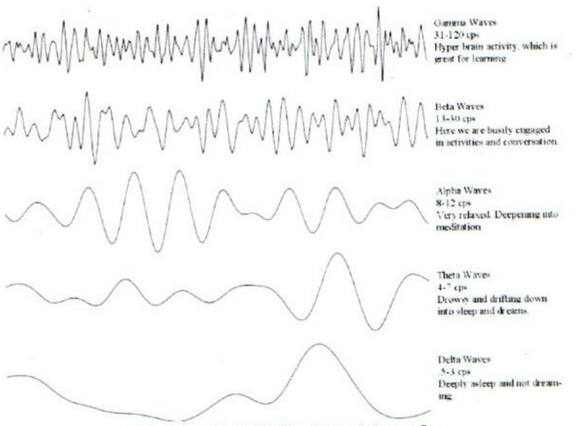

Figure 1: EEG signal bands

III. THEORETICAL CONSIDERATIONS

In this section, we discuss some of the related theoretical concepts.

A.EEG Signals

EEG is a non-invasive method to record electrical signals of the brain from the scalp. Electrical recordings from the surface of the brain or even from the outer surface of the head demonstrate that there is continuous electrical activity in the brain [1]. Much of the time, the brain waves are irregular, and no specific pattern can be discerned in the EEG. The EEG signals are commonly decomposed into five EEG signal bands based on the frequencies: delta, theta, alpha and beta. Figure: 1 shows a few examples of the brain waves. Beta waves represents arousal state of human brain. These are relatively low amplitude and high frequency of all the brain waves. Their frequency ranges from 12 to 40 Hz's (cycles per second) and usually has a low voltage between 5 and 30 µV. A person who is in fully engaged mind is in Beta state

i.e. talking, debating,speech..etc. Alpha wave represents non-arousal state. These are slower and high at amplitude when compared to beta waves. Their amplitude ranges from 8 to 12 Hz (cycles per second) with 30–50 µV amplitude. A person is awaken and taking rest after done with any work/task is in Alpha state .Examples – A person takes a break form a speech/lecture, A person walks in the ground is also in alpha state . Theta waves are slower and high at amplitude compared to alpha and beta waves. Their frequency ranges from 4 to 8 Hz (cycles per second and 20 µ V amplitude. A person who takes time off from any work and begins today sleep or in drowsy is in Theta state. A person in sleep/dream sleep with little bit conscious or idle state like driving in freeways or repetition nature of driving compared to city road driving with traffic. Delta waves are the final state of the human. Delta waves are very slow and high amplitude compared to alpha and theta waves. Their frequency ranges below 4Hz (cycles per second). The frequency never goes to zero, means the brain is dead. A person who is in deep sleep /dreamless sleep is in delta state.

BCI

BCI is an AI system that can recognize patterns from the brain signals. BCI system working has 5 consecutive stages.1) Signal acquisition – Capture brain activity and may also perform noise reduction and artefact processing.2)Pre-processing or filtering – It prepares the signal in a suitable form for further processing. 3)Feature Extraction – It identifies the discriminant features as vector from the processed signals. 4)Classification- It classify the brain signals by taking Feature vectors into account. 5) Control interface – Finally it translate the classified signals into commands for the connected devices.

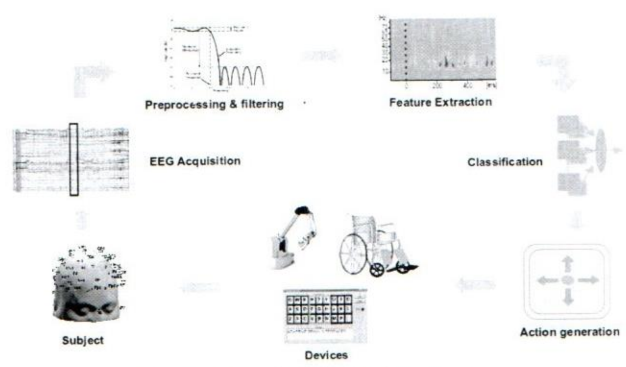

Figure 2: BCI block Diagram

Pre-processing

There are several objectives when pre-processing of EEG signals. Main objective is identifying and removal of artefacts. Artefacts are nothing but unwanted patterns which are caused by the underlying physiological events of interest like eye movements, muscle movements and some are due to electrical field changes. Methods for processing artefacts in sleep EEG have been reviewed in a general context in [2] whereas the specific application to infants and newborns (which are subject to similar forms of artefacts) are considered in [3]. Frequency selective filters (low-pass, high-pass, band-passand band-stop) have been generally used in artefact processing especially for muscle artefact removal [4].

Feature extraction

The main objective of the feature selection step in pattern recognition is to select a subset from large numbers of available features.

