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Advanced EEG Signal Based Min to Mean Algorithm Approach For Human Emotion Taxonomy And Mental State Analysis

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Abstract: With electroencephalography (EEG) brain waves alone, it is full-scale phenomena in the field of computer-brain interface DNN, CNN, and SVM have improved detection and prediction accuracy in a number of researches during the last several years. But when it comes to recognizing global reliance, both deep learning and SVM have obvious limits. Pre-processing, extraction capabilities, and network design are the most common techniques used in deep learning models today, yet they are still unable to produce reliable results in noisy and sparse datasets. Any dataset, no matter how little or large, may suffer from poor SVM performance due to overlapping target instructions and boundaries. There are many different sorts of emotions that may be classified using the particular approach employed in this research. In order to get a whole picture of a person's mental state, it is best to use a "Min of mean" proposed technique. After comparison to the referential mean, a feeling is divided into one of four emotional quadrants. The MIN Max range is used to further split the emotion into 12 subcategories based on the amount of arousal. The proposed set of rules performed better than existing methods. Research on multi-class emotion reputation has shown that, compared to more recent studies, the proposed technique may be rather strong. It is possible to analyze a person's mental health by using the emotional spectrum, which has an accuracy rate of above 90%.

Keywords: DNN, CNN, SVM, Min of mean, referential mean, MIN MAX Range.

1. INTRODUCTION

Emotions are a useful model for how people think. It is very significant in one's inner thoughts. If someone were to understand the feelings of another, many problems may be addressed. Interpersonal verbal communication may also gain significantly from the inclusion of informational sentiments. People nowadays are interested in other people's emotions and their non-verbal communication style. It's not only out of curiosity; rather, it's crucial in the modern world for a number of reasons. In the commotion of urban life, people are unable to regularly communicate with one another and distinguish themselves. Researchers' interest in themes connected to emotion detection is sparked by a variety of circumstances. Due to pressure and stress at work, individuals are becoming more psychologically unstable, which encourages the growth of mental illnesses and hopelessness. In today's environment, frequent occupational intellectual health examinations are necessary. There are additional fields where extensive research on emotion recognition is necessary, notably for people with disabilities. Theys can't convey their feelings with words or facial gestures. Therefore, further research into this issue is required to provide a means of communication, cures, and appropriate care. There are several ways to learn about the physiological signals influencing the change in mood. Using brain encephalographic markers, actual meaning may be deduced from the emotional data captured by the EEGheadset interface. For people who are unable to accurately convey their sentiments via facial expressions or other physiological

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markers, This interface is more accurate and realistic. In the meanwhile, the main techniques used in emotion identification include physiological indicators and symptoms, textual content, voice, and facial expressions. Physiological signs may also more accurately reflect individuals's true emotional states than facial gestures, words, or voices, which are more easily influenced by subjective factors in people.

As a consequence, an increasing number of researchers are using physiological data, especially EEG signals, to identify emotions. The scalp's electrical activity may be recorded using an EEG machine. Non-invasive electrodes are placed on the scalp during the process. After a stimulus or a movement, it captures the voltage fluctuations supplied by cutting-edge ionic internal brain neurons. Microvolts are the unit of measurement for voltage. An EEG is a long-term recording of the brain's spontaneous electric activity using a few scalp electrodes, which is often known as a "EEG." Using these electrodes, voltage levels in the brain may be measured in relation to the rest of the brain.

It is a very interdisciplinary subject, with machine learning, artificial intelligence, and brain-computer interface being the main fields of study. Emotion detection has gotten a lot of interest in the recent decade because of its many uses in science, gaming, advertising and marketing, e-learning, and mental tests.

This is a departure from prior work, which focused on refining the extraction of characteristics or comparing different classification models for a given emotion detection using datasets such as DEAP and SEED. A collection of EEG channels that may be the same for each individual is utilized to extract features. Prediction and classification tasks typically employ techniques like DNN, CNN, and SVM. These databases hold emotional alerts for a certain period of time in a controlled setting. But it's impossible to catch every signal in a certain length of time. The way the brain functions is intricate, unique to each person, and changes depending on how we are feeling. For each emotion, each letter has a number of excitation times in c computer language. Real analysis of the emotional signals gathered in the natural world is thus anticipated by making huge applications the major focus.

However, there are positive constraints to both deep learning and SVM when it comes to recognising popular dependence. The crucial emotion detection methods, such as function extraction, pre-processing, and community structure, are what drive those models' efficacy. However, such models are still unable to achieve a respectable level of accuracy due to the small and noisy datasets. Despite the dataset being very dimensional, low SVM performance is caused by overlap in target classes and boundaries [2].

The goal of this project is to design a categorization algorithm that can handle any database size. Using the Epoc 14 channel EEG Headset, these emotional impulses were recorded. An individual's capacity for powerful emotional response to a positive stimulus depends on their gender, age, and other factors. For example, warnings of various length are collected, and a referential suggest report is made by taking into account the average of all emotions. Emotional signs are classified according to how far they differ from a reference point in the prediction of their expected mean. This may be applied to every feature in the characteristic set. The most often matching emotion groups are determined by manually classifying the feelings. The component that follows provides a detailed explanation of the methodology used in the suggested procedure.

