EEG-Based Emotion Recognition Using Wavelet Features and SVM Classification

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***Abstract*—Artificial Intelligence and Machine Learning are two critical areas of the broader Computer Science domain that is responsible for the development of cognitive solutions. AI makes possibility to create the systems that are able to solve the problems that were earlier solved by human's brain, ML creates the algorithms to analyze the big data to make possible decisions and predict the behavior. While working on emotion recognition systems, AI and ML try to determine emotional background based on subtle physiological signs including EEG, which greatly enhances human-computer interaction. This is backed up by affective computing which makes input to areas like gaming, medicine and education including the procedures used to treat depression. SMI eye-tracking spectacles and the 62-channel ESI NeuroScan System were used to record EEG data and eye movements. The EEG signals though, are nonlinear, non stationary and contaminated by noise calls for efficient preprocessing, feature extraction and classification. Proposed method the pre-processing phase includes the application of the Finite Impulse Response low-pass filter with the amplitude characteristics dependent on the frequency range between 0 and 75 Hz and the sampling frequency is 200Hz to maintain signal stability. Feature extraction uses wavelet filter banks for splitting EEG signals into five sub-bands; alpha, beta, gamma, delta and theta. Similar to entropy, for each of 62 channels, the energy is computed and extracted as 620 features from the signal. Entropy is directly associated with signal variance, whereas wavelet energy describes the distribution of the frequency of the signal. Feature reduction applies a class of methods called Principal Component Analysis which aims at converting many correlated features into a set of principal components that are not at all correlated. The extracted components are then passed through Support Vector Machine for emotion classification with 71.2% accuracy. The results are then compared against RF as well as XGBoost. In general, it is observed that accuracy of recognition does not decrease due to inter session and inter subject fluctuation.**

***Index Terms*—component, formatting, style, styling, insert**

I. Introduction

Artificial intelligence (AI) and Machine Learning (ML) are key fields in computer science, gaining significant attention for their applications in cognitive tasks. AI enables computer systems to think, learn, and carryout operations that need human cognition, including decision-making processes.ML is a branch of AI that primarily deals with algorithm that analyze large datasets to make predictions and inform decisions. In emotion recognition systems, AI and ML can interpret physiological signals to assess individuals' emotional states. However, as these technologies evolve, researchers face challenges in keeping up with the rapid advancements in AI and ML within cognitive domains [1]. The combination of AI technology with technological advancement has significantly influenced the progression of human-computer interaction, establishing a novel connection between people and computers. Human-machine communication(HMI) refers to the numerous forms of interface in which humans participate while interacting with computers. Traditional technology interfaces, especially in the last couple of years, have changed from a mechanical interface to artificially intelligent interfaces closer to human reasoning. Knowledge of these modes of communication is critical in appreciating how technology becomes a part of the life, workplace, and society. Cognition is an important aspect of human behavior and can only be replicated in machines if designers combine emotional factors. Affective computing helps improve the humanoid aspect of interactivity

