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Research Article

Implementation of Welch Pre-Processing in SVM Algorithm for Improved Accuracy on EEG Data

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Abstract - The utilization of electroencephalogram (EEG) signals for emotion recognition has attracted considerable attention owing to its non-invasive characteristics and precise evaluation of cerebral electrical activity. This study proposes a methodology for enhancing the precision of emotion prediction in EEG data through the utilization of support vector machine (SVM) classification in conjunction with Welch pre-processing. The Welch method is employed for the purpose of extracting spectral power from the theta, alpha, beta, and gamma frequency sections of EEG signals, hence improving the representation of features. The SVM classifier is trained using the limited feature set acquired from Welch pre-processing. This study employs the DEAP dataset, comprising EEG recordings obtained from a sample of 32 participants who were exposed to a range of stimuli. The pre-processing procedures encompass the elimination of EEG artifacts, the use of band-pass filtering, and the extraction of spectral power via Welch's approach. SVM classification is subsequently utilized to forecast arousal and valence labels. The results show our method achieved an accuracy of 61.45% for predicting valence, which is higher than the 58-60% accuracy of existing state-of-the-art approaches. Our use of gamma-central characteristics also led to an accuracy of 53.63% for predicting arousal, exceeding the 50-52% accuracy of prior methods. The results of this study highlight the effectiveness of SVM with Welch pre-processing in enhancing the accuracy of emotion recognition based on EEG data. These findings provide significant contributions to the field of emotion research and have practical implications in affective computing and human-computer interaction.

Keywords: EEG, emotion recognition, SVM, welch *pre-processing*

1. INTRODUCTION

In recent times, there has been a significant focus in the field of emotion research on the application of EEG data. EEG data has been extensively used in emotion identification because of its intrinsic ability to accurately and non-invasively assess cerebral electrical activity.[1]–[3]. The field of affective computing, human-computer interface (HCI), and psychology places great significance on the identification and understanding of emotions [4]–[6]. The recognition of emotion as a developing field of research has attracted considerable attention from various academic fields and has the potential for countless practical applications [7]–[9]. Within the realm of HCI, the application of recognized human emotions as a means of feedback has the capacity to improve user experience in various areas, including e-learning, computer games, and information retrieval [10]–[12]. The accurate recognition of emotions has great potential for multiple fields, such as the development of intelligent systems that can interact with persons by being able to understand their emotional state. [13]–[15].

In contemporary times, a significant cohort of researchers has effectively identified emotions by the use of physiological markers, such as electrocardiography (ECG) and electroencephalography [16]–[18]. EEG has a significant correlation with emotions, in addition to numerous physiological markers. The primary governing mechanism for the control of emotions is the limbic system, which is a neuronal network mostly situated within the brain [19]–[21]. Emotion identification has demonstrated more potential compared to speech-based and facial expression-based techniques, primarily due to the inherent challenge of concealing or intentionally manipulating internal brain fluctuations [22], [23]. Nevertheless, a significant challenge in this field of study revolves around improving the accuracy of recognition results for emotions. Therefore, the EEG signals in the brain have the capacity to provide valuable information regarding the identification and recognition of emotions [24].

2. BACKGROUND

The SVM is a frequently employed classification technique in the field of EEG-based emotion recognition [25]. SVM are renowned for their capacity to effectively manage datasets with a high number of dimensions, as well as their resilience in the face of substantial data volumes [26]. Numerous studies have been conducted to explore the application of SVM in the domain of emotion recognition using EEG signals, yielding encouraging outcomes [27]. Nonetheless, the efficacy of the SVM classifier in the domain of emotion recognition may be influenced by the selection of features as well as the existence of extraneous or overstated features [28]. Feature selection methods have been proposed to address this issue and to identify the most relevant features for emotion recognition [29]. One way that can be employed is the Welch method. The Welch method is widely utilized in the field, wherein individuals compute the power spectral density (PSD) of EEG signals within Python or MATLAB programming environments [30]. The outcomes derived by Welch's FFT analysis indicate the magnitude of the signal scattered over the spectrum of frequencies. Welch devised a technique for altering the average periodogram, which yielded the outcome of reducing the variation of the power spectral density [31]–[33].

