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EMOTION DETECTION BY EEG SIGNALS

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Abstract - This project report examines the issues and difficulties of research project that was intended to evaluate the state of mind of a subject through Electroencephalogram (EEG). This work prompted the improvement of ongoing framework for investigation of brainwaves through EEG. EEG estimation is non invasive, have a high affectability to get data about the inward (endogenous) changes of mind state, and offer a high time determination in the millisecond range.

On account of the last property, these information are especially suited for studies on mind instruments of psychological passionate data handling which happens in the millisecond run. It has been outstanding that particular cortical and sub-cortical mind framework is used and have been separated by local electrical exercises as per the related emotional states.

There are critical difficulties must be confronted for creating effective EEG signals for recognition of emotions, for example,

(i) outlining a convention to stimulate one of a kind feeling than different feelings

(ii) build up a proficient hardware and algorithm for expelling noises from the EEG signal. What's more, distinct exercises of the mind cause distinct EEG characteristics waves, it has been endeavored to make examination of this brain exercise related to attention and meditation easy by doing analyses of EEG signals.

***Key Words*:** LSTMs, SVMs, KNN

1.INTRODUCTION

Automated examination of the physiological signals like EEG has turned out to be more broad amid the most recent 3 decades for advancement of Brain computer interfaces to incorporate regions such as lie recognition, stress & emotion estimation. So this spark enthusiasm for exploring whether a feeling can be perceived just by observing physiological reaction. Although emotional data could likewise be recovered from different modalities like subject's face appearances, content, motions, and so forth. Be that as it may, these can be deliberately adjusted. This prompted the advancement of emotion recognition strategies, human physiological signals, for example, heart rate, skin conductance, cardiovascular action, neural reactions (EEG), and so forth.

Late investigates on the human EEG uncover that mind activity assumes a noteworthy part in the evaluation of emotions. Advance, perceiving emotional states from neural response is a successful method for executing BCIs. BCI frameworks make a correspondence channel between the mind and PC by procuring, examining and classifying neural exercises under specific simulations, and create control signals for existent globe applications in areas including clinic, psychiatry, security, military, law requirement and broadcast communications. Consequently, programmed emotion acknowledgment from EEG signals is acquiring more consideration these days. An EEG signal represents an electrical action of brain with its amplitude ranges from 10 to 100 microvolts whereas frequent lies in the scope of 0 to 100H

Catching these varieties and investigating them, it is conceivable to portray the associated emotional state. Area of affective evaluating has been broadly investigated with regards to human neural reactions. Some beforehand distributed works uses measurable elements of EEG that automatically do the recognition of emotions, DWT and lifting based wavelet changes in combination with spatial filtering to take out emotion based features through EEG so as to characterize happiness, bitterness, disgust, and fear feelings.

DWT based strategies are not all that most loved because of extensive list of features. Another research examines the utilization of optimization strategies involving diverse sizes of sliding windows, standardization approaches, filtering techniques and dimensionality depletion algorithms on time and frequency domain elements of EEG signals to differentiate wonderful, unbiased, and repulsive emotional states with the help of SVM. This is trailed by strategies that include the use of brief time Fourier Transform(FT) and Fast Fourier Transform(FFT) to the obtained EEG signals to characterize sentiments of happiness, sorrowness, outrage, and joy/fear utilizing SVM but with less exactness.

The combination of EEG with other physiological signals, for example, skin conductance, BVP and respiratory rate has been investigated effectively to characterize calm neutral and negative energized feelings utilizing GA and Elman neural system. The entire list of features involves linear elements of EEG in conjunction with disordered invariants like inexact entropy, fractal and correlation dimension. Encourage an arrangement of algorithms order human feelings by evaluating power spectrum density took after by the extraction and examination of five EEG control bands with the standardized EEG sub bands utilizing Bayesian system and SVM. The extraction strategies of linear features stifle the phase data associated to the morphology of non linear and non stationary EEG waves and in this manner are less exact.

2. Body of Paper

Chapter 2: BACKGROUND STUDY

Emotions play a crucial part in individuals' regular day to day existence. As indicated by hypotheses, emotions are the state of feeling that outcomes in physical and mental changes that control our conduct. Emotion recognition have expanded essentially in the course of recent decades with the commitment of many fields which incorporates brain science, neuroscience, medication, humanism, and considerably computer science. In perceiving emotions, mind activity play a vital part in inspiration, discernment, cognition, consideration, learning and basic leadership. Evaluating emotions from the human cerebrum waves is very new and compelling zone of research. EEG is identified with electric potential in various districts. This was considered to be one of the imperative methodology.

In 1924 Hans Berger presented the idea of Electroencephalogram (EEG). The signals of EEG are recording utilizing electrical action of the cerebrum from the scalp. The EEG movement is very little, measured in miniaturized scale volts (mV). Mind cells persistently send messages to each other that can be gotten as little electrical impulses on scalp. The way toward getting and recording the impulses is called an EEG. An ordinary EEG implies that you have a simple pattern of brainwave movement.

An unusual perusing implies that irregular examples of cerebrum movement are being delivered.