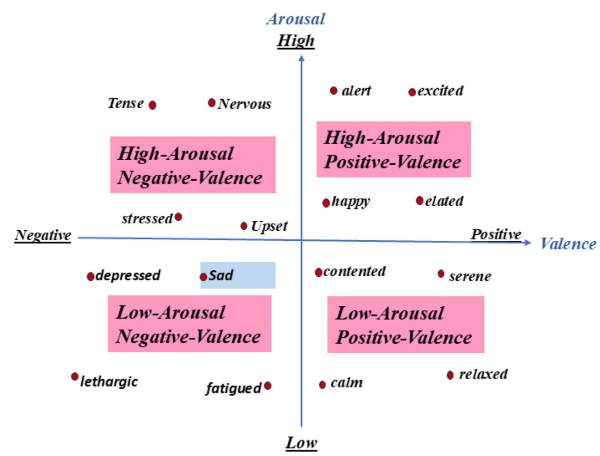

Fig. 1. Emotion Model

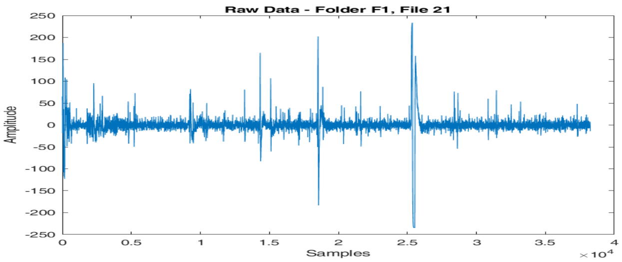

Fig. 2. Raw EEG signal of Positive Emotion

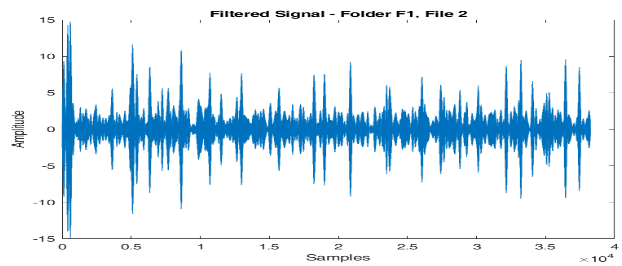

Fig. 3. Filtered signal of Positive Emotion

in areas still very useful, including games, medicine, and learning. As applied to some diseases, for example, in medicine it can help to develop therapeutic regimens for such diseases as depression. A good foundation for affective computing includes the identification and perception of emotions.

Emotions can be extracted by physiological signals. Emotional models and appraisal theories classify emotions into discrete categories, such as ‘primary’ or ‘basic emotions,’ believed universal, like happiness or sadness. Ekman’s model identifies six universal emotions through facial expressions. Dimensional models quantify emotions using valence, arousal, and control, distinguishing between circumplex (circular) and vector patterns shown in Fig 1. The physiological signals of EEG are rich in information and from an electrical signal viewpoint they are nonlinear, nonstationary, and noisy. Klonowski have pointed out that in EEG signals the statistical properties of the signals are nonunique. Furthermore, the EEG signal usually includes interference originated from muscles (EMG) movements; eye movements (EOG) and other adversative activities, interferences due to movement of electrodes or cables [2].

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Continuing researchers have put their effort to respond to these presumptions. The nonlinear part of the EEG signal data was analyzed using empirical mode decomposition techniques [3]. To overcome non-stationarity, some domain-based adaptation strategies have been developed [4], [5]. Signal filtering and feature extraction methods have often been applied to eliminate noise from EEG signals [6], [3] have used emotion recognition from EEG data involve classification techniques including: Extreme Gradient Boost (XGBoost), Random Forest (RF), Decision Trees (DT), and Support Vector Machines (SVM). The non-stationary nature of EEG signals may take intra variability or inter subject variability in the sense that the signals may vary in different sessions with the same subject and different subjects. But according to [7] cultural differences on participants was not consistent with reduced efficiency of facial expressions recognition.

As the technology improves along with the improvement in computational capabilities, the use of ML methods to classify emotions from EEG data in BCI has become more popular. Techniques like Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) Networks are widely used in the field of Emotional Recognition [8], [9], [10] and [11]. Since there is a growing interest based on emotion identification through EEG, this paper aims to conduct systematic literature review to discuss trends, datasets, classifiers and research contribution in this category. The paper is structured into five sections: Organization of the work presented include: introduction, research methodology, results and analysis, discussion of results and future work, and findings. This article employs a ML method. SVM for extracting the emotions from clean EEG signal . The algorithm decomposes the raw signal into Finite Impulse Response ‘Low pass filter. The Feature extraction is performed by wavelet transform and Principal Component Analysis for feature reduction. SVM is used for classification emotions.

The article is structured as shown below: Section 2 highlights the suggested techniques for EEG pre-processing and Feature extraction is given in section 3. Section 4 provides results and observations; Section 5 follows with a conclusion.

II. Proposed approach

Implemented EEG based Identifying emotion system is shown in the Figure 1 below. The raw data is processed through preprocessing from which the EEG signal is obtained. Consequently, the following characteristics of EEG signals are selected from the original dataset: The identified EEG characteristics are finally classified by the classifier. The next step by step clarification outlines the model as follows. Figure [4] explaining the whole procedure of the emotion identification system using EEG data is also provided.