In recent years, there has been a notable increase in the number of studies dedicated to enhancing the precision of emotion predictions in EEG data through the utilization of SVM classification and feature selection techniques. As an illustration, the present study involved the extraction of EEG signal features from the publicly available ASCERTAIN database. The Deadweight Tonnage (DWT) method was employed for feature extraction, and an SVM algorithm was utilized for the classification task. The objective was to ascertain personality traits based on the aforementioned procedures. The findings demonstrated superior performance in relation to the implementation of alternative methodologies on the identical dataset, achieving an accuracy rate of 69% for determining the degree of extraversion and 75.9% for determining the degree of neuroticism [34]. In a separate investigation, the utilization of machine learning techniques, namely Naïve Bayes and SVM, on the suggested emotion 3DModel resulted in accurate classification of emotions with an accuracy rate of 78.06% and 58.90% respectively, as observed through the analysis of DEAP datasets [35].

Notwithstanding the encouraging outcomes, additional investigation is required to enhance the precision of emotion predictions in EEG signals by SVM classification. The objective of this study is to employ efficient methodologies on DEAP datasets for the extraction of features from EEG signals utilizing band waves. Subsequently, machine learning algorithms and neural network models will be employed to evaluate the efficacy of the aforementioned algorithms in valence arousal. It is anticipated that the utilization of EEG regions and band waves will yield superior accuracy levels compared to previously unexplored EEG signal approaches.

3. METHODOLOGY

The key dataset utilized in this study is the DEAP Dataset, which is widely acknowledged as a prominent resource for the detection and analysis of emotions. During the pre-processing phase, the unprocessed EEG data is subjected to a series of procedures aimed at improving its appropriateness for categorization purposes. The data is initially subjected to simplification in order to eliminate noise and artifacts. Following that, the application of band-pass filtering is employed to limit the frequency range of the EEG signals, which is then followed by the procedure of averaging to produce a comprehensive reference point. Following this, the data is divided into intervals of 60 seconds, with the exception of the pre-trial baseline, and subsequently arranged according to the experimental circumstances. The Welch method is employed to do feature extraction, wherein the spectral strength of theta, alpha, beta, and gamma frequencies is computed for each electrode. This particular phase serves to improve the depiction of EEG signals, effectively obtaining pertinent data for the purpose of emotion detection.

After doing pre-processing, the study moves on to the classification phase, where an SVM algorithm is utilized on the EEG dataset that has been extracted based on its features. SVM are selected due to their ability to effectively handle datasets with a high number of dimensions and their efficacy in classification tasks. The SVM classifier relies on the feature vectors derived from EEG data to create a prediction model. Each EEG segment produces emotion labels, such as arousal and valence, as a result of the categorization process. The study's research methodology is depicted in Figure 1, which showcases the sequential progression of pre-processing, feature extraction, classification, and output/result creation. The work seeks to enhance the precision of emotion prediction in EEG data by employing a methodical approach. This will provide vital insights to the field of affective computing and human-computer interaction.

