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James Khamthung
Southern Methodist University, khamthung@gmail.com

Nibhrat Lohia
Southern Methodist University, nlohia@smu.edu

Seement Srivastava
Southern Methodist University, seemants@smu.edu

Multi-Class Emotion Classification with XGBoost Model Using Wearable EEG Headband Data

James Khamthung[1], Seemant Srivastava[1], Nibhrat Lohia[1]
[1] Master of Science in Data Science, Southern Methodist University, Dallas, TX 75275 USA
{jkhamthung, seemants, nlohia}@smu.edu

Abstract. Electroencephalography (EEG) or brainwave signals serve as a valuable source for discerning human activities, thoughts, and emotions. This study explores the efficacy of EXtreme Gradient Boosting (XGBoost) models in sentiment classification using EEG signals, specifically those captured by the MUSE EEG headband. The MUSE device, equipped with four EEG electrodes (TP9, AF7, AF8, TP10), offers a cost-effective alternative to traditional EEG setups, which often utilize over 60 channels in laboratory-grade settings. Leveraging a dataset from previous MUSE research (Bird, J. et al., 2019), emotional states (positive, neutral, and negative) were observed in a male and a female participant, each for 3 minutes per state while watching movie scenes designed to stimulate emotions. The dataset comprises 2548 features extracted statistically from each sliding time window (mean, median, standard deviation, etc.). Employing XGBoost, a subset of the top 100 features is selected from the original 2548, achieving an exceptional accuracy of 99.1%. This research aims to make significant contributions to accurately classify human emotion while advancing EEG-based sentiment classification for future real-time emotion prediction applications.

1 Introduction

Electroencephalography (EEG) is a non-invasive neuroimaging technique that records and measures the electrical activity generated by the brain using electrodes placed on the scalp. These electrodes detect and amplify the tiny electrical signals produced by neurons, allowing researchers and clinicians to observe the brain's dynamic activity in real time. EEG provides valuable insights into brain function, revealing patterns of electrical activity associated with different mental states, cognitive processes, and emotional responses. This technique has diverse applications beyond clinical diagnosis, extending to fields such as neuroscience research, cognitive psychology, and brain-computer interface development. By monitoring the brain's electrical signals, EEG enables the study of various brain functions and facilitates a deeper understanding of neurological conditions and cognitive processes.

Furthermore, integrating EEG with machine learning has paved the way for innovative applications in diverse domains. In the realm of Brain-Computer Interfaces (BCIs), EEG signals serve as a crucial input, allowing individuals to control external devices or interfaces directly with their thoughts. In healthcare, EEG-based machine learning applications contribute to the development of advanced diagnostic tools, personalized treatment strategies, and real-time monitoring of neurological conditions. Beyond healthcare, EEG combined with machine learning has found applications in entertainment and gaming, enabling more immersive experiences by adapting content based on users' cognitive states. In neuromarketing, EEG data analysis aids in understanding consumers' emotional responses to products and advertisements, shaping more effective marketing strategies. Sports performance enhancement benefits from EEG by providing insights into cognitive aspects, helping athletes optimize their mental preparation and focus. Additionally, EEG-based machine learning applications have been explored for security purposes, utilizing brainwave patterns for biometric identification and authentication. These examples showcase the versatility of EEG combined with machine learning across various sectors, driving advancements in technology and human-computer interaction. Emotion recognition is a vital component of understanding human behavior and well-being. It has far-reaching implications for various industries, from mental health monitoring to personalized user experiences in fields such as entertainment and marketing. Traditionally, emotion recognition has heavily relied on expensive and resource-intensive electroencephalography (EEG) laboratories with a multitude of channels for data collection, making it inaccessible to many and impractical for real-time applications. An additional note on structure, in general, I frown upon subsections in the Introduction section; however, when done appropriately, they can be very useful to segment the information.

However, the deployment of Laboratory-Grade EEG Equipment comes with its own set of challenges. The traditional setup involves the placement of 64 or more electrodes on the scalp, necessitating meticulous preparation and precise placement. This process often requires the application of conductive gel to ensure a good electrical connection between the electrodes and the scalp. While these high-density configurations provide detailed and accurate data, the setup is inherently messy and time-consuming. Moreover, the need for skilled technicians to handle the intricate electrode placement and maintenance makes this approach both labor-intensive and expensive. The requirement for a controlled laboratory environment further limits the accessibility of this technology, hindering its widespread use in real-world applications.

