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Emotion Recognition using Gradient Boosting Machine Algorithm

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Abstract*: *The technological advancements are helping the medical field by introducing more sophisticated equipment. One such equipment is Electroencephalography (EEG) which helps in reading the brain waves. Brain waves are the reflection of the actual emotions raised in the brain cortex. Various algorithms have been proposed for effectively recognizing the emotions using the EEG data. But, the accuracy has been always a matter of fact which throws a challenge to the researchers. Hence, in this paper we have proposed an effective machine learning techniques Gradient Boosting Algorithm which can classify and predict the emotion more accurately.

Index Terms*: *Electroencephalography, Machine Learning, Gradient Boosting, Brodmann's.

I. INTRODUCTION

Emotions are the mental state [1-3] variously associated with the behavioral response, feeling, and thoughts along with certain grade of either the pleasure or the displeasure [4-5]. It is usually interwind with mood, personality, temperament, motivation and the disposition [6]. During the recent past, much of the research on emotions has been contributing by various fields like psychology, neuro science, medicine, sociology of emotions and computer science [7] have set out emotions as the involving physiological components, cultural or emotional labels (viz., Happy, Angry, Sad, Surprise and more), with expressive actions of the body, and appraisal of the contents and the situations. These emotions also help us in taking decisions in few aspects. Therefore emotions recognition plays a vital role is in the technological era.

Emotion recognition is a process of identifying human emotions may it be through facial expressions or by verbal expressions. Expressions showcase how we feel in our heart or brain. The emotions are expressed by those people who have proper functionality of the brain. As per the literature it is learnt that there are about 40 different emotions. However, as per the Schener's Components processing model of emotions [8], there exists five crucial elements of emotions. Similarly the findings of [9] proved that there are about six fundamental emotions viz., "Angry, Disgust, Happiness, Fear, Sadness and Surprise. " He has developed 'Wheal of Emotions as shown in fig.1. To classify these emotions broadly, these emotions may be differential based on similar constructs in the field of affective neuroscience. Thus, the classification of these emotions is made by measuring two aspects such as Arousal and Valence [10]

To identify the emotion there is a need for sophisticated techniques. The emotion recognition may be done by various way viz., by facial image processing, emotion recognition using voice data, GSR, RR, EMG, emotion recognition using EEG signal [11].

However, it is evident that the facial expressions may mislead the internal emotions of the human. The only way to access and recognize the actual emotion is through reading the brain signals through EEG. There are different types of EEG scan devices with 10-20 probes, 32 probes and 64 probes. The below fig.1 a & b depicts 32 & 64 probes EEG Scan cap.

(a) 32 Channel Cap

(b) 64 Channel Cap

Fig.1: 32 & 64 Electrodes Caps

Though there are more number of probes there are about 8 probes signals which are very important to recognize the emotion. Therefore, in the paper we have utilized EEG for emotion recognition. The rest of the paper is arranged as the section-II deals with related work and section-III elaborates on details of EEG. In section-IV, the methodology is explained which used to analyse the EEG signal to recognize the emotion and section-V demonstrates about the experimental results. Finally, the paper is concluded in section-VI.

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II. RELATED WORK

The Literature unfolds the methodologies adopted till recent years. The used methodologies are of both supervised and unsupervised techniques [12 – 19]. The recent advancements have even made use of the latest machine learning techniques. [11] Has done a survey on various algorithms for emotion recognition. The effectiveness is observed in KNN. However, the KNN algorithm has a problem of overfitting. In [20], the experimentation has been done on multiclass classification using Gradient Boosted trees.

III. ELECTROENCEPHALOGRAPHY (EEG)

An Electroencephalogram (EEG) is method for detecting the electrical activities in the human brain with the help of small (electrodes) metal discs attached to the scalp. The brain cells communicate via the electoral impulses and are active all the time. Earlier, this EEG is used to diagnose epilepsy monitoring, Sub-cortical movement disorders, migraine etc., later, many, researchers have stated studying the EEG signals for identifying the emotions from the brain also. This study made lot of researches to focus in this area. Whatever the emotions generated from the human brain. The signals from different neurons in the brain also respond accordingly various researchers have used different techniques to detect these emotion using EEG signals.