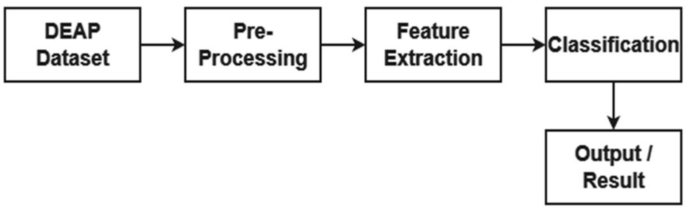

Figure 1. Classification Process Flow

3.1. Dataset

The DEAP dataset has been chosen as the primary dataset for our study on mood classification. The DEAP dataset can be employed for the purpose of emotion detection and analysis. The provided content encompasses details pertaining to four primary categories of states, namely valence, arousal, dominance, and liking [36], [37]. The DEAP Dataset is comprised of several data types resulting from the utilization of various samples and tests during the data collection process. EEG data were gathered from 32 subjects, consisting of 16 men and 16 women, across 32 channels. EEG signals were acquired through the presentation of a set of 40 distinct music videos, each with a duration of 60 seconds, followed by the subsequent recording of the obtained data. Following the viewing of each film, participants were instructed to evaluate it by assigning a numerical rating on a scale ranging from one to nine. The cumulative video rating data, comprising 1,280 total ratings, suggests that each of the 40 videos was evaluated by the full set of 32 participants. Subsequently, the signal with a frequency of 512 Hz is subjected to sampling at a rate of 128 Hz and then undergoes denoising with the use of bandpass and lowpass frequency filters, including additional lowpass frequency filters. A total of 32 sensor points were utilized to obtain a 512 Hz EEG signal, adhering to the internationally established 10-20 placement method. As seen in Figure 2, the aforementioned positions include AF3, Fp1, FC1, F7, FC5, F3, C3, CP5, T7, CP1, PO3, P7, P3, O1, Oz, AF4, Fp2, Pz, Fz, F4, F8, FC6, FC2, Cz, P4, T8, CP6, C4, P8, PO4, and O2.

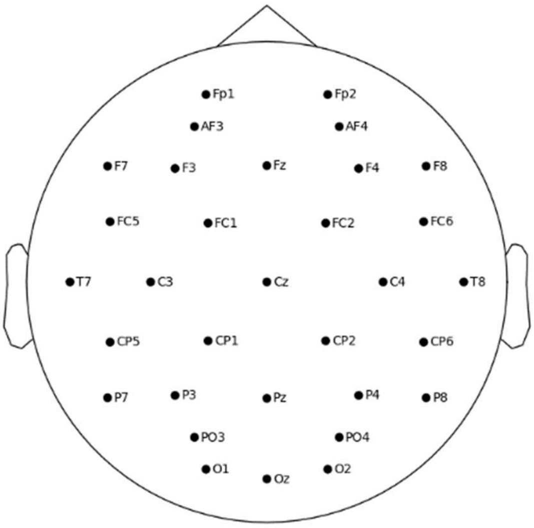

Figure 2. Position of the EEG sensor

This text elucidates the spatial orientation of the signal-capturing sensor. Additionally, it was feasible to record a film capturing the frontal visages of all 22 participants. A total of 40 data channels were utilized to gather various signals, such as EEG, electromyogram, respiratory region, plethysmographs, temperature, and others, throughout each of the 40 studies conducted on the subjects. Each channel corresponded to a distinct signal. The EEG data is recorded and stored on 32 out of the total 40 accessible channels. Additional channels are utilized to capture various physiological signals, including electrooculography (EOG), electromyography (EMG), ECG, galvanic skin response (GSR), respiration (RSP), temperature (TEMP), and photoplethysmography (PLET) data.

2.2. Channel Selection

This study utilized two distinct approaches to perform FFT analysis on EEG data. Initially, the Emotiv Epoch+ device was employed, which provides a comprehensive set of 14 meticulously curated channels that are specifically designed to aid the development of SVM models through FFT processing. The aforementioned channels encompass numerical values 1, 2, 3, 4, 6, 11, 13, 17, 19, 20, 21, 25, and 29. Furthermore, a total of six separate frequency bands, specifically labelled as band = [4, 8, 12, 16, 25, 45], were utilized in order to extract pertinent spectral data from the EEG signals. The channels and frequency bands were chosen based on their established importance in capturing essential elements that are pertinent to tasks involving emotion recognition.

