EEG BASED PERSON'S EMOTION RECOGNITION

Tushar Hande[1], Shruti Warade[2], Tejashri Shingade[3], Dipali Dhake[4]
[1,2,3]*Department of E&TC, PCCOER, Ravet, Pune, India*
E-mail: [1]tusharvhande@gmail.com , [2]shrutiwarade@gmail.com, [3]tejashrishingade25@gmail.com

Abstract—The leading goal of this paper is to discern emotion from Electroencephalogram EEG signals of human brain activity. Emotion categorization from EEG data has lately received a lot of attention, thanks to the growing development of various machine learning algorithms and numerous onto this of the brain to a computer interface for normal people. Researchers have only a rudimentary understanding of the bonding between various emotional states and mainly EEG parameters until now. Throughout the process, we systematically perform feature extraction. The retrieved primary features are stated, and the classification result validates their effectiveness. This study systematically uses EEG characteristics for emotion classification and provides an efficient feature classification approach for optimal results. This paper uses the support vector machine (SVM) and k-nearest neighbor (KNN) classifier for persons' emotion recognition. Also, results are validated with performance parameters i.e., accuracy.

Keywords: **Machine learning(ML), support vector machine (SVM), k-nearest neighbor (KNN).**

I. INTRODUCTION

Even though human emotional experience plays an important part in our daily lifestyle, we still have a limited scientific grasp of human emotions. The advancement of emotional sciences is critical for the advancement of human psychology and the application of the many sections. When robots are integrated into the system to help with emotion identification, productivity increases and expenses decrease in several ways. [1]. Because it directly measures real feelings, the electroencephalogram (EEG) produces better results. EEG is a non-invasive, high-resolution electroencephalogram. The rapid development of new wearable, minimum cost wireless wearable headsets that can measure EEG signals without the need for qualified specialists has greatly extended its usage in other fields such as sleep management, e-learning, video games, the cyber world, medical science, and so on. This literature review covered contemporary EEG-based emotion recognition algorithms, which will be useful to researchers in this field. Several researchers research EEG signals to get maximum accuracy. Text [10], voice [6], facial expression [6], and gesture can all be used to recognize emotions. EEG signals can be used to determine emotions and mental states in individuals in real-, including attention levels. This data can be utilized as feedback to trigger various actions in technologically advanced applications, such as changing the scene in a virtual reality environment or fine-tuning lecture delivery in an E-learning system. [10].

Various machine learning and deep learning techniques have been presented for emotion recognition based on speech signals. It is observed that the speech signals are sensitive to various noise, language, intonation, age, and external disturbances. Thus, EEG signals can be a good choice that is independent of the language, age, intonation, and external noise [1][2][3][13]. Machine integrations into society, such as in education, can be discovered by observing students' mental states in relation to the content of the instructional materials, which might be engaging or non engaging. Medical practitioners would be able to study their patients' mental health and provide more constructive treatment to help them improve their health. The military will be able to train their recruits in virtual environments while simultaneously analyzing their mental state in combat situations. e, computer integrations with society, such as in education, where assessments of pupils' mental states toward instructional resources can be classified as engaging or non engaging.