A. *Preprocessing*

Raw EEG signals for feature extraction, and classification must eventually undergo various pre-processing steps to eliminate noises and artifacts for which could complicate the extraction of emotions. This is achieved by considering ‘preprocess‘ function filters EEG data to retain frequencies between 0 and 75 Hz, resulting in a new matrix using a 200 Hz sample frequency. We use a low-pass filter with a Finite Impulse Response (FIR) design, which effectively reduces high-frequency noise and stabilizes the signal for further processing. A bandpass filter was not chosen, as it could introduce instability to the processed EEG data due to the specific frequency characteristics of EEG signals shown in Fig 2 and 3.

The low-pass filter’s cutoff frequency f_c is set to 75 Hz, ensuring that frequencies above this threshold are attenuated.

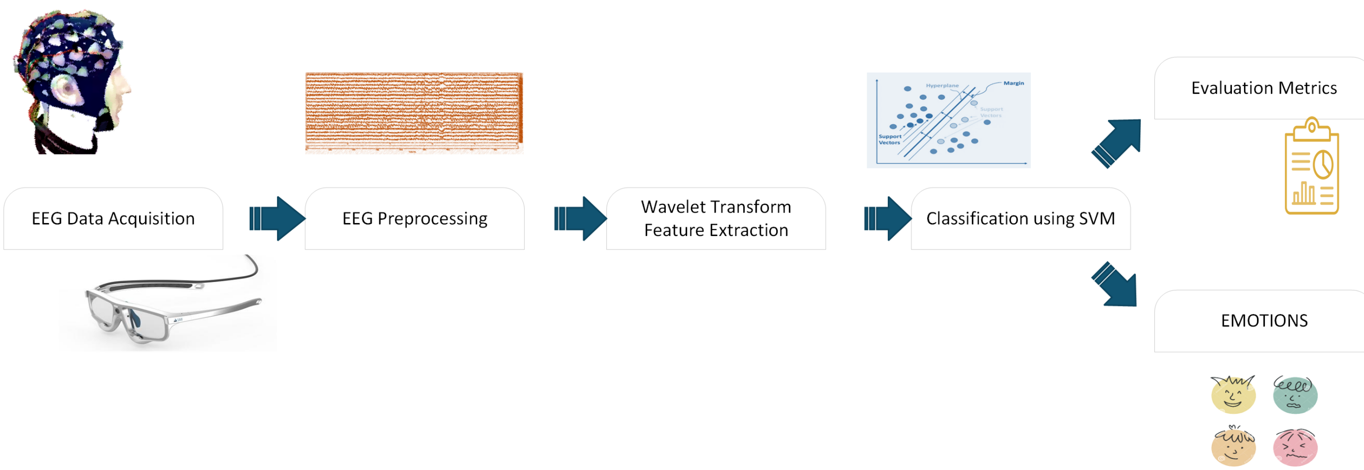

Fig. 4. SVM based Emotion Recognition System

The function employs an FIR filter, which is generally stable and linear phase, making it well-suited for biomedical signal processing like EEG. The FIR filter order, N, is chosen to balance between accuracy and computational efficiency; typically, we set $N = 5$, but this can be increased to $N = 10$ if further noise reduction is needed.

Mathematical definition of low pass fir filter is based on impulse response $h[n]$:

$$y[n] = \sum_{k=0}^{N} h[k] \cdot x[n-k] \quad (1)$$

where $y[n]$ denoted as clean signal at a moment n, $x[n-k]$ represents the original signal delayed by k samples, and $h[k]$ represents the filtering parameter at index k.

By applying this filter, the function provides a clean and stable EEG signal matrix ready for feature extraction, preserving frequencies up to 75 Hz and ensuring data consistency at a 200 Hz sampling rate.

B. Feature Extraction

In the feature extraction phase, processed EEG data is segmented into five frequency sub-bands—alpha, beta, gamma, delta, and theta using wavelet filter banks. Wavelet filter banks apply a series of filters to separate different frequencies within the EEG signal, preserving the temporal and frequency characteristics of the signal components. Each filter stage consists of low frequency(approximation coefficient) and a high frequency passing filters (detail coefficient), where each application divisions the frequency band. This iterative process continues by passing the approximation coefficients through additional filters until the desired frequency ranges for each sub-band are achieved. Since these filters are applied in sequence, they are referred to as filter banks. The wavelet transform [12] is applied individually to each of the 62 EEG channels, and for each channel and sub-band, entropy and energy features are extracted, resulting in 10 features per channel. This leads to a total of 620 features across all channels. The entropy E and energy W of the wavelet-transformed signals are calculated as follows: Entropy E quantifies the uncertainty or randomness in the EEG signal, which reflects the complexity of brain activity. An Expression of entropy is as follows:

$$E = -\sum_{i=1}^{N} p_i \log(p_i) \quad (2)$$

where total number of states is denoted by N and the probability of every state given the signal is represented by p_i.