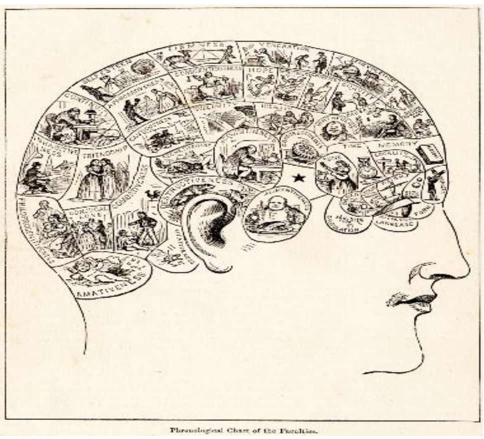


Fig.2: Phrenological Chart of the Faculties

There are 3 broad categories of human emotions such as basic, motivational and self-conscious or social [16]. The basic emotions are further classified to six different emotions viz., Happy, Sad, Fear, Disgust, Anger and Surprise. These emotions are identified based on the range and values of the frequency bands of the EEG signals. The cerebral signals that are observed in the scalp (EEG) shall be in the range of 1-20 Hz. The activities below or above the range of 1-20 Hz are likely to be artificial as per the standard clinical readings. The waveforms are further categorized into bandwidths namely Delta, Theta, Alpha, Beta, Mu and Gamma. However, the frequency bands of Mu and Gamma fall above the standard range. The frequency band widths are listed in the table-I given below.

Table – I: Frequency Ranges

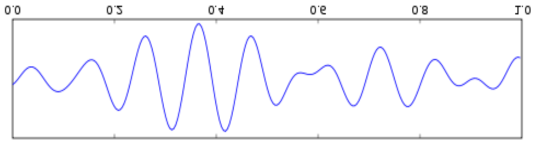
Band	Frequency
Delta	< 4 Hz
Theta	4 – 7 Hz
Alpha	8 – 15 Hz
Beta	16 – 31 Hz
Gamma	> 32 Hz
Mu	8 – 12 Hz

Further, the frequency band upon improvements, the ranges are shown in the table-II given below.

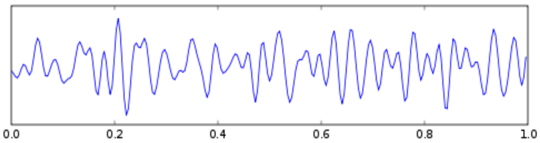
Table – II: Improved Frequency Ranges

Band	Frequency
Delta	< 4 Hz
Theta	≥ 4 & < 8 Hz
Alpha	≥ 8 & < 14 Hz
Beta	≥ 14 Hz

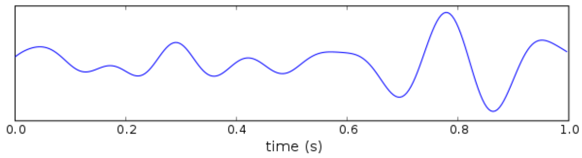
The wave patterns of the frequency bands are shown below in fig.3



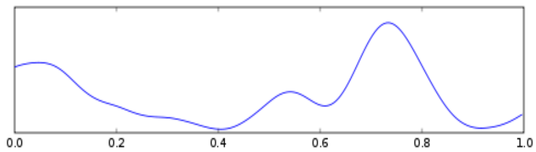
(a) Alpha



(b) Beta



(c) Theta



(d) Delta

(e) Gamma

Fig.3: Frequency Curves of EEG Waves

The signals are captured from either 32 probably 64 probes. We use 32 & 64 probes cap, we need to get the frequency from the following probes only according to Brodmann-1909 [21-22] viz., F7, F5, F7, CP5, P7, P3, 01, 02, P4, P8, C6, T8, C5, F8, CP6. As most of the emotions are derived from the electrode nodes. Hence, the data extracted from these electrodes are processed which results in reduction about 38 - 39%.