II. METHODOLOGY

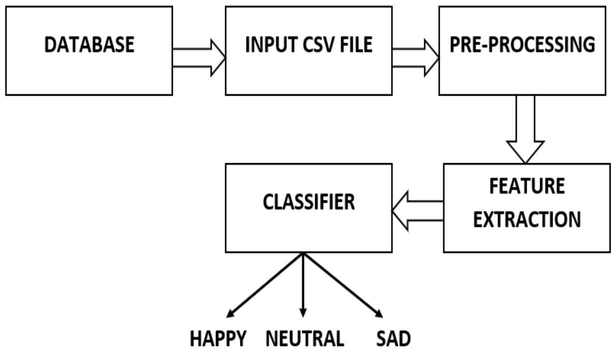

Fig. 1. Schematic of the proposed system

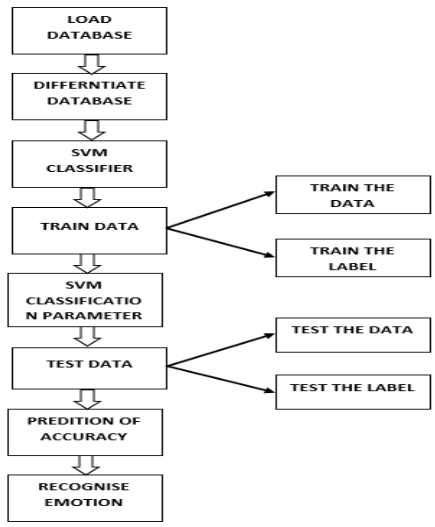

Fig. 2. flow of the proposed system

A. EEG database

The "EEG During Mental Arithmetic" database of a total of 36 subjects is provided in EDF (European Data Format) format. Each folder contains two signal recording files per subject:

- There arerecordings of a subject's background EEG signal, which is recorded before the mental arithmetic task.
- There are somerecordings of EEG signals ongoing the mental arithmetic task.

In this dataset all subjects are divided into two groups namely:

- Group "G" (24 subjects) performing a good quality count
- Group "B" (12 subjects) performing bad quality count.

B. Preprocessing

We're extracting frequency bands right now. Decomposing EEG signals into distinct frequency bands and then working on each band is a frequent strategy in emotion detection algorithms. After that, the raw EEG data is down-sampled. Band-pass filters between 1Hz and 100Hz can be used to extract frequency bands from raw EEG signals. [5] Use a filter to pre-process data and extract frequency bands. Noise, blurry signals, and undesirable artifacts can all be removed.

C. Feature Extraction

Feature extraction is a method for extracting features that can be used to classify varied data, with each feature containing some significant information about the signal [2].

D. Classifier

To create emotion detection systems, the retrieved features are subsequently identified using pattern classifiers Over the conventional SVM, the suggested technique uses a Feed-Forward Artificial Neural Network as a classifier [2]. We acquire a single data value or feature value from the retrieved features, which is passed to the classifier [10]. Following that, the classifier takes decisions thatare based on the circumstances. EEG signals have already been classified into distinct emotional classes using linear classifiers. Converting the feature vector into one of the different emotional states is done with classifiers. We will use artificial neural networks for the categorization procedure in this project. As a result, the characteristics can be estimated in five frequency ranges. Ranges are mentioned sequentially below.

- Delta Wave

Delta waves are waves that occur between the frequencies of 0 and 4 Hz and are observed during profound sleep or coma. The amplitude of such waves is greater than 100 microvolts per second. On the x-axis, time is in seconds, while on the y-axis is a Delta wave.

- Theta wave

Theta waves have a frequency range between 4 and 8 Hz. In a focused state, theta rhythms are observed during creative thought. During a short-term memory test, such waves are also detected. A Theta wave is depicted in the illustration, with the x-axis representing time in seconds.

- Alpha wave

Alpha waves are found between the frequency ranges of 8 and 13 Hz. During a condition of relaxation and tranquility, these waves arise in the occipital lobe of the brain. It has also been discovered that the activity of the Alpha rhythm correlates with a person's visual functionality. The x-axis shows time in seconds, and the picture depicts an Alpha wave.

- Beta Wave

Beta waves can be found between the frequencies of 13 and 30 Hz. These waves originate in the brain's central region and are linked to anxious thinking and active concentration. The x-axis of a beta wave is time measured in seconds.

- Gamma Wave

Gamma waves are found in the 30-100Hz frequency range. These waves are related to multi-tasking and a conscious waking state of mind. On the x-axis, it is time in seconds, and on the y-axis, it is a Gamma wave.

III. Experiment on Database

We used the Physio net database with mental arithmetic stimulus for the experimentation. This database recorded monopolar using a Neurotome EEG 23-channel system. All recordings are artifact-free EEG segments of 60 seconds duration. In this experiment, 36 subjects are used.

TABLE I. COMPARISON OF ACCURACY

Database	**Classifier**	**Accuracy**
(Physio net) EEG During Mental Arithmetic	SVM	84.71
	KNN	66.9

The above table compares the accuracy of the support vector machine method to the k-nearest Neighbor approach. In that experiment, we can see that the accuracy of the support vector machine (SVM) algorithm is higher than that of the k-nearest neighbor technique (KNN).

