Channel Selection Method for Efficient EEG-Based Emotion Analysis

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Declaration

It is hereby declared that

1. The thesis submitted is our own original work while completing degree at Brac University.

2. The thesis does not contain material previously published or written by a third party, except where this is appropriately cited through full and accurate referencing.

3. The thesis does not contain material which has been accepted, or submitted, for any other degree or diploma at a university or other institution.

4. We have acknowledged all main sources of help.

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Abstract

Emotion can be defined as a complex reaction pattern that takes into account a person's behavioral and physiological characteristics. Neural impulses from different regions of the human brain are integrally responsible for generating and processing emotion. Among the existing emotion recognition systems electroencephalogram (EEG) offers the most effectiveness in capturing emotional states in humans. However, recognition of human emotions using EEG signals is quite a challenging task because it requires a balanced tradeoff between retaining the important features of the EEG signals and maintaining computational efficiency at the same time. Working on the DEAP dataset, this paper introduces a novel method of brain source localization (BSL), AgLORETA, as a refinement of the popular BSL method eLORETA. The focus of this designed AgLORETA algorithm is to iteratively refine a core element used in the inverse problem solution calculations of the conventional source localization problems, the lead field matrix. This refinement is done with the view of achieving accurate source localization results allowing us to find the regions of the human brain that generate most neural activity. The utilization of these regions is made while mapping the activities to the electrode channels placed across the scalp in 10-20 systems. The top 10 most active EEG channels have been selected in this approach. To investigate the performance of the selected channels, a combination of two EEG-based feature engineering techniques Hjorth parameters and Permutation Entropy have been applied to the EEG data. The two feature extraction methods have been chosen through various preliminary experimental trials. Finally, the EEG data is validated after feature extraction using some ML classifiers such as SVM, Decision Tree, Random Forest, and KNN. We have compared the AgLORETA algorithm with traditional dSPM, sLORETA, and eLORETA, in a similar approach and achieved promising performance, showing the highest accuracy amongst all. Thus computational complexity is reduced through the 10 selected channels out of the 32 channels of the dataset using AgLORETA.

Keywords: emotion recognition; emotion analysis; computational complexity; multichannel EEG signals; source localization; dSPM, eLORETA, sLORETA, AgLORETA, Hjorth, Permutation Entropy, Support Vector Machine (SVM), Decision Tree (DT), Random Forest (RF), and K-Nearest Neighbor (KNN), high activity brain regions, optimally selected list of channels;

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Chapter 1

Introduction

1.1 Introduction

Emotions are a vital part of the day-to-day lives of human beings. [53] We, as humans, are capable of making rational decisions based on these emotions. Because it is the very way we react to our surroundings in certain situations.[2] Therefore, a scientific understanding of human emotions can be very beneficial from various viewpoints.

There are a number of applications for emotion recognition. For instance, emotion recognition can play a crucial role in helping people who can understand emotions but are unable to express them. Moreover, it is also used to enhance the interactivity of HCI (human-computer interaction) environments as well as in the creation of robots that can comprehend human emotions and respond to them.

Usually, doctors or psychologists talk to patients to assess their emotional states before providing the results of the diagnosis. This strategy is certainly not scientific and makes it challenging to implement daily emotional health monitoring. Thus, several emotion sensing and recognition frameworks using multi-modal bio-signals are suggested as alternatives for human emotion detection. These frameworks make it possible for lifeless sensors or computers to understand the objective emotional states of the human mind, which are used to monitor emotional health and make a preliminary diagnosis of potential mental illnesses, sleeping disorders, epilepsy (a condition that causes seizures repeatedly), brain tumors, strokes, degeneration of brain tissue, Alzheimer's disease, various head injuries, etc.[2] All these only add to the growing importance of emotional recognition in today's world.

In recent years, several physical or physiological metrics have been used as a means of detecting human emotion. Different researchers made use of certain facial expressions, verbal expressions, and even body language for this purpose. Certain electric potentials have also been used, such as electrocardiogram (ECG), skin conductance (SC), electromyogram (EMG), etc. [19]. These measurements can be considered an indirect emulation of human feelings. The pursuit of directly recognizing emotions from brain signals represents an important step toward emotional intelligence. That's why increasing efforts are being made toward emotion identification using electroencephalograms (EEG) in recent times.

EEG, or electroencephalography, is a fascinating and essential instrument in the fields of neuroscience and medicine [32]. This noninvasive neuroimaging method offers us a glimpse of the complex operations of the human brain. Our understanding of everything from fundamental brain functioning to intricate cognitive processes and neurological illnesses is aided by the use of the EEG, which records electrical activity produced by the brain's neurons. Our understanding of cerebral activity has been changed by the ability of EEG to record the electrical symphony within our brains, and this ability continues to influence developments in neurology, psychology, and other fields.

This research aims to extract the most relevant EEG features while reducing noise and redundancy by using some advanced techniques of brain source localization, such as BEM, dSPM, eLORETA, sLORETA, etc., and select an optimal set of channels corresponding to the most active brain regions responsible for generating the neural impulses. This research also intends to investigate a few existing feature extraction methods and implement those on the data of the selected set of channels. To create a practical yet effective emotion detection system with minimum bias, the main goal is to reduce computational complexity using a small but ideal number of EEG channels.

1.2 Problem Statement

Emotion recognition using EEG signals is a developing topic of study, on which this research is thoroughly focused. The DEAP dataset[10] used in the paper carries EEG signals from 40 channels. As EEG signals collect data directly and continuously from various brain regions through the electrodes placed all over the human scalp, they certainly contain a vast amount of information. Data from all the signals are not necessarily useful while working on emotion recognition. Because data of the EEG signals from the 40 electrodes often contain redundant information as well as unnecessary noise which doesn't contribute to capturing human emotional states accurately. Moreover, when data from all 32 channels are used for an experiment, it only increases the computational complexity of the process.[10] On the other hand, cutting down the number of channels using different methodologies and algorithms has often resulted in decreased accuracies, suggesting that important emotional cues might have been overlooked in the process. Additionally, some of the methodologies of brain source activity localization developed by the researchers in the field lack accurate analysis owing to subtle assumptions, resulting in biased forward and inverse models. Therefore, the reduced number of channels achieved using the existing methods is often not precise and promising enough. Hence, a methodology that effectively balances accuracy and computational efficiency is crucial. The paper works to address this trade-off from a few perspectives.

1.3 Research Objective

Emotion recognition using EEG signals has gained immense popularity in recent years. Working with the DEAP dataset[10], the paper aims to achieve a better emotion recognition technique with reduced computational complexity, focusing on the following objectives:

- Reducing the number of channels applying brain source localization is the main objective.
- Use a combination of two feature extraction methods from a set of selected existing ones based on the results of the preliminary experimental analysis, on the reduced set of channels.
- Introducing a refined version of the existing inverse model eLORETA of BSL.
- Evaluating the performances using popular state-of-art classification models after applying feature extraction techniques on the selected channels.

Chapter 2

Literature Review

A literature review is a critical evaluation of the main content of previously published writing on a specific topic. The goal of a literature study is to learn about earlier writing and become familiar with its approaches and strategies on that particular topic. As this research is working on Channel Selection Methods For Efficient EEG-Based Emotion Analysis, in the literature review, this paper notes down other existing papers methods and the algorithms used. This paper made an effort to collect several works of literature that are relevant to the papers domain, where the same task is accomplished in various ways.

2.1 Review of Existing Related Works

In the paper "EEG channel selection strategy for deep learning in emotion recognition" [33], it is mentioned that one of the most important aspects that needs to be taken into account while processing EEG signals is feature engineering. It is closely tied to the best choice of measuring electrodes and involves a number of EEG signal preparation techniques. For instance, some of the important processes can be feature extraction, filtering of the different bands of received frequency signals, a method called 'downsampling' etc. The authors in the paper made use of the RCA (Reverse Correlation Based Algorithm) algorithm in order to get information about channels that closely represented emotional states. Eventually, an optimal selection of electrodes from 11 channels was made. In the paper, the authors also made use of the 2D model of valence-arousal, proposed by Russell. The emotional changes in the model range from 1 to 9, with 5 being neutral. Later, all the experiments on the EEG signals from the selected channels were done on a CNN architecture consisting of a total of nine layers. Two layers were for input and output, and the rest were seven hidden layers. The result of all these experiments showed that the learning time was dramatically shortened for both arousal and valence. The time gain ranged from 29.68 minutes to 79.77 minutes, with an average of 49.53 minutes for arousal and 48.05 minutes for valence. Moreover, the arousal categorization accuracy was improved. Although the valence categorization accuracy was slightly worse than expected, this difference was not statistically significant.
However, the authors of a different study by Avidan, Yazdchi, Baharlouei and Mahnam,[36] sought to create an algorithm that could estimate just valence as a continuous variable while utilizing the fewest features and channels possible. This study allowed for more practical application as the emotions they worked with were contin-

uous and not discrete. For the feature selection part of the study, irrelevant features were excluded using several regression based methodologies. This helped the authors avoid all kinds of over-specification problems, which eventually resulted in a reduction in computational complexity. From the entire dataset, 3216 significant features were selected through the application of an algorithm (RReliefF). Those were passed onto three different convolutional regression models (LR, SVR, and MLP) for further specific results on emotion recognition. The evaluation of various feature categories revealed that gamma band-related variables were more important for recognizing emotions than any other band of frequencies. F7-F8 and FC2-T7 were chosen as the best channels. These channels had the best single electrode feature accuracies. Moreover, an important finding of this study that should be taken into account is that the chosen characteristics and electrodes were more accurate in estimating lower valence (negative emotions) than higher values (positive emotions).

Researchers in the article "Emotion recognition based on EEG features in movie clips with channel selection" [22] focused on the categorization of EEG signals relevant to positive and negative emotions, using channel selection to investigate the valence dimension. The effective categorization of EEG signals associated with various emotions was obtained through the strategic use of channel selection and machine learning algorithms. This categorization technique was done by channel selection during preprocessing. Self-Assessment Manikins (SAM) questionnaires were used by the researchers to assess emotional states, generating useful data for further study. For the categorization of EEG data, two machine learning approaches were used by them which are the k-nearest neighbor (kNN) and the multilayer perceptron neural network (MLPNN) algorithm. Surprisingly, the MLPNN and kNN algorithms achieved average overall accuracies of 77.14% and 72.92%, respectively. The essential components affecting classification performance were discovered to be feature and channel selection. Also, utilizing the MLPNN algorithm, dynamic channel selection was crucial in finding the most effective channels, resulting in the successful selection of five channels, which are AF3, FC2, O1, P3, and Fp1, from an initial set of 32 channels. This paper suggested potential future research directions, such as investigating different frequency bands in emotional activity analysis and incorporating additional physiological signals such as body temperature, blood pressure, respiratory rate, and GSR to improve emotion classification efforts.

In the paper "PNN for EEG-based Emotion Recognition" [18], researchers used the probabilistic neural network (PNN) as a classifier and extracted features from four EEG frequency bands to distinguish different emotional states within a dimensional valence-arousal emotion model. In addition, they provided a channel selection strategy that is intended to reduce the number of EEG channels used in classification, thereby improving computing efficiency and ease. This paper proved the value of the probabilistic neural network (PNN) as an effective strategy for EEG-based emotion identification, outperforming the support vector machine (SVM). Also, this study emphasized on the higher frequency bands, which are beta and gamma, in emotion categorization, and it also outperformed lower frequency bands like theta and alpha. The ReliefF-based channel selection technique simplifies the practical use of EEG channels while preserving robust classification accuracy with PNN. The findings pave the way for further study into multiple classification algorithms, alternative feature extraction methodologies, and the effect of different frequency bands

