RECOGNITION OF HUMAN EMOTIONS BASED ON EEG BRAINWAVE SIGNALS USING MACHINE LEARNING TECHNIQUES-A COMPARATIVE STUDY

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Abstract:
This study constructs an emotion identification system based on a valence/arousal paradigm using electroencephalography (EEG) signals. Logistic regression is used for feature selection with correlation coefficient score applied to guarantee that such a model does not overload the data, randomized divides among all occurrences are performed. The performance of emotion recognition systems improves caused by means of brain waves is determined by the methodologies used to features extracted, the selection of features, and the classification process. Inside this paper, several machine learning techniques are used viz. Multilayer Perceptron, Logistic Regression, Random Forest, Gaussian Naïve Bayes, Decision Tree, Support Vector Machine, and ensemble techniques with voting classifiers. To complete the build and creation of an expert the system for automatic detection of emotions from EEG data, this kind of comparison research utilizing machine learning must be laid out on this subject. The experiment has been carried out for all the Machine Learning techniques using all attributes. Experiments have demonstrated the efficacy of the proposed method with 98.45% accuracy for Decision trees and random forest Classifiers.

Keywords: Emotion Recognition, Logistic Regression, Machine Learning, Voting Classifier, Ensemble technique.

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Introduction

The BCI allows the human to share information with the brain electronic equipment such as a mobile phone or a computer [1] BCI systems are based on noninvasive (EEG), cortical surface (ECog), and intracortical recording equipment that analyzes electrophysiological signals. Every continual work does have its own set of advantages and disadvantages. The forehead is used to record electroencephalographic (EEG) signals. EEG-based BCIs are the easiest & lightest BCI recording methods because they are non-invasive. EEG, on the other hand, does have a limited frequency band and stereo vision, increasing the susceptibility to power line carrier disturbance or other distortions such as cranial muscular electromyography (EMG) or electrooculographic (EOG) activities [2]. According to the study, Emotions are relevant to human cognition, especially in logical decision, vision, human contact, and creativity. Machine learning has looked to fill the emotional void, particularly in HCI, by combining technology with emotions [3]. Emotional state detection that is self-contained and non-invasive could possibly be valuable in numerous fields, including human-robot interaction and mental health treatment. It can bring a new level of engagement between the user and the gadget, as well as allow tangible information to be obtained without relying on focusing on verbal communication using the help of the growing availability of low-cost electric vehicles. Brain signals information has become more economical for the purchasing sector as well as research, necessitating the requirement for self-classification without specialist advice. As a result, stationary techniques like as time windowing, as well as feature extraction of data within a window, must be introduced. There are a variety of statistics that can be generated from EEG windows, all of which have their own set of benefits and drawbacks. Depending on the purpose, each has varied categorization efficacy. Feature selection is required to locate meaningful data and simplify the model development process that conserves time and computational resources throughout the processes of classification of data. The fundamental problem statement is that an internal evolutionary search of the datasets' 2550 dimensions was carried out for the next 20 centuries with a citizenry of twenty people For the optimized dataset, the system chose 99 characteristics for mental state and 500 attributes for emotional state [4]. which was incomparable to the previous due to its greater variety of classes. There is a lot of promise in developing categorization algorithms that can be used in actual-world decision-making aids. In the case of mental health systems, responding to emotional states can improve interaction., hat dealing with emotion, can help with a general assessment of problems, and how to solve them. The Muse headband's EEG sensors TP9, TP10, AF7, and AF8 are some examples. Per the worldwide standard EEG. It can be observed in this Figure 1. This shows that psychological response has changed much more statistically meaningful characteristics for categorizing, whereas state of mind requires roughly 80% less. The system chose 40 attributes for the Mind Bigdata EEG problem set [5].

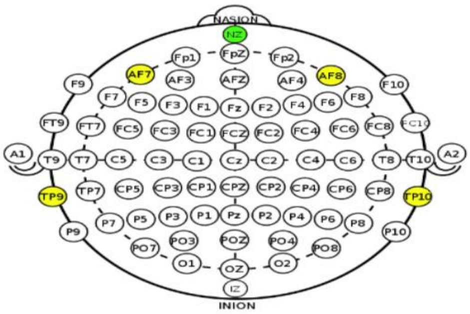


Fig. 1. The Muse headband's EEG sensors TP9, TP10, AF7, and AF8 are placed in accordance with global norms EEG positioning system.

The primary objective of this research is to conduct a comparative analysis and application of various standard machine learning techniques, with a specific emphasis on accuracy. To achieve this goal, the study carefully selects three distinct classes, namely positive, neutral, and negative, from each sample within the dataset. By considering these three classes, the research aims to examine how well the chosen machine learning algorithms can effectively differentiate and classify emotions into these categories. The comparative analysis will provide insights into the strengths and weaknesses of each technique, allowing for a comprehensive evaluation of their performance in accurately recognizing and categorizing emotions. Ultimately, the research aims to contribute to the advancement of emotion recognition systems by identifying the most suitable machine learning approaches for accurately distinguishing between positive, neutral, and negative emotional states.