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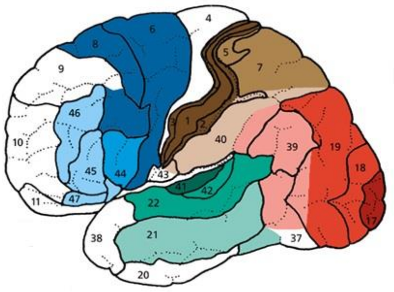

Fig. 4: Cytoarchitectural areas of human Cortex according to Brodmann-1909

Hence, is this paper, we have utilized these electrodes signals only to recognize the emotions. Research studies showcase the usage of machine learning techniques such as neural networks along with the statistical features that are extracted from the frontal lobe EEG for classification of emotional states.

IV. METHODOLOGY

In this paper, we proposed to implement machine learning techniques for accurate classification of emotions. In [11][19], the authors have analysed about 50-60 different models such as SVM(3 varients), KNN with N = {1,2,3,4,5,8}, PNN, LDA etc. However, the experimental results hardly reaching to 95%accuracy level, 70% while using K=8, and 95% when K=5, 86.5% when K=4. But none of the techniques could crossover 95% of the accuracy. Hence, in this paper we have proposed a novel technique such as Gradient Boosting Machine. The Gradient Boost algorithm is the widely used machine learning technique that best fits for regression and classification problems. It gives a prediction model which is in the form of a group of the weak prediction models. The Gradient Boosting gives best results as it is robust and can perform well on a dataset on which minimal effort is spent on cleaning and can also learn much complex non-linear decision boundaries through boosting. The gradient boosting algorithm is as follows:

1. Initialize the proposed model with constant value:

$$F_0(x) = argmin \sum_{i=1}^{n} L(y_i, \gamma)$$

2. For m = 1 to M:

   I. Compute *pseudo-residuals*:

$$r_{im} = -\left[\frac{\partial L(y_i, F(x_i))}{\partial F(x_i)}\right]_{F(x)=F_{m-1}(x)} \qquad for\ i = 1, \ldots\ldots, n$$

   II. Fitting a base learner (e.g. tree) $h_m(x)$ to pseudo-residuals, (training it using the training set $\{(x_i, r_{im})\}_{i=1}^{n}$)

   III. Computing multiplier γ_m by solving the below one-dimensional optimization problem:

$$\gamma_m = arg\min_{\gamma} \sum_{i=1}^{n} L(y_i, \quad F_{m-1}(x_i) + \gamma h_m(x_i))$$

   IV. Updating the model:

$$F_m(x) = F_{m-1}(x) + \gamma_m h_m(x)$$

3. Output $F_M(x)$

For classification of the data, we have considered about 80% of the data is used for training and 20% for testing. The accuracy score was found to be 99.29%. The experimentation was done using two different datasets in which one dataset is a standard Kaggle dataset on which most of the authors have worked and the second dataset is extracted by us using Neuro Scan 500 devise on 10 subjects of male subjects 5 and 5 female subjects as some of the previous works have not maintained this balance of gender. The Experimental results clearly specify that the Accuracy of Gradient boosting machine algorithm is pretty much higher when compared to the other models viz., KNN, Adaboost or SVM classifiers.

Similarly the Experimentation has been conducted on both male and female adult subjects of each of 5 numbers for finding the emotions through the EEG signals. One of the team members also have been the subject among the male subjects. The extraction of the data has to be done in an extremely trained manner. Initially the subjects have to be trained on how to be stable while extracting the EEG data as the signals might deviate even if the eyelids are blinked unnaturally.

The following subsections elaborates on materials and setup & feature selection:

A. MATERIALS & SETUP

The experimentation has been conducted on male adult subjects for real-time data corresponding to four emotions viz., Neutral, Happy, Angry and Sad by using a NeuroScan equipment having 64 electrodes (EEG Cap). There are various types of electrodes like Reusable disks, EEG Caps, Adhesive Gel Electrodes, Subdermal Needles etc. However, the frequency of each emotion varies from adult subject to child subject. Hence, the frequency values and ranges differ from subject to subject depending upon the age of the subject. The EEG cap is fixed to the head and all the electrodes are filled with an adhesive gel to decrease the impedance. For obtaining the noise free values of emotions, having low impedance is very much essential. The values of the emotions are extracted from the subjects after observing the low impedance levels in all the electrodes.