IV. Conclusion

In this paper for the experimentation, we used the physio net EEG mental arithmetic database for persons' emotion recognition. By comparing the accuracy of SVM and KNN algorithms, we can see that SVM is superior to KNN in terms of accuracy. A direct technology interface between a brain and a computer will be possible in the future with the help of a brain-computer interface

V. References

[1] Bhangale, Kishor, and K. Mohana prasad "Speech Emotion Recognition Using Mel Frequency Log Spectrogram and Deep Convolutional Neural Network.". In *Futuristic Communication and Network Technologies*

[2] bhangale, Kishor & Kothandaraman, Mohana prasad Wireless Personal Communications "Survey of Deep Learning Paradigms for Speech Processing". 1-37. 10.1007/s11277-022-09640-y, 2022.

[3] Bhangale, Kishor Barasu, and K. Mohana prasad. "A review on speech processing using machine learning paradigm." *International Journal of Speech Technology* 24, no. 2 (2021): 367-388.

[4] Yalan Ye, Xin Zhu1, Yunxia Li, Tongji Pan, Wenwen He "Cross-subject EEG-based Emotion Recognition

Using Adversarial Domain Adaption with Attention Mechanism”, 11-04-2021.

[5] A. Hassouneh, A. M. Mutawa, and M. Murugappan, “Development of a real-time emotion recognition system using facial expressions and EEG based on machine learning and deep neural network methods,” vol. 20, p. 100372, 2020.

[6] T. Song, W. Zheng, P. Song, and Z. Cui, “EGG emotion recognition using dynamical graph convolutional neural networks IEEE Transactions on Affective Computing, vol. 11, no. 3, pp. 532–541, 2020.

[7] P. Zhong, D. Wang, and C. Miao “EGG-based emotion recognition using regularized graph neural networks,” IEEE Transactions on Affective Computing, pp. 1–1, 2020

[8] A. Blanco C. Vanleer, T. K. Calibo, and S. L. Firebaugh “Single-trial cognitive stress classification using portable wireless electroencephalography,”, Sensors (Switzerland), vol. 19, no. 3, pp. 1–16, 2019.

[9] X. Pope, G. B. Bian, and Z. Tian, “Removal of artifacts from EEG signals: a review *Sensors (Switzerland)*, vol. 19, no. 5, pp. 1–18, 2019.

[10] A. J. Casson, “Wearable EEG and beyond,” Biomedical Engineering Letters, vol. 9, no. 1, pp. 53–71, 2019

[11] S. M. Alarcao and M. J. Fonseca, “Emotion’s recognition using EEG signals: a survey,” IEEE Transactions on Affective Computing, vol. 10, pp. 1–20, 2019

[12] M. Ali, A. H. Mosa, F. Al Machot, and K. Kyamakya, “Emotion recognition involving physiological andspeech signals: a comprehensive review,” in *Recent Advances in Nonlinear Dynamics and Synchronization*, pp. 287–302, Springer, Berlin, Germany, 2018.

[13] A. Sonawane, M. U. Inamdar and K. B. Bhangale "Sound-based human emotion recognition using MFCC & multiple SVM," *2017 Inte. Conf. on Info., Comm., Instrumentation and Control (ICONIC)*, 2017, pp. 1-4, DOI: 10.1109/ICOMICON.2017.8279046

[14] Wei-Long Zheng, Jia-Yi Zhu, and Bao-Liang Lu, “Identifying Stable Patterns over Time for Emotion Recognition from EEG”, IEEE 2016.

[15] Danny Oude Bos, “EEG-based Emotion Recognition, The Influence of Visual and Auditory Stimuli” Department of Computer Science, University of Twente, 2016.

[16] P. Ackermann, C. Kohl Schein, J. Á. Bitsch, K. Wehrle, and S. Jeschke, ‘‘EEG-based automatic emotion recognition: Feature extraction, selection and classification methods,’’ in Proc. IEEE 18th Int. Conf. E-Health Netw., Appl. Services (Healthcom), Sep. 2016,

[17] Wei-Long Zheng, Yong-Qi Zhang, Jia-Yi Zhu, Bao-Liang Lu "Transfer Components between Subjects for EEG based Emotion Recognition”, 2015

[18] Robert Jenke, Angelika Peer, Member, Martin Buss, “Feature Extraction and Selection for Emotion Recognition from EEG” Vol. 5, No. 3, July-September 2014