on emotion categorization accuracy.
Another study titled "elieff-based EEG sensor selection methods for emotion recognition" [19] applied three different strategies to detect the best channels while capturing EEG signals in order to precisely classify four states of human emotion (joy, fear, sadness, and relaxation). As we already know that the most refined information related to emotion processing comes from frontal and parietal lobe sensors placed on the scalp, most researchers concern themselves with channel selection using data from sensors located in these parts of the brain. This study is no exception to that. Firstly, a succession of band pass filters were used for feature extraction. The raw data, divided into specific frequency bands, was processed, and each band's power was then estimated using a method called '512-point fast Fourier transform' or in short, FFT. Four of the most significant features from each of the 32 channels of the dataset were shortlisted. Then, using a ReliefF algorithm, the weight of each feature was computed, and the features were all ranked according to the weight obtained. A higher weight indicated the greater importance of that particular feature, and the opposite was true for features with lower weights. Secondly, channel selection was done on the basis of two main theories, one considering a 'feature' as a unit and the other considering each 'channel' as a unit. The first way of selecting channels was to include channels with the top-N features. The other approach was to simply calculate the weight of the entire channel (using MRCS: mean-ReliefF-channel-selection), regardless of what features it carried. If the weight of a channel is higher, it indicates that the channel has a positive contribution, and a lower channel weight would indicate the opposite. This was to estimate how much the channel as a whole contributed towards the goal of emotion classification. The results obtained were further optimized with the use of a Support Vector Machine classifier. The channels here (SVM-MRCS) were chosen on the basis of their respective weights and contributions to emotion classification accuracy in comparison with the classifier. Lastly, MRCS and SVM-MRCS were fairly compared, and the results suggested that SVM-MRCS certainly performed better in terms of channel selection. The study also showed proven results regarding high frequency bands being more crucial for processing emotions in general.
In the research paper "Emotion recognition with machine learning using eeg signal" [23], a variety of approaches are used to extract characteristics from EEG signals in three domains that are time, frequency, and combined time-frequency. The wavelet transform was used to divide these signals into precise frequency bands, reducing time-resolution loss. Choosing the suitable main wavelet was a critical step in this procedure. Previous studies have investigated the use of several classifiers, such as KNN, ANN, and SVM, to characterize emotions based on retrieved EEG data. This research successfully built an emotion recognition system based on EEG data and machine learning algorithms, and it showed exceptional accuracy in recognizing emotional states. Also, the SVM classifier with the RBF kernel achieved excellent performance in the beta frequency band, using 10 EEG channels out of 32. In addition, the SVM classifier outperformed the KNN and ANN classifiers in terms of emotion recognition accuracy. Finally, the researchers suggested that other transformations, such as linear discriminant analysis or independent component analysis, could be used to improve the performance of the recovered data.
A research by Tong, Zhao, and Fu [26] focuses on the ReliefF algorithm application for optimizing the EEG channel selection process. Its main goal is to select optimal

combinations of electrodes and reduce EEG channels in brain data. With this goal in sight, at first the frequency of EEG data is observed. Later, filtering through a bandpass filter is done. According to the findings of several observations, the authors further conducted feature extraction, so that signals could be recognized and classified. The research also stated that finding the appropriate features gives us confirmation of subsequent data processing. Also, the paper focused more on learning the time domain features than the frequency domain features. This entire feature selection part was done based on principal component analysis (PCA). A single and multi-feature comparison chart was also given, from which we learned that the energy, energy ratio, root mean, and entropy characteristics of not too good bands have been extracted. Finally, after feature extraction and algorithm application, average recognition accuracy reached 72.03% and 71.7% in two batches of experiments with 13 channels and 6 channels, respectively.

Researchers explored the most relevant EEG channels in order to decrease computing complexity and noise in the paper "Emotion recognition using a reduced set of EEG channels based on holographic feature maps" [40]. In this paper, researchers used the ReliefF model, neighborhood component analysis, and computer-generated holography. ReliefF and neighborhood component analysis techniques are used for optimum electrode selection, and computer-generated holography was used to create holographic feature maps in this paper. Also, machine learning and deep learning methods are used in conjunction with these efforts to extract characteristics and categorize emotions within a three-dimensional emotional space. Significantly, this research achieved cutting-edge emotion identification results, with outstanding accuracy rates of 90.76% for valence, 92.92% for arousal, and 92.97% for dominance. Also, researchers suggested looking at cross-dataset validation, real-time implementation, and gender-specific emotion recognition for any future developments.

According to a paper by Moctezuma and Molinas [31], the EEG signals are first divided using either the EMD or the DWT. Then, for each sub-band, they compute attributes like instantaneous and total energy as well as Higuchi and Petrosian fractal dimensions. To build a model for each subject, these features are fed into the local outlier factor (Lof) method. The objective is to eliminate cases that are unrelated to the subject and learn from the model. The authors reduce the necessary number of EEG channels by using the NSGA-III. With a small subset of EEG channels, they can identify a person and reject invaders using this method. Resting-state EEG signals are easier to acquire than task-based EEG signals and can provide more stable and reliable features for biometric identification. In contrast to deep learning methodologies, which require a lot of data and training time, the authors stress that their methodology can be effective with less data. Resting-state EEG signals can also provide a more natural and less stressful environment for the subject, which can lead to more accurate results. In future studies, the authors will address their methodology in comparison to other feature extraction and selection approaches as well as session-to-session variability analysis. Additionally, they point out that their strategy can be applied to other biometric modalities, such as electromyography (EMG) and electrocardiography (ECG), as well. Overall, [31] presents an innovative approach to biometric identification using EEG signals and provides valuable insights for future research in this area. By using resting-state EEG signals and a minimal subset of channels, this approach has the potential to be a more efficient and accurate method for biometric identification.

In order to increase the precision of emotion recognition utilizing electroencephalography (EEG) signals, this research by Gannouni, Aledaily, Belwafi, and Aboalsamh [35] investigates a novel technique. By providing a cutting-edge channel selection technique that adjusts to unique brain function and emotion states, the study tackles the shortcomings of current techniques. To increase accuracy, it also uses epoch identification, which identifies the peak of emotional excitement. The research uses the numerator group-delay function to identify epochs inside each emotional state and the zero-time windowing method to retrieve immediate spectral information. Using the DEAP database, two classification methods—a quadratic discriminant classifier (QDC) and a recurrent neural network (RNN)—are deployed and assessed. Results show that the suggested technique performs competitively, averaging an accuracy rate of more than 89%. The approach also improves accuracy by 8% over existing algorithms for identifying nine emotions. The proposed method performs better than similar methods that merely deal with three to four emotions. The study emphasizes the method's potential for affective computing, advancing the creation of EEG-based systems for automatic emotion recognition with ramifications for a number of industries, including psychology, marketing, and healthcare.
From the research titled "channel selection method based on cnnse for eeg emotion recognition" [29], we learned that the researchers proposed a novel channel selection framework, CNNSE. This framework is used in research to select optimal EEG channels. The article examines wavelet entropy along with the wavelet coefficient (WEAVE). In this study, two strategies have been proposed to process signals: perform channel selection and use all channels for research. Since, using all channels carries more computational complexity and overfitting problems, using a channel selection algorithm would be much more effective. It also discussed different channel selection methods proposed in recent years. In this study, after processing the data, feature extraction is done for each sample of 7440 samples, which contains 32 EEG channels. Here, for feature extraction, the wavelet transform was used. And for channel selection, the Squeeze-Excitation block was used, which consisted of three main operations: squeeze, excitation, and reweight. The result of this research showed that using 7 channels led the authors to achieve an accuracy rate of 69.59%, and using 18 channels led to 73.74% accuracy. In conclusion, after comparing all the results of the datasets, the paper claimed that the new method that has been proposed worked greatly in reducing the number of channels and obtaining a high recognition rate. In this method, different emotions are classified using SVM, and 7 and 12 channels were selected that provided the best results for valence emotion recognition. Thus, this study provided a new idea in the EEG channel selection study through the application of a new method (Squeeze-Excitation).
The study by Joshi and Ghongade [30] discusses the difficulties that students in the 14–25 age range encounter as a result of anxiety, nervousness, and stress. According to the paper, the authors significantly reduced the number of EEG channels to gauge anxiety or stress intensity and take the necessary actions so that physical and psychological issues can be avoided. The paper used feature extraction methods like Hjorth Parameters, DE, and the Linear Formulation of DE. The research emphasizes how crucial it is to create a simple yet accurate and practical method for identifying emotions in people and providing them with the assistance they require. Additionally, the article highlights the significance of scientific research in analyzing the mental health of humans and handling pressure, which is caused by competition,

fears, etc. All of these are discussed to reduce the number of electrodes used and present a novel "Hierarchical Spatial-Temporal Neural Network model" for EEG emotion recognition. [30] also examined the importance of using fewer electrodes. In a nutshell, [30] provides valuable insights and their potential applications for society.

The authors of the paper "A review of channel selection algorithms for eeg signal processing" [14] primarily addressed why improving the efficiency and accuracy of EEG signals is important, and then they discussed how that can be achieved efficiently. According to them, the working strategy involves generating candidate channel subsets using search algorithms and evaluating their performance using various techniques. The channel selection techniques are done using 5 main categories, which are named as filtering, wrapping, embedded, hybrid, and human-based techniques. For the process of channel subset generation, all five of these techniques are reviewed. While reviewing, the study found out some advantages of the filtering techniques but this yields low accuracy in some cases, since in this technique the combinations of different channels are not considered. It is determined that filtering techniques are less computationally expensive than wrapping techniques. The reason is that both classifying and searching algorithms are used here for each candidate's evaluation. Then, based on recursive channel elimination, come embedded techniques. Since contrast wrapping techniques are computationally less expensive, they are used. Lastly, hybrid techniques are a combination of both wrapping and filtering techniques. In this research, researchers primarily focused on identifying efficient channels by overviewing different techniques used for channel selection and their applications in various EEG signal processing tasks.

The research by Moctezuma, Abe, and Molinas [39] provides a study that takes a CNN-based approach to investigate how human emotions differ from EEG channels. The paper, which made use of the DEAP public dataset, discovered that when it came to emotion recognition, utilizing just one EEG channel was just as accurate as using all 32. The research also suggests a technique for selecting EEG channels that is more accurate than using all 32 channels and uses the NSGA-II. [39] made use of the DEAP public dataset, which includes 32 participants' self-reported emotional reactions to 40 music videos along with their EEG signals. The EEG data were bandpass filtered and segmented into 1-second epochs as part of the research's preprocessing. The individuals' emotional reactions were then classified based on the EEG data by the study using a CNN-based methodology. According to the paper, emotion detection using a single EEG channel was just as accurate as using all 32 channels. The authors also found out that the choice of EEG channels had a big impact on how well people could recognize emotions. To select the most useful EEG channels for emotion identification, [39] suggested an optimization strategy using NSGA-II. The research discovered that employing the optimal mix of EEG channels led to greater accuracy than using all 32 channels. The paper makes a contribution to the field of emotion recognition by proving the efficiency of using a single EEG channel and outlining a method for choosing meaningful EEG channels through optimization. The discovery has ramifications for the creation of wearable technology that can instantly identify human emotions.

The role of emotion in human communication is first discussed in the paper by Wang, Hu, and Song [28], along with how physiological signs like EEG can accurately depict emotional states. There are four main steps in the suggested process:

Data with a high density of EEG were gathered. The STFT program then generated the EEG spectrogram. A spectrogram is used to compute the NMI connection matrix. In this paper, it is found that the following technique can reduce channels that utilize the connection matrix. To find the best subset of EEG channels for wearable technology to recognize emotional states, the study suggests a channel selection strategy. The proposed method beats previous methods in terms of accuracy and efficiency, according to the paper's comparison of the two. Also, the DEAP dataset was used in this paper. The result of this paper showed that the suggested method can be used to select the best EEG channel subsets, and it also achieved a high accuracy of 73.64% for arousal and 74.41% for valence with the SVM model. References to related studies on emotion identification and EEG seizure detection are also provided in the publication. Potential applications for the proposed approach include virtual reality emotion recognition, human-robot interaction, and mental health monitoring. This concludes that optimal channel selection can be done by using this method, and researchers proved that it maintained a high accuracy and reduced hardware complexity so that it is suitable for designing wearable devices in the future.

The authors of the study [20] focused on getting a desired level of reduced channels while maintaining accuracy. A band-pass filter is one of the benefits of Wavelet, and another benefit is denoiser, which also estimates inter-segment regularity, and is a proxy for determining the pattern's form. The study states that for feature selection, NMI has been proposed. WEAVE is proposed to categorize high/low levels of valence and arousal emotions. SVM is also discussed in this study. To reduce the mistranslation effect, the RBF kernel function has been applied, by which a subject of grouping was conducted as this function calculates each person's transformation matrix (from the EEG characteristics, which are connected to their own emotion rating). Later, through the use of five main steps: Segmentation, Extraction of Wavelet features, formation of WAEVE, value computation (NMI), Analysis of features, and channel reduction with the help of NMI, SVM classification, the proposed method has been justified. At the end of the research, the analysis shows that arousal got less accuracy, which is 76.8% to 73.5%, whereas valence got better accuracy than this, which is 76.8% to 73.5%. Moreover, the NMI algorithm allows a reduction of 32 to 16 EEG channels, with a less than 8% accuracy loss.

This paper by Yildirim, Kaya, and Kilie" [38] gives an idea about a critical need in the realm of human-computer interaction, directed by the increasing demand for applications that can recognize and respond to human emotions. The goal of those applications is to smooth the path to more natural and effective communication between humans and computers, which requires the creation of reliable automatic emotion recognition systems. This study concentrates on recognizing emotions from Electroencephalogram signals, which are a type of physiological information that depicts the brain's electrical activity. EEG signals are extremely helpful for emotion identification algorithms because they provide a discrete and challenging to fake source of emotional information. Finding the most important elements in EEG signals that may accurately reflect various emotional states is one of the primary problems in this field. The research uses a thorough methodology, extracting a total of 736 characteristics from the EEG data based on spectral power and phase-locking values. These characteristics provide a rich dataset for emotion detection by capturing details about the frequency and phase connections of brain activity. This study is unique in that it chooses the most important elements for emotion identification using swarm intelligence (SI) algorithms. In this case, feature selection is done using SI algorithms, such as Cuckoo Search (CS), Particle Swarm Optimization (PSO), Dragonfly Algorithm (DA), and Grey Wolf Optimizer (GWO), which are commonly employed for optimization tasks. Using this method, it is possible to identify the subset of traits that are most useful for differentiating between positive and negative emotions. These feature selection procedure findings are stunning. The study offers average accuracy rates for multiple categorization algorithms ranging from 56.27% to 60.29%. Notably, the average accuracy maintains an incredibly high 60.01% even when the feature count is lowered by 87.17% (from 736 to 94.40 features). This shows how well the chosen characteristics work to extract the essence of emotional states from EEG data. Additionally, the study pinpoints particular scalp electrode sites that are particularly significant for emotion identification. The study reveals 11 prominent electrode channels dispersed across distinct brain areas by examining attributes that are consistently chosen by all SI algorithms across several participants. The ability to identify the most informative recording spots is crucial for improving EEG-based emotion identification systems.

