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EEG-based Emotion Recognition: Assessing Misclassification Rates Using Machine Learning Techniques

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Abstract: - Everyday human interaction heavily relies on emotions, which play a pivotal role in fostering genuine human-machine interaction. Emotional equilibrium is crucial for individual well-being, with regular meditation being a widely acknowledged means to achieve it. This study delves into the effect of meditation on emotional responses using Electroencephalography (EEG) technology. EEG can establish correlations between mental attributes and emotional states, with four emotions (Thrilled, Angry, Sad, and Relax) used as categorized stimuli based on valence-stimulation.

Functional connectivity in EEG brainwave activity is compared during these four emotions both before and after meditation sessions. Results demonstrate that meditation promotes more cohesive emotional experiences, albeit with a reduction in classification accuracy observed after an 8-week meditation regimen. This research utilizes EEG data to develop a classification system for discerning familiarity levels within EEG signals, employing the Hjorth Descriptor to condense signal characteristics into three distinct criteria. A Multilayer Perceptron classifier, leveraging input parameters, achieves a peak accuracy of 96% through a combined application of three functions.

Keywords: Electroencephalograph (EEG), Emotion, Brain-Computer Interface (BCI), EEG Emotion Classification, Machine Learning (ML).

INTRODUCTION

Emotions play a crucial role in daily life, and the management of emotions and self-regulation are fundamental skills for personal and professional growth. Undergraduate (UG) students, due to their age and the pressure to excel academically, often experience significant emotional turmoil and uncertainty about their future. Employing established introspection techniques can help individuals feel more grounded and peaceful, offering substantial benefits for trainees in their daily lives [4,5]. Research has demonstrated the positive impact of mental exercises on well-being and contentment, attracting increasing interest from Western scientists and neuroscientists.

This study aims to contribute to this field by investigating whether undergraduate students' reflective practices enhance their emotional stability and cognitive abilities, including problem-solving skills [1]. The results of the experiments are intriguing, highlighting the benefits of simple reflection techniques such as introspective attention.

1.1 Electroencephalography

Electroencephalography (EEG) is a technique utilized to record electrical brain activity through electrodes positioned on the scalp. It serves as a monitoring tool for brain activity during cognitive processes. Electroencephalograms (EEGs) provide visual representations that aid in understanding and diagnosing various brain conditions. In 1929, Dr. Hans Berger introduced the first EEG machine, marking a significant milestone in neuroscience.

Multichannel EEG testing employs a large number of electrodes to gather comprehensive brain activity data. Video EEG recordings typically involve scalp electrodes, although recordings with electrodes placed directly on the brain are also feasible. Several non-invasive methods, including functional magnetic resonance imaging (fMRI), magnetoencephalography (MEG), near-infrared spectroscopy (NIRS), and EEG, are utilized to capture brain signals. The advantages of EEG include its high temporal resolution, non-invasiveness, ease of use, and cost-effectiveness.

Measurement techniques enable the categorization of EEG activity into three types: spontaneous, triggered prospective, and single neuron [2,3]. Spontaneous tasks involve measurements taken from either the scalp or the brain. Scalp measurements typically yield EEG amplitudes ranging from 1 to 100 V, whereas measurements taken

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farther from the brain result in amplitudes of about 1 to 2 mV. Continuous EEG recordings are obtained from either the scalp or the brain of an individual throughout a spontaneous task, with the duration of the recording determined by the experiment's design.

Stimulus-induced potentials in EEG, elicited by stimuli such as music or film, are referred to as evoked potentials. Signal averaging and the presentation of a series of stimuli are essential when studying evoked potentials. In this study, we employ an impromptu task and utilize the scalp as the sensor for EEG recordings.

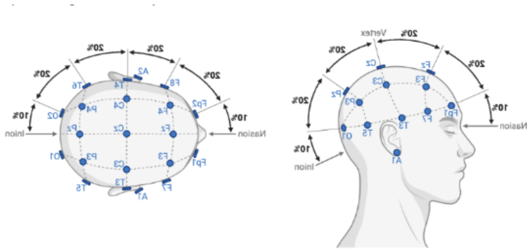


Fig 1.1: Electrode Positioning System [18]

1.2 EEG Electrode System

In the majority of cases, EEG recordings are conducted employing the International 10-20 electrode placement methodology. The numerical designations "10" and "20" correspond to standardized distances between adjacent electrodes, spanning either anterior-posterior or lateral dimensions across the entire cranium. These distances are precisely determined by referencing two anatomical landmarks: the nasion (midpoint of the forehead) and the inion (at the top of the head), as depicted in the Numeral reference system. Electrodes are affixed directly to the scalp, with each electrode denoted by a letter signifying its specific cortical region (e.g., F for frontal, FP for prefrontal, T for temporal, P for parietal, O for occipital, and Z for midline).