(a) NeuroScan Device

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(b) Connecting Equipment

(c) 64 Electrode EEG Cap

Fig.5: (c) NeuroScan EEG Equipment Setup

B. FEATURE SELECTION

Literature research has specifically pointed out to 15 electrodes [21-22] which are mainly responsible for identifying the emotions viz., FP1, FP2, FP7, FPz, Fz, F3, F4 and F8. The above emotions can be clearly captured from the selected 8 electrodes.

V. RESULTS & DISCUSSION

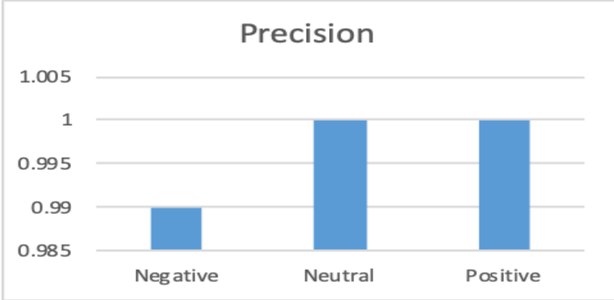
The Experimentation has been carried out using Python programming technology. The Hardware specifications are processor being Core i5 with 8 GB RAM and 1TB HDD. For initial experimentation Kaggle Dataset with about 2548 records of 500MB size CSV file has been used for experimentation. The efficiency of the Gradient Boosting Machine algorithm is measured by finding the accuracy of the proposed model. The proposed model's accuracy is observed to be 99.29% when the confusion matrix obtained after the execution of the proposed model is shown in Table-III and the performance of the model for emotion states is shown in Table-IV.

Table -III: Confusion Matric of emotion states

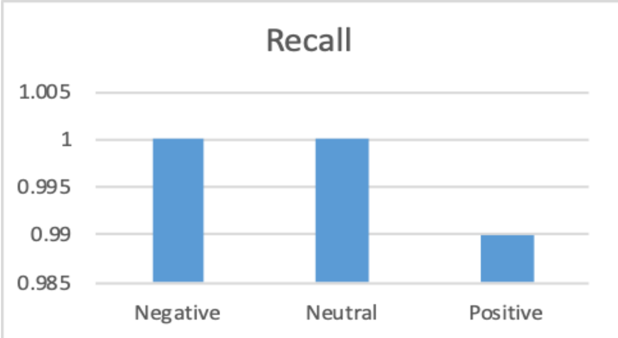
	Negative	Neutral	Positive
Negative	132	0	1
Neutral	0	147	0
Positive	0	0	147

Table -IV: Model Performance Score for emotion states

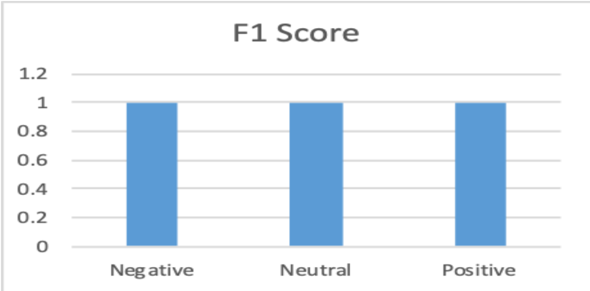
	Precision	Recall	F1 Score	Support
Negative	0.99	1.00	1.00	132
Neutral	1.00	1.00	1.00	147
Positive	1.00	0.99	1.00	148



(a)Precision



(b) Recall



(c)F1 Score

Fig.6: Performance Score of emotion States

Table -V: Accuracy of GBM and KNN

Dataset	KNN Classifier				Gradient Boosting
	K = 2	K=4	K=5	K=8	
Kaggle Dataset	93.91	93.44	94.14	92.97	99.76
Extracted Dataset	88.10	87.27	91.43	90.48	94.21