2. LITERATURE REVIEW

There has been a significant growth in interest in using thought EEG data to identify emotions during the last 10 years. It is a completely interdisciplinary field with linkages to artificial intelligence, brain research, and psychology. Numerous characteristic extraction and selection techniques, together with the first stages of the identification device, have been employed in previous investigations. On pre-existing datasets like SEED and DEAP, several researchers have been working. Applying a deep generalised canonical correlation evaluation together with an interest method is strongly advocated in [3]. (DGCCAAM). There are five categories for emotions. using a function-fusion technique that is motivated by emotions. To improve the feature, a quick-time Fourier remodel is used (STFT). We examine the EEG record's differential entropy (DE) characteristics. This observation makes use of the SEED-V database. Utilizing 3 modalities, an accuracy of 82.11 percent was attained. Six statistical EEG sign characteristics are shown in [4] that may be utilised to assess emotions using information from the DEAP dataset. Algorithms PCA and ReliefF are used to choose the channel. A type accuracy charge of 81.87 percent applies to SVM. To make the characteristic vector from the SEED database smaller, the researcher employed PCA. SVM can categorise emotions into three groups: good, bad, and neutral. The accuracy was judged to be eighty-five.85 percent. On the DEAP database, [6] a multimodal classification technique is utilised. Using data from 14 electrodes, the 168 characteristics of each situation were computed. As classifiers for categories, KNN, SVM, and selection timber are used. KNN achieved the extraordinary outcomes. Valued at 77.54 percent, dominance was revised to 79 percent. It rose to 78.88 percent when the same functions and SVM classifier were used. For better

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precision, [7] makes use of the multi-elegance category approach. For the purpose of determining the best candidates, the researcher used particle swarm optimization (PSO). Multi-degree linearly declining inertia weight (MLDW) allows the set of rules to behave more properly. High arousal-excessive feelings, low arousal-immoderate feelings, high arousal-excessive feelings, and coffee arousal-poor feelings are the four emotional states found by SVM. The calculated accuracy came out to an average of 76.67 percent. A technique for choosing a contemporary channel has been developed by Sofen Gannouni[8]. it really operates by using 0-time windowing to estimate signal epochs. With enough temporal precision, spectral facts may be derived from an EEG signal using the numerator group elimination characteristic. The choice of channels is a consequence of the voting process. Choosing the channel with the most votes is the next step in determining the epoch timings. QDC and RNN are tested using the DEAP database. The computed accuracy is 89 % with 9 emotions. Table 1 of this file provides a brief analysis of the relevant study's literature review. S. L. Bangare et al. [16-18] worked in Machine learning, Image processing and IoT domain. Xu Wu et al [19] shows security work. N. Shelke et al. [20] have proposed LRA-DNN methods. S. Gupta et al. [21] has shown extraction methods use. G. Awate et al. [22] CNN method-based work is good. A. Seekoli et al. [23] and J. Alanya-Beltran et al. [24] and S. D. Pande et al.[25-27] have done empirical research on machine learning.

Table 1 Literature Survey of Related work

Author	**Number of Emotion Types**	**Feature extraction algorithm**	**Number of electrodes**	**Classifiers**	**AVG Accuracy (%)**
Rahman, Md Asadur [5]	2 emotions +ve and -ve	Principle Component Analysis	32	SVM	85.85
Ackermann, P., Kohlschein[9]	3 emotions (anger, surprise, other)	Minimum redundancy maximum relevance (mRMR)	32	SVM - Random Forest	60
Pane, E. S., Hendrawan[10]	4 emotions (happy, sad, angry, and relaxed)	Time and frequency domain features	5	Decision tree algorithm	81.64
Ahirwal, M. K. & Kose,[11]	4 emotions (angry, sad, happy, and relaxed)	Time-domain features, frequency domain features, and entropy	32	ANN	93.75
Ren, F., Dong[12]	4 emotions	The probability distribution for wavelet packet coefficients	3	SVM	70.5
Ranganathan, ., Chakraborty[13]	9 emotions	Spectral features	32	DBN	79.2
Liu, Y. & Fu[4]	9 emotions	The fusing of 6 statistical features	32	SVM	81.87
Sofen Gannouni[8]	9 emotions	ZTWBES(zero-time windowing – based epoch estimation and relevant electrode identification	Adaptive	RNN	89.33

It has been highlighted that most study is done at the contemporary database to improve classification precision. The recommended set of guidelines for the min of the mean was developed often with the goal of recognising a broad variety of emotions while also working well for smaller datasets. For categorizing many emotions , the method known as the min of the mean is used exclusively. It's really potent for one to sear qualities. It is necessary to produce an initial reference mean record in order to measure distance and determine the MIN MAX variety of the primary emotion training hen. Emotions may be categorized as either furious, calm, highly delighted, or sad by comparing the least distance from the four fundamental emotions. A more detailed

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breakdown of subclasses may be achieved by putting the MIN Max range of the key emotion classes on the graph. This procedure was carried out for each and every one of the function collection's attributes. If numerous characteristics are collected, the voting method is utilized to categorize the emotion. The phase that follows provides excellent details on the methodology behind the suggested set of rules.