Despite the challenges posed by the complexity and expense of Laboratory-Grade EEG Equipment, numerous successful research studies have been conducted using this technology, particularly in medical and university research facilities. The high-density electrode configurations and precise data acquisition capabilities of these setups have enabled researchers to delve deep into understanding various aspects of brain function and neurological disorders. However, the extensive resources and expertise required for handling such equipment have limited its application primarily to controlled research environments within medical institutions or universities. This concentration of usage in specialized settings underscores the need for more accessible and practical alternatives that can extend the benefits of EEG technology to a broader range of applications and industries beyond the confines of academic and medical research.

Fig. 1. Muse headset, a wearable EEG device used for brainwave data collection, equipped with four EEG electrodes strategically positioned at TP9, AF7, AF8, and TP10 locations on the scalp

In contrast to the intricacies of Laboratory-Grade EEG Equipment, the emergence of devices like the Muse EEG wearable represents a significant breakthrough. With its user-friendly design, the Muse EEG headband offers a more accessible alternative to traditional EEG setups. Featuring only four dry electrodes, this wearable eliminates the need for conductive gel, streamlining the setup process and making it less messy. Released less than a decade ago, the Muse EEG headband allows users to effortlessly wear and connect to various devices, providing a hassle-free means of tapping into EEG data. This simplicity not only enhances user experience but also broadens the scope of potential applications beyond specialized research settings.

Moreover, the Muse EEG wearable has demonstrated its effectiveness in various medical research studies. Successful applications include stress [7] and anxiety [8] detection, where the device's portability and ease of use contribute to accurate and reliable data collection in real-world scenarios. Additionally, Muse has shown promise in stroke detection research [11], showcasing the versatility of this wearable in medical contexts. The combination of affordability, simplicity, and successful medical applications positions devices like Muse as transformative tools in the field of EEG-based research, offering opportunities for wider adoption and impacting diverse areas of healthcare and beyond. Hence, the inclination towards utilizing data from devices like Muse becomes evident. The streamlined and cost-effective nature of Muse EEG wearables, coupled with their successful applications in various medical research areas, aligns with the broader goal of making EEG technology more accessible and impactful. By leveraging the advantages of Muse, this study aims to contribute to the expansion of EEG-based research beyond traditional confines, fostering innovation and accessibility in fields ranging from healthcare to personalized user experiences.

The Muse EEG wearable device, with its accessible and unintrusive design, emerges as a key enabler in advancing emotional classification research. By democratizing access to reliable emotional data, Muse contributes to the development of comprehensive models that can be applied in real-world scenarios. This democratization of emotional insights has the potential to revolutionize mental health care, human-computer interaction, and various industries, fostering a deeper understanding of individuals and promoting overall well-being.

While many emotion classification studies have achieved high accuracy using various techniques, there is an ongoing pursuit of improving and refining these models for even greater precision. Hybrid deep learning, in particular, has showcased remarkable success in emotion recognition from EEG data, as demonstrated by studies using lab-grade EEG datasets like DEAP [4]. Additionally, random forest and deep neural networks have also achieved high accuracy using the MUSE dataset [5]. However, the integration of complementary techniques like XGBoost presents an intriguing avenue for enhancing classification accuracy further. XGBoost, known for its efficiency and robust performance, could enhance sentiment classification further, offering a synergistic approach alongside deep learning methodologies. This study aims to explore the capabilities of XGBoost in EEG-based sentiment classification, leveraging its efficiency and robustness to achieve improved accuracy and generalization. Through innovative model architectures, hyperparameter optimization, and tailored feature engineering, this research seeks to contribute to the ongoing evolution of affective computing and push the boundaries of emotion recognition capabilities.

The quest for accurate EEG-based emotional prediction faces challenges stemming from the limitations and costs associated with conventional lab setups. This research addresses this disparity by focusing on practical solutions, notably leveraging the Muse EEG headband as a cost-effective alternative with promising potential. The study aims to enhance sentiment classification accuracy by exploring the capabilities of XGBoost in EEG-based sentiment classification. With a focus on real-time emotion prediction, the research explores novel model architectures, hyperparameter optimization, and EEG-specific feature engineering to advance affective computing. The significance lies in bridging the accessibility gap and making EEG technology valuable across diverse industries, particularly in real-time sentiment analysis, mental health monitoring, and personalized user experiences.