The study by the authors Farokhah, Sarno, and Fatichah [42] discusses the importance of and difficulties of utilizing EEG data to detect emotions. The suggested method comprises picking the most accurate 2D CNN architecture and the optimal channels for emotion identification. The main focus of the proposed method is employing only selected channels. The study selected 10 channels and used the proposed method for providing results on the basis of a CNN architecture. The study also analyzes the accuracy rates of previously proposed methods in the same field. To accomplish the proposed method, the data was downsampled to 128 Hz, EOG artifacts removed, and bandpass frequency filtering performed from 4-45 Hz. The STFT method is used to transform raw EEG data, which is later stored as RGB images using the MATLAB (octave and oc2py) library in Python. Once the Spectrogram generation is complete, emotions have been classified. After the experimentation, the study produces a table, where the precision, recall, accuracy, and Fl score of 32 channels have been shown. Among them, the 10 best channels were selected to compare with the NCA and ReliefF methods, which also use 10 channels. After conducting two experiments—emotion recognition for intra-subject and emotion recognition for inter-subject—this comparison was applied. Therefore, the experiment shows both the results using 32 channels and 10 channels. The study works with three aspects. The improvement of accuracy performance while employing 32 channels, both intra- and inter-subject, has been one of them. Another one is to select the most significant channels only. Third, the trade-off between the complexity of the design and the performance metrics is considered. This study shows a simpler and more effective method for EEG channel selection.

In a paper by Meng, Yan, and Xu, they tried to point out that in the study of EEG, the researchers have increasingly concentrated on particular brain areas and frequency bands in [21]. In order to extract EEG features for this research, EEG electrodes are divided into several areas based on symmetry and distance principles. They do, however, draw attention to an important drawback of this strategy, namely the disregard for emotional connections and variations across particular EEG channels. This error may have an effect on both the efficacy of emotion detection systems and the representation of EEG features. The research suggests a unique channel selection strategy based on "maximum correlation, minimum redundancy" to solve this constraint. This method's central premise is to carefully pick EEG channels that are both significantly linked to emotional states and barely redundant with one another. With the help of this technique, the channel selection procedure will be optimized for better emotion identification precision. They outline their approach, which includes computing feature weights for each EEG channel using the ReliefF algorithm. In order to apply various weights to information, ReliefF evaluates the association between each feature (in this example, the EEG channel) and the emotional category. The study emphasizes how this process enables measurement of the relationship between each channel and emotional states. The researchers then move on to channel redundancy after calculating channel weights. The redundancy between EEG channels is measured using mutual information. This stage makes sure that the chosen channels supply diverse and non-redundant information, in addition to being highly relevant to emotions, in order to increase classification accuracy. An experiment and assessment part is included in the paper's conclusion. In this section, the writers go over the findings of their research, which include pinpointing the best pathways for emotional analysis. They illustrate how channel weights are distributed among various brain areas and sexes, showing that some regions, like the frontal and temporal lobes play a more important role in processing emotions. By assessing the correctness of several emotion classifications, the authors further demonstrate the potency of their channel selection strategy.

While some researchers are working on getting optimal results using existing methods and algorithms, others are proposing new models with different methodologies and algorithms. Research with a similar vision was done by some authors [24], who proposed a hybrid model. The reason behind calling this model a 'hybrid' is because their work focused not only on feature and channel selection but also on sample selection. In addition to that, they emphasized the importance of having a set of hardware with simplified sensor structures so that we can use EEG-based emotion detection effortlessly and continuously in our daily lives. To be more precise, the desired framework suggested having three things; an internet-enabled system, a suitable, non-complicated hardware setup, and an ideal data processing plan. For the purpose of making the sensor setup simple, a very obvious step was feature and channel selection. Firstly, the feature extraction in this paper was done through primary spectral processing (EEG signal processing). Some existing, less important feature removal techniques were also applied. Next, for each channel, a feature vector with just the important parts was created. All these vectors then formed a universal vector set with the help of the DE (Differential Entropy) method. On the basis of this DE feature selection, a sparsity-constrained fitness function was deduced. The guiding principle was that the original vector should be replaced if the newly generated one resulted in a greater value of the fitness function. The scheme developed in the research had 5 channels with 40 features, which provided them with a recognition accuracy of 69.73%. The reason this scheme works so well is that it takes into account the connection between features, channels, and a QDA classifier. This clearly achieved better accuracy than ReliefF and mRMR. Also, the usage of the suggested technique was extremely important in cutting the number of channels to almost 1/4-1/3, which was the main motive.

In a different study titled "EEG emotion recognition using improved graph neural network with channel selection" [43], the authors suggested a novel method for classifying emotions using electroencephalography (EEG) data. This method has important medical implications, particularly for the study of autism and the identification of emotions in pregnant women. They focus on the inherent heterogeneity in the number of EEG channels used for data collection, and this can make simulating the information flow in the human brain challenging. To solve this problem, they provide a brand-new model called the channel selection graph neural network (CS-GNN). In order to capture both intra-channel and inter-channel EEG properties, this model makes use of both 1D convolution and graph convolution approaches, giving a thorough knowledge of the challenging EEG data. The authors also add functional connectivity data to the network structure to further simulate the complex connections between various brain areas. Their method's adaptable channel selection mechanism, which enables the dynamic selection of EEG channels based on attention distribution within the graph structure, is one of its significant innovations. The experimental findings using a variety of EEG datasets, including as DEAP-Twente, DEAP-Geneva, and SEED, show the CSGNN model to perform exceptionally well, outperforming other models in the categorization of emotions. Interestingly, the model retains competitive accuracy levels even when only 20% of the EEG channels are used, demonstrating its cost-effectiveness. Overall, this research makes a substantial contribution to the realm of affective computing by providing a potential method for EEG-based emotion recognition and by opening up a wide range of healthcare applications.

Another study on emotion recognition by Zheng, and Lu [17] used Deep Belief Network (DBN) models. In this research, researchers used EEG-based emotion detection models. Mainly, they worked on the emotions that are positive, neutral, or negative. For feature extraction, researchers used three different approaches in this paper. They are the supervised and unsupervised fine-tuning, unsupervised pre-training. They also used Differential Entropy (DE) as a useful feature to evaluate the complexity of EEG data and separate low and high-frequency energy patterns. The testing results supported the durability of the selected electrode set pools, resulting in consistent performance across individuals and trials. In this paper, the SVM model achieved the highest accuracy by using the 12 selected channels. These findings highlight DBN models' better performance over shallow alternatives such as Logistic Regression (LR) and SVM, which proves the dependability of DBN models in recognizing distinct emotional states from brain activity patterns. Finally, for future improvement, researchers suggested the use of Electroencephalography (EEG) data as a dependable resource for emotion recognition in the context of real-world applications enabled by wearable devices and advanced electrode technologies.

To understand the neural activity of the human brain, which is required for the successful diagnosis of various neurological disorders such as epilepsy, depression, and schizophrenia, brain source localization (BSL) is one of the most effective methodologies, as stated in the paper "A robust eloreta technique for localization of brain sources in the presence of forward model uncertainties" [44]. Among the popular techniques for source localization, exact low-resolution electromagnetic tomography is one of the most accurate ones. This source localization technique is highly sensitive to forward-model uncertainties. Variations in the head geometry while constructing the head model, variations in conductivity, and even electrode positioning may result in uncertainties that are capable of faulty lead field matrix creation. Such a lead field matrix, even with a slight mismatch, can significantly degrade localization accuracy.

Potential solutions to this problem include beamformers, Bayesian approaches, and conductivity fitting. However, none of these approaches have successfully solved the issue. Therefore, to address this problem, the researchers of this paper [44] have developed a robust modification of eLORETA that iteratively works to minimize the uncertainties mentioned above. The introduced ReLORETA reliably localizes high brain activity regions, computed using an optimally regularized lead field matrix.
The lead-field matrix is one of the important components for EEG source localization as it aids in associating particular brain regions with the electrode signals. The author of the paper titled "Computation of the lead-field matrix" detailed how they implemented the AAL2 atlas together with the standard 10-20 EEG system to build such matrix using MNE-Python and the Matlab FieldTrip toolbox [45]. The focus here was to make it possible to incorporate this model into neural simulations, thereby increasing the accuracy of the EEG forward model. The work identifies several important issues, such as the errors most likely to be made in localization when the head models, conductivity, or electrodes changes. To address these concerns, they analyzed various numerical approaches, for example, the Boundary Element Method, Finite Element Method, or Finite Difference Method. In terms of performance, BEM was more favorable than both FEM and FDM because of its speed, but also accuracy. The source model helped enhance their work by enabling them to create BEM models of the head using the fsaverage MRI template. But they did recognize shortcomings to their approach, such as the absence of structures beneath the cortex such as the cerebellum and thalamus and the method used for generating the surface source. Their artificial intelligence model still needs to be improved and they argued that modeling the head with FEM is one way to achieve it. This study emphasizes the need for improving lead-field matrices for EEG based mapping of brain activity to achieve better results.
According to a paper by the researcher Pascual-Marqui, it is possible to perform multi-channel EEG/MEG source localization with no error by adopting a completely new approach [7]. Recording errors are common and often unavoidable because of noise and the approximations of the head. This paper presents sLORETA (standardized low resolution brain electromagnetic tomography) and eLORETA (exact low resolution brain electromagnetic tomography) as potential solutions to these issues. They refine source localization by mapping the electrical signals from the brain to the scalp electrodes. The central focus of this study is the estimated lead-field matrix method, which describes the relationship between the recorded scalp potentials and brain electrical sources. In addition, eLORETA is a true inverse solution instead of just an approximate one, unlike sLORETA which simply provides reasonable estimates without biases. This also sheds light on the more intricate structures of the biological signals and noise. Other inverse techniques such as weighted minimum norm solutions and adaptive quasi-linear imaging are also investigated. These conditions reveal the improvements done, but defects in the head modeling still need further improvements. This research corresponds to efforts dealing with enhancing EEG-based brain mapping for the accurate identification of the active regions in the brain.
Another study by the researchers Pascual-Marqui, Faber, Kinoshita addresses the accuracy of EEGs and MEGs in neuroimaging with a focus on concentration as well as errors [25]. The study analyses sLORETA, eLORETA, Minimum Norm Estimate (MNE), Dynamic Statistical Parametric Mapping (dSPM), and Linearly

Constrained Minimum Variance Beamformers (LCMVB). It's demonstrated in the findings of the study that sLORETA and eLORETA enable zero-error localization, on the other hand MNE, dSPM, and LCMVBs have difficulty preserving accurate localization. The hypothesis of false positive activity is also researched; identifying inactive areas of the brain as active. It has been established that MNE, dSPM, and LCMVBs are overestimate neural activities, unlike eLORETA where false activations are at their lowest, and thus more reliable.In addition, eLORETA does provide more accurate estimates of functional connectivity than all other methods of analysis. This supports the claim of a better comprehension of cerebral interrelations. As a result, this demonstrates how crucial the choice of inverse modeling technique is in EEG and MEG research which are explicitly concerned with the activations of neural systems in the head. This corroborates and provides additional validation on the efficiency of eLORETA as an estimation technique.
The paper by L´opez, Penny, Espinosa, and Barnes proposed a Bayesian framework for MEG source reconstruction, addressing lead-field matrix uncertainties that arise from head shape variations, electrode placement errors, and tissue conductivity differences [11]. Although this work's focus is not EEG, it is relevant because it is a method for computing forward solutions of the brain source localization which is also used for EEG specific data. Brain source localization methods traditionally assume a perfectly known lead-field matrix. But in reality, the perfect lead field matrix is very complicated to achieve and is capable of degrading the quality and accuracy of the BSL outcomes significantly. To overcome this, the authors introduce a probabilistic approach that accounts for these uncertainties, making neural source estimation more robust and reliable. Their method frames MEG source localization as a Bayesian inference problem, where both source activity and lead-field uncertainties are modeled as probabilistic variables. By iteratively updating prior distributions, the framework reduces errors caused by inconsistencies in the forward model. This results in more accurate localization compared to traditional techniques like Minimum Norm Estimation (MNE) and beamformers, though at the expense of higher computational costs due to iterative sampling. The study underscores the critical impact of lead-field variability on localization accuracy, demonstrating that flexible prior modeling enhances stability and precision. These findings highlight the need for more refined forward modeling techniques in EEG/MEG research, offering a promising direction for improving brain activity mapping in real-world applications.