Time–frequency features

Time–frequency analysis is a powerful tool which allows decomposition of signals into both time and frequency [5]. Time–frequency analysis is a powerful tool which allows decomposition of signals into both time and frequency [5]. It thus provides a means for analyzing signals which are non-stationary, such as sleep EEGs. In the analysis of such signals one is often interested in the evolution of the frequency content with time. This is particularly important in the analysis of sleep EEGs where many of the events (e.g. arousals, sleep spindles, alpha intrusions) are manifested by sudden changes in amplitude and frequency characteristics. Some of the more commonly used time–frequency methods in the analysis of sleep EEGs are highlighted below,

Short time Fourier transform (STFT)
The wavelet transform
Matching pursuits (MP)
Empirical mode decomposition (EMD)

E. Classification

Once features are extracted from a signal then grouping these features by using classification that is assigning the feature vector into a discrete number of groups: one for each class to be classified. For instance, in sleep staging we have to consider two stages spindle and non-spindle. Here classification is based on similarity between the features of the same group.

i. Neural network (NN) classification (supervised learning) - Multilayer perceptron (MLP)

Neural networks or artificial neural networks (ANN) are mathematical models inspired by neuronal interactions in the brain and can be used to model a wide range of complex systems. ANNs become capable of modeling very complex nonlinear systems [6].

ANN consists of following components [7][8][9]

Input
An arbitrary no. of hidden layers
An o/p layer
A set of weights & biases between each hidden layer , w & b
A choice of activation functions for each hidden layer.

When counting the No. Of layers you have to exclude the Input layer. Each iteration of the training process has the following steps:

Calculating the predicted output - feed forward
Updating weights & bias – back propagation.

iii. KNN

The K-nearest neighbor algorithm is one of the simplest supervised learning algorithms. It simply measures the distance between the new data point to all the other training data points. The distance measure can be either Euclidean or Manhattan. In k-NN classification, the output is a class label. An object is classified by a plurality vote of its neighbors, with the object being assigned to the class most common among its k nearest neighbors. If k = 1, then the object is simply assigned to the class of that single nearest neighbor. While designing a model we have to specify the n_neighbors value as a integer to classify the data object.

iii. Random Forest

Random forest is also a supervised classification methodology which combines the multiple algorithms of same type to form a powerful prediction model i.e.multiple decision trees. It works by generating multiple decision trees and fit a model by giving each training object to every tree and assign the class label, which more no. of trees produce as a result.

iv. GaussianNB

Naive Bayes classifier is a supervised learning algorithms based on applying Bayes' theorem with the "naive" assumption of conditional independence between every pair of features given the value of the class variable. Bayes' theorem states the following relationship, given class variable Y and dependent feature vector X_1 through X_n,

$$P(Y|X_1,\dots,X_n) = \frac{P(X_1,\dots,X_n|Y)P(Y)}{P(X_1,\dots,X_n)}$$

Using the naive conditional independence assumption that

$$P(X_i|Y, X1, X2, \dots X_{i-1}, X_{i+1}, \dots X_n) = P(X_i|Y)$$

The class conditional probability is calculated through

$$P(X_1,\dots,X_n|Y) = \prod_{i=1}^{n} P(X_i|Y)$$

Gaussian is used in classification and it assumes that features follow a normal distribution and the class conditional probability is calculated through:

$$P(x_i \mid y) = \frac{1}{\sqrt{2\pi\sigma_y^2}} \exp\left(-\frac{(x_i-\mu_y)^2}{2\sigma_y^2}\right)$$

IV. RESULTS

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Generally sleepy spindles are present in the Theta waves, whose are slower and high amplitude when compared to Alpha and Beta waves and the frequency in ranges from 4 – 8 Hz.

A. Data

I considered the data which are collected from single Electroencephalography (EEG) using Brain Computer Interface (BCI) from the electrodes C3-A1, O1-A1, C4-A1 and O2-A1. Data set contains 251038 instances and 10 attributes.

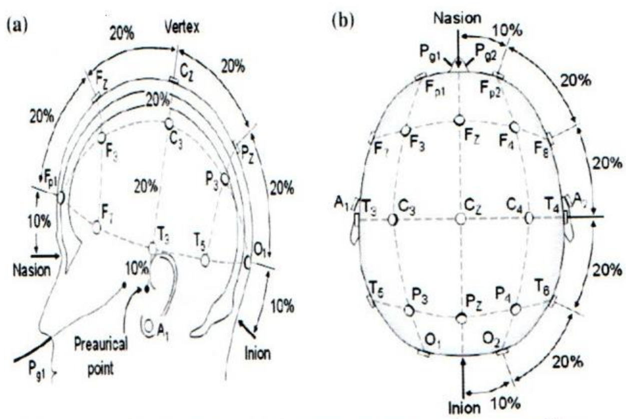

Figure 2: Electrode placement over scalp according to the international 10-20 system. a) As seen from left side. b) As seen from top

The signal of this data set was sampled with a frequency of 250Hz. Fig.2 illustrates the position of electrodes on 10 -20 system.