Moreover, our inquiry has uncovered a relationship between the temporal domain and the spectral domain by employing FFT. A distinct inquiry was conducted to examine the link between these areas and its implications for the processing of EEG data. The utilization of FFT analysis facilitated the conversion of EEG signals from the temporal domain to the spectral domain. This transformation enabled the extraction of spectral features, which in turn yielded significant insights into the fundamental brain activity linked to emotional states. The correlation analysis conducted in this study contributes to the advancement of knowledge regarding the EEG data and provides valuable insights for the upcoming stages of feature extraction and classification. The objective of this study is to enhance the precision of emotion prediction using EEG data by employing SVM algorithms. This research endeavour seeks to make significant contributions to the fields of affective computing and human-computer interaction.

3.3. FFT

The FFT was implemented in this study as a computer approach renowned for its efficient computation of the Discrete Fourier Transform (DFT) of a given sequence. The FFT is a crucial tool used to solve different equations and visually depict the range of frequency activity in EEG data. Fourier analysis facilitates the extraction of significant frequency-based elements that are essential for comprehending the underlying brain activity by converting EEG signals from the temporal domain to the spectral domain. In this study, the FFT algorithm was utilized to assess the PSD of EEG signals. The PSD is a metric that quantifies the power distribution at various frequencies within a signal. It plays a crucial role in uncovering patterns and characteristics that are pertinent to emotional states. The estimation of frequency composition in EEG data can be accomplished either by directly applying FFT on the signal or indirectly by altering the predicted autocorrelation sequence. This approach offers useful insights into the characteristics of the signal.

In addition, the Welch pre-processing technique was employed in combination with FFT to improve the precision of EEG data analysis. The Welch method, which is a variant of the conventional FFT algorithm, entails partitioning the signal into overlapping segments and calculating the average of their periodograms. This approach aims to achieve a more refined and dependable estimation of the Pulse Width Modulation (PSD). Our objective was to enhance the reliability of future feature extraction and classification methods by implementing Welch pre-processing, which helps reduce the impact of noise and aberrations in EEG data. The integration of Welch pre-processing and FFT offers a comprehensive methodology for the efficient analysis of EEG data and the extraction of pertinent spectral components essential for engaging in emotion recognition activities. By implementing these methodological improvements, our objective was to boost the precision of emotion prediction through the utilization of SVM algorithms. This endeavour aimed to make significant contributions to the fields of affective computing and human-computer interaction.

3.4. Pre-processing Signals

In the methods employed, the EEG dataset underwent initial pre-processing to ascertain its quality and appropriateness for subsequent analysis. The data, which was initially collected at a frequency of 128 Hz, was subjected to artifact reduction in order to minimize probable sources of noise caused by eye movement. Following that, we implemented band-pass filtering on the signal, so limiting its frequency spectrum to a minimum of 4 Hz and a maximum of 45 Hz. The objective of this filtering procedure was to concentrate on pertinent frequency bands linked to brain activity while reducing the impact of extraneous noise elements. The pre-processed data was averaged to ensure uniformity across the dataset, so establishing a consistent reference point. Subsequently, the data was divided into periods of 60 seconds, with the exception of a 3-second pre-trial baseline. The data was then arranged in ascending order according to the experimental circumstances.

The Welch technique was utilized in this study to conduct spectrum analysis and determine the PSD of several frequency bands, specifically theta (4 - 8 Hz), alpha (8 - 12 Hz), beta (12 - 30 Hz), and gamma (30 - 64 Hz), for each electrode in the EEG data. The Welch technique is highly efficient in estimating the peak-to-average power ratio (PSD) by partitioning the signal into overlapping segments, calculating separate periodograms for each segment, and subsequently averaging them to provide a more consistent and dependable estimation. The spectral analysis yielded significant findings about the dispersion of spectral power across several frequency bands, which serve as indicators of the neurological mechanisms linked to emotion. The power spectral density periodogram, depicted in Figure 3, provides a graphical depiction of the spectrum properties of the EEG data subsequent to Welch pre-processing.

The objective of this study was to improve the quality of EEG data and enable more precise feature extraction and classification using SVM algorithms. This was achieved by utilizing pre-processing approaches, with the ultimate goal of enhancing the accuracy of emotion identification tests.