2.2 Key Findings of the Reviewed Papers

After reviewing and analyzing the existing literature in this field, it is evident that many research efforts have contributed significantly to EEG-based signal processing for the purpose of efficient emotion recognition. These studies investigated and explored various feature extraction techniques, algorithms, classification models and brain source localization techniques. However, there are several limitations which are noted below. These shortcomings in the reviewed studies highlight areas that require further investigation and improvement.

- Some researchers assumed idealized lead-field matrices which are not in alignment with the actual lead field matrix. Because in reality, variations in head geometry of certain subject participants exist, electrode place issues may have occurred or varied tissue conductivity may have encountered. Therefore, these assumptions resulted in inaccurate calculation of the forward models in the brain source localization approaches.

- Another major limitation involving the forward model construction is that most of the researchers worked with the peripheral regions of the brain only, excluding the parts such as cerebellum, thalamus, and hippocampus which are considered to be major areas of emotion processing. The refined versions of MNE which are dSPM and sLORETA, often fail to localize the activities generated in those deep locations of the brain, far from the electrode, thus struggling with spatial blurring and depth related biases.

- A popular inverse model of source localization eLORETA tries to improve on the flaws mentioned in the previous point. Although it does its job quite well, the lack of a perfectly constructed lead field matrix in the forward model makes it biased, affecting the overall localization accuracy.

- Furthermore, methods like beamformers and functional connectivity analysis suffer from false positive activations, resulting in misleading interpretations of brain network interactions.

Reflecting on these limitations, it is safe to assume that there are scopes for improving the brain source localization methods by focusing on how the true lead field matrix can be obtained, one that will result in zero-error source localization, maintaining the computational efficiency. Thus, the aim of this research is to optimize channel selection focusing on enhancement of the existing techniques to ensure more reliable identification of brain activity regions related to emotion processing.

Chapter 3

Dataset Description

This paper uses the DEAP (Database for Emotion Analysis using Physiological Signals) dataset[10], which is a widely used resource for studying emotion detection. It contains EEG data collected through 40 electrodes placed on different regions of the scalp, along with 8 other auxiliary channels. However, data from only 32 electrodes, as depicted in figure 3.1 hold the most necessary information for emotion analysis.

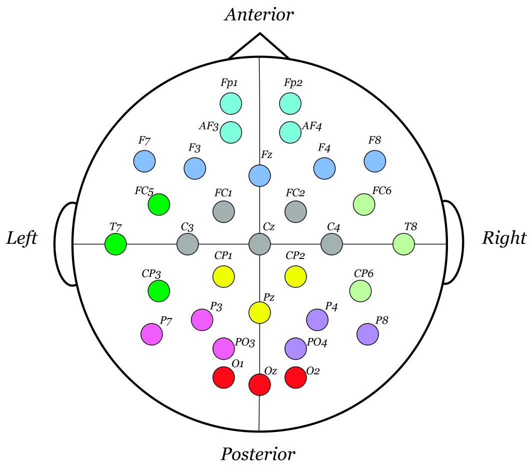


Figure 3.1: 32-Channel EEG Electrode Placement by Brain Region

Brain Region	Electrode
R^1 (prefrontal)	Fp1, Fp2, AF3, AF4
R^2 (frontal)	F7, F3, Fz, F4, F8
R^3 (left temporal)	FC5, T7, CP5
R^4 (right temporal)	FC6, T8, CP6
R^5 (central)	FC1, C3, Cz, C4, FC2
R^6 (left parietal)	P3, P7, PO3
R^7 (parietal)	CP1, Pz, CP2
R^8 (right parietal)	P8, P4, PO4
R^9 (occipital)	O1, Oz, O2

Table 3.1: Brain Regions and Corresponding Electrodes

A total of 32 participants watched 40 videos each while their EEG data were recorded. Data was collected at a sampling rate of 512 Hz, for 63 seconds, with each video being 60 seconds long along with 3 seconds of pretrial baseline. Two versions of the DEAP data [10] are used in the work; the original raw data in biosemi format and the Python preprocessed version. A brief discussion of each of the versions is given below for a better understanding of the overall dataset.

3.1 Original BioSemi Version

The Biosemi version of the DEAP dataset contains EEG and physiological recordings collected using the BioSemi ActiveTwo system, stored initially in ".bdf" format files. Each .bdf file is divided into two parts: the header, which is a fixed 256 bytes and contains metadata like participant ID, session details, number of channels, and sampling rate, and the data section, which holds the actual signal recordings. Each file corresponds to one participant's neural and physiological responses to the aforementioned emotional video stimuli having 40 trials of 60 seconds each. The version includes data from all 48 channels, categorized as follows: 32 EEG channels using the 10-20 system, 8 peripheral physiological channels (e.g., Electrooculogram (EOG) for eye movements, skin conductance, respiration, plethysmography, and temperature), and 8 auxiliary biosignal channels (EXG1-EXG8), along with a status (stim) channel for event markers.[10]

Each channel contains 30,720 samples and is stored as 24-bit integers (3 bytes per sample) in an interleaved format, ensuring synchronized recordings across all channels. At each time point, the first sample comes from Channel 1, the next from Channel 2, and so on up to Channel 48, before moving to the next time point. Each trial's data size is:
48 channels$\times$30,720 samples per channel$\times$3 bytes per sample=4.42 MB per trial.

For 40 trials, this totals approximately 176.8 MB per participant file, containing a total of 58,982,400 data points.

The version's sampling rate and filtering is in alignment with standard EEG preprocessing protocols, ensuring high signal quality. With its rich combination of EEG and physiological signals, this dataset provides a strong foundation for studying emotional responses, conducting EEG source localizations, and analyzing brain activity patterns.

3.2 Preprocessed Python Version

The version contains the already downsampled (from 512 Hz to 128 Hz) data from all 40 channels for further usage. Here, the total dimension of the dataset is 32x40x40x8064 which is demonstrated below.

The version of the DEAP dataset also includes the ratings of each video given by the participants in terms of arousal, valence, like/dislike, dominance, and familiarity for easy analysis of emotion. A detailed 4D as well as 3D visualization of this version

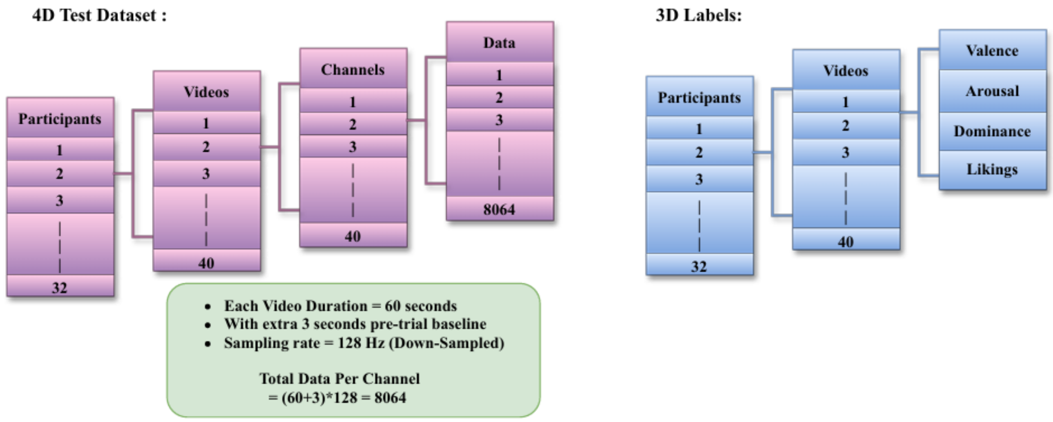


Figure 3.2: 4D and 3D Data Representation

of the dataset is shown in figure 3.2. Here, arousal refers to the intensity of the emotion, while valence refers to whether the emotion is positive or negative[1]. The raw EEG signals of 3 channels for Participant No. 3 are plotted in figure 3.3 for visualization.

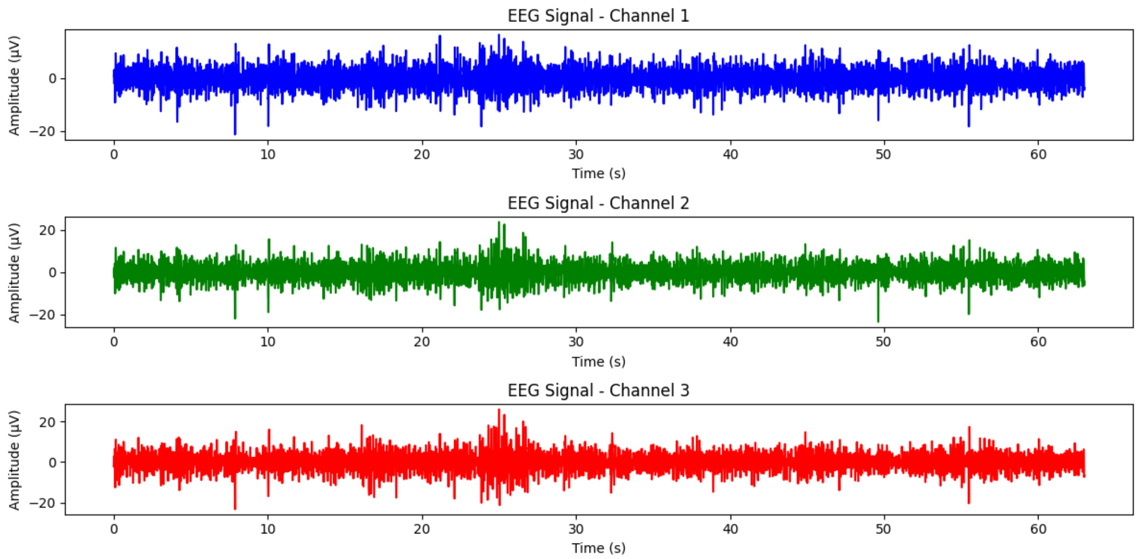


Figure 3.3: EEG Signals (128 Hz)

Chapter 4

Data Preprocessing

4.1 Python Version Preprocessing

Analyzing data from the DEAP dataset is quite a challenge due to its extensive 4-dimensional structure. As the version of the dataset (.dat format) has already been preprocessed, we just simply reshaped the data for the convenience of using it in further analysis. Here, the dimension of the version has been reduced to **1280**x32x7680 by merging the no. of participants and no. of videos; (32x40)=1280 while all the other features remain intact.

4.2 BioSemi Data Preprocessing

The biosemi data of the DEAP dataset is used in this study to efficiently run all the brain source localization (BSL) methods. Compared to the .dat format data, the Biosemi data (.bdf) is bulky and requires proper preprocessing to successfully apply the intended methodologies.

Firstly, all .bdf format files are converted to .fif format. The Flexible Image Format (.fif) is the standard file format used in MNE for storing EEG/MEG along with various other details. This conversion is necessary to ensure compatibility with the MNE library and to utilize the "fsaverage" templates and other .fif files required for accurate source localization, which are not directly available for the DEAP dataset.

Now the data for each of the participants in each .fif format file underwent the subsequent steps of downsampling, cropping, EEG channel extraction, montage setting, and noise reduction one by one. As mentioned above, the initial dataset in the Biosemi format contains 48 channels and 1980928 samples per channel for each subject, recorded at a sampling rate of 512Hz, implying huge data volume and processing complexity. So, the first step is down-sampling the data from 512 Hz to 64 Hz. This step essentially preserves the spectral characteristics of the EEG signals and ensures a reduction in the computational load as well as efficient memory management, significantly reducing the number of samples per channel.

Next, the 3 seconds pre-baseline trail is removed from here too, cropping the data, retaining 3,840 samples (60 seconds x 64 Hz) per channel. To enhance the signals, a bandpass filter of 1-30 Hz frequency is applied. For capturing the most meaningful

EEG data this range of filtering is selected, discarding the unwanted low frequency drifts and high-frequency noise, retaining the core frequency bands.

As most of the methodologies intended to be used are EEG-specific, our next goal is to extract only the EEG channels. However, to do so, removing the projections that come inherently with all the channels in the Biosemi format is necessary. Because without removing the projections it is not possible to change the channel types of the rest of the channels other than the main 32 electrodes on the scalp. On the contrary, these projections are important as some artifacts and noise may appear in the data without it. Therefore, the projections are temporarily removed, all the other channels except the EEG-specific ones are kept and then the projections are restored by reapplying them.

Lastly, since BioSemi systems use a common mode sense (CMS) or driven right leg (DRL) reference rather than a traditional custom reference, referencing is a crucial step that must be handled during preprocessing. Therefore, to align the EEG channels with the standard 10-20 system, which is mainly done for efficient brain source localization outcomes, referencing is applied. Here, the average signal from all EEG channels is calculated and then the average value is subtracted from each channel, minimizing noise and unwanted artifacts, making the EEG signals cleaner and more reliable for analysis.