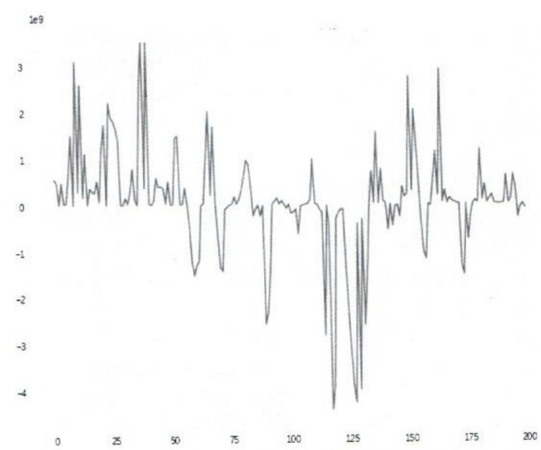

Figure 4. Theta signals from EEG C3-A1 electrode

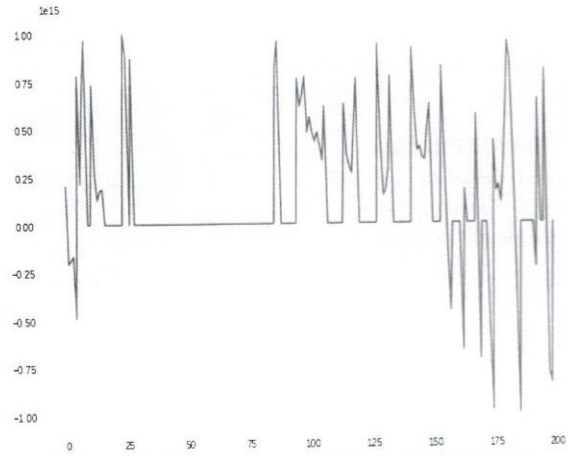

Figure 5. Sleepy spindles from EEG C3-A1 electrode

B. Performance evaluation

Accuracy,precision and sensitivity or recallare the statistical measures to evaluate the performance of any binary classifier. All possible outcomes of a classifier is represented in the form of Confusion matrix as shown is a Fig.6

	Predicted 1	Predicted 0
True 1	TP	FN
True 0	FP	TN

Figure 6: Confusion Matrix

Accuracy is the proportion of the true results in the dataset.

$$\text{Accuracy} = \frac{tp + tn}{tp + fp + tn + fn}$$

Precision measures the ability of the classifier not to lable as positive if sample that is negative .

$$\text{Precision} = \frac{tp}{tp + fp}$$

Recall measures the ability of the classifier to find all the positive samples.

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$$\text{Sensitivity} = \text{Recall} = \frac{tp}{tp + fn}$$

NN-MLP result:
If I consider 2 layers MLP with 100 neurons in each and 10 epochs while fitting the model then the result in accuracy is:98.46 %

K-NN result:
Confusion matrix is
[62102 0]
[62 596]

Statistical measures are:

	Precision	recall
0	1.00	1.00
1	1.00	0.91

Accuracy: 99.9%

Random forest result:
Confusion matrix is
[62102 0]
[345 313]

Statistical measures are:

	Precision	recall
0	0.99	1.00
1	1.00	0.48

Accuracy: 99.45%

Gaussian NB result:
Confusion matrix is
[62102 0]
[345 313]
Statistical measures are:

	precision	recall
0	0.99	1.00
1	1.00	0.48

Accuracy:99.45%

All the analyzedclassifiers performance is shown in Table1.

Classifier	Accuracy
NN-MLP	98.46 %
K-NN	99.90%
RF	99.45%
NB	99.45%

Table 1: Performance analysis

V.CONCLUSION AND FUTURE SCOPE

In this we utilize electroencephalography (EEG) signals using Brain computer Interface (BCI). Generally these sleepy spindles are present in the theta waves, whose are slower and high amplitude when compared to Alpha and Beta waves and the frequency in ranges from 4 – 8 Hz. Here we analyses the performances of different supervised classification methodologies. Among all these classifiers K-Nearest Neighbor (K-NN) classifier gives highest accuracy 99.90% when compared to Neural Networks, Random Forest, Gaussian Naïve Bayes classifiers. In future we directly identify the spindles from the theta waves instead of combining theta and spindles separately and also try to use the dimensionality reduction technique while consider the feature vector for classification.

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