Odd-numbered electrodes are situated on the left hemisphere, while even-numbered electrodes are mirrored on the right hemisphere. Conventionally, electrodes A1 and A2 establish reference connections with the earlobes. EEG recordings ranging from 2 to 256 channels can be captured using diverse electrode arrays. For enhanced spatial resolution, alternative systems such as the 10-10 or 10-5 systems may be employed. In this investigation, a total of 14 electrodes were deployed, arranged in accordance with the 10-20 configuration.

A mosaic describes the arrangement of connections between the electrodes and the recording networks [6,8]. Referential montage and bipolar montage are the two most common types of EEG montage.

a) Relative: the difference between the active electrode and the recommended electrode (earlobes or mastoids) is calculated.

b) Bipolar: Two active electrodes are used to differentiate potential outcomes.

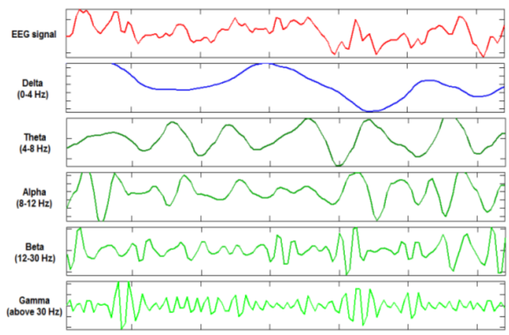


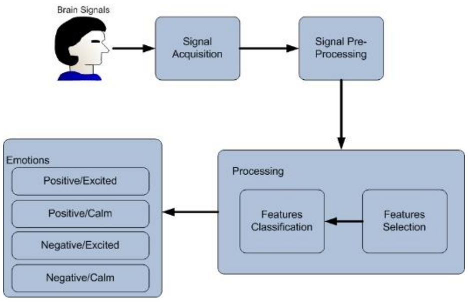
Fig 1.2: Frequency EEG

1. Motivation:

As per the World Health Organization, unpleasant emotions like stress and worry rank as the second leading cause of global mortality, trailing only heart disease. The study of emotions serves multifaceted purposes, encompassing Human-Computer Interaction (HCI) design and comprehension of mental processes underpinning critical tasks. It is imperative to devise mechanisms for transitioning individuals from states of heightened arousal to states of subdued mental stimulation. Compared to alternate methods like facial or voice recognition, EEG stands out for its swiftness, reduced susceptibility to errors, and heightened reliability in emotion recognition. Accurate emotion recognition is pivotal for fostering natural human-machine interactions.

Parents are increasingly concerned about their children's achievements, emotional well-being, and social conduct in an intensifying competitive environment, contributing to heightened worry and tension among learners. Preventing mental breakdowns amid high-pressure situations or challenging tasks necessitates cognitive monitoring, notably load measurement of working memory. Cognitive demands associated with tasks such as information retrieval and mathematical computations exacerbate the strain on students' cognitive faculties.

Effectively managing stress and anxiety during high-stakes scenarios hinges upon prioritizing mental and physical well-being. Meditation emerges as a time-honored method for self-regulation, offering avenues for stress mitigation. Additionally, the mirror assumes significance across psychological, spiritual, and physiological domains, serving as a vital tool for introspection and self-reflection.



.**Fig 2.1: Architecture EEG [19]**

2. Problem Definition:

An in-depth investigation into the impact of meditation on emotional responses is conducted, focusing on comparing mental strain before and after meditation through the completion of seven mathematical tasks. Additionally, emotional analysis is performed using electroencephalography (EEG) alongside other physical modalities.