Chapter 5

Work Plan

Focusing on efficient channel selection methods for EEG signals, the work plan can be broadly outlined in figure 5.1.

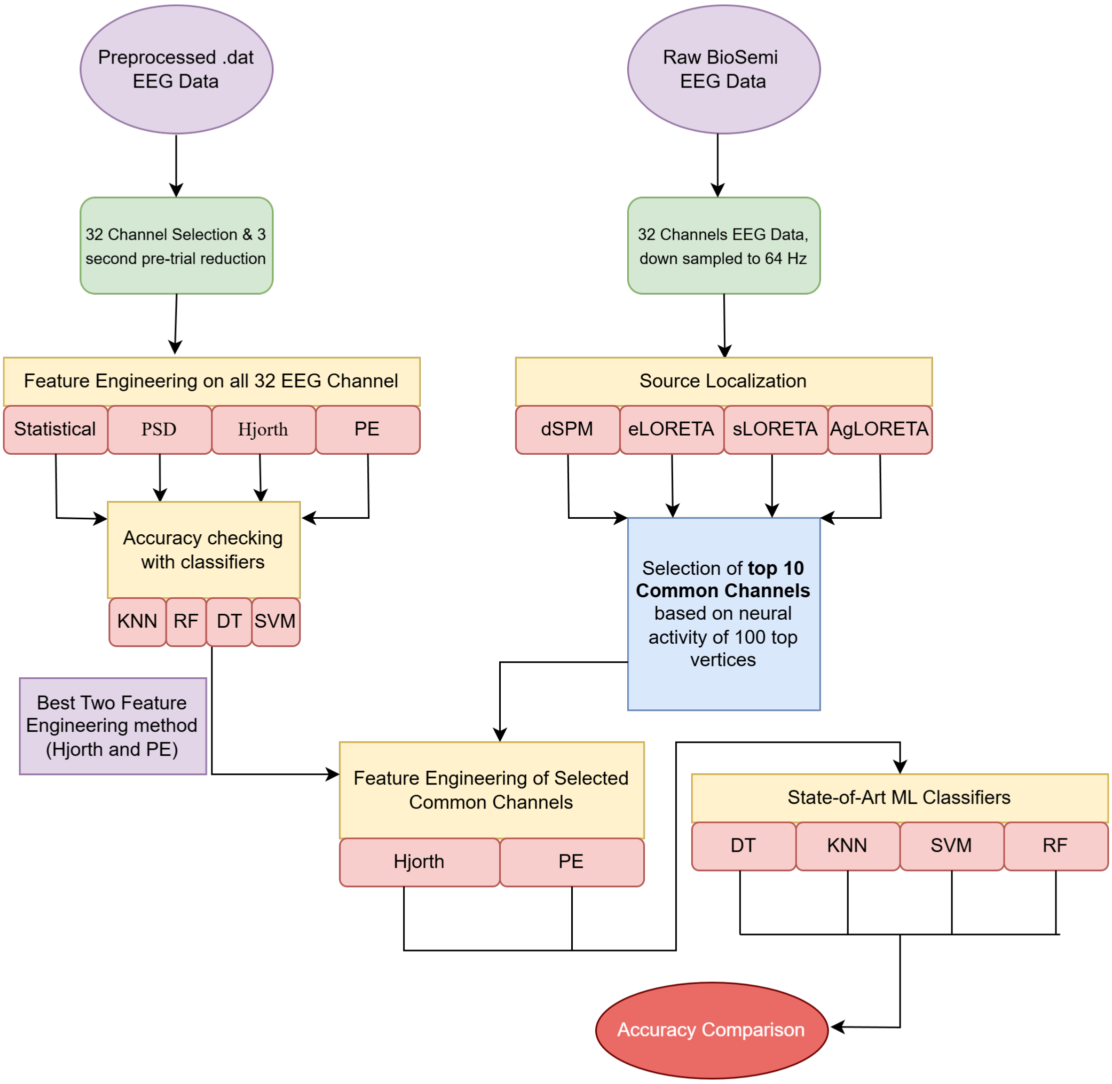


Figure 5.1: Work Plan

Chapter 6

Methods

The models and methods that are used in the research have been discussed in brief.

6.1 Description of the Feature Extraction Models

Feature extraction is an efficient technique utilized to decrease resource requirements while retaining crucial information. The process of feature extraction is essential for enhancing the effectiveness and precision of machine learning models. In this paper, four different methods have been used to extract features from the DEAP dataset.

6.1.1 Method 1: Statistical

Arithmetic Mean - The arithmetic mean is the count of the average or central location of a dataset. It is calculated by dividing the summation of all the values by the number of values.[37] However, the arithmetic mean is sensitive and may not represent the actual central value of a very skewed distribution. Nonetheless, the arithmetic mean remains one of the most commonly used measures due to its simplicity. It applies to most real-world data that often follow normal or symmetric distributions.[37] So the equation is 6.1

$$AMean = \frac{1}{N}\sum_{i=1}^{N} x_i \tag{6.1}$$

RMS - The root mean square, or RMS, is a statistical concept that can offer gentle insight into how quantities vary over time. To calculate RMS, one first observes each data point with care. One then seeks to understand how far above or below the average each observation lies, by squaring these distances. The average of those soft distances from the center is then taken. Finally, to appreciate the overall typical variation, one calculates the soft square root of that average.[41] This RMS value characterizes the natural fluctuations with empathy. Engineers apply this technique to help ease understanding of fluctuating electrical signals, where voltage and currents ebb and flow.[41] Thus the formula is 6.2

$$RMS = \sqrt{\frac{1}{N}(x_1^2 + x_2^2 + ... + x_N^2)} \tag{6.2}$$

Standard Deviation - Standard deviation reflects how unified or diverse a set of values is. It indicates how closely grouped the typical observations sit near the average. To determine this, each value's distance from the mean is first noted.[16] These variances are then averaged in a manner accounting for both concentration and spread. The outcome conveys the overall tendency of data to stray near or far from the central theme. As such, standard deviation enhances statistical portraits, helping reveal patterns across variations. Whether distributions are compact or widespread, they inform meaningful decisions under uncertainty. This respectful measure of diversity proves vital wherever natural fluctuations must be deftly navigated.[16] The formula for STD is 6.3

$$STD = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(x_i - AMean)^2} \tag{6.3}$$

6.1.2 Method 2: Power Spectral Density (PSD)

The power spectral density elaborates on how the power of a signal is distributed across different frequencies. It shows the power of a signal or time series changes with frequency. This paper used a method called Fourier transform to convert the auto-correlation function of a signal. The way the power of a signal or time series is distributed across the different frequencies can be illustrated by PSD.[5] PSD is very helpful in signal processing and is mostly used in describing random signals or characterizing dynamic signals. It also helps in understanding how different frequencies are influenced by different signals. Moreover, the total area under the PSD curve is equal to the total power in the signal.[4] The presence of the dominant frequencies in the signal is indicated by high peaks on the PSD curve. After calculating the PSD, it can detect the frequency that is in a signal, and by that, this paper can also identify if any patterns are repeating themselves. However, this method is very useful in characterizing sound signals, optics, electronics, and other areas where frequency analysis of signals is important.[5] From the papers [4] and [5] the equations 6.4, 6.5 and 6.6 of PSD can be derived.

$$DiscreteFourierTransform, X[k] = \sum_{n=0}^{N-1} x_n.e^{-i2\pi kn/N} \tag{6.4}$$

$$Periodogram, P_k(f) = \frac{1}{L}|X_k(f)|^2 \tag{6.5}$$

$$OverallPSDEstimation, \hat{P}(f) = \frac{1}{K}\sum_{k=1}^{K} P_k(f) \tag{6.6}$$

6.1.3 Method 3: Hjorth Parameters (indicators of statistical properties)

Hjorth parameters were initially presented as quantitative terms that generally characterize an EEG trace. These descriptive parameters are entirely based on time but they can be derived also from the statistical moments of the power spectrum.[8] For this technique, factors include Activity, Mobility, and Complexity. These factors describe a signal's amplitude variance, frequency variance, and shape of a signal, respectively.[13] The technique connects a traditional frequency-domain explanation

with a physical time-domain interpretation. Additionally, the parameters are derived from the idea of variability, which grants them an additive quality, allowing the measured values to apply to any fundamental components that make up a complex curve through superimposition.[34]
The Hjorth Activity parameter is related to the signal's variance. Mathematically it can be represented as 6.7-[13]

$$Activity = var(y(t)) \tag{6.7}$$

Hjorth Mobility parameter stands for the average frequency or the ratio of standard deviation in the power spectrum. Mathematically it can be represented as - 6.8[13]

$$Mobility = \sqrt{\frac{var(y'(t))}{var(y(t))}} \tag{6.8}$$

The Hjorth complexity parameter is determined by dividing the Hjorth mobility of the signal's first derivative by the signal's own Hjorth mobility. Mathematically it can be represented as -6.9[13]

$$Complexity = \frac{mobility(y'(t))}{mobility(y^(t))} \tag{6.9}$$

6.1.4 Method 4: Entropy-Based - Permutation Entropy

Since the EEG waveform can be described as a sequence of ordinal patterns, Permutation Entropy (PE) can easily help to analyze the relative occurrence of each of these patterns using the relative frequencies vector.[27] This is a robust time series that provides a quantification measure of the complexity of a dynamic system by capturing the order relations between values of a time series and extracting a probability distribution of the ordinal patterns. It relies on the notions of entropy and symbolic dynamics.[27] Mathematically Permutation Entropy can be described as - 6.10[27]

$$PE_D = -\sum_{i=1}^{D!} \pi log_2(\pi) \tag{6.10}$$

6.2 Description of Classifier Models

This research employs four types of classifiers, which are briefly discussed here.

6.2.1 Support Vector Machine (SVM)

An effective and powerful supervised machine learning model for regression and classification applications is the Support Vector Machine (SVM). The data points of different classes with the largest margin by finding the hyperplane that best divides it is the primary objective of support vector machines (SVM). The gap between the closest data points from each class and the hyperplane is known as the margin. As an exam, if we think of two dots, one blue and one red, SVM will find the most suitable line that will separate them and it will ensure that the line is as far away as possible from the nearest dots of either color.[47] SVM can handle non-linearly separable data by using the kernel approach, which converts the data into a higher-dimensional space where a linear separation is feasible.[47] However, SVM can be computationally taxing, taking a lot of time and resources to train, especially when dealing with big datasets. Due to their resilience and versatility, SVM is widely used in machine learning despite having challenges.[47]

6.2.2 Decision Tree

A decision tree is one type of machine learning model that creates predictions by creating a structure similar to a tree by iteratively dividing the data into subsets according to feature values. It has four main components. Those are root nodes, internal nodes, branches, and leaf nodes. The model begins at a root node.[48] After that it proceeds to ask a sequence of either yes or no questions about the features. Each question generates a whole new branch that goes to a new node. This procedure keeps going until the data is sufficiently divided, coming to a stop at leaf nodes that offer the last estimate. Decision trees work well for both regression and classification applications. As their characteristic is similar to the human decision-making process, they are simple to comprehend and interpret. However, with little changes in the data, they can become unstable and prone to overfitting, which can significantly alter the tree's structure.[48]

6.2.3 Random Forest

Random forest is a machine-learning technique that is a collection of multiple decision trees. In this process, Random Forest can make more accurate and robust decisions or predictions. Every single decision tree in a random forest is trained on a random portion of the dataset and the features to make it diverse. By doing this it can introduce variability and lower the chances of overfitting.[9] In this case of classification, each tree in the random forest method emits a vote, and after voting the class that received the majority of the votes is selected as the final decision. On the other hand, for regression tasks, it calculates the average prediction of all the trees and then decides the result.[1] The Random Forest often produces forecasts that are more accurate than those of a single decision tree since it combines several trees. This is so that overfitting is lessened by the randomization. In conclusion, a random forest is a machine-learning method that discusses all the trees in its forest and then decides what to do.[9]

6.2.4 K-Nearest Neighbors (KNN)

K-Nearest Neighbors is a very simple and powerful ML classification algorithm, operating on the principle of proximity. In training data, KNN predicts the class label of a new point using the labels of its nearest neighbors.[12] The locality of the algorithm determines the choice of K with smaller K values leading to more localized predictions and the other leading to a more generalized classification. Being simple, KNN is used very frequently over various ML tasks, to handle large datasets and low-dimensional spaces.[12]

6.3 Source Localization Methods

There are few methods for source localization, which are widely popular. To know about source localization, understanding these methods are important.