Furthermore, this research aims to contribute significantly to the field by investigating the effectiveness of XGBoost in EEG-based sentiment classification using Muse data. Through this exploration, we anticipate achieving higher accuracy rates compared to existing research endeavors. The outcomes of this study are expected to offer valuable insights into the viability and potential applications of the proposed approach, laying the groundwork for further enhancements and real-world implementations.

2 Literature Review

In this literature review, our exploration of EEG-based emotion analysis encompasses four key areas: studies conducted with laboratory-grade EEG equipment, those utilizing the Muse EEG wearable device, medical and physiological applications beyond emotion analysis, and XGBoost applications in EEG signal analysis. This fourfold approach allows us to delve into insights from high-quality laboratory settings and emerging wearable technologies, as well as explore the broader scope of EEG applications in medical and physiological domains, including the innovative use of XGBoost algorithms. Through this comprehensive analysis, our objective is to contribute to the advancement of effective and accurate classification methods while highlighting the diverse potential of EEG technology across various fields.

2.1 Emotion Sentiment Classification Model Using Laboratory-Grade EEG Equipment Data

A comprehensive dataset for analyzing human affective states (referred to as DEAP) was introduced in a previous study, wherein EEG and peripheral physiological signals were recorded from 32 participants as they viewed 40 one-minute music video excerpts. Participants also provided ratings for various emotional dimensions [1]. The process of collecting such data in a laboratory setting, which involves capturing both EEG and peripheral physiological signals simultaneously, underscores the challenges and resource-intensive nature of stimulus selection and data integration. This foundational work contributes significantly to the field's understanding of utilizing EEG data for emotion analysis, paving the way for further advancements in subsequent research sections, which explore more cost-effective and accessible methodologies.

The study conducted by Kulkarni et al. (2021) makes a significant contribution to the field of emotion classification through the utilization of EEG-based methodologies, which represent a transformative approach within affective computing [2]. Conventional techniques, such as facial expressions or voice tone analysis, often produce inconclusive or biased results, prompting researchers to seek alternative methods like EEG (Encephalogram) analysis. Specifically, the research focuses on analyzing human affective states using the DEAP dataset, a comprehensive resource for emotion analysis utilizing physiological signals. This dataset comprises 40 channels and involves the participation of 32 subjects who viewed 40 one-minute music video excerpts, providing evaluations for each video based on dimensions such as Valence, Arousal, Dominance, and Liking. Through this detailed exploration, the study demonstrates the potential of EEG-based emotion analysis to uncover intricate aspects of human affective states, highlighting its relevance and applicability in understanding emotional responses. Furthermore, the study underscores the importance of utilizing high-quality, multimodal datasets like DEAP to advance our understanding of emotion recognition through EEG signals.

Furthermore, the groundbreaking work by Kumar and Molinas (2022) not only contributes to the broader landscape of EEG-based emotion analysis but also highlights the significance of utilizing datasets derived from laboratory settings [3]. The study strategically employs two well-established EEG emotion datasets, SEED and DEAP, emphasizing the reliability and richness of data obtained in controlled laboratory environments. Recognizing the critical role of accurate emotion recognition across diverse sectors, including healthcare, education, marketing, and manufacturing, the researchers construct classification models that delve into the complexities of human emotions. Through the careful preprocessing of EEG signals, involving the decomposition into five distinct rhythms and the computation of differential entropy (DE) features, the study achieves remarkable results. Particularly noteworthy is the superior performance of the CNN-based method, attaining an impressive F1-score of 93.7% for the SEED dataset and 94.5% and 94% for high vs. low arousal and high vs. low valence classes in the DEAP dataset, respectively. The use of datasets from laboratory-grade EEG equipment not only bolsters the robustness of the study's findings but also sets a benchmark for future research endeavors in the realm of EEG-based emotion analysis.

In the quest to identify emotions from EEG signals, representing the intricate brain activities of individuals, recent advances in machine learning algorithms have propelled the exploration of brain-computer interfaces for a broad spectrum of applications. Emotion categorization from EEG data has gained significant attention. The study conducted by Akshay et al. (2023) employs the DEAP dataset with 32 channels for EEG recording and excels in classification accuracy using the random forest machine learning (ML) algorithm [16]. In the subject-specific experiment, an average best accuracy of 91.26% is achieved, while in the subject-dependent experiment, the model reaches the best accuracy of 78.5% for the random forest classifier. The proposed method outperforms previous studies, particularly in the context of a four-class problem, where it surpasses previous accuracies, which were limited to 71.43%. This accomplishment underscores the potential of employing EEG data from high-resource lab settings for robust emotion recognition, setting a benchmark for more accessible and economical approaches discussed in the following sections.