According to existing literature, the term "feeling" encompasses various heightened states of awareness, ranging from extreme happiness to anger, influencing mood, attitude, and motivation. These emotional states play a significant role in shaping both physiological and cognitive behaviors, with the intensity of emotions closely linked to the level of arousal in the nervous system. Emotions trigger changes in behaviors, bodily responses, and cognitive processes, responding to both internal and external stimuli. Although universally experienced, the expression and perception of emotions vary widely among individuals, making their identification sometimes challenging. From a psychological perspective, emotions are considered internal states that evoke reciprocal changes in bodily reactions, behaviors, and cognitive functions.

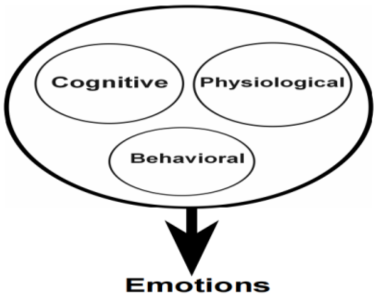


Fig 3.1: Emotion Components

3. Feature Extraction and Classification

The term “extraction" refers to the process of converting raw data into numerical features that can be manipulated without losing any original information. Compared to directly applying artificial intelligence algorithms to unprocessed data, this method yields more favorable results. Function extraction plays a crucial role in the emotion categorization process when utilizing EEG data for emotion detection [10,11,21]. The accuracy of emotion classification heavily depends on the thoroughness of function extraction.

This study aims to extract and evaluate the most relevant EEG features for identifying and classifying emotional states. Specifically, we compare the classification performance of 10 sets of EEG functions, including statistical, wavelet, fractal measurement, Hjorth parameters, higher-order spectra, spectral power, worsening, nonlinear, connectivity, and graph metric attributes. These sets have demonstrated reliable efficacy in previous studies on emotion recognition. For brevity, we present the top 5 attribute collections, comprising statistical, wavelet, fractal measurement, Hjorth parameters, and higher-order spectral characteristics.

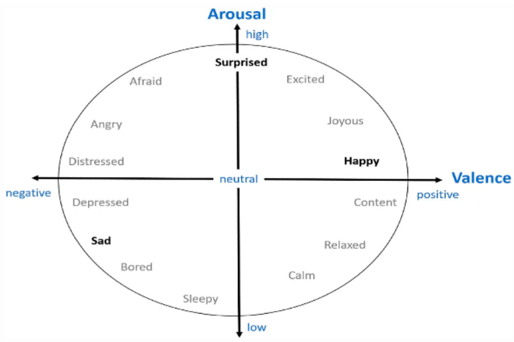


Fig 4.1: 2D Emotions [20]

4.2 Hjorth feature:

The parameters are Activity, Mobility, and Complexity. They are commonly used in the analysis of electroencephalography signals for feature extraction.

Hjorth features are a set of parameters used in the analysis of biomedical signals, particularly in the field of electrophysiology. These features were introduced by Bjorn Hjorth and are commonly used to characterize the signal's time-domain properties. Hjorth features provide information about the signal's activity, mobility, and complexity. Here, I'll explain the mathematical calculations involved in computing the three primary Hjorth features: activity, mobility, and complexity.

Activity (also known as the mean square root or signal energy):

Activity represents the overall power or energy of the signal. To calculate the activity, you can follow these steps:

a. Compute the mean of the signal, μ (mu).

b. Calculate the variance, σ^2 (sigma squared), of the signal by taking the average of the squared differences between each data point and the mean.

c. The activity is the square root of the variance, i.e., Activity = $\sqrt{(\sigma^2)}$.

Mobility:

Mobility characterizes the signal's frequency content or its variation over time. To calculate the mobility, you need to perform the following steps:

a. Differentiate the original signal, x(t), to obtain the first derivative, dx(t)/dt.

b. Calculate the activity of the first derivative using the method described above (activity of dx(t)/dt).

c. Calculate the activity of the original signal (activity of x(t)).

d. The mobility is the ratio of the activity of the first derivative to the activity of the original signal, Mobility = (Activity of dx(t)/dt) / (Activity of x(t)).

Complexity:

Complexity measures the signal's waveform irregularity or its deviation from a pure sine wave. To compute the complexity, follow these steps:

a. Differentiate the original signal, x(t), twice to obtain the second derivative, $d^2x(t)/dt^2$.

b. Calculate the activity of the second derivative using the method described above (activity of $d^2x(t)/dt^2$).

c. Calculate the mobility of the first derivative using the steps described above (mobility of dx(t)/dt).

d. Calculate the complexity as the ratio of the mobility of the first derivative to the activity of the second derivative, Complexity = (Mobility of dx(t)/dt) / (Activity of $d^2x(t)/dt^2$).