6.3.1 Boundary Element Model

The Boundary Element Method (BEM) is a widely used approach for solving the forward problem in EEG source localization, which involves determining how electrical activity from neural sources inside the brain propagates to the scalp electrodes. Unlike volumetric methods, which require discretizing the entire head volume into small elements, BEM simplifies the computation by only discretizing the boundaries between different tissue layers. The human head is modeled as a set of three conductive layers, brain, skull, and scalp, each with distinct electrical conductivities. To represent these layers, triangular surface meshes are created. These surfaces serve as the boundaries where electrical potentials are calculated, reducing computational complexity while maintaining accuracy. In [6] & [15], the mathematical framework of BEM is based on solving Poisson's equation 6.11, which governs the propagation of electrical potentials ϕ in a conductive medium:

$$\Delta\cdot(\sigma\Delta\phi) = -\sigma \cdot J \tag{6.11}$$

Here, ϕ is the electric potential, σ is the conductivity of the medium, and J is the primary current density from neuronal sources. Since the head is modeled as multiple compartments with different conductivities, continuity conditions must be satisfied at each boundary. These conditions include potential continuity across boundaries, represented as 6.12

$$\phi_1 = \phi_2 \tag{6.12}$$

at the interface between two layers, and current continuity, where the normal component of the current must be conserved, given by 6.13

$$\sigma_1 \frac{\partial \phi_1}{\partial n} = \sigma_2 \frac{\partial \phi_2}{\partial n} \tag{6.13}$$

where n is the normal vector at the boundary. By applying Green's theorem, the Poisson equation can be converted into an integral equation 6.14 over the boundary surfaces.

$$\phi(r) = \int_s G(r, r')\sigma(r')\frac{\partial \phi(r')}{\partial (n)} \tag{6.14}$$

where G(r,r') is Green's function, representing the fundamental solution to Laplace's equation, and S represents the boundary surfaces. The BEM method then discretizes these boundary surfaces into small triangular elements, leading to a system of linear equations 6.15.

$$A\phi = BJ \tag{6.15}$$

where A is the system matrix derived from boundary conditions, ϕ is the vector of surface potentials, and B relates the surface currents to the source currents. Finally, the lead field matrix K, which maps source currents to sensor voltages 6.16, is obtained by solving the BEM system.

$$V = KJ \tag{6.16}$$

where V is the vector of EEG sensor voltages and J is the vector of source dipole currents. This framework allows BEM to efficiently compute the forward model while reducing computational complexity compared to volumetric methods, making it a preferred choice for EEG source localization.

6.3.2 dSPM

Dynamic Statistical Parametric Mapping, widely known as the dSPM method, is an advanced technique in EEG analysis for source localization. By statistically normalizing the estimated brain activity, it succeeds over the Minimum Norm Estimate (MNE) in terms of accuracy and noise resistance. It is beneficial for researching the dynamic brain system which includes emotion, and recognition.[49] dSPM can be used as a statistical tool to track where and when brain activity occurs. dSPM compares the recorded EEG signals from the scalp to a model that predicts the flow of electrical currents through the brain. Thus, dSPM produces a detailed, dynamic representation of brain function. It is commonly referred to as a statistical parametric map, it shows the location of the active brain area and the time when that activity occurred. This makes it an effective technique for researching how the brain handles emotions, reacts to stimuli, or completes challenging tasks.

MNE-Based Source Estimation

Estimating J through the Minimum Norm Estimate (MNE), as shown in 6.17

$$J_{MNE} = (G^T G + \lambda I)^{-1} G^T X \tag{6.17}$$

where:

- λI = Regularization term to control noise
- J_{MNE} = Raw MNE source estimate[49]

However, MNE has localization bias, meaning it favors sources closer to the scalp and produces highly variable estimates.

dSPM Standardization

To fix MNE's limitations, dSPM normalizes the estimated source activity by dividing it by the standard deviation of noise at each source location. The final dSPM solution is given in equation 6.18.

$$J_{dSPM} = \frac{J_{MNE}}{\sigma J} \tag{6.18}$$

where:

- σJ = Standard deviation of noise sensitivity at each source location
- This step removes bias and ensures that sources with high noise sensitivity are adjusted appropriately.[49]

In detail, the formulation can be given as equation 6.19

$$\sigma_J{}^2 = diag((G^T C_N^{-1} G)^{-1}) \tag{6.19}$$

where C_N is the noise covariance matrix.
The reliability and comprehension of source calculation are enhanced by dSPM's ability to produce values that are similar to z-scores due to these statistical modifications.

6.3.3 sLORETA

Standardized Low-Resolution Brain Electromagnetic Tomography, widely known as sLORETA, is an advanced method for EEG source localization. It works based on the standardization of current density estimated for source localization.[50] This results in higher precision and reliability. That is why sLORETA is a popular technique for localizing EEG sources. Its zero localization error for single point sources in noise-free conditions, depth-compensated estimation, distributed source model, Improved signal-to-noise ratio, and computational efficiency have made it a widely used technique for source localization.[52] Its working mechanism is mostly predicting that the electrical activity of the brain is spatially smooth, which means that nearby neurons typically activate simultaneously.[50] For sLORETA, the forward problem describes how neuronal currents inside the brain produce EEG/MEG signals at the scalp and the inverse problem aims to reconstruct the neural sources (current density J) from measured EEG signals (ϕ). The method has no unique solution, hence it solves the EEG inverse problem.

Mathematical Representation 6.20:

$$\phi = KJ + c1 \tag{6.20}$$

Where:

- ϕ (scalp potentials) are EEG signals recorded at NEN_{ENE} electrodes.
- J (primary current density is Unknown neural sources at NEN_{ENE} electrodes
- K (lead field matrix) describes how sources J project onto the electrodes.
- $c1$ is an arbitrary constant (due to reference electrode placement).[3]

The goal of sLORETA is to estimate J given and K. sLORETA standardizes the minimum norm estimate (MNE) to correct for localization errors. The standardization process involves adjusting for source variance.

sLORETA Solution:

$$\hat{J} = T\phi \tag{6.21}$$

where in equation 6.21:

$$T = (K^T K + \alpha I)^+ K^T \tag{6.22}$$

With:

- α: Regularization parameter (controls smoothness).
- I: Identity matrix.
- T is the inverse operator that maps EEG signals to estimated sources.[3]

Here, in sLORETA, the solution is standardized by its variance. This is the unique characteristic of sLORETA. So final equation is 6.23.

$$\hat{J}_{\text{sLORETA}} = \frac{\hat{J}}{\text{var}(\hat{J})} \tag{6.23}$$

This ensures that sources are estimated in a statistically unbiased manner, eliminating localization errors. The variance of J is computed as equation 6.24.

$$\text{var}(\hat{J})^T = (K^T K + I)^{-1} K^T H K (K^T K + I)^{-1} \tag{6.24}$$

Where:

- H is the centering matrix.[3]

The final sLORETA estimate is 6.25.

$$J_{\text{sLORETA},l} = \frac{J_l}{S_{J,ll}} \tag{6.25}$$

Where:

- J_l is estimated source activity at voxel l.
- $S_{J,ll}$ is variance at voxel l[3].

This ensures that there is no localization error and that all estimated sources have comparable statistical reliability. In this research, sLORETA played a vital role since it provides a reliable framework for estimating neural activity.

6.3.4 eLORETA

Exact Low-Resolution Brain Electromagnetic Tomography, known as eLORETA, is a technique that uses EEG signals to identify the location of brain activity. When many sensors (EEG electrodes) are placed on someone's scalp to detect electrical activity and identify the areas of the brain that are causing that activity precisely, eLORETA works as a best fit in such a situation.[52] For example, it acts as a detective - EEG signals are the clues, and eLORETA is a tool that assists in locating the brain's source with these clues. This is a reliable localizing method with no localization bias, providing zero error localization in the case of nonideal conditions – that is, the presence of noise. eLORETA's extremely precise design is its unique feature. Even in cases where the signals are weak or noisy, it incorporates math and physics to determine the most likely places rather than only speculating about where the activity might occur. This is called the "Inverse Problem", which is solved by simply going backward from the EEG signals to determine which areas of the brain are most likely producing them. The working mechanism of this method utilizes the brain source amplitudes $y(n)$ and tries to minimize the errors while reconstructing

the sources.
The general form of the cost function is 6.26.

$$minJ(||V - LJ||^2 + \alpha J^T WJ) \tag{6.26}$$

where:

- V represents the measured EEG data (voltages at the scalp).
- L is the lead field matrix, describing how brain sources project onto the scalp sensors.
- J represents the estimated current source densities (brain activity) that we aim to find.
- α is the regularization parameter, controlling the trade-off between data fidelity and smoothness.
- W is a weighting matrix that imposes spatial constraints, ensuring the smoothness of the solution.[52]

Now, the inverse solution in eLORETA is obtained by minimizing the following cost function 6.27:

$$\min y(n)(S_{cl}(n) + \alpha y(n)^T W y(n)) \tag{6.27}$$

Here, the stability of the solution is ensured by the regularization term $\alpha y(n)^T W y(n)$, whereas S_{cl} (n) quantifies the degree to which the estimated sources correspond to the actual EEG data.[51] eLORETA successfully recognizes the complex structures of the brain rather than assuming it is perfectly smooth. It takes the messy structure of the brain with folds, layers, and different tissue types. Hence, it results in more accuracy.
In this research, eLORETA has played a significant role. Because it simplifies data without sacrificing important details, it makes the process easier. It helps us see how emotions are expressed in brain activity more clearly, almost like switching from a blurry image to a high-definition view of the brain.

Chapter 7

Work Process

The experimental process consists of two stages: Feature Engineering and Brain Source Localization. Finally, the performance of the proposed approach is evaluated.

7.1 Preliminary Feature Engineering

For the feature engineering part, the paper applies a diverse set of feature extraction techniques based on different principles to capture the multifaceted nature of EEG waveforms using the reshaped (.dat) version of the dataset. From time-domain methods, this research paper uses Statistical Measures (a combination of Arithmetic Mean, Standard Deviation & Quadratic Mean) and Hjorth parameters (Activity, Mobility & Complexity). From frequency-domain methods, Power Spectral Density (delta, theta, alpha, beta, gamma) and from entropy-based methods Permutation Entropy is used. The goal here is to use two feature extraction techniques (one from the time-domain analysis method and one from the entropy-based method) based on the results of the experimental analysis for further usage in the brain source localization part. The methods are applied on the 7680 data (of .dat version) per channel per participant to extract the important features. For evaluation of the extracted features, it trains four state-of-art classification models: Support Vector Machine, Decision Tree, Random Forest and K-Nearest Neighbor and investigates the Valence and Arousal values using performance metrics such as accuracy, F1 score, recall, etc.

7.2 Brain Source Localization Using AgLORETA

When it is assumed that the Lead Field Matrix obtained from the forward solution (in our case, the BEM method) is accurate, the inverse solution using eLORETA theoretically gives us zero localization error for single-dipole sources. However, while identifying the exact sources of brain activities through source localization in practice, the true lead field matrix, H, is very complicated to calculate and researchers often tend to proceed with an assumed lead field matrix. As this matrix intrinsically characterizes the sensitivity of each of the EEG electrodes to potential neural source locations within the brain [46], a reliable source localization result without uncertainties cannot be obtained using such an assumed Lead Field Matrix. Therefore, to overcome this problem, the research aims to transform the Lead Field Matrix

obtained from the forward model with a transformation matrix R.
The approach of introducing a transformation matrix, R, is inspired by the work of the researchers Noroozi, Ravan, Razavi, Fisher, Law, and Hasan [44]. However, in this research, the regularization of the lead field matrix has been designed with R in a simple, novel approach, one that is also less complicated than the one implemented in the mentioned paper [44]. In the regularization algorithm, the concept of gradient descent is utilized to update the value of R at each iteration. The design of the loss function is also made meticulously, taking into account all aspects of loss calculation. The preprocessed Biosemi format data is used throughout the entire process of source localization calculations.

7.2.1 Forward Model Computation and Covariance Matrix

In source localization, it is required to compute the forward model using a standard head model. Usually, the head model is given by the MRI imaging of each participant's brain. However, the DEAP dataset does not come with MRI images of the participants' skulls. Therefore, the research has made use of the 'fsaverage' head model template designed by FreeSurfer, a widely used neuroimaging software, through the MNE library. This standard anatomical template allows to accurately map the brain's electrical activity to EEG sensor space. The source space is also created using the MNE library with `ico = 5`. This indicates the creation of a grid having 20,484 points distributed across both hemispheres (10,242 vertices per hemisphere) of the brain to map the electrical activities in the 3D space, with vertices having three components (x, y, z) each. In addition, a BEM model is created using `ico = 4`, where each layer (brain, skull, scalp) of the brain space is mapped into 1,280 triangular mesh-like areas. Finally, implementing the BEM model described above, and using the head model and source space, the forward solution is calculated. A covariance matrix is also calculated from the signals of the 32 channels, taking into account environmental noise and background brain activity.