The key Contribution of the article is as follows:

- Utilization of logistic regression for feature selection to prevent data overload in the model.
- Implementation of the randomized division of data occurrences for robust evaluation and testing.

- Exploration and evaluation of multiple machine learning techniques, including Multilayer Perceptron, Logistic Regression, Random Forest, Gaussian Naïve Bayes, Decision Tree, Support Vector Machine, Ensemble techniques with voting classifiers
- Demonstration of the impact of brain waves on enhancing the performance of emotion recognition systems.
- Achievement of a high accuracy rate of 98.45% for Decision Trees and Random Forest classifiers.
- Contribution to the development of an expert system for automatic emotion detection from EEG data.
- Provision of valuable insights for further research in affective computing, mental health assessment, and human-computer interaction.

1 Related works

Make the EEG emotions identification system a specific difficulty. By adhering to the 10-20 different state's insertion guidelines, quasi electrodes can be applied to the skull to help in the collection of brainwave signals using EEG data [6]The Fast Fourier transformation (FFT) is then employed to filter those devices' collected EEG signals to create regular groups like the δ (4 Hz), θ (4 Hz–7 Hz), alpha (8 Hz–13 Hz), beta (14 Hz–30 Hz), and gamma (>30 Hz) bands[7]. can have a direct impact on people's mental well-being. Since research suggests that various brain activities can induce distinct emotions, the differentia of respondence can be utilized to identify emotions based on EEG characteristics. A built-in vestibular device that enables the gathering of gyro and type of signal is also present in some of the low-cost wearable EEG headgear[8]Delta is associated with sleep and concentrated task, theta is associated with inhibition of elicited responses, alpha can represent the state of relaxation as well as inhibition control, beta ranges from calm to stressed and obsessive, including thinking, focus, alert, and anxiety, and gamma is associated with cognitive competence and revealed a denser network connection when it comes to thinking, focus, alert, and anxious, while gamma is associated with cognitive competence and revealed a denser network connection[8]. Figure 2 depicts a different classification of emotions, with Arousal levels ranging from high to low, with valence ranging from negative to positive. Depressed, for example, belongs to the low arousal and negative valence category of emotions [9]. The frequency band groupings used to classify human brain signals. Alpha is usually more noticeable in the back, Closing the eyelids causes movement to occur, and relaxing, opening the eyelids, or receiving a signal even by the situation (thinking and computation) [11].

Using the machine learning method to identify and with classifies distinct human emotions depending on EEG waves, the research explores human emotions.To simplify the characteristics, principal component analysis[12] (PCA) was employed. On the SEED dataset, PCA and SVM were used to categorise emotions into pleasant, unpleasant, and neutrality states. The reported accuracy rate was 85.85%. These findings have an important impact that decreasing the features size can practicing effective.On the AMIGOS physiological signal dataset [13] a deep CNN was used (electrocardiogram, galvanic skin response) to get the features of time, frequency, and nonlinear fields of physiological signals, the researchers applied advanced standard machine learning algorithms. The classification of emotional states is more precise using this method [14]. According to the valence/arousal paradigm[15]used The DEAP dataset containing EEG signals. to recognize an emotional state. Emotional states are categorized using SVM, k-NN, and ANN classifiers. Using an SVM with a radial basis function kernel that has been cross-validated, the experiment revealed Arousal accuracy was 91.3 percent, while valence accuracy was 91.1 percent in the beta frequency region. Long short-term memory (LSTM) was used to detect characteristics in EEG signals. close with the thick layer [16] utilized a method of deep learning to classify emotions from EEG signals, and features were categorized into low or high arousal, valence, and liking successively.