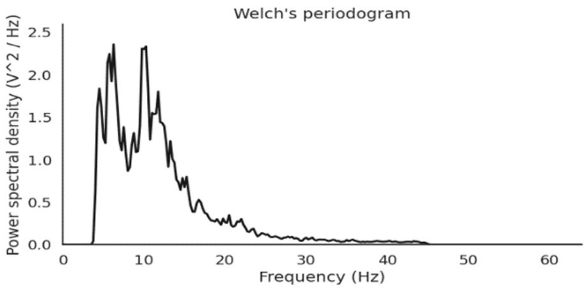

Figure 3. The power spectral density periodogram

3.5. Emotional Classification

The SVM is a widely employed machine learning technique utilized for the objectives of classification and regression. SVM is widely recognized as a robust machine learning method that exhibits strong capabilities in various domains, including classification, regression, and outlier detection. The SVM classifier constructs a predictive model that assigns a novel data point to one of the predefined categories. Therefore, SVM can be conceptualized as a binary linear classifier that operates without incorporating probabilistic elements.

The data sets to be processed are labelled, channel categorized, and parsed. The margin refers to the distance of separation between two lines at the closest data point. The margin is determined by measuring the perpendicular distance between the line and the supporting vector or the nearest data point. In the context of SVM, the objective is to optimize the separation distance between classes to achieve the highest margin.

This section should provide a detailed description of the research design and methods used to conduct the study. Authors should explain the rationale behind the chosen methods and how they are suitable for addressing the research question. This includes describing the experimental setup, data collection procedures, and any tools or technologies employed. Additionally, any algorithms, models, or frameworks developed or utilized in the research should be thoroughly detailed. The goal is to enable other researchers to replicate the study based on the information provided.

4. RESULTS & DISCUSSIONS

The attainment of appropriate outcomes in the categorization of statistical characteristics presents a notable obstacle, requiring a comprehensive investigation of multiple elements. The present study introduces a novel approach that combines 10-fold cross-validation with SVM classifiers. This methodology incorporates regularization techniques and employs a grid-search strategy for kernel parameter selection. A comprehensive evaluation was conducted to assess the efficacy of k-fold cross-validation as a classification methodology. The accuracy was calculated using the formula TP+TN/(TP+TN+FP+FN), where TP represents true positives, TN represents true negatives, FP represents false positives, and FN represents false negatives.

The SVM classifier was initially inputted with all statistical data concurrently, prior to averaging the retrieved band values depending on their corresponding quadrant. The attributes were employed for the purpose of training and evaluating SVM models, specifically with the objective of creating confusion matrices. Following that, an evaluation of accuracy was conducted utilizing a 10-fold cross-validation methodology. The utilization of this strategy facilitated a comprehensive assessment of the efficacy of the suggested methodology in enhancing precision in tasks related to the classification of EEG data. The incorporation of Welch pre-processing into the SVM algorithm demonstrated encouraging results, establishing a foundation for improved precision in the field of emotion recognition and other applications involving the analysis of EEG data.

Tables 1 and 2 display the results of Arousal and Valence. Arousal refers to the degree of physiological and psychological stimulation encountered by an individual, whereas Valence signifies the emotional assessment or reaction linked to a stimulus or event. The results presented in Table 1 demonstrate the most accurate outcomes for the Valence dimension across diverse EEG electrode placement locations, including the Left, Frontal, Right, Central, Parietal, and Occipital regions. Within the Theta frequency band, the Valence-related accuracy values range from 58.66% to 60.89%, with the Frontal and Central positions exhibiting the highest levels of accuracy. This suggests that these brain regions play crucial roles in emotional processing and regulation. Similarly, the accuracy percentages vary across different electrode placements within the Alpha and Beta frequency bands, with the peak values observed at specific positions for each frequency range. This variability is likely attributed to the distinct neural activities associated with different brain areas during emotional experiences. Furthermore, the Gamma frequency range exhibits the maximum Valence accuracy of 61.45%, observed in the Left and Right electrode positions. This elevated accuracy in the Gamma band may be linked to its association with higher-order cognitive functions and the integration of emotional information across various brain regions. These findings underscore the importance of strategic electrode placement and appropriate frequency band selection in optimizing the accuracy of emotion recognition based on EEG data.