Additionally, the study by M. Manjusha et al. (2016) on the classification of epilepsy risk level from EEG signals deserves mention. This achievement of a 93% classification accuracy underscores the effectiveness of their approach in discerning epilepsy risk levels from EEG signals [13]. Such high precision in analyzing neurological data highlights the potential applicability of EEG-based methodologies in various domains, including emotion recognition and affective computing.

Emotion recognition from EEG signals remains a challenging task, demanding extensive research to attain high accuracy. Researchers have put forth various feature extraction methods and machine learning models, often relying on datasets collected in resource-intensive lab settings. Notably, Dhara and Singh's research (2023) on "Emotion Recognition from EEG Data Using Hybrid Deep Learning Approach" presents a compelling solution. Their hybrid CNN-LSTM model, evaluated on the standard DEAP dataset, achieves outstanding test accuracies of 96.87% for valence and 97.31% for arousal dimensions [4]. Furthermore, this model reaches a state-of-the-art level of accuracy within the EEG-based emotion recognition domain. This achievement underscores the potential of deep learning techniques in enhancing emotion recognition accuracy, even with data from expensive lab equipment. Such accomplishments in high-resource settings set a benchmark for future developments and inspire progress in more accessible and cost-effective methods for EEG-based emotion analysis.

In another study, conducted by Chatterjee S et al. in 2022, their aim is to classify EEG signals into positive, negative, and neutral emotional states using a stacking-ensemble-based classification model [18]. Their approach, RLGB-SE, combines base classifiers such as random forest, light gradient boosting machine, and gradient boosting classifier, achieving an exceptional classification accuracy of 99.55%. Notably, this high accuracy, particularly when employing lab-grade EEG equipment, underscores the promise of their stacking strategy in advancing emotion classification research.

2.2 Emotion Sentiment Classification Model Using Muse EEG Wearable Device

Shifting our focus from resource-intensive lab settings to more accessible and cost-effective approaches. In the study by Laureanti et al. (2020), titled "Emotion assessment using Machine Learning and low-cost wearable devices," the effectiveness of the MUSE headband [17], alongside the Shimmer GSR+ device, in gauging individuals' emotional states during stimulus exposure is assessed. Despite the inherent complexity, machine learning techniques were utilized to extract features and train binary classifiers, resulting in accuracies ranging from 53.6% to 69.9%. These findings highlight the MUSE headband's capability to provide valuable insights into emotional states, showcasing its potential for practical applications.

The research conducted by Bird, J. et al. (2018), which introduces sentiment classification using EEG brainwave data acquired through a commercial Muse EEG headband [12]. Utilizing the Muse EEG headband equipped with four EEG sensors (TP9, AF7, AF8, TP10), they meticulously curated a dataset aimed at categorizing mental states associated with relaxation, neutrality, and concentration. The study explored various features extracted from the EEG headband, emphasizing the activity and frequency levels of signals, such as alpha, beta, theta, delta, and gamma waves. Through systematic evaluations, including 10-fold cross-validation, the researchers assessed the performance of feature selection and classification methods. Their findings revealed that, out of a vast pool of over 2100 features, only 44 were essential for achieving accurate mental state recognition. This streamlined approach, particularly when coupled with classical classifiers like Bayesian Networks, Support Vector Machines, and Random Forests, not only enhanced the accuracy of EEG-based emotion analysis but also reduced computational complexity. As a result, it offered significant potential for optimizing human-machine interaction through EEG-based mental state recognition.

Furthermore, studies led by the same authors (Bird, J. et al., 2019) focus on the crucial role of feature selection in optimizing EEG-based emotion analysis for precise mental state recognition [5]. which introduces sentiment classification using EEG brainwave data acquired through a commercial MUSE EEG headband. This headband features a low-cost setup with four electrodes corresponding to TP9, AF7, AF8, and TP10 locations, presenting an economical alternative to traditional EEG labs with extensive channels. The researchers invoke positive and negative emotional states using film clips with clear valence while also recording neutral resting data without stimuli. Statistical extraction of various brainwaves, including alpha, beta, theta, delta, and gamma, generates a substantial dataset. Feature selection based on OneR, Bayes Network, Information Gain, and Symmetrical Uncertainty scores results in a subset of 63 features with high Information Gain values. Ensemble classifiers like Random Forest, when applied to this subset, achieve impressive overall accuracy, surpassing existing methodologies by a notable margin. The best single classifier, a deep neural network, attains a high accuracy rate as well.