7.2.2 Regularization of the Lead Field Matrix

As mentioned earlier, this research aims to bring a novel approach for calculating the transformation matrix, R, to regularize the lead field matrix, H in this part,

$$\hat{H} = R.H \tag{7.1}$$

Here, $\hat{H}$ denotes the transformed or regularized lead field matrix, R denotes the transformation matrix and H denotes the extracted lead field matrix from the forward solution calculated in the previous section. The target here is to optimize R, to obtain a transformed lead field matrix $\hat{H}$ close to the true lead field matrix, which is used later in the inverse model to receive more accurate results of source localization.
Starting by assuming that R is nothing but an Identity matrix (I) of the same shape as the lead field matrix. To optimize R, at first, the differences in the results obtained from the transformation matrix are applied to the estimated brain source activities in the forward solution from the actual EEG sensor data that has been preprocessed earlier. This calculation of residuals is used in the loss function later.

$$r = x - \hat{H}.y \tag{7.2}$$

Here, r denotes the residuals, x denotes the EEG preprocessed data, H' is the transformed lead field matrix and y is the estimated brain source activities.
Next, while designing an optimal and fairly simple loss function, the process is divided into two parts. The first is the data fitting loss and the second is the regularization loss. The data fitting term includes the calculation of the squared Frobenius norm of the above residuals. This term minimizes the residuals by ensuring that the predicted EEG signals are in close approximation to the observed data. The second term focuses on penalizing the deviations of the transformation matrix from the Identity matrix at every iteration. A hyperparameter beta (β) is used as the weighing term here to determine how much penalty should be imposed on the deviations. Before applying the penalizing term β the squared Frobenius norm of the deviations of R from I is taken here as well. So, the whole loss function stands,

$$L(R) = ||r||_F^2 + \beta||R - I||_F^2 \tag{7.3}$$

Here, Data fitting term: $||r||_F^2$ Regularization Term: $\beta||R - I||_F^2$ Where, r: residuals β: regularization parameter R: transformation matrix I: identity matrix $||||_F$: Frobenius norm
Taking the first-order derivative of the loss function with respect to the residuals, this research gets the gradient below. This gradient essentially provides the direction and magnitude of the change of the transformation matrix required to make at every iteration to improve to better represent the true lead field matrix.

$$\Delta_R L = -2.r.y^T.H^T + 2.\beta.(R - I) \tag{7.4}$$

Here, $\Delta_R L$: gradient r: residuals y^T: transpose of the estimated brain source activity matrix H^T: transpose of the lead field matrix β: regularization parameter R: transformation matrix I: identity matrix
Using the gradient, we update R at each using an equation similar to gradient descent,

$$R_{t+1} = R_t - \eta.\Delta_R L \tag{7.5}$$

Here, η indicates the learning parameter and $\Delta_R L$ denotes the gradient. To indicate if the transformation matrix has reached its optimized state, convergence is checked by comparing the Frobenius norm of the gradient to the tolerance level parameter that has been taken as 1×10^{-6}. The selection of this value is crucial because the optimization continues until this condition is met. A large value for the tolerance level stops R from reaching the required optimization and the algorithm prematurely terminates. On the other hand, a smaller value R may result in excessive iterations, significantly increasing the computational cost for no logical reason. Therefore, tuning of this parameter is done and the value is finalized as 1×10^{-6} which successfully provides a balance between computational efficiency and solution accuracy.

$$||\Delta_R L||_F < tol \tag{7.6}$$

If the Frobenius norm of the gradient goes below the threshold, optimizing R is stopped and moved on to the next part of the calculation, or else, the optimization goes on. Lastly, the transformed lead field matrix is computed using equation 7.1 and using this new matrix in calculating the inverse solution with the eLORETA method described above.

The proposed algorithm is referred as AgLORETA for easier comprehension and usage throughout the report. The main steps of AgLORETA algorithm, specifically on how the transformation matrix R is optimized and the new lead field matrix is computed, are listed below.

7.3 AgLORETA Algorithm

Step 1: Initialize $R = I$, set hyperparameters & t = 1

Step 2: Compute Residuals using equation (7.2)

Step 3: Compute Gradient using equation (7.4)

Step 4: Update R using equation (7.5)

Step 5: Calculate the Loss function using equation (7.3)

Step 6: Check Convergence using equation (7.6), if it is true, go to the next step, if false, increment t and loop back to Step 4.

Step 7: Calculate Transformed Lead Field matrix using equation (7.1)

Step 8: Compute Inverse Solution applying eLORETA, using $\hat{H}$

The process is visualized in figure 7.1.

7.4 AgLORETA Flowchart

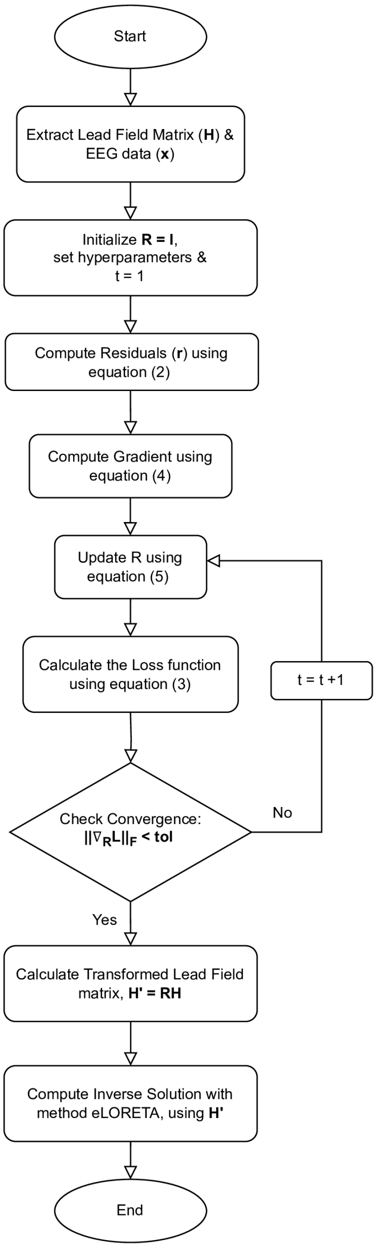


Figure 7.1: AgLORETA Flowchart

With the inverse problem being solved in the mentioned procedure from figure 7.1, the top 100 vertices showing the highest activity value is selected. Mapping of these vertices to the 32 channels is done and the top 10 common channels for all the participants are selected.
The data from the selected channels using the AgLORETA algorithm are validated using the preprocessed Python version (.dat format). The approach here is the same as discussed in the preliminary feature engineering part. Just the two selected feature extraction techniques are applied, and the rest remains the same.
In the same procedure, the BSL techniques of solving inverse problems, dSPM, sLORETA and eLORETA is also conducted for proper result analysis.

Chapter 8

Result and Analysis

8.1 Feature Engineering on All 32 Channels

Firstly, results from the preliminary analysis of the feature engineering part are discussed in the section. The tables 8.1 and 8.2 list the accuracy and F1 scores of the four classifiers applied to evaluate the usage of the four feature extraction methods.

Table 8.1: Result of DT and RF

Feature	SVM				KNN			
Extraction	F1 Score		Test Accuracy		F1 Score		Test Accuracy	
	Valence	Arousal	Valence	Arousal	Valence	Arousal	Valence	Arousal
Statistical	42.3%	42.8%	57.4%	58.2%	57.4%	59.3%	58.2%	59.8%
PSD	**42.8%**	42.8%	**58.2%**	58.2%	57.9%	57.9%	58.2%	58.2%
Hjorth	41.4%	42.8%	57.0%	58.2%	57.4%	58.7%	57.4%	59.0%
PerEn	41.4%	42.8%	57.0%	58.2%	**58.9%**	**59.7%**	**59.4%**	**60.2%**

Conducting a comparative analysis on table 8.1, it can be said that the performance of PSD for valence is the highest using the SVM model. Permutation Entropy performed best in the detection of both valence and arousal values, validated by the KNN classifier.

Table 8.2: Result of SVM and KNN

Feature	DT				RF			
Extraction	F1 Score		Test Accuracy		F1 Score		Test Accuracy	
	Valence	Arousal	Valence	Arousal	Valence	Arousal	Valence	Arousal
Statistical	55.3%	**58.2%**	55.1%	**58.2%**	53.8%	59.9%	55.1%	61.3%
PSD	55.0%	56.1%	54.7%	55.9%	60.5%	60.0%	60.9%	60.2%
Hjorth	53.3%	54.0%	53.1%	53.9%	**61.6%**	56.8%	**62.5%**	57.0%
PerEn	**57.2%**	55.8%	**57.0%**	55.5%	58.0%	**61.1%**	58.6%	**61.7%**

It is observed from table 8.1 too that permutation entropy and Hjorth parameters showed promising results using DT and RF. Figure 8.1, 8.2, 8.3 and 8.4 visualizes the overall valence and arousal performances for better comprehension.