These calculations provide quantitative measures that capture different aspects of the signal's characteristics, namely activity, mobility, and complexity. Hjorth features are widely used in various applications, such as the analysis of electroencephalography (EEG) signals in neuroscience research [2,7] or the characterization of muscle activity in electromyography (EMG).

4.3 Preprocessing

Two reprocessing techniques, a) removing artefacts and b) removing the sensation dates from reflected EEG data, are utilized before function elimination.

Tape-recorded EEG signals contain artefacts such eye activity, body movements, and line sound, which must be eliminated. Before the feature extraction method is applied, the FIR filter is used to filter out the noise in the EEG.

b) Essence Emotion Dates: The meditation EEG data is cleaned of emotional epochs after artefact removal. We extracted EEG signals into 7-second epochs, which we used to represent the time period of each picture estimate, and we used the extracted EEG signals for a feature removal method.

Point Estimation: Point estimation involves estimating a population parameter using a single value or point estimate. One common approach is to use the sample mean as an estimate for the population mean.

Let's consider estimating the population mean, μ, based on a sample of n observations, $x_1, x_2, ..., x_n$.

Sample mean (point estimate):

The sample mean, $\ddot{x}$ (x-bar), is computed as the average of the sample observations:

$\ddot{x} = (x_1 + x_2 + ... + x_n) / n$

Sample variance (optional):

If you want to estimate the population variance, σ^2, you can calculate the sample variance, s^2:

$$s^2 = [(x_1 - \ddot{x})^2 + (x_2 - \ddot{x})^2 + ... + (x_n - \ddot{x})^2] / (n - 1)$$

It's important to note that the sample mean is an unbiased estimator of the population mean. The sample variance is an unbiased estimator of the population variance when the sample is drawn from a normal distribution.

Interval Estimation:

Interval estimation provides a range of plausible values for the population parameter along with a level of confidence. The confidence interval indicates the level of uncertainty associated with the estimate.

Confidence interval:

A confidence interval is typically expressed as (estimate ± margin of error). The margin of error depends on the desired level of confidence and the sample statistics.

For estimating the population mean, μ, based on a sample of size n with known or assumed population standard deviation, σ:

If σ is known:

The confidence interval is given by:

$$\ddot{x} \pm z * (\sigma / \sqrt{n})$$

where z is the z-score corresponding to the desired confidence level. For example, for a 95% confidence level, $z \approx 1.96$.

If σ is unknown:

In this case, you can use the sample standard deviation, s, in place of σ. The confidence interval is given by:

$$\ddot{x} \pm t * (s / \sqrt{n})$$

where t is the t-score corresponding to the desired confidence level and degrees of freedom (n - 1). The t-score can be obtained from the t-distribution table or using statistical software.

The resulting confidence interval provides a range of values within which the population parameter is estimated to lie with the desired level of confidence.

These calculations demonstrate the basic mathematical formulas used in estimation theory for point estimation and interval estimation of population parameters. However, keep in mind that there are variations and extensions to these methods depending on specific scenarios and assumptions.

The experiment employs a variety of classifiers, including Logistic Regression, RF, DT, SVM, and KNN. It is a highly effective classifier that is nonlinear. They involve ascribing a function vector to a class on the basis of its immediate neighborhood. The closest neighbors of an attribute vector are defined in this work using Euclidean distance. With lower-dimensional attribute vectors, the K-NN may be effective. Classification formulae are used to organize 2, 3, and 4 emotional states [11,12]. In classification studies, the technique's efficacy is evaluated using the complication matrix (CENTIMETRES).

Accuracy, sensitivity, and specificity are the three metrics used in the aforementioned equation to determine a classification system's overall efficacy.

Accuracy:

Accuracy measures the overall correctness of the classifier's predictions.

Accuracy = (TP + TN) / (TP + TN + FP + FN)
where:
TP (True Positive) is the number of correctly predicted positive instances.

TN (True Negative) is the number of correctly predicted negative instances.

FP (False Positive) is the number of instances incorrectly predicted as positive.