This approach was examined using the DEAP dataset, which yielded an accuracy of 85.65 percent, 85.45 percent, and 87.99%. EEG signals were generated using unique sensors that assessed electrical activity in 21 healthy people using 14-channel recordings[17] used a DNN to classify EEG signals from the DEAP dataset were used to extract human emotions using a DNN([17]. Using the same dataset, the proposed method was compared against state-of-the-art emotion recognition software. The work demonstrated how DNNs can be used to do EEG-based emotion recognition, especially for large training datasets. While the patients gazed at photos, EEG signals were recorded, and four emotional stimulation models (happy, calm, sad, or frightening) were explored. For different frequency ranges, a statistical technique based on distinct features was applied in the feature extraction phase [18]. This quantitative technique identified features that outperformed univariate analysis features. Linear discriminant analysis, k-NN, nave Bayes, SVM, random forest deep learning, and four ensemble approaches are being used to produce the best attributes for emotion recognition. The results indicate that the proposed strategy performed well when it came to recognizing emotions. Based on the previously mentioned literature, based on several classifiers, conducted approaches for emotion detection have certain common and distinct difficulties, which can be summarized as follows. To begin with, the classifiers used in the literature are diverse. As previously stated, most of these emotion detection investigations employ various categorization techniques Second, various emotion states are employed to classify people. as upon literature bases, it found that emotion recognition with EEG dataset. As a result, it is necessary to improve the precision with which emotions are detected and classified while also reducing the complexity of the methods used [19]. which examined the multi-class classification technique as a strategy to increase accuracy, significant advancements were made. The period, bandwidth, and time-frequency aspects of EEG signals were initially used by the authors to extract a variety of properties. For selecting features, the researchers used a variation of the optimization by particle swarms (PSO) technique. Using a multi-stage linearly decreasing inertia weight, this approach was enhanced (MLDW). Four emotions, high-arousal-low-valence, reduced, and low-arousal-low-valence—were classified by the researchers using SVM. The typical precision stood at 76.67% [22].

By considering above literature, we found some research gaps:

- Limited exploration of alternative feature selection techniques.
- Insufficient exploration of other machine learning techniques.
- Lack of investigation into the interpretability of the models
- Generalization and external validation

2 Proposed Methodology

Recognizing the emotional states of a person from their EEG output is a challenging task. Machine learning methods have been employed in this research to utilize an EEG brainwave dataset and predict the state of mind. The projected states of mind are categorized as positive, negative, or neutral, which proves valuable for predicting the emotional state of an individual. To conduct this study, an Intel Processor Core i5 3.0 GHz with 8GB RAM size and a 64-bit operating system were utilized. The tools used in this research include Python libraries such as Matplotlib, NumPy, Pandas, sci-kit-learn, Seaborn, and Joblib, as well as Tensorflow, Keras, and Dash for simulation. These tools were employed within the Anaconda Navigator IDE version 3.7.4. In summary, this research outlines the development and functioning of a system that employs machine learning techniques to predict emotional states from EEG data. The hardware and software setup used, along with the specific Python libraries and tools, were detailed as part of the research methodology.

2.1Datasets Details

This data collection involves EEG brainwave data that has been processed using a preliminary statistical data extraction approach. The data were collected from two participants (one female and one male) in each of the three states: positive, neutral, and negative. Each participant's emotional state was categorized into three categories: positive, neutral, and negative. The participants were asked to experience and express these emotions while their EEG brainwave activity was recorded. The dataset provides insights into the patterns of brainwave activity associated with different emotional states. By analyzing these patterns, researchers can gain a better understanding of how emotions manifest in EEG signals and potentially develop models for emotion recognition or prediction.

2.2Data Preprocessing

Data preprocessing is the initial stage in developing a machine learning technique, and it marks the beginning of the process. The actual data often contains partial, unreliable, or erroneous information, which may include errors, anomalies, and missing values. Therefore, data preparation becomes essential as it involves cleaning, formatting, and organizing the original data to make it suitable for use by ML models.

In this research, the data was trained with missing values, and it was observed that there are 0 columns with missing values in the dataset. The datasets were described and organized into data frames, where each data point consists of multiple features, each having a value that varies within a range of random values. To ensure consistency and comparability between features, the data was scaled appropriately. By performing these preprocessing steps, the data becomes more reliable, consistent, and ready to be used by machine learning models in subsequent stages of the research.

2.3Feature Selection

In this research, an EEG Brainwave dataset was used, and a Logistic Regression model was applied for feature selection. The coefficients value of features obtained from the model, which represent the correlation between each input parameter and the target variable, were collected using the coef_ property. Logistic regression was chosen as the algorithm of choice for this study.

The coefficient's value was stored in a data frame along with its corresponding attributes. The data frame was then sorted in descending order based on the coefficient values. This allows for a rough correlation-based highlight score to be calculated. It should be noted that this score calculation assumes that the input parameters are on the same scale or have been appropriately scaled before fitting the model. For feature selection, a correlation coefficient score was computed, and only those attributes with an absolute value of the score greater than or equal to 0.5 were manually selected. Through this process, a total of 389 features were chosen for further analysis and modeling.

The flow chart in Fig. 2 illustrates the feature selection procedure performed manually. This step is crucial for identifying the most relevant features that exhibit a strong correlation with the target variable and can potentially contribute significantly to the model's predictive performance. Overall, this research follows a systematic approach in utilizing logistic regression, collecting coefficients, selecting features based on correlation scores, and presenting the findings through a flow chart, all contributing to a thorough and rigorous analysis.