3. METHOD

An information set must be gathered and preprocessed for a detection and prediction of emotions. device can derive its function. There have been previous studies that used a broader variety of feature selection approaches for emotion recognition. But they yielded a more limited collection of functions. It is important to note that the calculated accuracy of many function combinations varies with time.

The proposed technique is used at the classification stage. The primary goal of this technique is, it can be effectively used for tiny and noisy database, and it prevent effect of producing any false impressions while picking features.Voting was used to categorize emotions . Before labelling the emotion using the voting technique, it determines the emotion class for test function. The next section is going to discuss it in great detail. The grandeur would be associated with the feeling that garnered the most votes. Table 1 defines the initial approach of the suggested strategy.

3.1 Material used:

To gather mental signals, the Emotive Epoc 14-channel headset is employed Fig. 1 shows the EEG headgear used in the investigation. A range of EEG frequencies are represented by electrodes when using an EEG instrument. Raw EEG data may be broken down into discrete waves with varying frequencies using a fast Fourier reconstruction (FFT) method. One hertz (Hz) equals one cycle in two dimensions, which is why the frequency of electrical oscillations is measured in hertz. All key brain areas may be reconstructed and interconnected utilizing Emotive Epoc with enough insurance and electrode design.

Figure. 1 14 Channel Emotive Epoc EEG Headset

3.1 Locations of Sensor

Figure 2 displays the locations of the EEG electrode sensors on the skull. All of the advantages of a standard EEG system are offered with the Emotiv EPOC Flex Gel Sensors, plus mobility. Silver-chloride sensor sites and cables link to a small control box on the cap, allowing for portable and contextual EEG data gathering that is totally portable and wearable. It is placed on the head in accordance with the 10/20 rule. On the subject's head, these electrodes are positioned in accordance with specified locations.

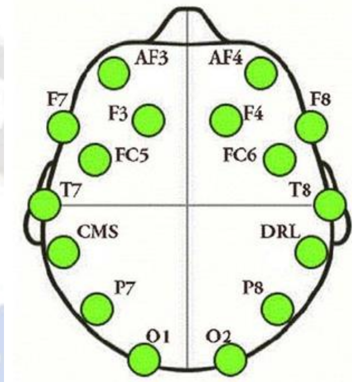

Figure. 2 Locations of sensors on the skull

3.3. Database Collection

Participation in this research was open to all healthy adults (male and female; mean age 35.55; standard deviation 16.97). Each participant has to sign an informed consent form before to participating. Thoughts, sounds, and video are used to elicit an emotional reaction from the participants. The emotional signal is gathered after each scenario identifies the kind of stimulus selected by the subjects. The concatenated EEG file has a total size of 41*(recording length in seconds * 128). There are 41 columns in all. Columns 0, 1, and 17:41 have been deleted from the report. There are 14 distinct sources of data in the last columns of the table.

“Dataset: 120 files: 30 emotion signals of each emotion type Angry, Calm, Happy, and sad emotion

[128*60] rows : signals are recorded for 1min at 128

[14]col : Electrodes

3.4 Pre-processing

Pre-processed warnings have a higher signal-to-noise ratio and may thus distinguish between experimental outcomes. This is accomplished by utilising band-pass filtering, which prevents frequencies outside of a certain range from passing while allowing frequencies within of it to do so. During pre-processing, anomalies and unnecessary channels are eliminated. Pre-processing entails 5 processes.

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The zero-phase degree of arrangement is now used for the low bypass clear out. The baseline may be removed from the data by including a baseline function when modelling a sum of capabilities toward the records. Through unbiased element assessment, linearly blended impartial assets are separated. Information distortions may be corrected by ICA since they are often neutral toward one another.

3.5 Feature Extraction:

Statistical modelling techniques are used to derive 24 EEG signal functions. The database generated 24 excellent qualities. Table 2 lists the first phases of the test's "strategy.