FN (False Negative) is the number of instances incorrectly predicted as negative.

Sensitivity (also known as Recall or True Positive Rate):

Sensitivity measures the proportion of actual positive instances that are correctly identified by the classifier.

Sensitivity = TP / (TP + FN)

Specificity (also known as True Negative Rate):

Specificity measures the proportion of actual negative instances that are correctly identified by the classifier.

Specificity = TN / (TN + FP)

These measures provide insights into the performance of a binary classifier:

Accuracy gives an overall measure of how well the classifier performs on both positive and negative instances. However, it may not be suitable when the classes are imbalanced.

Sensitivity focuses on correctly identifying positive instances and is useful when the goal is to minimize false negatives (e.g., in medical diagnostics, where it is important to identify all possible cases of a disease).

Specificity focuses on correctly identifying negative instances and is useful when the goal is to minimize false positives (e.g., in security systems, where it is important to avoid false alarms).

It's important to note that these measures provide valuable information, but they may not capture the complete performance of a classifier. Additional evaluation metrics, such as precision, F1 score, or ROC curves, can provide a more comprehensive assessment, depending on the specific requirements of the classification problem.

4. Machine learning methods for EEG Emotion Recognition

Emotional states can be inferred from EEG data using a variety of AI techniques, including Support Vector Machine (SVM), Random Forest (RF), and Decision Tree (DT). However, these methods employ superficial categorization strategies that primarily analyze EEG signals [7,8,20] based on their intrinsic properties, neglecting the rich temporal dynamics embedded within the signals.

Instrument for Vector Aid: The Support Vector Machine (SVM) technique is applicable to both classification and regression problems. In this analysis, we assign labels to each participant's emotional state, encompassing categories such as thrilled, anxious, disappointed, bored, drowsy, calm, apprehensive, furious, irritating, relaxed, and joyful. Initially, we focus on SVM's functionality in the multi-label category, akin to the binary category (predicated on valence and arousal).

In SVM, a line (in the case of 2-D data) or a hyperplane (in multidimensional data) is delineated [15,16] to act as a decision boundary. The decision-making process relies on the dot product of two characteristics: valence and arousal. In essence, the SVM algorithm identifies the predicted point on the plane and subsequently assigns it to the corresponding emotional category within the decision boundary.

Because of its foundation in ensemble learning, Random Woodland is also known as Random Choice Wood-land. During the course of the dataset's training, a number of distinct decision trees are developed. The decision during make predictions about the future class configuration of each individual decision tree. Overfitting in decision trees is addressed. The procedure consists of two stages, with bootstrapping being used for the first. In this procedure, we will generate random samples of n-tuples from the training data set, and then construct trees. To ensure that you end up with exactly k random trees, you should perform this step k times [9.10]. To classify the signal to one of its emotions, we will now go on to phase II, where the classifier for each random tree will be worked on for each unclassified tuple. Therefore, it is categorized into one of its feelings based on the majority vote, which is found by detecting the combination approximates from the k trees. Bagging is the process of combining the estimated values of several trees. As a result of this approach, a random tree of variable size and shape may be created from a single tree.

Ensemble Modelling Techniques Two or more prediction models can be combined into one workflow using a set. By considering the models collectively, a strategy of combination is used to improve the probability of a forecasting procedure's success. Incorporating versions and allowing them to vote in a democratic or elitist process is a simple ensemble method. After being trained, each of the designs assigns predicted ballot v to class(es) using a predetermined method:

Minimum/maximum likelihood; standard of chances; v = confidence v = Common Confidence Across All Versions In accordance with the chosen procedure, a liberty will undoubtedly provide a prediction as that of the class that has obtained the most stringent vote or collection of votes.

5.1 Collection of Data

Electroencephalogram (EEG) signals are monitored and analyzed to decipher and translate brainwave activity linked with emotional experiences. Feelings may be understood better by recording and analyzing the electrical patterns and frequencies produced by the brain during different emotional states. Examining the neural correlates of human emotion promises to shed light on the inner workings of the human mind, with practical implications for areas like emotion recognition and effective computing.