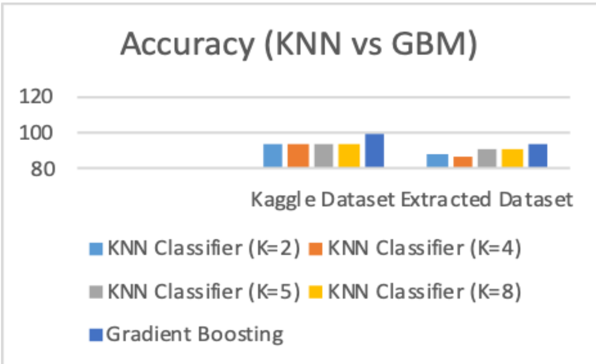


Fig.7: Graph of Accuracy between KNN and GBM

The model when compared to KNN model [23-30], the accuracy is found to be higher than the KNN. The experimentation has even been done for finding the emotions from the EEG signals based on the arousal and valence of the signals from α, β, θ, γ, μ, □ waves. It is observe that the accuracy is more than the previous models viz., generalized Gamma distribution. Table-II shows the accuracy of the proposed GBM model. Experimental results have been evaluated using Python environment are enclosed herewith in fig.-8.

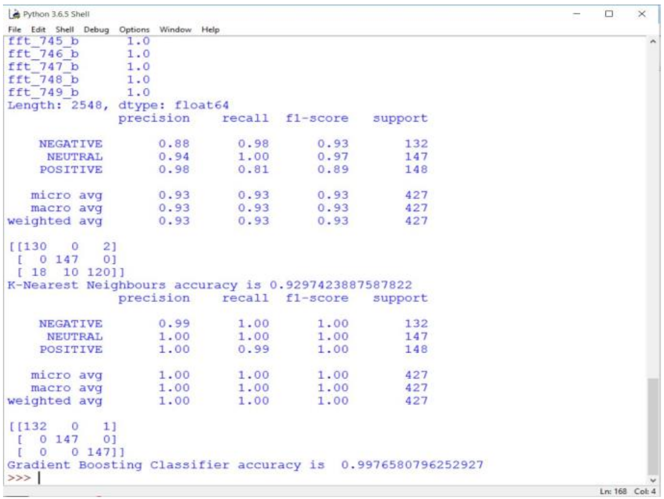


Fig.-8: Outputs of Precision and Recall under Python framework

VI. CONCLUSION

The experimental results clearly depicts that the models viz.,Gaussian mixture model, Gamma distribution, Weibul distribution of the popular classification models viz., SVM, KNN and Adaboost algorithms are less accurate than the proposed Gradient Boosting Machine model. The advantage of GBM is that it helps in improving the learning rate of weak learners. The learning is done the values coverage. Hence, the proposed model is better than the Existing techniques. However, the Accuracy shall further be improved if the EEG data of more subjects is extracted.