Wavelet energy W is a measure that takes into account the distribution of power over various frequency sub-bands:

$$W = \sum_{i=1}^{N} |c_i|^2 \quad (3)$$

where c_i are the wavelet coefficients in a specific sub-band, representing the energy content.

In the feature reduction phase, we apply Principal Component Analysis (PCA) [13] during the phase of feature reduction in order to decrease the number of features. PCA is a statistical technique that identifies principal components (PCs) by transforming correlated features into a set of uncorrelated features using singular value decomposition (SVD). The PCA process is as follows: Normalize the features by subtracting the mean to center the data. Compute the covariance matrix C of the normalized features:

$$C = \frac{X^T X}{N-1} \quad (4)$$

X denoted as matrix of centered information, and N is the number of samples.

Compute the eigenvectors as well as the eigenvalue of the covariance matrix to identify the primary components. Select the top k eigenvectors associated with the greatest eigenvalues to create a reduced feature set. PCA converts the high-dimensional feature set into a lower-dimensional space with primary components which capture the most significant information from the original features. This reduced feature

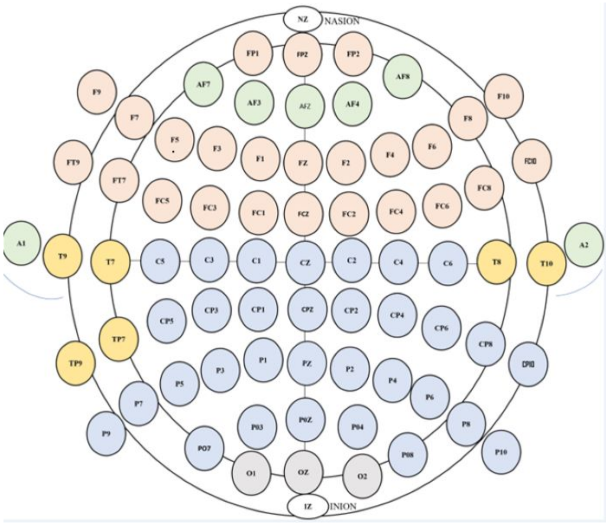

Fig. 5. Emotion Model

set is then used for further classification or analysis of EEG data.

III. Dataset

The type of development we have suggested for use here does so by applying a methodology gleaned from the SJTU Emotion EEG Dataset (SEED) [14], which has been generated from BCMI. Seventy-five trials of EEG data were recorded from fifteen subjects, seven male and eight female in a three-sessional, each consisting of fifteen trials. In each trial, the EEG signals were recorded while subjects watched Chinese film clips that evoked three emotions: that is the positive, neutral and negative type. There were 4 minutes of film clips and there were always two film clips illustrating one or the same emotion were shown without the other in between. Regarding video clips reactions questionnaire was fulfilled where people described their emotions after watched clip. The EEGs were recorded with 62 electrode cap in accordance with the universally accepted 10-20 system shown in Fig 5. In order to increase the speed of analyzing the data the EEG data was then down sampled to 200Hz; And, because all necessary EEG rhythm data is needed a 0-75Hz band pass filter was recommended.

IV. Results and Discussions

In order to convert the PCs from the previous phase into emotions, the SVM classifier will be supplied with them. SVM [15] is a supervised form of learning that can be utilized in classification problems most often. It is done by identifying a hyperplane that best fits the given data so as to categorise it into different classes. When it comes to a linearly separable emotion dataset, SVM tries to maximize the largest distance between the points belonging to two different classes which is called the margin and is further from the line, the closer it is to the support vectors. $\mathbf{x}_i \in \mathbb{R}^n$ represent the feature vector of the i-th data point, $y_i \in \{-1, +1\}$ denote the class label of $\mathbf{x}_i$, and $\mathbf{w} \in \mathbb{R}^n$ and $b \in \mathbb{R}$ represent the weights and bias of the model.