Table 2 Initial Strategy Used In The Experiment

Equipment used:	**Emotive Epoc 14 channel headset is used.**
Channels	AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4
Sampling Frequency	128Hz
Dataset:	Dataset: [120*[14*(128*recording time in seconds)] 120: Emotion signals 1 to 30 Angry, 31 to 60 Calm, 61 to 90 Happy, 91 to 120 Sad Dimension of each signal, [14] columns (channels) [128*recording time in seconds] rows
The method used for emotion elicitation	Ground truth method
Stimulus used	Audio, Video, Thoughts
Pre-processing	Filtering, Independent component analysis
Feature Extraction	Statistical modeling"
Features	"['Mean', 'STD', 'VAR', 'SKEW', 'Kurtosis', 'IEEG', 'MAV', 'MAV1', 'MAV2','SSI','VEEG','RMS','DASTD','AREG','HA','HM','HC','WL','POWER',' PERODOGRAM1','PERODOGRAM2','ENVOLEPE','PSD']"[2]

3.6 Annotations And Terminology Used in Proposed Method

This section introduces the important concepts and annotations. Comprehending what is being said is impossible without them. what we have got here thus far. Figure 3 depicts a mathematical model that must be grasped before any annotations or language can be discussed in depth. Figure 3

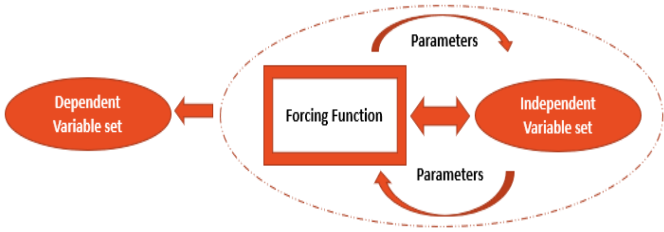

Figure. 3 Mathematical Model

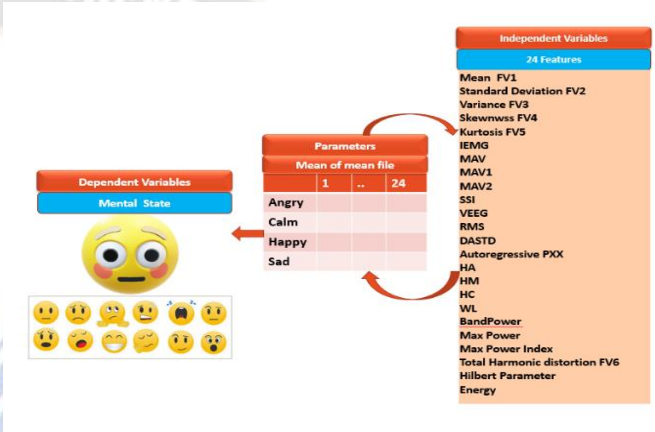

Figure. 4 Terminology of The Approach

Figure 4 lists the terminology utilised in the mathematical model.

- Dependent Variable Set: The collection of dependent variables consists of the output variables. In this case, the Emotion Class is responsible.
- The based Variable Set: Output variables provide the basis of the underlying variable set. Emotion's magnificence is on display here.
- Input variables are referred to as the unbiased Variables Set. The feature set is by far the most important factor in this scenario.
- The parameters include a reference file and a range of values.
- Out of control Extraneous characteristic: compelled Below are definitions for the terms.
- The unbiased variable set is referred to as EQ. It is the grouping of emotional moods.

- "EQ1: Angry state, EQ2: Calm State, EQ3: Happy State, EQ4: Sad State
  $EQ = \{EQ1, EQ2, EQ3, EQ4\}$
- $EQ1 = \{AQ1, AQ2, AQ3\}$ = {Nervous, Angry, Annoying},
- $EQ2 = \{CQ1, CQ2, CQ3\}$ = { Relaxed, Peaceful, Calm},

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- $EQ3 = \{HQ1, HQ2, HQ3\}$ = {Pleased, Happy, Excited}
- $EQ4 = \{SQ1, SQ2, SQ3\}$ = {Sleepy, Bored, Sad}}.
- EQ= { {Nervous, Angry, Annoying}, { Relaxed, Peaceful, Calm}, { Pleased, Happy, Excited} , { Sleepy, Bored, Sad}}.

$$EQ = \{\{AQ1, AQ2, AQ3\}, \{CQ1, CQ2, CQ3\}, \{HQ1, HQ2, HQ3\}, \{SQ1, SQ2, SQ3\}\}$$

- EL1 is the set of electrodes.
- EL1 = {AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4}
- The dependent variable set is denoted by FS1. It is the feature set.
- $RF_{Meanofmean}$ is a referential mean file. It is used as a Parameter for the classification of emotion in 4 main types Angry, calm, happy, and sad.

  Angry Mean = $\{A_{m1} \ldots\ldots A_{24}\}$

  Calm Mean = $\{C_{m1} \ldots\ldots C_{24}\}$

  Happy Mean = $\{H_{m1} \ldots\ldots H_{m24}\}$

Sad Mean = {Sm1……………………………Sm24}

Min-Max Rangefile" is a collection of feelings that includes angry, at ease, joyful, and depressed. It acts as a standard for breaking down emotions into 12 divisions.

Forcing Function:

Participants in this case had difficulty classifying the emotion at one point of the signal collecting level or experienced an unexpected change in mood. The signal is particularly difficult to pick up when emotional arousal is strong. Additionally, variations in information are brought on by variations in the members' skull shapes.

3.6.1 RFMeanofmea: Referential Mean File:

The steps for creating referential mean file are mentioned below.

Step1: 24 120 emotional cues are used to derive characteristics. It creates a feature set file with dimensions of [120*24].