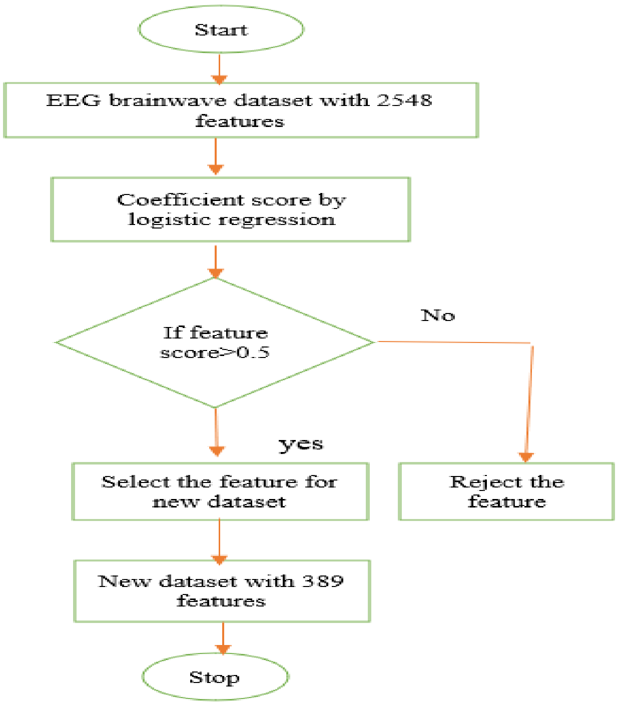


Fig.2 Flow chart of feature selection

2.4Classifications

Fig. 3 demonstrates the theoretical architecture of the proposed system. It illustrates the major phases involved in preprocessing, feature extraction, and classification stages. One of the key challenges in brain-machine interfaces is inferring observable and affective states from patterns and behaviors of brain activity captured in EEG signals. These signals, when used for classification tasks, are complex, nonlinear, and nonstationary, which necessitates the collection of large volumes of data. Additionally, statistical analysis of the waveforms is necessary to develop discriminative features for their characterization. The ultimate objective is to articulate a detailed strategy or system that can be physically validated, employing multiple frameworks and principles. Following this, various design components are integrated into the system. The system framework is illustrated in Figure 3.

Overall, this research presents an innovative approach to address the challenges associated with classifying complex brainwave signals, incorporating evolutionary optimization, bioinspired classifiers, and a comprehensive system design. The proposed framework aims to enhance accuracy while reducing resource requirements, thus contributing to advancements in the field of brain-machine interfaces.

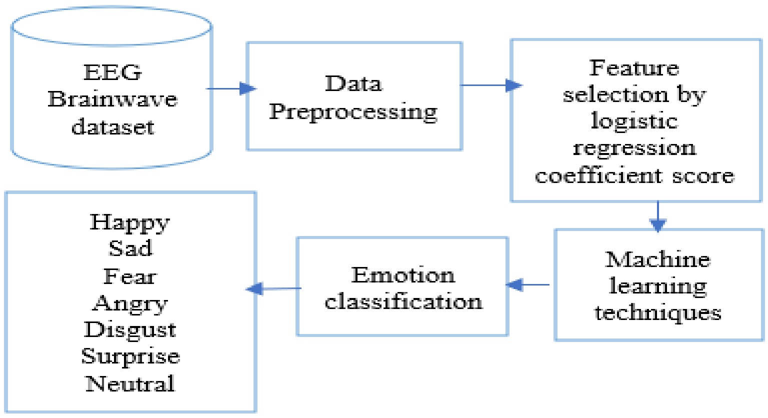


Fig. 3. system architecture of Emotion classification

Algorithm 1: Ensemble Technique with Voting Classifier Algorithm

Inputs:
- Training data features (X_train)
- Training data labels (y_train)
- Test data features (X_test)

Output:
Performance measurement(F1 Score, Precision, Recall, Accuracy)

Steps:
1. Initialize individual classifiers, such as MLP, Random Forest, Gaussian Naïve Bayes, Logistic Regression, Support Vector Machine, and Decision Tree.
2. Create a voting classifier by combining the individual classifiers.
3. Train the voting classifier using the training data (X_train and y_train).
4. Use the trained ensemble classifier to make predictions on the test data (X_test).
5. Output the predictions for further analysis or evaluation.

On this data set, the classifier's performance is assessed in terms of accuracy. The application provides an accuracy level of the emotion level analyzed according to the data set uploaded. Table 1 depicts different types of emotions with a range of values with emotions from the EEG sensor data results as shown below. Given labels 0, 1, 2 for positive (Happy, Surprise, Fear), negative (Sad, Disgust), and neutral conditions within the range of 100.