For SVM, the goal is to find a hyperplane that separates the classes as clearly as possible. The hyperplane can be defined as:

$$\mathbf{w}^T\mathbf{x} + b = 0 \tag{5}$$

where: $\mathbf{w}$ is the normal vector to the hyperplane, b is the bias term, which shifts the hyperplane.

For a new data point $\mathbf{x}$, SVM predicts the class by evaluating:

$$f(\mathbf{x}) = \text{sign}(\mathbf{w}^T\mathbf{x} + b) \tag{6}$$

If $f(\mathbf{x}) = +1$, then $\mathbf{x}$ is classified as class $+1$; otherwise, it is classified as -1.

The distance between the hyperplane and the closest data points is called the margin, abbreviated as M. The following limitations are imposed by SVM in order to maximize this margin: the norm of $\mathbf{w}$ must be minimized under the constraint that the data points must be properly identified.

$$y_i(\mathbf{w}^T\mathbf{x}_i + b) \geq 1 \quad \forall i \tag{7}$$

The objective of SVM is to minimize $\frac{1}{2}\|\mathbf{w}\|^2$, as this maximizes the margin $M = \frac{1}{\|\mathbf{w}\|}$. Thus, the optimization problem becomes:

$$\min_{\mathbf{w},b} \frac{1}{2}\|\mathbf{w}\|^2 \tag{8}$$

subject to

$$y_i(\mathbf{w} \cdot \mathbf{x}_i + b) \geq 1 \quad \forall i \tag{9}$$

When the data is not linearly separable, we introduce slack variables $\xi_i \geq 0$ to allow some misclassifications:

$$y_i(\mathbf{w}^T \cdot \mathbf{x}_i + b) + \xi_i \geq 1 \tag{10}$$

The objective function now includes a penalty for these misclassifications, controlled by a parameter C:

$$\min_{\mathbf{w},b,\xi} \quad \frac{1}{2}\sum_{j=1}^{d} w_j^2 + C\sum_{i=1}^{N} \xi_i, \tag{11}$$

where $\mathbf{w} = [w_1, w_2, \ldots, w_d]^\top$ is the weight vector in d-dimensional space

where C is a regularization parameter that balances maximizing the margin and minimizing the misclassification error.

SVM is typically solved by transforming the above primal problem into a dual problem using Lagrange multipliers α_i. The dual formulation is:

$$\max_{\alpha} \sum_{i=1}^{N} \alpha_i - \frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{N} \alpha_i\alpha_j y_i y_j(\mathbf{x}_i \cdot \mathbf{x}_j) \tag{12}$$