The review displayed in [2] presents the emotion recognition framework utilizing Electroencephalogram (EEG) signals, for investigating 4 emotional states, joy, relax, pitiful, and fear. The assessment of grouping, knearest neighbour (kNN) algo, and SVM were used the same as a classifier for feature extraction. Five right handed volunteers within the age group of 18-25 years participated in the study. A 128 channel electrical flag imaging framework. SCAN 4.2 software and an altered 64 channel Quick Cap with installed Ag/AgCl electrodes were utilized to procure the EEG signals.

The test comes about show that normal test precision is 66.51% for grouping four emotional states acquired by utilizing frequency area components and SVM. 24 The EEG signals detected in human scalp were used to develop a real time emotion monitor showing emotional states of people, so that they can express their thoughts and feeling .The emotions were extracted from emotion indicators or indices, using relative power value from EEG. The study of emotions like happy, sad, fear, peace which were calculated using formulas as below; For fear = relative power of Beta wave of T3/ relative power of Alpha wave of T3 For Sad =1/ relative power of Alpha wave of T3* relative power of Alpha wave of T5 For Peace= relative power of gamma wave of T5/ relative power of alpha wave of CP5 For Happy= 1/ relative power of Alpha wave of C4 The left temporal lobe decreased in alpha wave for negative emotions, were the alpha wave decreased in C4 in happy emotion, the increase of beta wave was observed in the left temporal lobe in fear emotional state and in the peace emotional state the gamma wave are seen to be increased in T5 [3].

Mahalanobi Distance Based Classifier is able to determine EEG patterns by Using several EEG

Electrodes- Fabio Babiloni et al. (2001) took 8 subjects and collected EEG signals on 4 electrodes, C3, P3, C4, P4.Each and every electrode is placed on the scalp according to 10-20 standard system of electrodes. Reduced set of recording electrodes were used by quadratic classifier based on MD classifier to detect EEG patterns so that emotions can be detected. Covariance and diagonal matrix were used by the classifier to detect imagination of movement. The accuracy obtained was 98% .By this accuracy it was made easy for Brain Computer Interface to use Mahalanobi distance classifier in which important factor was reduced set of recording electrodes [5].

The Real Time Based SVM for Recognition of Emotions with the help of EEG - Viet Hoang Ah et al. (2012) used Russell's circumflex model in which two techniques were used. Higuchi Fractal Dimension algo and SVM was also used the same as the classifier. One of the approach was the machine learning where EEG signals of each and every subject is taken under consideration and second one was the machine learning where EEG of each individual subject were taken. EEG signals of various subjects has distinct characteristics and due to this second approach was used instead of first approach that is of machine learning and five states of emotions were determined after calculating the average accuracy of 70.5%.The conclusion at the end was that the model should be improved since emotions and accuracy both were very small for real applications [6].

Towards Emotional alert Computing: It is the Integrated Approach proposed strategy for the grouping of neurophysiological information into four emotional states. These enthusiastic states were gathered amid uninvolved survey of passionate pictures chosen from IAPS. It embraces the independency of two emotive measurements. These are named as excitement and valence. For the judgment of enthusiastic states between EEG signals evoked by lovely and repulsive boosts, two stage order strategy was utilized, which likewise differ in their excitement/intensity levels. The arousal judgment was involved by first classification level. After performing arousal judgment, the valence judgment was applied. For the discrimination of emotions, there were two factors used named as the Mahalanobis Distance based classifier and Support Vector Machine. For the MD, gained classification rates were 79.5% and for SVM the gained rates were 281.3%.The first step towards number of applications including the sphere of human computer interaction was the robust classification of objective emotional measures. This procedure used the bidirectional cognitive model to get the provoked neurophysiological emotional reactions. These responses were classified by means of data mining methods [4].

Chapter 3: DETAILED DESIGN

The dataset I used was obtained from three sources. First, Temple University Hospital and Kaggle data from2010 to 2014 from Li et. al (2014), published as a UCI dataset. Second,

The features of our dataset contain brain waves ranging from Infra to Gamma.

Chapter 4: IMPLEMENTATION

In implementation I have performed the following tasks to get dataset on which I applied machine learning and deep learning algorithms.

4.1 Data Pre-processing

I preprocessed and converted each dataset, which had hourly information, to a time series so that it can be used towards solving a supervised learning problem. I removed columns such as date, hour, year and month. All NA values were replaced with 0. I then encoded the categorical feature direction using Label Encoder. I applied feature scaling using Min-Max Scaler.

4.2 Training Models:

I first applied Machine Learning to train our dataset. I applied SVR or Support Vector Machine with radial basis kernel.

I compared the results obtained by applying Deep Learning. I first applied LSTM having 128 nodes in the input layer and a single hidden layer with 50 nodes. I trained the model for 25 epochs and the training took nearly 48seconds.

