EEG Based Emotion Recognition System for Special Children

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ABSTRACT

Electroencephalography, one of the finest modality to study neural basis of cognition is majorly used in the area of emotion recognition. There is a major problem faced by specially abled children in comprehending and conveying emotion. Music has been used as a promising medium to evoke and study emotion over the past decade. The subjects produce alpha waves majorly while listening to music in a general relaxed state and produce large amount of beta and gamma waves while introspecting the music. The waveforms vary depending upon every individuals perception to that particular stimuli. Through our work we have proposed a continuous emotional recognition system by giving music as a stimuli that could aid in continuous patient monitoring. We have used random forest algorithm to classify the emotions and later integrate it to a patient monitoring system.

CCS Concepts

Applied computing~Health informatics

Keywords

EEG; BCI; developmental disorders; machine learning; IoT.

1. INTRODUCTION

Emotion plays a significant role in our lives paving way to express what we feel as well as understand others. It is indeed difficult for the children with mental disorders who have impaired communication to understand as well as express their emotion.According to literature, children with developmental disorders which occur individually as well as intertwined, such as Autism Spectrum Disorder (ASD), Attention Deficit/ Hyper attention Disorder (ADHD) and Down syndrome have difficulties in expressing as well as comprehending emotion [1,2,3]. Music has been proved as a powerful medium to elicit emotions in the field of cognitive neuroscience [4,5,6]. In our work, we have classified the emotion of special children as a part of building a continuous patient monitoring system based on our previous work [7] .

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Electroencephalogram (EEG) measures the ionic current flow between neurons by placing suitable scalp electrodes. These EEG signals have proved to play a vital role in study and recognition of the mental and emotional state of people who need special monitoring and care. We use Power spectral Density based features obtained from the raw EEG signal to classify the emotions of the children. Machine learning techniques are widely used in recent times for prediction purposes. Supervised learning method is a recognised set of machine learning algorithm that frame hypothesis based on user-given features [8]. We have used four supervised machine learning methods, to classify the emotions and a comparative study was done based on their performance. The results obtained were then given as an alert text to the caretaker based on the concept of IoT.

2. Methodology

EEG recordings were obtained from 18 children (Mean age: 13 years) of BVSN Murthy Center for Special Children shown in Fig.1. This center is a unit of Public Health Center, India. Prior permission from the management, teachers and the physician was obtained. Prior consent was also obtained from the parents of all the subjects. The subjects were of varying developmental disorders namely ASD, ADHD and Down Syndrome. ASD is a heterogeneous developmental disorder involving multiple nervous system dysfunctions. ADHD is a type of brain disorder typically associated with symptoms such as inattention and hyperactivity. Down syndrome is a genetic disorder that is marked by a pattern of physical growth delays and mental instability. A common trait in these disorders is that they are neuro developmental and are generally found in children in their early stage of development. The subjects involved in study did not have any hearing impairment as the experiment performed in this work required the subjects to listen to music.

Fig.1: BVSN Murthy Center for Special Children

Lists of twenty songs of varying genre in their native language were chosen to be as a stimulus. Four songs from the list were played in earphones to every subject for 30 seconds each and the readings were recorded using wearable EEG device by Neurosky. The subjects were asked to close their eyes while listening and the test was conducted in a silent environment.

Table 1: Demographic details of subject under study

Type of Disorder	No. of Children
Autism Spectrum Disorder	6
Attention Deficit/Hyper Attention Disorder	6
Down Syndrome	6

Brain waves are of five major types. Delta waves lie in the range of 1-3 Hz, theta waves are in the range of 4-7 Hz, alpha waves are in the range of 8-13 Hz and beta waves lie in the 14-30Hz. Gamma waves are in the range of 31-50Hz. The waves in each range are unique hence the emotion pertaining to these frequency ranges can be studied distinctly.