subject to

$$\sum_{i=1}^{N} \alpha_i y_i = 0 \tag{13}$$

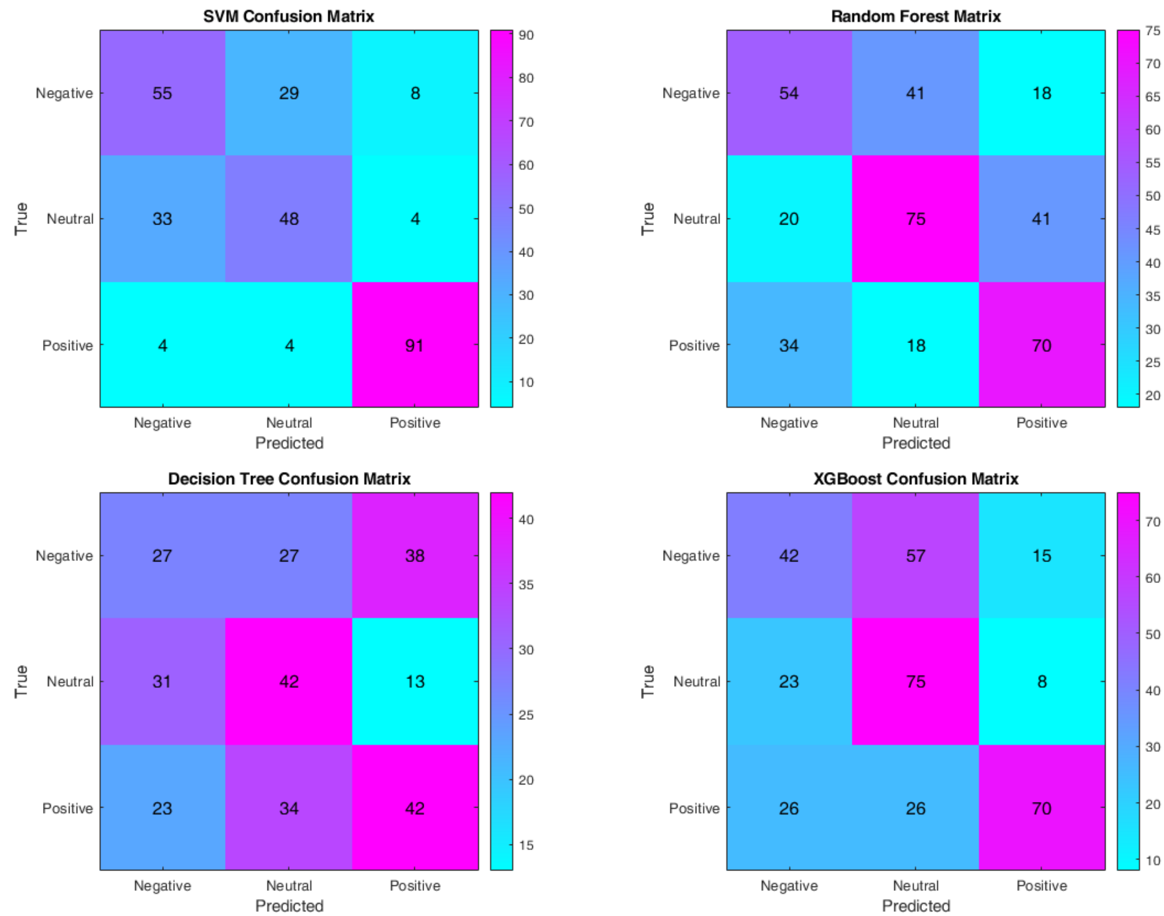

Fig. 6. Confusion Matrices of SVM and other Classifiers

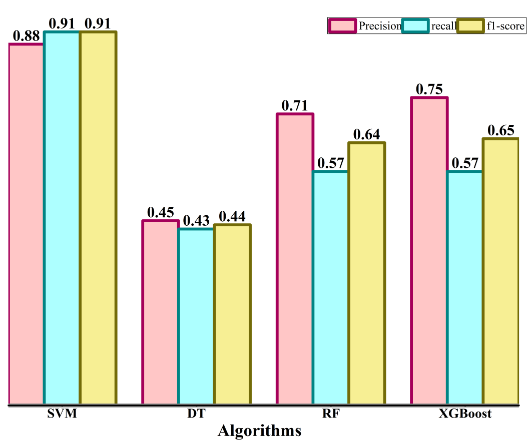

Fig. 7. Comparison of performance metrics precision, recall, and F1-score of different classifiers

where α_i are the Lagrange multipliers.

If the data is not separable by a straight line in the original feature space then we use a “Kernel Trick” to get a new feature space in which the data is linearly separable. The kernel function $K(\mathbf{x}_i, \mathbf{x}_j)$ replaces the dot product $\mathbf{x}_i \cdot \mathbf{x}_j$:

$$K(\mathbf{x}_i, \mathbf{x}_j) = \phi(\mathbf{x}_i) \cdot \phi(\mathbf{x}_j) \tag{14}$$

kernels have

$$K(\mathbf{x}_i, \mathbf{x}_j) = \sum_{k=1}^{d} x_{ik} x_{jk}, \tag{15}$$

$$K(\mathbf{x}_i, \mathbf{x}_j) = \left(\sum_{k=1}^{d} x_{ik} x_{jk} + 1 \right)^{d}, \tag{16}$$

$$K(\mathbf{x}_i, \mathbf{x}_j) = \exp\left(-\frac{1}{2\sigma^2} \sum_{k=1}^{d} (x_{ik} - x_{jk})^2 \right), \tag{17}$$

Once the optimal α_i values are obtained, the decision function for a new data point $\mathbf{x}$ is:

$$f(\mathbf{x}) = \text{sign}\left(\sum_{i=1}^{N} \alpha_i y_i K(\mathbf{x}_i, \mathbf{x}) + b \right) \tag{18}$$

where b is computed using the support vectors.