	# mean_0_a	mean_1_a	mean_2_a	mean_3_a	mean_4_a	mean_d_0_a	mean_d_1_a	mean_d_2_a	mean_d_3_a	mean_d_4_a	...	fft_741_b	fft_742_b	fft_743_
0	4.62	30.3	-356.0	15.6	26.3	1.070	0.411	-15.70	2.06	3.15	...	23.5	20.3	20
1	28.80	33.1	32.0	25.8	22.8	6.550	1.680	2.88	3.83	-4.82	...	-23.3	-21.8	-21
2	8.90	29.4	-416.0	16.7	23.7	79.900	3.360	90.20	89.90	2.03	...	462.0	-233.0	-233
3	14.90	31.6	-143.0	19.8	24.3	-0.584	-0.284	8.82	2.30	-1.97	...	299.0	-243.0	-243
4	28.30	31.3	45.2	27.3	24.5	34.800	-5.790	3.06	41.40	5.52	...	12.0	38.1	38

5 rows × 2549 columns

Fig 5.1: Dataset.

5.2 Misclassification and Error rate:

We have used two different classifiers—Random Forest and the Support Vector Machine—to make this determination, so let's have a look at the results of the former first. Each input is evaluated in a window size of 2 seconds, with a step size of 0.125 seconds, and the whole thing is sampled at a whopping 128 hertz. Here, we've used quick Fourier transform before applying the classifier; this splits the data into distinct frequency bands that may be put to good use in emotion recognition, including the theta, alpha, low beta, high beta, and gamma bands. After determining via trial and error that 512 decision trees is the best size for analyzing an arbitrary forest, we split the work into six concurrent tasks and put it into action. Originally, just the SVC classifier was used for SVM's screening and training processes. However, we had to make a few adjustments due to inappropriate accuracy values. At first, we applied PCA after pre-processing the data with function scaling. Then, we used pipelining alongside Grid Browse's cross-recognition functionality to zero down on the SVC kernel's optimal set of parameters. Using these settings, we were able to achieve the highest level of accuracy for a range of effective measures. We also experimented with different examination and training established sizes, ultimately settling on 80% for training and 20% for testing. By employing these supplementary methods in addition of the traditional SVM, we were able to increase the accuracy by 5%.

In machine learning, the misclassification error rate (also known as the classification error rate) is a metric used to evaluate the performance of a classification model. It represents the proportion of misclassified instances in the predicted results. The mathematical calculation of the misclassification error rate is as follows:

Misclassification Error Rate = (Number of Misclassified Instances) / (Total Number of Instances)

To calculate the misclassification error rate, you would typically follow these steps:

- Train your classification model using a labeled training dataset.
- Make predictions on a separate evaluation dataset using the trained model.
- Compare the predicted labels with the true labels from the evaluation dataset.
- Count the number of instances where the predicted label differs from the true label.
- Divide the count of misclassified instances by the total number of instances in the evaluation dataset to obtain the misclassification error rate.

The misclassification error rate provides a measure of the model's performance in terms of the percentage of instances that are misclassified. It is an important evaluation metric, especially in binary classification problems. However, it is essential to consider other evaluation metrics as well, such as accuracy, precision, recall, F1 score, or area under the ROC curve, depending on the specific requirements and characteristics of the classification problem.

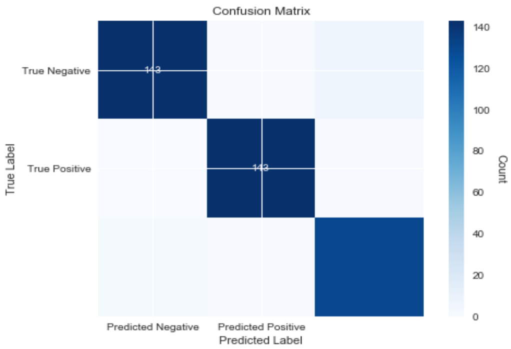


Fig 5.2: Confusion Matrix

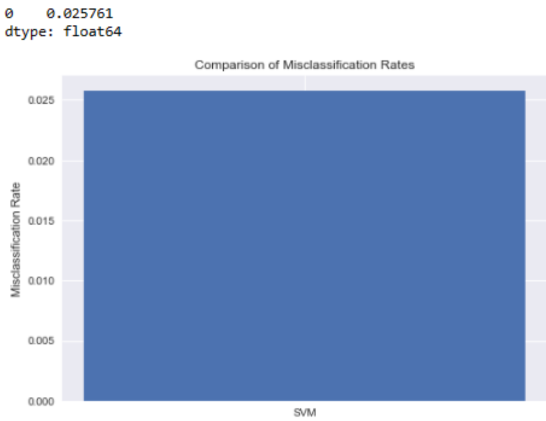


Fig 5.3: Misclassification Rate

6. RESULTS

Here, we show the results we got from implementing the suggested layouts in DEAP. To determine if the selected 5 networks are likely to supply sufficient details to carry out exact EEG-ER classification, we first assess the information itself for link between each of the picked 5 networks and the other channels.