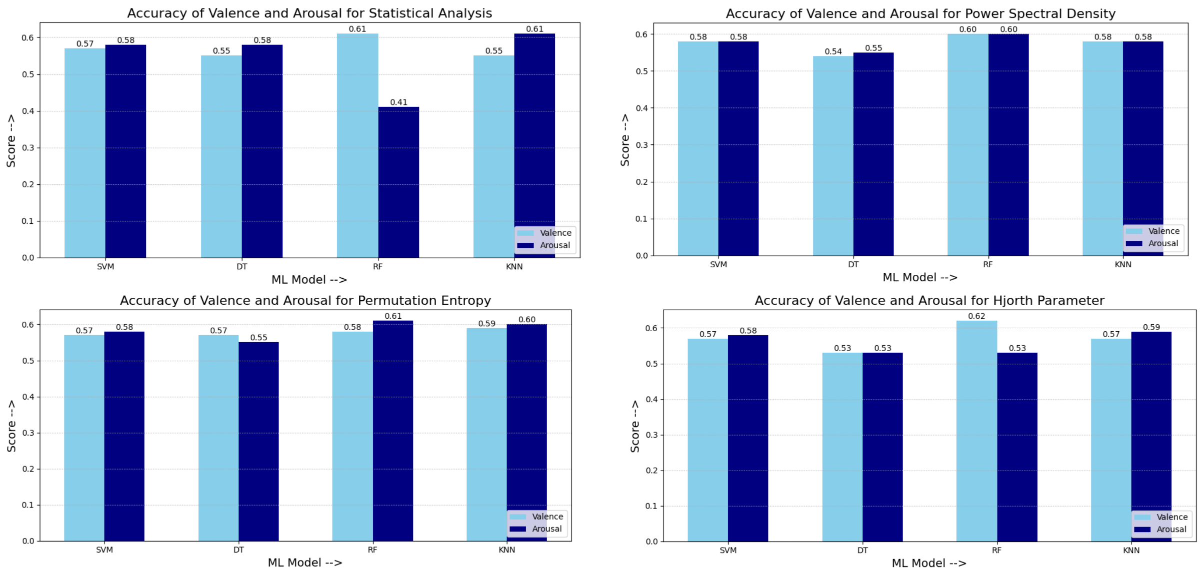


Figure 8.1: Accuracy of Valence and Arousal for different models

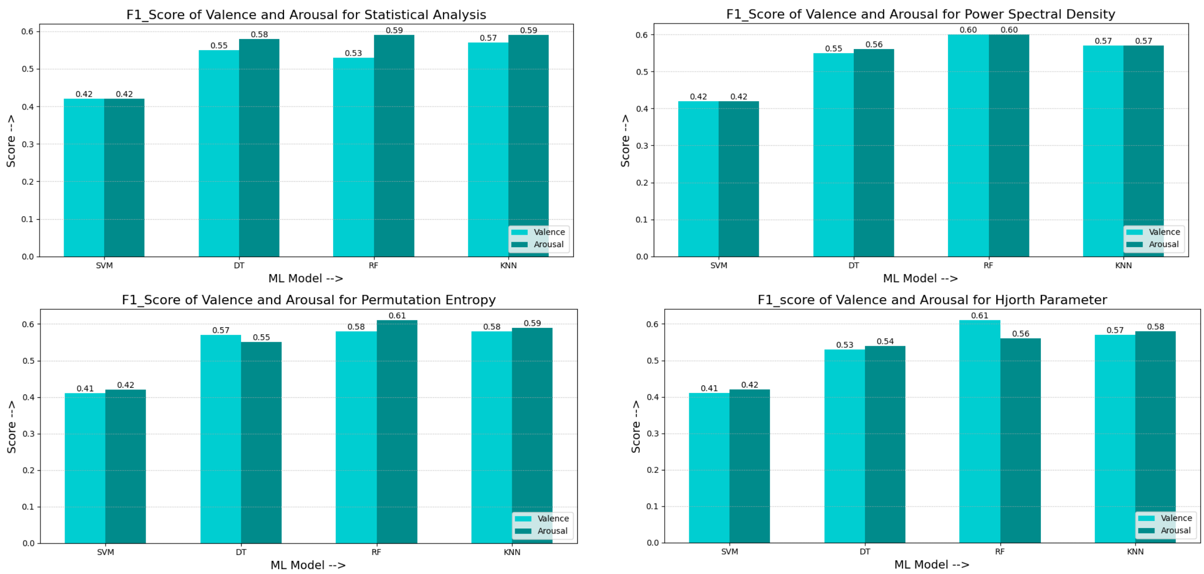


Figure 8.2: F1 Score of Valence and Arousal for different models

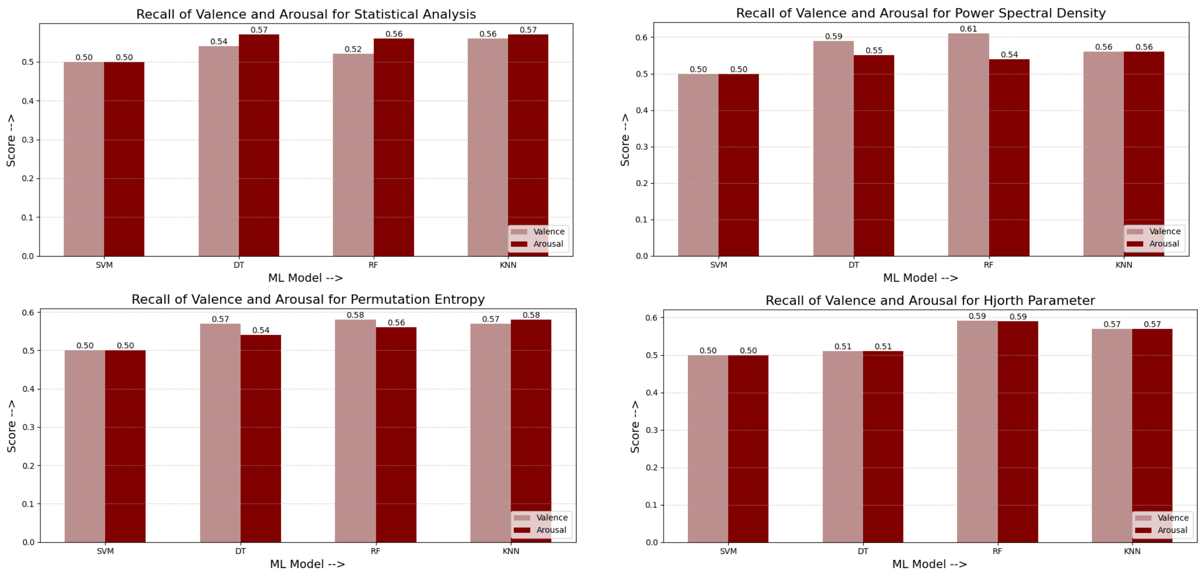


Figure 8.3: Recall of Valence and Arousal for different models

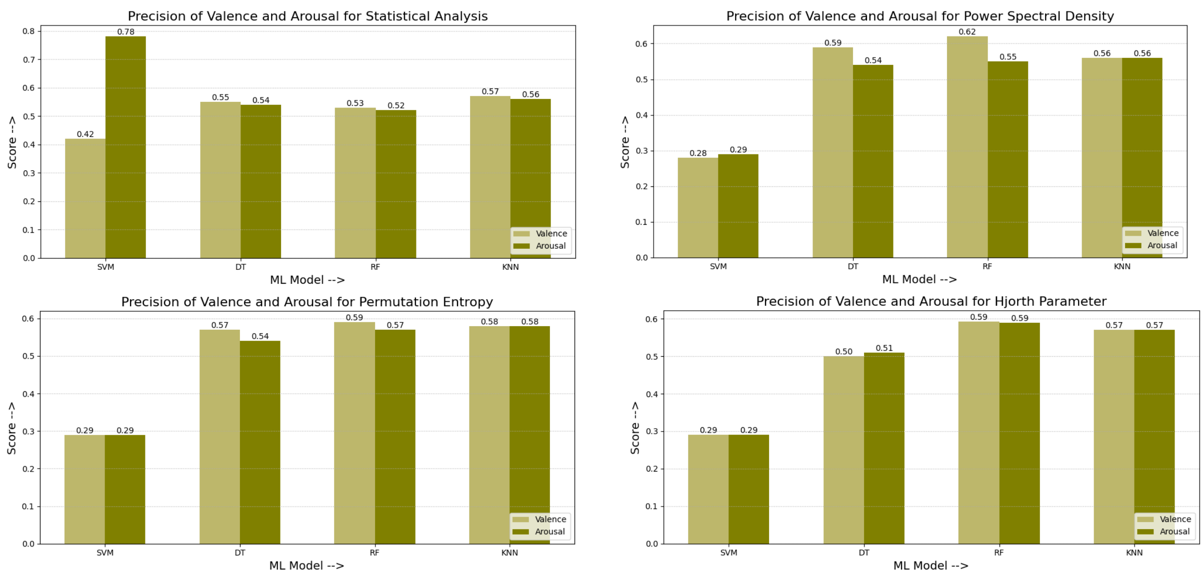
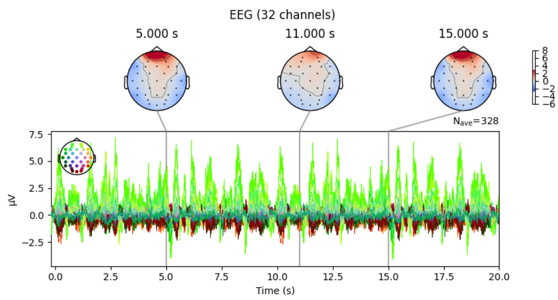


Figure 8.4: Precision of Valence and Arousal for different models

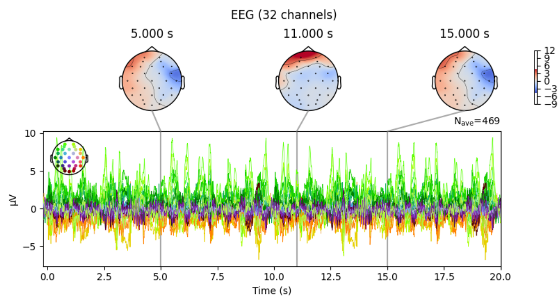
From the discussion above, it is evident that the EEG based feature extraction methods mostly showed better performance compared to the general statistical ones. Hence, the paper uses Hjorth parameters from time-domain analysis and Permutation Entropy from frequency domain analysis to validate the results of the next part.

8.2 Brain Source Localization Results

In this part, the results of the brain source localization part are discussed. As the DEAP dataset used in this paper contains EEG data from 32 participants, an overview of the processed EEG signal distribution across different channels over time for two random participants after applying the forward model of the brain source localization is shown below. The graphs (8.6) and (8.5) visualize the topographical map of brain activity in two fixed time frames, for comprehension of the signal fluctuations both over a shorter and larger time frame. For Participant 9, figure (8.6a) and Participant 16, figure (8.6b), the signals from all channels are shown for the smaller time frame of 0.5 seconds. Whereas, for Participants 4, figure (8.5a) and 24, figure (8.5b) the plotting over a larger time frame of 20 seconds is demonstrated. The plots for the latter two participants exhibit a dense and noisy distribution, while the former two provide a neat view. Whenever the green lines, mainly representing the frontal region of the brain, appear highly scattered, the topographic map of that area shows the highest activity(red).

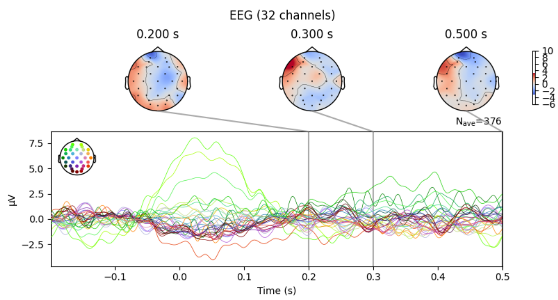


(a) Participant 04

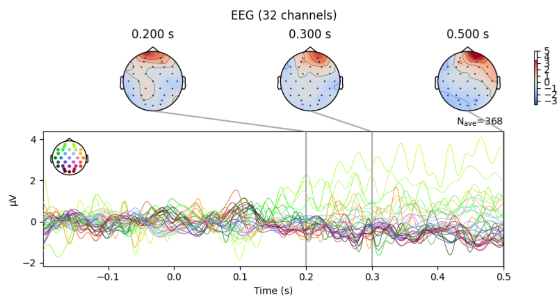


(b) Participant 24

Figure 8.5: Signal plot over 20 seconds



(a) Participant 09



(b) Participant 16

Figure 8.6: Signal plot over 0.5 seconds

The research aims to evaluate the accuracy of various EEG source localization methods like dSPM, sLORETA, eLORETA, and an improvised version of eLORETA, AgLORETA to find the most active EEG channels associating brain activity. In the paper by the researchers - Noroozi, Ravan, Razavi, Fisher, Law, and Hasan [44], they have made use of a complex approach including calculations of Hessian Matrix, application of LM Algorithm, use of both first and second order derivatives in the calculation of the transformation matrix R, etc. to create ReLORETA, another regularized version of eLORETA. But this research applies a simpler approach towards solving the regularization which is also computationally less expensive than the ReLORETA approach, from which its approach is originally inspired. A brief comparative analysis is given in table 8.3.

Table 8.3: ReLORETA vs AgLORETA

Feature	**ReLORETA**	**Our Algorithm (AgLORERTA)**
Optimization Target	Directly solves inverse problem iteratively	Optimizes R first, then solves inverse problem
eLORETA Computation	Every iteration	Only once, after convergence
Computational Advantage	Expensive due to repeated matrix inversions	Faster as eLORETA is computed only once

So at first, the source estimates for the source localization methods are determined to provide an activation level to each vertex. Then the top 100 most active vertices are identified based on their activation levels for each method. These vertices correspond to the brain regions exhibiting the highest neural activity, which are the most relevant for EEG-based source localization.
After that, this research mapped these vertices to their corresponding EEG channels using the Lead Field Matrix which establishes a relationship between brain sources and the scalp EEG signals, allowing to determine which EEG channels are most influenced. This process generated some EEG channels corresponding to the top 100 vertices for each localization method.
Then the selected EEG channels from all four source localization techniques are analyzed to find the common channels among them. By comparing these common channels, the best localization results are determined.

The AgLORETA method identifies the following most active EEG channels:

FC1, CP1, AF3, P7, CP5, O1, C3, PO3, F3, P3

These channels are determined to be the most relevant for EEG source localization and are used for classification.

After applying the two feature extraction techniques mentioned above, four machine learning classifiers are trained and tested to assess the channels. They are:

- Random Forest (RF)
- Support Vector Machine (SVM)
- Decision Tree (DT)
- K-Nearest Neighbors (KNN)

The accuracy values are from table 8.4.

Table 8.4: Accuracies of Different Models

Method Used	Random Forest	Support Vector Machine	Decision Tree	K-Nearest Neighbor
DSPM	58.59%	59.77%	58.20%	61.33%
eLORETA	59.77%	**61.72%**	58.59%	**62.50%**
sLORETA	60.16%	61.33%	58.59%	60.16%
AgLORETA	**59.98%**	**61.72%**	**59.38%**	**62.50%**

According to table 8.4, dSPM performs the poorest of all the methods across all the classifiers, with the lowest classification accuracy. This suggests that the dSPM approach to source localization is less effective for identifying the most relevant EEG channels. On the other hand, eLORETA outperformed both sLORETA and DSPM, achieving better classification accuracy across all classifiers. This proves that eLORETA is very reliable in estimating the source activity. However, the proposed method of this research, AgLORETA, which has been tuned by optimizing the beta parameter (0.1) and learning rate (0.001), demonstrates superior performance across almost all classifiers **(Random Forest - 59.38%, SVM - 61.72%, Decision Tree - 59.38%, KNN - 62.5%)**. Specifically, AgLORETA and eLORETA both attain the highest accuracy of 62.50% with KNN, indicating that AgLORETA does not negatively impact classification.
In brief, the accuracy table highlights AgLORETA as a promising technique for EEG source localization and channel selection. It has performance comparable to or exceeding that of existing methods like dSPM, eLORETA, and sLORETA. Its performance across multiple classifiers after application of feature engineering methods of PE and Hjorth parameters suggests that the tuning of the lead field matrix improves the competitive accuracy while maintaining a comparatively lower computation load.

Chapter 9

Conclusion

While all 32 channels of the EEG signal work for emotion understanding, recognition, and analysis, many of them carry redundant or poor-quality data. Processing them all increases the computational complexity. Reducing channels helps to improve the emotion classification accuracy and decrease the setup time. Therefore, reducing the number of channels plays a vital role in reducing the computational complexity. Additionally, the reduced number of channels needs to be selected in a certain manner so that it does not achieve a lower accuracy rate. Therefore, filtering potentially useful information is vital. Hence, source localization worked best in locating the precise locations in the brain. Advanced EEG source localization techniques (dSPM, sLORETA, and eLORETA) have been used to estimate brain activity with improved accuracy and minimal localization errors. Hereafter, the dual-regularized eLORETA, the newly introduced AgLORETA, has generated precise and promising results. This achieves the main focus of this research, building a computationally inexpensive channel-selection method. In addition, the combination of the feature extraction methods resulted in better accuracy with fewer channels. Hence, the computational complexity has been reduced.

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