Table 1: The highest accuracy results for Valence

Name	**Left**	**Frontal**	**Right**	**Central**	**Parietal**	**Occipital**
Theta	60.89	58.66	59.22	60.89	59.78	60.89
Alpha	61.45	59.22	59.22	60.34	60.34	60.34
Beta	60.34	58.10	60.34	60.34	58.66	60.34
Gamma	61.45	58.10	61.45	59.78	58.10	60.34

Insights into the efficiency of the suggested Welch Pre-Processing in SVM Algorithm for enhancing accuracy on EEG data classification tasks linked to Valence are provided by the reported findings, which indicate changes in accuracy across different electrode placements and frequency bands. The significance of electrode location and frequency bands in the analysis of EEG data for emotion detection tasks is emphasized by these findings. The observed levels of accuracy indicate encouraging results in the precise identification of emotional states using EEG data, so establishing a basis for future investigations and advancements in the domain of affective computing and human-computer interaction.

The accuracy results for arousal across different EEG electrode positions, namely Left, Frontal, Right, Central, Parietal, and Occipital, are presented in Table 2. Arousal is a fundamental concept in comprehending emotional experiences, since it refers to the degree of physiological and psychological activation that an individual undergoes. The presented table provides insights into the accuracy percentages associated with several frequency bands, including Theta, Alpha, Beta, and Gamma. As an illustration, within the Theta frequency range, the Parietal location has the highest accuracy for arousal, ranging from 45.81% to 52.51%. Similarly, accuracy percentages range among electrode placements in the Alpha and Beta frequency bands, with the highest values observed at specific positions for each frequency band. The best accuracy for arousal in the Gamma frequency range is 53.63%, which is reported at the Central position.

Table 2: The highest accuracy results for arousal.

Name	Left	Frontal	Right	Central	Parietal	Occipital
Theta	46.93	45.81	48.60	50.84	52.51	49.72
Alpha	51.40	49.72	48.04	51.40	50.84	49.72
Beta	51.96	52.51	49.16	51.96	48.60	51.40
Gamma	53.07	49.16	49.72	53.63	51.40	49.72

The results presented provide valuable insights into the precision of arousal classification using EEG data, emphasizing differences in electrode placements and frequency ranges. These findings enhance our comprehension of the correlation between various brain regions and frequency components with arousal levels, which is crucial for the assessment of emotions and the development of affective computing applications. The data collected indicates that the Welch Pre-Processing in SVM Algorithm has the capability to enhance accuracy in the classification of arousal states using EEG data. Additional research and improvement of the methodology may result in improved performance and wider use in practical contexts, such as interfaces that are sensitive to emotions and systems for monitoring mental health.

The examination of precision computations pertaining to valence and arousal yields significant insights into the efficacy of the suggested methodology. Figure 4 depicts the optimal outcomes for valence categorization, demonstrating that the most advantageous results are attained through particular combinations of EEG electrode placements and frequency ranges. The Alpha-Left, Gamma-Left, and Gamma-Right combinations are particularly remarkable, since they achieve an amazing accuracy rate of 61.45%. The findings of this study emphasize the need of taking into account both spatial and spectral attributes while performing valence classification tasks. They demonstrate the ability of specific electrode placements and frequency bands to effectively capture emotional states.