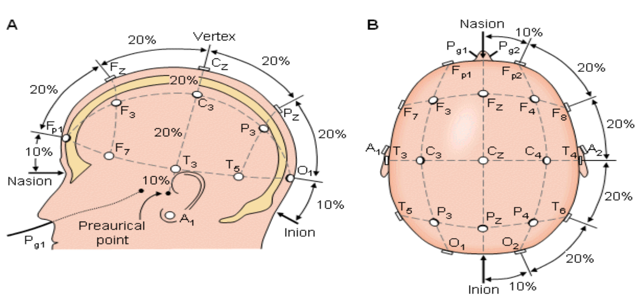


Fig.2: International 10-20 electrode system

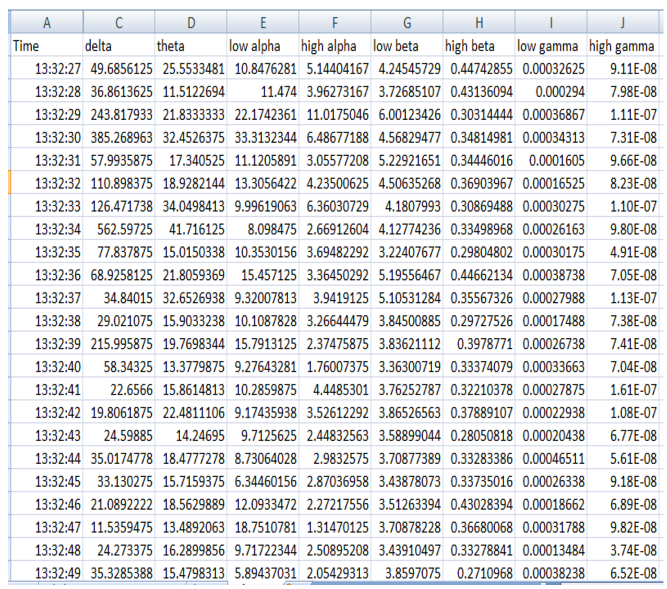
3. Neurosky Mindwave Mobile Headband

The Mindwave headband is a customary product that is proprietary to NeuroSky [9]. It is a wearable device. The EEG electrode lies in the sensor that has to placed above the forehead in the frontal parietal region per International 10-20 electrode system shown in Fig.2. The 10% and 20% marked in the figure represent the total front-back or right-left distance in the skull. The electrodes are placed in the 10-20% positions after measuring the scalp distance of each subject. Fig 3 shows the Mindwave device. Mindwave is a wearable EEG device by Neurosky. It is a wireless device that works on Bluetooth Low Energy technology. The device is interfaced to a system to retrieve the live recordings which are then processed. The device outputs 12 bit Raw-Brainwaves in the range of 3 - 100Hz with sampling rate at 512Hz. The outputs are then split into power spectrums as alpha, beta, gamma based on the frequency range and used for further processing Fig.3 represents the sample readings obtained from the EEG device that are categorised as infrared, delta, alpha, theta, beta and gamma based on frequency range.

Fig.3 MINDWAVE device

The data recorded from the device initially contains timestamp values along with the PSD for each frequency spectrum/band. The average PSD for each frequency band are calculated and this data is used for further analysis.

Fig.4 represents the average PSD values for each wave type at a specific timestamp (measured in sec).



A	C	D	E	F	G	H	I	J
Time	delta	theta	low alpha	high alpha	low beta	high beta	low gamma	high gamma
13:32:27	49.6856125	25.5533481	10.8476281	5.14404167	4.24545729	0.44742855	0.00032625	9.11E-08
13:32:28	36.8613625	11.5122694	11.474	3.96273167	3.72685107	0.43136094	0.000294	7.98E-08
13:32:29	243.817933	21.8333333	22.1742361	11.0175046	6.00123426	0.30314444	0.00036867	1.11E-07
13:32:30	385.268963	32.4526375	33.3132344	6.48677188	4.56829477	0.34814981	0.00034313	7.31E-08
13:32:31	57.9935875	17.340525	11.1205891	3.05577208	5.22921651	0.34446016	0.0001605	9.66E-08
13:32:32	110.898375	18.9282144	13.3056422	4.23500625	4.50635268	0.36903967	0.00016525	8.23E-08
13:32:33	126.471738	34.0498413	9.99619063	6.36030729	4.1807993	0.30869488	0.00030275	1.10E-07
13:32:34	562.59725	41.716125	8.098475	2.66912604	4.12774236	0.33498968	0.00026163	9.80E-08
13:32:35	77.837875	15.0150338	10.3530156	3.69482292	3.22407677	0.29804802	0.00030175	4.91E-08
13:32:36	68.9258125	21.8059369	15.457125	3.36450292	5.19556467	0.44662134	0.00038738	7.05E-08
13:32:37	34.84015	32.6526938	9.32007813	3.9419125	5.10531284	0.35567326	0.00027988	1.13E-07
13:32:38	29.021075	15.9033238	10.1087828	3.26644479	3.84500885	0.29727526	0.00017488	7.38E-08
13:32:39	215.995875	19.7698344	15.7913125	2.37475875	3.83621112	0.3978771	0.00026738	7.41E-08
13:32:40	58.34325	13.3779875	9.27643281	1.76007375	3.36300719	0.33374079	0.00033663	7.04E-08
13:32:41	22.6566	15.8614813	10.2859875	4.4485301	3.76252787	0.32210378	0.00027875	1.61E-07
13:32:42	19.8061875	22.4811106	9.17435938	3.52612292	3.86526563	0.37889107	0.00022938	1.08E-07
13:32:43	24.59885	14.24695	9.7125625	2.44832563	3.58899044	0.28050818	0.00020438	6.77E-08
13:32:44	35.0174778	18.4777278	8.73064028	2.9832575	3.70877389	0.33283386	0.00046511	5.61E-08
13:32:45	33.130275	15.7159375	6.34460156	2.87036958	3.43878073	0.33735016	0.00026338	9.18E-08
13:32:46	21.0892222	18.5629889	12.0933472	2.27217556	3.51263394	0.43028394	0.00018662	6.89E-08
13:32:47	11.5359475	13.4892063	18.7510781	1.31470125	3.70878228	0.36680068	0.00031788	9.82E-08
13:32:48	24.273375	16.2899856	9.71722344	2.50895208	3.43910497	0.33278841	0.00013484	3.74E-08
13:32:49	35.3285388	15.4798313	5.89437031	2.05429313	3.8597075	0.2710968	0.00038238	6.52E-08