Table 1: Different types of emotions with range (min, max) with Different labels for positive-negative, and Neutral (0,1,2)

Range of values	Sentiment Emotions	Emotion category
50-100	Positive	Happy
1-40	Positive	Surprise
41-49	Positive	Fear
50-100	Neutral	Neutral
1-49	Neutral	Angry
50-100	Negative	Sad
1-49	Negative	Disgust

Algorithm Overview

Naïve Bayes Algorithm

An algorithm called Naive Bayes is a type of classification algorithm. is a quick, accurate, and procedure that is dependable Naive Bayes classifiers have high accuracy and speed on massive datasets. The Naive Bayes algorithm requires a collective probability P. (A, B). There is the possibility of both A and B occurring at the same time, given that the factors are unconnected.

$$p(A|B) = \frac{P(B|A)P(A)}{P(B)} \quad (1)$$

$$p(A|B) = p(A|B) \times p(B) \quad (2)$$

$$P(x_i|y) = \frac{1}{\sqrt{2\Pi\sigma_y^2}} \exp(\frac{-(x_i-\mu_y)2}{2\sigma_y^2} \quad (3)$$

Equation 3 reflects the Gaussian Naive Bayes utilized here, with Gaussian Naive Bayes being employed because of the features' minor Gaussian distribution.

Logistic regression

It is a distinct algorithm this could be applied to any multi-class or binary classification problem. Logistic regression performs discrete classification of sets of data inside a decision function for a Boolean class (passing or failing). The regression hypothesis explains why linear and logistic regression is similar.

$$h_\Theta(x) = \frac{1}{1 + e^{(-\Theta^T x)}} \quad (4)$$

$$h_\Theta(x) - \Theta^T x \quad (5)$$

$$f(z) = \begin{cases} \Theta_0 + \Theta_{1x1} + \Theta_{2x2} + \Theta_1\,9_{x1}9 \ \leq\ 0 \\ 1 \quad otherwise \end{cases} \quad (6)$$

Where θ indicates the parameters equation 4 indicates the logistic regression hypothesis and equation 5 indicates the linear regression hypothesis. It is desirable to use all attributes to establish the separation across subclasses where 5f (z) indicates the pattern's class.

SVM

EEG multichannel data were arranged in space to collect the input, with the numeric columns determining the distinct attributes. Different types of data are separated using the greatest possible detachment When training and testing, the velocity w and bias b must be approximated by solving a quadratic equation [23]. SVM is thus a p-complete problem because it can be solved in time complexity. A training dataset of *n* points of the form is provided

$.(x_1, y_1), \ldots.. (x_n, y_n)$

And *you* either are 1 or -1 each denoting the class to which the point x_i

$$w^T x\text{-}b=0 \quad (7)$$

Where w is the normal vector

$$w^T x\text{-}b=1 \quad (8)$$

Anything on or above this line belongs to a single class,

Label.

$$w^T x\text{-}b=\text{-}1 \quad (9)$$

Anything on or above this line belongs to a single class, labeled -1.

Random Forest algorithm

The algorithm was based on the leaves, or final decisions, of each base station to arrive at its con conclusion because the system depends on taking the average, results of many different decision trees, which improves its accuracy. Random forest works like this, choose random samples Start creating a decision tree for each sample from a set of data, and In Figure 4, use it to create accurate results. It will also be necessary to consider additional elements, such as fine-tuning classifier parameters, to increase classification accuracy and the efficiency of computing cost by speeding up data processing [24] Consider voting for each of the potential outcomes. As the last estimation, select the prediction with the most votes. Set a $n_{estimator} = 100$ parameter with Random Forest.

Bagging with the training set replaced, Y is answered by sampling a selection randomly from a training phase X. Forecasts for unknown substances after training can be accomplished by taking an average of the predictions from all individual regression trees or, in the case of decision trees, by taking the average of the forecasts from all individual decision trees of all individual predictions decision trees. The majority votes. Random forests can also perform feature bagging, which is a random subset of bagging. When using the Random Forest Algorithm to solve nonlinear equations, the mean squared error (MSE) is used to determine how data branches from each node.

$$MSE = \frac{1}{N} \Sigma_{i=1}^{N} (fi - yi)^2 \quad (10)$$

Where N represents the total of pieces of data

fi is the value returned by the model and *I* am the actual value for the data point.

This algorithm determines the distance between each node's expected actual value and the predicted actual value, assisting you in determining which branch would be the best fit for your forest? The value of the data points you're testing at a specific node is *Yi*, while the decision tree's value is *fi.*

Multilayer Perceptron

It's a neural net with multidimensional input-output modeling. A Multilayer Perceptron has incoming and outgoing layers, as well as each or even more convolution layers thought up of stacked nerve fibers [25]. Neurons in a Multilayer Perceptron can use any arbitrary non-linear activation, with exception of nerve fibers in a Perceptron, that provides an encoder that tries to impose a threshold.