Step 2: The mean of each feature's angry, calm, happy, and sad states is calculated.

- Angry Mean = {Am1………………………..A24}
  - Calm Mean = {Cm1…………………………C24}
  - Happy Mean = {Hm1……………………….Hm24}
  - Sad Mean = {Sm1……………………………Sm24}
- A minimum [4*24] dimensional mean file is prepared. where each row denotes the minimum of the mean for each feature's angry, calm, happy, and sad emotions. The average of the mean file of 24 characteristics for the emotions of Angry, Calm, Happy, and Sad is shown in Table 3.
- A mean file of [4*24] dimensions is produced. where each row denotes the average of the mean for each feature's angry, calm, happy, and sad emotions. The average of 24 aspects of the angry, calm, happy, and sad emotions is shown in Table 3.

Table 3 Meanofmeanfor24feature: RFMeanofmea

	Angry	Calm	Happy	Sad
Mean	-5.89E-19	-4.45E-19	5.31E-19	-4.07E-19
STDDEv	0.163943	0.166845	0.146946	0.143131
VAR	0.030517	0.030052	0.024944	0.024471
Skew	0.259426	0.702313	0.569911	1.23472
Kurtosis	24.89917	10.22524	30.1283	31.99606
IEEG	836.3248	842.7331	575.7628	687.0578
MAV	1.29E-05	1.95E-05	1.73E-05	1.23E-05
MAV1	0.058442	0.062112	0.044852	0.049922
MAV2	1638.734	1629.98	1101.094	1362.672
SSI	247.0576	212.9055	157.6071	182.2315
VEEG	0.030517	0.030052	0.024944	0.024471
RMS	0.163933	0.16683	0.146933	0.143122
DASTD	0.00109	0.001248	0.000995	0.000488
AREG_PXX	0.837401	0.631482	0.642969	0.887735
HA	0.030517	0.030052	0.024944	0.024471
HM	0.132829	0.127513	0.130701	0.129529
HC	1.281373	1.321213	1.307146	1.288851
WL	0.056774	0.061703	0.039255	0.014373
Bandpower	0.030513	0.030046	0.02494	0.024468
Peridogram1	0.001396	0.001511	0.001078	0.000898
Peridogram2	150.0333	129.9333	125.3	142.6333
Envlope	-15.2272	-12.0899	-13.7224	-17.6222
Hilbert	1.31E-07	1.17E-06	3.24E-07	9.54E-07
PSD	3.05E-05	3.15E-05	1.95E-05	1.84E-05"

With this file, we can see whether the computed test signal mean matches up with that of our reference means. In order to define the emotional state of the test signal, this file determines the minimum gap between the computed mean and the reference mean. Angry, calm, happy, and sad are the four basic categories.

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3.6.2 Min Max Range File

The Min Max variety report must be developed, and this requires mastering the classification of emotion subtypes based only on the good and bad varieties of the core emotion.

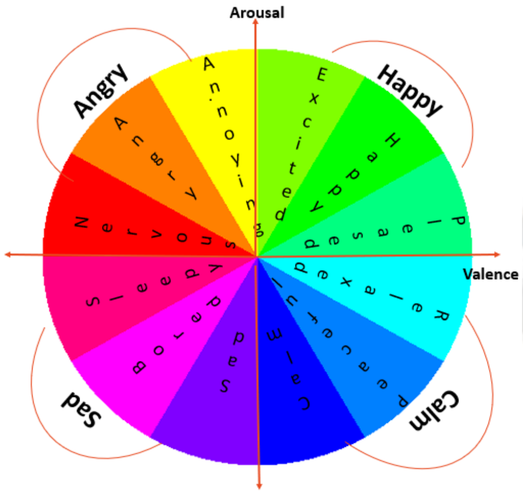

Figure. 5 Emotion Classification Wheel

Figure. 6 Min Max Range on Emotion Spectrum

The emotion classification wheel is shown in Figure 5. move for the emotions of wrath, calm, happiness, and sadness from high to low, fine to horrible. It shows how different emotion types are categorised according to the intensity of the experience. With the help of the MIN MAX range, this wheel is intended to help users recognise the many emotion subtypes. Angry Min to Max, Calm Min to Max, Happy Min to Max, and Min to Max (sad) The MIN and MAX phases for each emotion elegance are listed in table 4. The subtypes of emotion are then determined by matching this range with the test emotiotion signal.