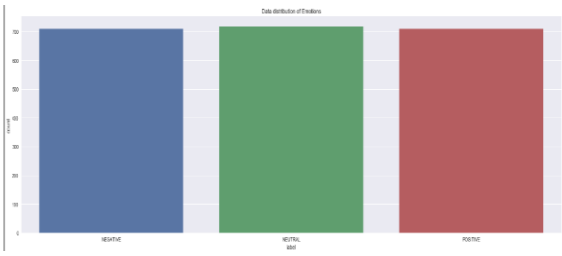


Fig 6.1: EEG Emotions

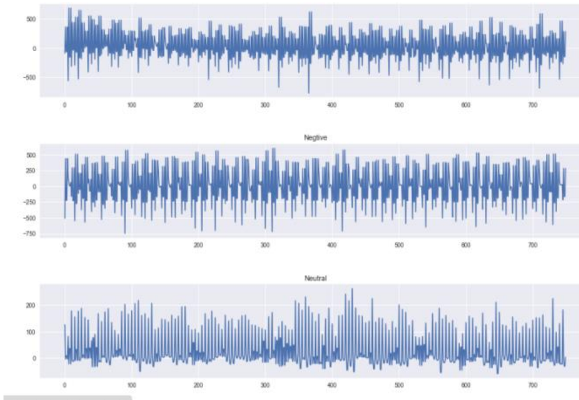


Fig 6.2: EEG Emotions Waves.

Dataset Name	Algorithm Name	Accuracy	Precision	Recall	f1score
EEG Brain Wave	RF	96.95550351288055	96.89947089947091	96.80027628272124	96.83929124231977
EEG Brain Wave	DTC	96.72131147540983	96.58101050108235	96.62312838483594	96.59641528891062
EEG Brain Wave	DTC	96.72131147540983	96.58101050108235	96.62312838483594	96.59641528891062

Fig 6.3 :Results Table.

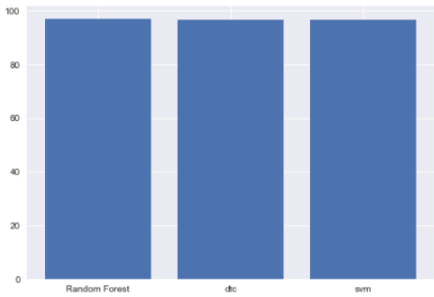


Fig 6.4: Algorithm Comparison

7. CONCLUSION

The creators of this software set out to make it easier for those who are struggling with their emotions or physical abilities to share their thoughts and feelings with the world. This would make it much easier for the disabled person to communicate with the outside world. One of the greatest difficulties in signal processing is the use of EEG signals as a setting for communication between a human and a gadget. We have used a dataset of 32 EEG recordings, taken from a total of subjects. Bandpass filtering was used to preprocess the data, eliminating any recurring patterns outside of a 4-45 Hz range. As a result, the EEG signal will be purified of any noise or artefacts. The resulting signal is clean, and the functions may be extracted from the tidy data with minimal effort by employing Wavelet decomposition. It sets out to present several therapies that may be used to take into account emotions by way of both verbal and electroencephalographic (EEG) brain data. The EEG signals were deconstructed by wavelet transformation in order to extract features, and they were then classified using the extracted features' derived requirements values. We've used two kinds of specifications—valence and arousal—across three different classifiers to accomplish this task: support vector machines, random forests, decision trees, and binary classifiers. These numbers are used in a multi-tag classification process to determine the subject's emotional state. We successfully used EEG signals to categorize emotions in our experiment. The results of the above experiment show that the Random Woodland classifier outperformed the SVM in every respect. The Random Forest classifier, which makes use of Wavelet Decay, outperforms the SVM classifier, which makes use of the standard deviation PCA approach, in terms of accuracy.

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