Ensemble Techniques

Ensembles are an area of machine learning technique in which several base models are combined to form a single model. ideal prediction models. In machine learning applications, voting is the most basic method of combining classifiers[26]Numerous predictions with a variety of properties are developed and ensembled to form the finished prediction in voting. There seem to be two kinds of voting: hard voting and soft voting. The popular vote is used in hard voting, while In soft voting, the classification label's expected probabilities sum is averaged. To train the predictive models in this research, th, naive Bayes, Gaussian Nave Bayes, multilayer perceptron, random forest, decision tree, and logistic regression are used, and Utilizing hard voting, their outcomes are coupled to form the finished predictive model. as well as soft voting[27]

Performance measurement

The performance of machine learning in class prediction was investigated by a confusion matrix [28]. Calculated the confusion matrix's accuracy, specificity, precision f1-measure, recall, and misclassified value. The recognition rate is defined as the percentage calculated as the sum of predictions several predictions. predictions, which is commonly referred to as how frequently the classifier is correct.T_P, is the result when the proper prediction of the positive class is made by the framework., while, T_N, Whenever the model accurately forecasts the negative class. The classification performance is determined by summing the performance of every cycle of data analysis utilizing T_P,T_N,F_P, and F_N calculations:

$$\text{Misclassification Rate} = \frac{\text{amount of wrong predictions}}{\text{amount of predictions}} \quad (11)$$

$$Accuracy: \frac{Tp+TN}{TP+TN+FP+FN}\times 100 \quad (12)$$

Precision: Precision is described as the percentage of successfully predicted favorable findings to all found to predict going great that occur.

$$Precision: \frac{TP}{TP+FN} \quad (13)$$

Recall: The percentage of accurately guessed going great to all favorable inferences is described as recall.

$$Recall = \frac{TP}{TP+FN} \quad (14)$$

F1 Score: The F1 score is calculated as the weighting factor of recall and precision.

$$F1\ Score = \frac{2 * Precision * Recall}{Precision + Recall} \quad (15)$$

Confidence Score:

The calculation of the confidence score is below.

$$CI = \bar{x} \pm z\frac{s}{\sqrt{n}} \quad (16)$$

Where,

CI=Confidence Score

$\bar{x}$=Sample mean

Z=confidence level value

s=sample standard deviation

n=sample size

The bootstrap method is used to create a confidence score for the proposed model.

Results and Discussion

A model with manually selected 389 features was trained after data pre-processing and feature selection. 70% of the data is used for training, and the remainder 30% is used for testing. A class label distribution in a predictive model is shown in figure 5.

Figure 5: class distribution for the predictive model.

Applied six machine learning techniques and ensemble techniques to investigate and compare the performance of these methods for tracking emotion from EEG brain wave data on the same data set. In Fig.4 it is observed that class distribution is equal with selected features. Python programming has been used to implement various architectural designs. Before the architecture is implemented, appropriate codes are used to divide the data for testing and training. The performance and suitability of these models were investigated by 30% of the data in the testing sets. For each Machine learning technique, evaluated the measure misclassified rate, accuracy, precision, F1 measure, and recall. The performance of these models was also tested on a testing data set, and accuracy was ate obtained ned. it can be observed from Table. 2 ensemble techniques DT and RF achieved the greatest accuracy.

Table 2: Comparison of machine learning model performance.

Measure	Machine learning techniques						Ensemble Techniques		
	MLP	RF	GNB	LR	SVM	DT	DT+RF	LR+SVC	GNB+MLP
Misclassified rate	22	32	253	15	20	35	20	23	23
Accuracy	96%	94.96	54%	96%	96.27%	96%	96.87	96%	96.38%
Precision	96%	89%	81%	97%	97%	95%	96%	93%	93%
F1 Score	94%	94%	63%	97%	95%	95%	96%	94%	95%
Recall	95%	98%	51%	97%	96%	95%	95%	97%	97%

The accuracy confusion matrix could've been generated & displayed in Fig. 6 since just concerned with both the arousal dimension i.e., High Arousal and Low Arousal, accordingly Kuhn 1998. It will display in real-time using a dash application, when it starts the EEG file test with Person data then, Machine Learning with the Best-Model process to detect the individual emotion level[30], may optimize the work pressure on an individual. In Figure 6 we minimized the negative state classification error with the voting classifier The confusion matrices[31]of ensemble techniques as shown below in figure.7.