Table 4 A- Min Mean Max Range Of Emotion

Emotion	**Angry**			**Calm**		
Sub Emotion	**Nervous**	**Angry**	**Annoying**	**Relaxed**	**Peaceful**	**Calm**
Range	**Min**	**Mean**	**Max**	**Min**	**Mean**	**Max**
Mean	-1.18E-17	-5.89E-19	2.99E-18	-1.47E-17	-4.45E-19	9.23E-18
STDDEv	6.66E-02	1.64E-01	3.02E-01	1.05E-01	1.67E-01	3.01E-01
VAR	4.43E-03	3.05E-02	9.14E-02	1.10E-02	3.01E-02	9.03E-02
Skew	-5.34E+00	2.59E-01	4.42E+00	-3.80E-01	7.02E-01	2.70E+00
Kurtosis	3.16E+00	2.49E+01	1.07E+02	4.00E+00	1.02E+01	2.81E+01
IEEG	2.39E+02	8.36E+02	1.88E+03	2.21E+02	8.43E+02	2.09E+03
MAV	3.25E-06	1.29E-05	3.04E-05	4.24E-06	1.95E-05	1.14E-04
MAV1	3.31E-05	5.84E-02	2.69E-01	1.11E-03	6.21E-02	3.59E-01
MAV2	3.46E+02	1.64E+03	3.93E+03	4.75E+02	1.63E+03	3.85E+03
SSI	3.49E+01	2.47E+02	7.19E+02	4.67E+01	2.13E+02	5.71E+02
VEEG	4.43E-03	3.05E-02	9.14E-02	1.10E-02	3.01E-02	9.03E-02
RMS	6.66E-02	1.64E-01	3.02E-01	1.05E-01	1.67E-01	3.01E-01
DASTD	3.23E-04	1.09E-03	2.19E-03	5.77E-04	1.25E-03	2.35E-03
AREG_PXX	7.43E-02	8.37E-01	2.29E+00	8.51E-02	6.31E-01	2.36E+00
HA	4.43E-03	3.05E-02	9.14E-02	1.10E-02	3.01E-02	9.03E-02
HM	1.12E-01	1.33E-01	1.51E-01	9.50E-02	1.28E-01	1.46E-01
HC	1.19E+00	1.28E+00	1.39E+00	1.20E+00	1.32E+00	1.57E+00
WL	1.01E-02	5.68E-02	1.46E-01	1.88E-02	6.17E-02	1.23E-01
Bandpower	4.43E-03	3.05E-02	9.14E-02	1.10E-02	3.00E-02	9.03E-02
Peridogram1	1.23E-04	1.40E-03	7.61E-03	2.03E-04	1.51E-03	1.16E-02
Peridogram2	8.80E+01	1.50E+02	2.64E+02	2.50E+01	1.30E+02	3.80E+02
Envlope	-4.26E+01	-1.52E+01	3.04E+00	-3.50E+01	-1.21E+01	9.95E-01
Hilbert	-1.09E-14	1.31E-07	2.47E-06	-5.37E-15	1.17E-06	2.01E-05
PSD	2.84E-07	3.05E-05	2.92E-04	8.38E-07	3.15E-05	3.94E-04

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Table 4 B- Min Mean Max Range Of Emotion

Emotion	**Happy**			**Sad**		
Sub Emotion	**Pleased**	**Happy**	**Excited**	**Sleepy**	**Bored**	**Sad**
Range	**Min**	**Mean**	**Max**	**Min**	**Mean**	**Max**
Mean	-8.31E-18	5.31E-19	1.45E-17	-5.06E-18	-4.07E-19	5.00E-18
STDDEv	5.18E-02	1.47E-01	2.66E-01	4.56E-02	1.43E-01	3.19E-01
VAR	2.68E-03	2.49E-02	7.10E-02	2.08E-03	2.45E-02	1.02E-01
Skew	-1.57E+00	5.70E-01	4.43E+00	-3.12E+00	1.23E+00	1.11E+01
Kurtosis	4.01E+00	3.01E+01	1.70E+02	3.74E+00	3.20E+01	2.18E+02
IEEG	1.62E+02	5.76E+02	1.59E+03	1.84E+02	6.87E+02	1.58E+03
MAV	8.82E-07	1.73E-05	5.71E-05	1.93E-06	1.23E-05	5.66E-05
MAV1	1.19E-03	4.49E-02	1.99E-01	3.31E-05	4.99E-02	2.63E-01
MAV2	2.53E+02	1.10E+03	2.83E+03	2.53E+02	1.36E+03	3.15E+03
SSI	3.03E+01	1.58E+02	5.71E+02	1.81E+01	1.82E+02	5.35E+02
VEEG	2.68E-03	2.49E-02	7.10E-02	2.08E-03	2.45E-02	1.02E-01
RMS	5.18E-02	1.47E-01	2.66E-01	4.56E-02	1.43E-01	3.19E-01
DASTD	1.43E-04	9.95E-04	1.85E-03	1.84E-04	4.88E-04	9.31E-04
AREG_PXX	3.03E-02	6.43E-01	4.13E+00	9.91E-03	8.88E-01	7.96E+00
HA	2.68E-03	2.49E-02	7.10E-02	2.08E-03	2.45E-02	1.02E-01
HM	1.07E-01	1.31E-01	1.51E-01	1.10E-01	1.30E-01	1.54E-01
HC	1.21E+00	1.31E+00	1.50E+00	1.17E+00	1.29E+00	1.38E+00
WL	9.27E-03	3.93E-02	7.02E-02	8.63E-03	1.44E-02	1.96E-02
Bandpower	2.68E-03	2.49E-02	7.10E-02	2.08E-03	2.45E-02	1.02E-01
Peridogram1	2.36E-05	1.08E-03	3.09E-03	2.90E-05	8.98E-04	4.79E-03
Peridogram2	3.70E+01	1.25E+02	4.61E+02	3.00E+01	1.43E+02	3.24E+02
Envlope	-5.72E+01	-1.37E+01	-1.93E+00	-4.64E+01	-1.76E+01	-3.25E+00
Hilbert	-3.06E-15	3.24E-07	4.41E-06	-8.73E-15	9.54E-07	9.04E-06
PSD	1.07E-08	1.95E-05	8.46E-05	7.01E-09	1.84E-05	2.31E-04