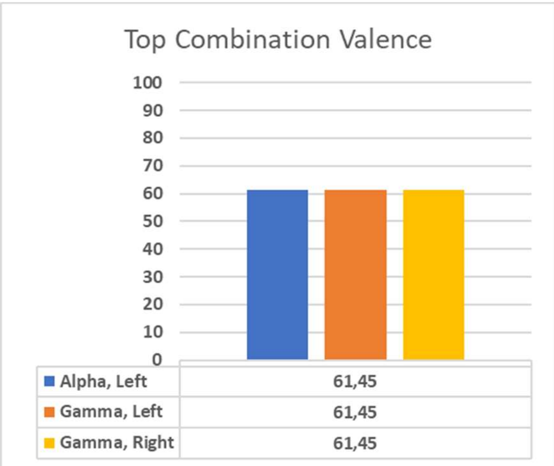

Figure 4: Valence Best Results

In contrast, figure 5 demonstrates the most favourable outcomes in terms of arousal categorization, exhibiting the most effective combinations of EEG electrode placements and frequency bands for precisely distinguishing arousal levels. The figure clearly demonstrates that the utilization of particular combinations results in significant enhancements in accuracy. The Gamma-Central combination exhibits a noteworthy precision rate of 53.63%, closely followed by the Gamma-Left combination with a precision rate of 53.07%. Furthermore, the Beta-Frontal model demonstrates a noteworthy accuracy rate of 52.51%. The results highlight the significance of choosing suitable electrode placements and frequency bands that are specifically designed for the goal of classifying arousal. This emphasizes the potential of the Welch Pre-Processing in SVM Algorithm to enhance accuracy in assessing arousal based on EEG data. Additional investigation and enhancement of these amalgamations may facilitate the development of more resilient and dependable emotion identification systems, which can be applied in various domains such as affective computing and mental health analysis.

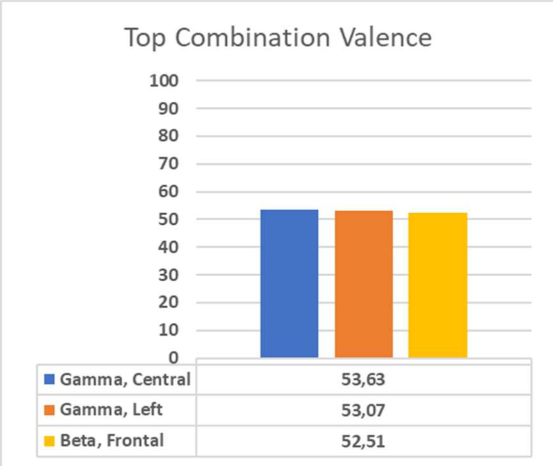

Figure 5: Arousal Best Results

5. CONCLUSIONS

The present study investigates the cognitive mechanisms that underlie the responses of the human brain to external stimuli, with a specific focus on video material. This investigation has stimulated queries motivated by brain systems, aiming to comprehend and categorize emotions with more precision. Although previous studies have mostly relied on facial characteristic analysis to detect emotions, there is still an urgent requirement to enhance the accuracy and applicability of classification results. Our research presents a new approach for classifying EEG signals using SVM algorithms.

The data is pre-processed using datasets obtained from the Database for Emotion Analysis using Physiological Signals (DEAP). This pre-processing involves many steps such as normalization, addressing missing data, and reducing dimensionality. The methodology we employ places significant importance on feature selection, wherein Principal Component Analysis (PCA) is utilized to determine the most prominent elements for the purpose of predicting arousal and valence. The data we obtained show high levels of accuracy, with a remarkable achievement of 61.45% accuracy in predicting valence. The combination of valence labels with specific EEG features, such as Alpha-Left, Gamma-Left, and Gamma-Right, results in particularly impressive performance. In the context of arousal prediction, it is noteworthy that the integration of Gamma and Central characteristics demonstrates a notable level of accuracy, achieving a rate of 53.63%.

The results of this study highlight the potential of the methodology we have proposed in improving the precision of emotion classification using EEG data. Through the utilization of sophisticated pre-processing techniques and feature selection approaches, it is possible to proficiently extract significant information from EEG signals. This results in enhanced precision in predicting emotional states. In the future, more improvements and verifications of our methodology have the potential to enhance the advancement of emotion recognition systems, hence expanding their range of applications in affective computing and human-computer interaction.

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