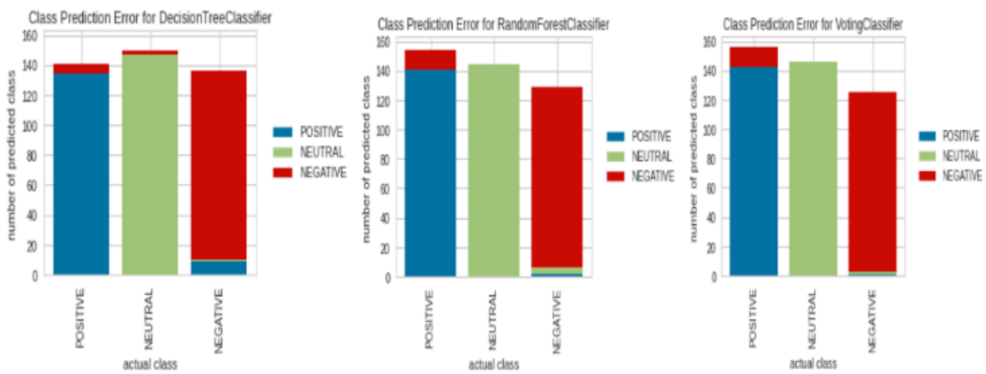
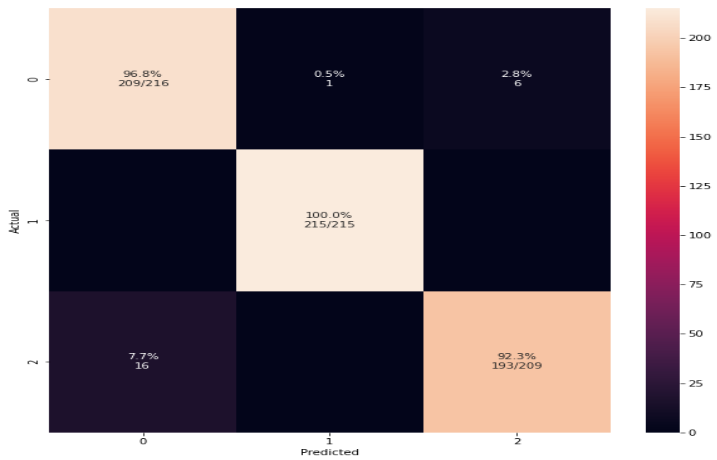
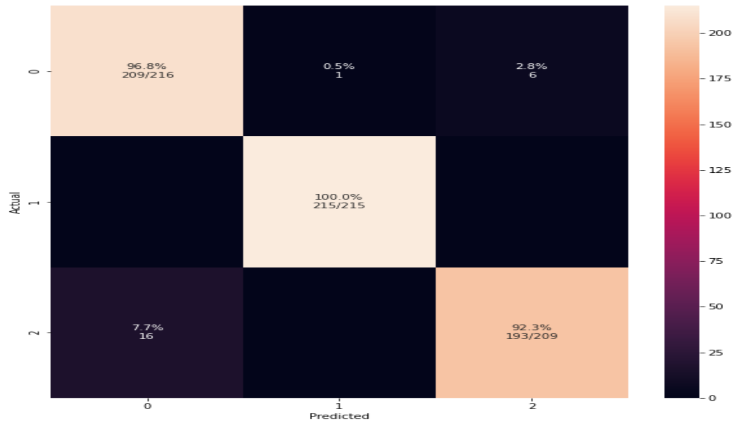


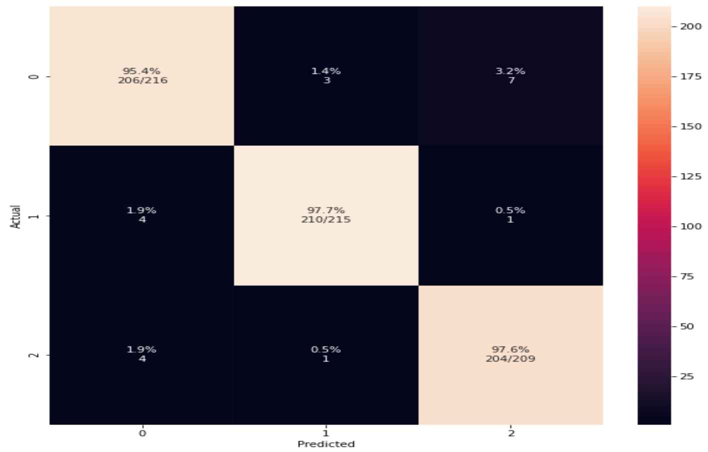
Figure 6: Comparison of Class prediction error



(a)



(b)



(C)

Figure. 6. Confusion matrices of Ensemble techniques(a) Multilayer Perceptron with Gaussian Naïve Bayes (b) Logistic regression with Support vector machine (c) Decision Tree with Random Forest.

In Figure 7. the performance accuracy of different classifiers is shown in which Gaussian Naïve Bayes attained 54% and Multilayer Perceptron, Decision Tree, Support Vector Machine, Logistic Regression, performance reached greater than 94% and RF and MLP[29]Achieved the highest. This may be because the Random Forest classifier has characteristics that prevent it from overfitting. In general, all classifiers were able to recognize emotions in the EEG Brainwave dataset, as well as categorize and process them.