3.7 Steps of Min of Mean Algorithm"

With a 4*24 measuring reference, the top agencies of the emotional class [Angry, Calm, Joyful, Sad] report. Emotional expression in four classes

a. The input signal is a test signal.

b. Compute the test signal's 24 characteristics.

c. Compare the first feature's value with the mean values for angry, calm, happy, and sad.

d. Determine the difference between the test mean and the reference mean.

e. "Carry out the aforementioned action for each of the 24 features and determine the mean of the means for all the features

[Tmeanofmean1, TmeanofSTDEv2, TmeanofVAR3, TmeanofSKEW4, TmeanofKurtosis5, TmeanofIEEG6, TmeanofMAV7, TmeanofMAV18, TmeanofMAV29, TmeanofSSI10, TmeanofVEEG11, TmeanofRMS12, TmeanofDASD13, TmeanofAREG_PXX14, TmeanofHA15, TmeanofHM16, TMEANOFHC17, TMEANOFWL18, TMEANOFBANPOWER19, TMEANOFPERODOGRAM20, TMEANOFPERODOGRAM21, TMEANOFENVOLEPE22, TMEANOFHILBERT23, TMEANOFPSD24]

f. finally, one emotion is detected for the given test signal as a result of the above classification strategy.

g. Classification of emotion in 12 emotion classes {{Nervous, Angry, Annoying}, {Relaxed, Peaceful, Calm}, { Pleased, Happy, Excited} , { Sleepy, Bored, Sad}}.

h. For each emotion class, find out its maximum and minimum values. Set your feature's MIN/MAX range on the MIN/MAX range of the most common emotional classes. Every feature in the feature set was put through the same process. Figure 5 shows the MIN MAX Range of the Mean Feature

a. „

Figure. 7 MIN MAX Range of Mean Feature

b. Find out the complete mental state of the test emotion signal based on the votes achieved by each emotion class.

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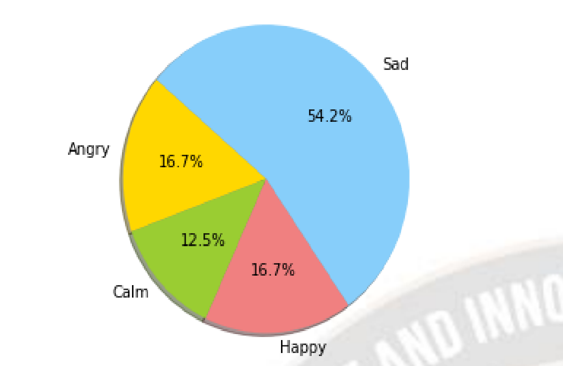
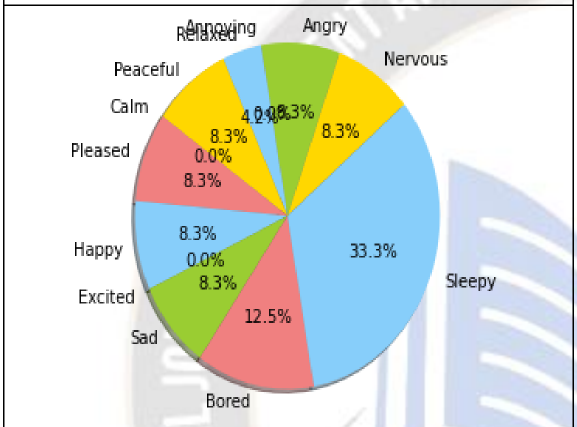
In table 4, the complete mental state analysis of the Sample input signal is shown.

Table 5 Mental State Analysis





The person is 16.67% Nervous.
The person is 8.33 % Relaxed.
The person is 0.0 % Annoying.
The person is 8.34 %Relaxed.
The person is 16.67 % Peaceful.
The person is 0.0 % Calm.
The person is 16.67% Pleased.
The person is 16.67 % Happy.
The person is 0.0 % Excited.
The person is 16.67 % Sad.
The person is 25.0 % Bored.
The person is 66.67 % Sleepy.

4. RESULT ANALYSIS

Table 5 shows the average accuracy of the imply algorithm for each function. It is determined by dividing the complete range of accurate predictions by the full range of samples in each emotion magnificence. The allocated entry sign for emotion for each function was marked. Based on the feeling magnificence that gained the most votes from the functions, the final label is selected. The table below calculates the accuracy of each characteristic's prediction for the angry, calm, happy, and unhappy emotion training.