SVM is compared with other methods such as Decision tree(DT), Random Forest(RT) and XG Boost(XGB). Decision trees are a powerful hierarchical model used for classification. The confusion matrices of these algortithms shown in Fifure 6.

The nodes represent tests on attributes, the branches show test outcomes, and the leaf nodes indicate class labels. The path from the root to a leaf forms classification rules. Decision trees are versatile and effective for both classification and regression tasks. They handle non-linear relationships with ease, and are known for their accuracy, stability, and interpretability. Decision trees [16] support decision-making by mapping outcomes, costs, and utilities - that's why they're so widely used in supervised learning. Random Forest (RF) and XG Boost (XGB) model are among the most efficient and popular ensemble learning algorithms used for classification problem. RF [17] constructs many decision trees using bagging and random feature with majority voting to decrease misclassification so as to minimize over fitting. It performs well with large, high-dimensional data and robust but computationally costly and somewhat less transparent because it is an ensemble method. In contrast, XGB [18] is a large scale to tree based gradient boosting algorithm which builds a sequence of tariff trees that minimize the weighted loss function with each tree being built to reduce the error of the prior tree. It updates an efficient function with a form of additional penalty added in as a form of regulation, making it faster and improved in efficiency over the traditional gradient boosting techniques. The main advantage of RF is that it is easy to implement and works well in many tasks, while XGB has a better predictive power and is faster but has delicate parameters' setting. They are widely applied in medical applications, fraud detection systems, emotion classification, and recognition system.

Throughout this study, key performance metrics such as accuracy, precision, recall, and F1-score were employed to assess model effectiveness. They are shown in Figure [7] and [8]. Accuracy, provides an overall sense of model performance. Precision, can be given as:

$$\text{Precision(P)} = \frac{correctpredictions}{correctpredictions + incorrectpredictions} \tag{19}$$

Recall, also known as sensitivity or the true positive rate, is defined as:

$$\text{Recall(R)} = \frac{correctpredictions}{correctpredictions + incorrectnegatives} \tag{20}$$

It reflects the model's effectiveness in identifying actual positives. The F1-score combines precision and recall:

$$F1 = \frac{2 \cdot P \cdot R}{P + R} \tag{21}$$

A high F1-score indicates balanced precision and recall. In this experiment, segmenting EEG data showed improved accuracy and insights into sections with the most brain activity. SVM achieved the highest accuracy of 70.25% (recall 90 %), with optimal parameters identified through grid search. Random Forest performed well with 58.3% accuracy and an F1-score of 0.64%, using a polynomial kernel of degree 3. Logistic Regression was the most consistent across data splits, yielding high recall (85–100%) but lower precision in positive emotion

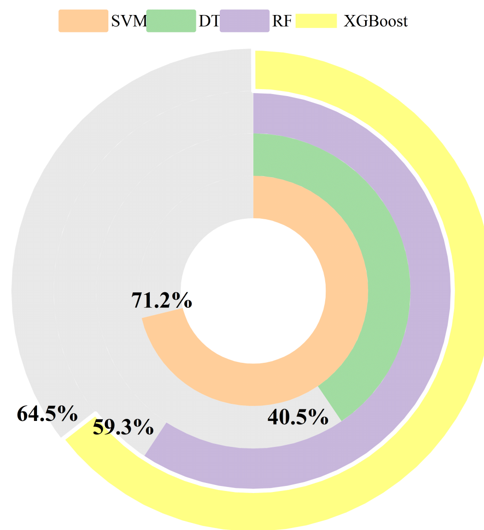

Fig. 8. Accuracy of the various methods of classification

classification. This analysis suggests that segmenting data enhances model performance, with Logistic Regression showing the most stable results overall.

Conclusion

The primary aim was to examine the neural processes underlying reward/pleasure circuits as well as determine what parts of the brain convey emotive information. When employing SVM, RF, DT, and XGBoost classifications, the accuracy varied between 71.2%-40.5% while F1 scores varied between 90%-44%. No specific algorithm was observed to perform better than the others, however, SVM had the highest overall accuracy for positive, negative and neutral sentiment data. It is for these reasons that these studies showcase the potential of classic ML algorithms for emotion recognition and features optimization.

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