Fig.4: Sample snapshot of the data with average PSD values for each wave

3.1 Classifiers Used

3.1.1 Naïve Bayes

In machine learning, naive Bayes classifiers are probabilistic classifiers that was derived from Bayes' theorem along with few assumptions. Naive Bayes classifiers are scalable, requiring a number of parameters linear in the number of variables features in a learning problem, likelihood training can be done by evaluating a closed-form expression, which takes linear time, rather than by expensive iterative approximation as used for many other types of classifiers[10]. Since probability plays a major role in Neural Data Analysis, we have used it in our study

3.1.2 K-Nearest Neighbor (K-NN)

K-NN is a non-parametric machine learning algorithm used for classification and regression. The algorithm uses "K" near points from the input space. In K-NN classification, the output is a class membership. An object is classified by a majority vote of its neighbors, with the object being assigned to the class most common among its K nearest neighbours (K is a positive integer, typically small). If K = 1, then the object is simply assigned to the class of that single nearest neighbor.

The neighbours are taken from a set of objects for which the class for K-NN classification or the object property value for K-NN regression is known[11].

3.1.3 Support Vector Machine (SVM)

SVM is a discriminative classifier and contains a separating hyperplane. Given labeled training data, the algorithm outputs an optimal hyperplane which classifies new examples.

SVM is associated with kernel functions. These kernel functions are important in fitting the SVM model to the data if the data are linearly inseparable [12]. In our experiment, we have used sigmoid kernel.

3.1.4 Random Forest

Random forest is based on Decision tree classifier. Random Forest performs classification and regression based on a forest of trees that uses random inputs. The main purpose of using a Random Forest algorithm is to improve the accuracy of prediction. By growing an ensemble of trees, classification accuracy increases.

These forests use randomly selected inputs or combinations of split inputs at each node to grow the tree. It is found to be robust to outliers and noise. It is very simple to implement and can be easily parallelized. It also gives useful estimates of errors, strength, correlation and variable importance.[13,14]

4. RESULTS AND DISCUSSIONS

In our study, the PSD values obtained after performing fourier transform to the raw signal were then averaged to get the mean value. The mean PSD value of all the brainwaves: delta, theta, alpha, beta, and gamma were fed as features to the classifier. Four Supervised Machine learning classifiers namely K-NN, Bayesian Classifiers, SVM and Random Forest were used to classify the emotions as Happy, Sad and Neutral based on the PSD features of the dominant wave obtained for each time interval of the song. Fig.5 represents the classification accuracy, precision and recall percentages of each classifier used.

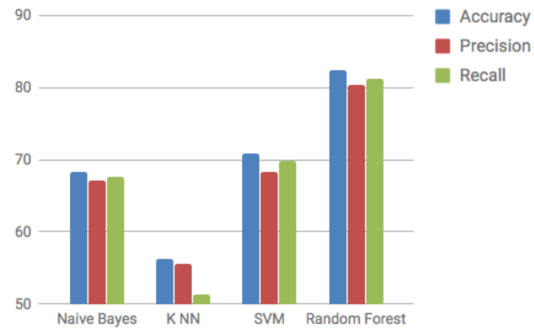


Fig. 5: Classification results

Among the classifiers which were used, Random forest algorithm produced the greatest accuracy of 82%, proving that it's the best classifier amongst the ones used. This is because random forest is an ensemble method which is formed by multiple base classifiers. Therefore it produces less variance and it reduces overfitting since the method averages several trees[13,14].

Our next step in this process is to build a continuous patient monitoring system, for which we will be deploying the device and using the same protocol in several other special children care centres across our country to develop a more efficient model with lot of subjects taken into account. We will also be working towards emotion classification by giving visual stimuli, for the ones who have hearing impairments to build a more comprehensive patient monitoring system. Our work will also involve clinical trials for which we will be collaborating with physicians.

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