Table 6 Accuracy Of 24 Features In Percentage

Accuracy in Percentage				
Feature	Anger	Calm	Happy	Sad
Mean	43.33333	0	56.66667	10
STDDEv	10	43.33333	0	53.33333
VAR	43.33333	10	10	63.33333
Skew	56.66667	20	20	50
Kurtosis	10	90	0	20
IEEG	13.33333	46.66667	63.33333	20
MAV	13.33333	33.33333	0	63.33333
MAV1	0	40	70	3.333333
MAV2	43.33333	10	66.66667	16.66667
SSI	43.33333	10	63.33333	6.666667
VEEG	43.33333	10	10	63.33333
RMS	10	43.33333	0	53.33333
DASTD	13.33333	60	30	90
AREG_PXX	0	100	0	0
HA	43.33333	10	10	63.33333
HM	46.66667	43.33333	3.333333	6.666667
HC	43.33333	40	0	6.666667
WL	13.33333	56.66667	33.33333	100
Bandpower	43.33333	10	10	63.33333
Peridogram1	6.666667	30	3.333333	66.66667
Peridogram2	53.33333	6.666667	63.33333	6.666667
Envelope	3.333333	60	6.666667	46.66667
Hilbert	90	16.66667	3.333333	3.333333

In table 6, prominent features for each emotion class are mentioned. The accuracy of classification is more than 50% by using these features.

Table 6 Prominent Features Of Emotion Class

Emotion	Prominent Feature
Anger	Peridogram2, Skew, Hilbert
Calm	Kurtosis, DASTD, AREG_PXX, WL, Envolope
Happy	Mean,IEEG,MAV1,MAV2,SSI, Peridogram2,
Sad	STDEv, VAR, MAV, VEEG, RMS, DASTD, HA, WL, BANDPOWER, Peridogram2,

Table 3 contrasts the accuracy reached using the suggested method with the modern classification techniques at the same database.

Table 7 Comparative Analysis of Results

Classification Techniques	Average % Accuracy
KNN	29.17
SVM	44
DNN	33.33
Lassov Regression	**78.02**
Random forest	**72.66**
Min of Mean Algorithm	**90**

As can be seen in the table above, the accuracy of the database obtained using existing classiification approaches was calculated less successfully than the recommended way. Despite the modest amount of the database, SVM performs poorly. Overlapping aim teachings and foggy output class boundaries are the causes. The crowded and constrained database prevented DNN from functioning effectively. Lassov regression and random forest both produced interesting results. This study provides a fresh tool for classifying emotion into 12 intricate categories. The suggested approach provides a radical examination of the mental state and performed well for a small, noisy database. For each feature in the feature set, the accuracy of emotion recognition is calculated using this technique. Anger, calm, pleasure, and disappointment are the four categories into which emotions fall when the least amount of difference across approaches to each feature is measured. For further categorization, it was split into the Minima and Maxima groups. Additionally, it works well when applied to tiny datasets. The recommended method's anticipated average accuracy is 90%.

5. CONCLUSION

A person might feel a variety of emotions at once and be in a mixed emotional state, which frequently causes mood swings or a mood disorder. This research study offers a thorough examination of mental state at that specific moment in time. A novel classification approach for identifying emotions from EEG data is the min of mean technique. This approach contrasts the difference between the computed mean and the referential mean. The Min of Mean algorithm classified emotions such as anger, calmness, happiness, and sadness with an average accuracy of 90%, 100%, 70%, and 100%, respectively. Our investigation showed that the suggested approach was a good choice in this field and outperformed prior studies.

6. FUTURE WORK

To recognise emotions using EEG waves, a combination of expertise from the domains of engineering, computer technology, and psychology is required. Existing emotion recognition algorithms, however, need further investigation in the fields of neuroscience and psychology or a multi-modal approach that combines models for EEG-based emotion detection with methods for image processing. Individuals who struggle to communicate their emotions and those who do well under pressure can benefit from this training. Finding simple data for the emotion class in this study is a commendable endeavour. Labeling emotions is a crucial task since human moods may change quickly. By increasing the number of signal gathering trials for each mood quality, this issue may be overcome. The quantity of the database must be substantial in order to improve the classifiers' accuracy. [2]. The development of wearable gadgets based on IoT-based technologies may expand the scope of this study. Caretakers may take advantage of early intervention by being aware of the character's unsafe emotional domain. Additional effort must be made with complex emotions like pride, wrath, and rage.

Support: This work has not received any outside funding.

Institutional assessment board statement: The objectives of this study's research were met in accordance with the guidelines outlined in the Helsinki declaration. This study's goal is in no manner to identify or address any affected person's contamination. The greatest applications for this study's findings are scholarly and personal.

Data Access Declaration: The research study makes use of its own database, which was compiled during the database collection phase.

The authors claim to have no competing interests.

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