REFERENCES

1. Panksepp, Jaak, "Affective neuroscience: the foundations of human and animal emotions" ([Reprint] ed.), Oxford [u.a.]: Oxford Univ. Press. p. 9, 2005.
2. Damasio AR, "Emotion in the perspective of an integrated nervous system" Brain Research. Brain Research Reviews. 26 (2–3): 83–86, May 1998.
3. Davidson, edited by Paul Ekman, Richard J., "The Nature of emotion: fundamental questions", New York: Oxford University Press. pp. 291–93, 1994.
4. Cabanac, Michel, "What is emotion?" Behavioural Processes 60(2): 69-83, 2002.
5. Scirst Daniel L., "Psychology" Second Edition. 41 Madison Avenue, New York, NY 10010: Worth Publishers. p. 310, 2011.
6. Robert Plutchik and Henry Kellerman, "Theories of Emotion", Academic Press.
7. Thoits PA., "The sociology of emotions". Annual Review of Sociology. 15: 317–42, 1989.
8. Scherer KR, "What are emotions? And how can they be measured?" Social Science Information. 44 (4): 693–727, 2005.
9. P. Ekman et al, "Universals and cultural differences in the judgments of facial expressions of emotion," Journal of Personality and Social Psychology, vol. 53, no. 4, pp. 712–717, Oct. 1987.
10. Chung SY and Yoon HJ, "Affective classification using Bayesian classifier and supervised learning", 12th International Conference on Control, Automation and Systems (ICCAS); 2012; JeJu Island, South Korea.
11. Soraia M.Alarcao and Manuel J F, "Emotions Recognition Using EEG Signals: A Survey", IEEE Transactions on Affective Computing, pp:01-20, 2017,
12. Hari Krishna Vydana, et al., "Improved emotion recognition using GMM-UBMs". 2015 International Conference on Signal Processing and Communication Engineering Systems
13. B. Schuller, G. Rigoll M. Lang. "Hidden Markov model-based speech emotion recognition". ICME '03. Proceedings. 2003 International Conference on Multimedia and Expo, 2003.
14. Poria, Soujanya; Cambria, Erik; Bajpai, Rajiv; Hussain, Amir, "A review of affective computing: From unimodal analysis to multimodal fusion". Information Fusion. 37: 98–125, September 2017.
15. Caridakis, George et al., "Multimodal emotion recognition from expressive faces, body gestures and speech", IFIP the International Federation for Information Processing. 247. pp. 375–388, September 2007.
16. Sujeeth .T, Y. Srinivas, Nagesh Vadaparthi, "Emotion Recognition Based on Generalized Gamma Distribution", International Journal of Engineering & Technology, 7 (2.19) (2018) 21-25.
17. Liu J., et al., "Emotion detection from EEG recordings based on supervised and unsupervised dimension reduction", Concurrency and Computation Practice and Experience, Wiley, 2018, pp.:1-13.
18. S. Koelstra, et al., "DEAP: A database for emotion analysis; Using physiological signals", IEEE Transactions on Affective Computing, vol. 3, no. 1, pp. 18-31, 2012.
19. Abeer Al-Nafjan, et al., "Review and Classification of Emotion Recognition Based On EEG Brain-Computer Interface System Research: A Systematic Review", Applied Sciences, MDPI, 2017, 7, 1239.
20. Deepak Kumar Sharma, et al., "Predicting the Algorithmic Time Complexity of Single Parametric Algorithms using Multiclass Classification with Gradient Boosted Trees", proceedings of 2018 Eleventh International Conference on Contemporary Computing (IC3), 2-4 August 2018, Noida, India.
21. Adrian Rodriguez Aguinaga, et al., "Classification model of arousal and valence mental states by EEG signals analysis and Brodmann correlations", (IJACSA) International Journal of Advanced Computer Science and Applications, Vol. 6, No. 6, 2015.
22. Brodmann K., "Comparative Localization Theory of the Cerebral Cortex: Illustrated in its Principles on the Basis of Cell Construction", Published by Leipzig: Barth, 1909.
23. R. Khosrowabadi, H. C. Quek, A. Wahab, and K. K. Ang, "EEG-based Emotion Recognition Using Self-Organizing Map for Boundary Detection," in ICPR, 2010, pp. 4242–4245.
24. L. Brown, B. Grundlehner, and J. Penders, "Towards wireless emotional valence detection from EEG," in IEEE EMBS, 2011.
25. T. F. Bastos-Filho, A. Ferreira, A. C. Atencio, S. Arjunan, and D. Kumar, "Evaluation of feature extraction techniques in emotional state recognition," in IHCI, 2012, pp. 1–6.
26. S. K. Hadjidimitriou and L. J. Hadjileontiadis, "Toward an EEG Based Recognition of Music Liking Using Time-Frequency Analysis," IEEE Transactions on Biomedical Engineering, 2012.
27. H. Xu and K. N. Plataniotis, "Affect recognition using EEG signal," in MMSP, 2012, pp. 299–304.
28. M. Murugappan and S. Murugappan, "Human emotion recognition through short time Electroencephalogram (EEG) signals using Fast Fourier Transform (FFT)," in CSPA, 2013, pp. 289–294.
29. S. Hatamikia, K. Maghooli, and A. M. Nasrabadi, "The emotion recognition system based on autoregressive model and sequential forward feature selection of electroencephalogram signals," Journal of medical signals and sensors, vol. 4, no. 3, 2014.
30. Z. Mohammadi, J. Frounchi, and M. Amiri, "Wavelet-based emotion recognition system using EEG signal," Neural Computing and Applications, pp. 1–6, 2016.

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