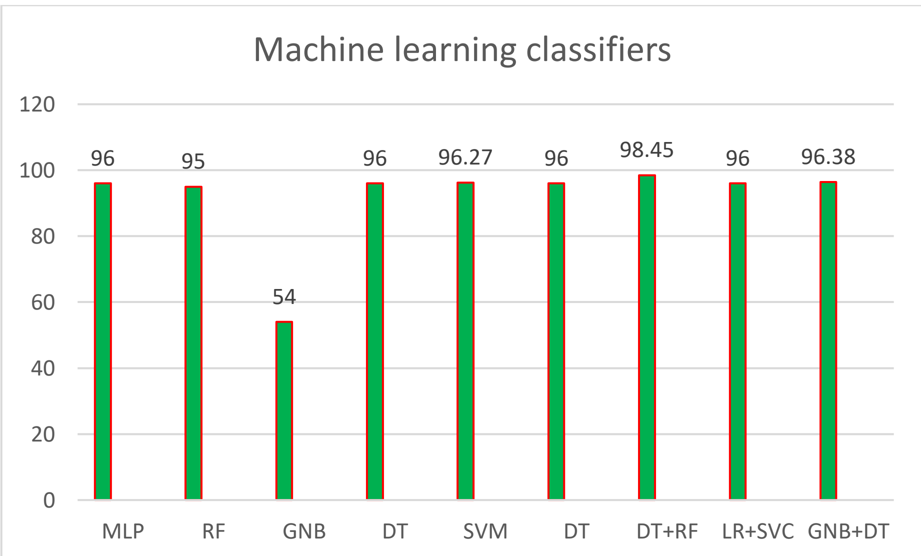


Figure 7. Comparison of different classifiers' accuracy.

In this paper, six basic emotions like happiness fear, surprise, disgust, anger, and sadness are used and they are classified under three categories positive -2, neutral-1, and negative-0.

The confusion matrix to assess the validity of user data is shown in Figure 8. which depicts the highest confidence score with Happy emotion.

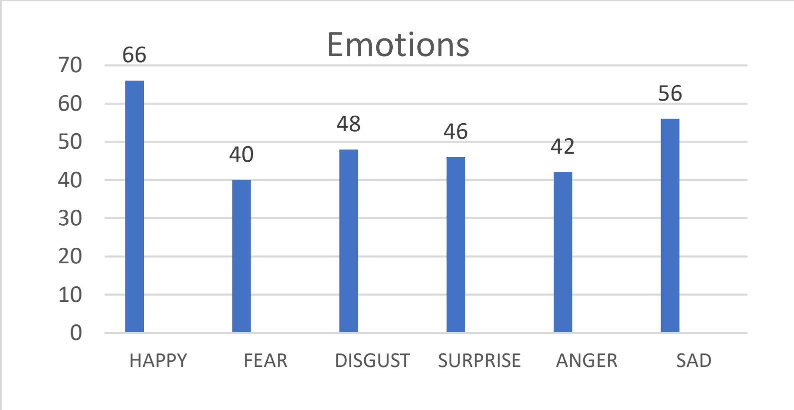


Figure 8. Emotions with a Confidence score

In this Study Classification with different machine learning techniques Gaussian and Naïve Bayes attained 54% and Multilayer Perceptron, Decision Tree, Support Vector Machine, Logistic Regression, and random forest performance reached greater than 90% and ensemble techniques achieved the highest accuracy at 97%. Compared the proposed model with different existing models as shown in Table 3.

Table 3: Comparative Analysis

Study	Classifiers	Datasets	Accuracy (%)
The proposed method	MLP+RF	EEG Brainwave Dataset	99%
[20]	Deep convolution neural network (CNN)	DEAP dataset	58% in valence and 29% in arousal
[21]	NeuCube-based spiking neural network	The smaller size of the DEAP dataset	84%
[22]	SVM	DEEP	82%

conclusion

The use of single and ensemble algorithms to quantify data from four spots on the participant's scalp into an emotional representation of how they were feeling at the time. The techniques demonstrated that a commonly produced EEG velcro strap with a low resolution may be used to classify a participant's emotional state. For feature selection used logistic regression to calculate the correlation coefficient score based on this set of 389 features. There is a lot of promise in developing categorization algorithms that can be used in true decision-making systems Reacting to emotional responses can help. interactions and, in the case of mental health systems, aid in the overall assessment of problems and how to solve them. When with the use supervised technique, the results are much better than the other individual models. The present output is a web application, but future work will include developing an application that people can easily use as an android app and translating the entire system into their EEG sensor emotion signal in machine learning algorithms performance. Tuned with *n_estimator=100* parameter for random Forest, with this parameter got 98.45% accuracy of ensemble technique of Decision tree and random forest with *voting=soft* classifier which is higher as compared to other classification algorithms and with this ensemble we have achieved balanced class prediction also. Discovered that the proposed strategy performs adequately if using standard classification algorithms. Experiments show that traditional machine learning techniques produce acceptable data and evaluate knowledge about crucial temporal channels that control human emotions.

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CONFLICT OF INTEREST

No conflict of interest

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