I then applied Random Forest with changing depths

4.3 Pseudocode

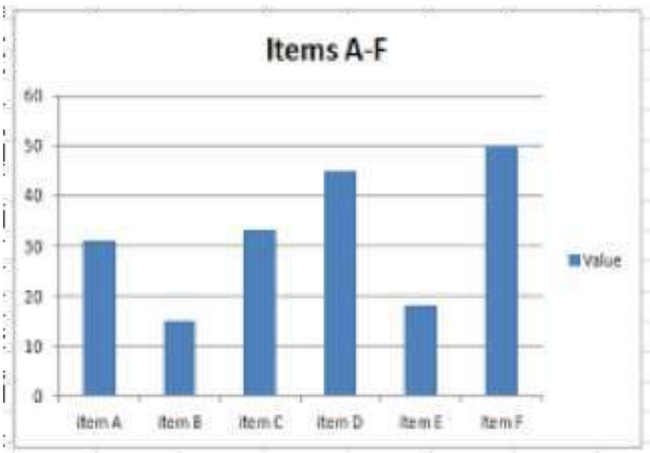
```
procedure : ANN(D,n)
        Input D = {(x_i^(i), y^(i))_{i=1}^n}_{i=1}^*
        Randomly Initialize all weights and threshold

repeat
        for all (x^(i),y^(i)) ϵ D do
                compute a_m according to current parameter (m= 1 to 10)
                compute cost J_a (forward)
                compute b_l according to parameter a & J (l= 1to 5)
                compute cost J_b (forward)
                compute y_predicted
                compute error Δ_b (backward)
                update weights using the error
                compute error Δ_a (backward)
                update weights using the error
        end for
        until achieve stopping condition( number of epochs)
end procedure
```

Figure 4.3: Pseudo-Code of ANN: Screenshot from our word processor.

After training and testing models of Machine Learning and Deep Learning

	Variance (R2 value)	Root Mean Squared Error
Random Forest	0.79	42.14
SVM	0.92	24.86
Naïve Bayes	0.91	26.21

Charts



5. CONCLUSIONS

Design of machine has been tested by making a software based on Fast Fourier Transform to convert input frequency domain signals into time domain for better visualization. The test subjects were of Indian origin, 1825 age group both males and females. During testing, they had been asked to think different thoughts to verify the machine is working

Manufacturing of a single channel cost efficient EEG machine prototype is discussed in this paper. It does not use complex algorithms like face detection to improve accuracy. Proposed model may be utilized as an alternative in place of the available models. The acceptability of proposed scheme may be considered as it is a cheaper in comparison to other options available. It can be tested by asking subject to blink eyes rapidly.

Blinking eyes will change the wave pattern being observed on the screen. This design can be coupled with cost efficient high processing capable micro controllers like Raspberry pi to make it n-channel machine and use it for further research. By making adequate adjustments it can be used in real time applications as described in this paper.

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REFERENCES

[1] C. Frith, and R Corcoran, “Exploring ‘theory of mind’ in people with schizophrenia,” Psychological Medicine, vol. 26, no. 3, pp.521-525, 1996.

[2] R.W. Picard, E. Vyzas and J. Healey, “Toward Machine Emotional Intelligence: Analysis of Affective Physiological State”, IEEE T. Pattern Anal., vol. 23, pp.1175-1191, 2001.

[3] D. P. Subha, P.K. Joseph, R. Acharya and C.M. Lim, "EEG

Signal Analysis: A Survey", Journal of Medical Systems, vol. 34, no. 2, pp. 195-212, 2010.

[4] L. Zylowska, " The Mindfulness Prescription for Adult ADHD", Trumpeter, Boston and London, 2012.

[5] "Electroencephalography", En.wikipedia.org, 2017. [Online]. Available: https://en.wikipedia.org/wiki/Electroencephalography. [6] M. A. Khalilzadeh, S. M. Homam, S. A. Hosseini and V. Niazmand, "Qualitative and Quantitative Evaluation of Brain Activity in Emotional Stress", Iranian Journal of Neurology, vol. 8, no. 28, pp. 605-618, 2010.

[6] "Electroencephalography", En.wikipedia.org, 2018. [Online]. Available: https://en.wikipedia.org/wiki/Electroencephalography. [6] M. A. Khalilzadeh, S. M. Homam, S. A. Hosseini and V. Niazmand, "Qualitative and Quantitative Evaluation of Brain Activity in Emotional Stress", Iranian Journal of Neurology, vol. 8, no. 28, pp. 605-618, 2010.

[7] "5 Types Of Brain Waves Frequencies: Gamma, Beta, Alpha, Theta, Delta", Mental Health Daily, 2017.

[Online]. Available: http://mentalhealthdaily.com/2014/04/15/5-types-of-brainwavesfrequencies-gammabeta-alpha-theta-delta/.

[8] Gevins, A., Smith, M., McEvoy, L., Leong, H., Le, J.: Electroencephalographic imaging of higher brain function, Philosophical Transactions of the Royal Society, ser. B London, U.K.,vol. no. 354, pp. 1125–1134, 1999.

[9] Babiloni F., "Linear classification of low-resolution EEG patterns produced by imagined hand movements", IEEE Transaction Rehab. Eng., vol. 8, pp. 186–188, June, 2000