Additionally, a subsequent study from the same year further investigated the potential of EEG-based emotion analysis using wearable devices, indicating the ongoing evolution and refinement of methodologies in this field. This research investigates the use of evolutionary algorithms to select discriminative EEG features and optimize Artificial Neural Networks (ANNs) [6]. Utilizing a Muse EEG headband with four electrodes, experiments encompassing attention state classification, emotional sentiment classification, and number guessing tasks were conducted. The results obtained demonstrate the effectiveness of this approach, with an Adaptive Boosted LSTM achieving remarkable accuracies of 97.06% for emotional sentiment classification and 84.44% for attentional state classification. The adoption of a Muse EEG headband, known for its cost-effectiveness and practicality, underscores the advancements in EEG-based emotion analysis facilitated by wearable devices.

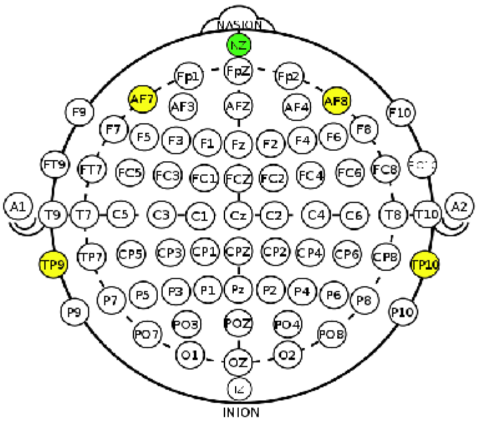

Fig. 2. Four-electrode setup for Muse EEG headband. Adapted from Bird, Jordan & Ekart, Aniko & Buckingham & Faria, Diego (2019)

The dataset collected through this setup serves as a valuable asset for further exploration into accessible and accurate emotion recognition methodologies. These findings highlight the promising potential of low-cost EEG setups in achieving exceptional accuracy in emotion recognition tasks, thus encouraging the investigation of practical and economical alternatives for EEG-based sentiment classification.

2.3 Medical and Physiological Applications Beyond Emotion Analysis Utilizing Muse EEG Wearable

Beyond emotion analysis, wearable EEG devices demonstrate remarkable accuracy and potential for diverse medical and psychological applications. Arsalan et al. (2019) showcase this potential by effectively classifying perceived mental stress using the Muse EEG headband's four electrodes, achieving high accuracy rates [7]. Their findings highlight the suitability of low-cost EEG setups for robust data collection, paving the way for precise model development in addressing mental health concerns.

Additionally, the same author (Arsalan et al. 2020) introduced a trait anxiety detection framework leveraging the device's data quality to distinguish between anxious and non-anxious individuals [8].

Wearable EEG devices demonstrate remarkable potential for data-driven model development across various medical and psychological applications. The effectiveness of neurofeedback in treating PTSD is underscored, highlighting the device's role in mental health therapy and its ability to provide precise data crucial for advancing therapeutic interventions [9].

Furthermore, the capability of a 4-electrode Muse EEG device in classifying cognitive fatigue with high accuracy is demonstrated, paving the way for robust models to detect cognitive fatigue and improve interventions for individuals experiencing mental exhaustion [10].

Additionally, the utility of the Muse EEG headband for predicting stroke severity is emphasized, facilitating the development of models for early stroke diagnosis and patient triage, thereby enhancing the efficiency of healthcare delivery and improving patient outcomes [11].

Collectively, these studies underscore the accuracy and reliability of data collected using wearable EEG devices, emphasizing their pivotal role in building robust models for a wide range of medical and psychological applications. The high-quality data provided by these devices opens new avenues for precise and effective healthcare solutions.

2.4 XGBoost Applications in EEG Signal Analysis

XGBoost offers numerous advantages that make it well-suited for EEG data classification tasks. Its ability to handle large datasets, deal with missing values, and prevent overfitting makes it a powerful tool in the realm of EEG signal analysis. The versatility and robustness of XGBoost make it particularly promising for accurately classifying EEG data, thus paving the way for more efficient and reliable processing.

In this study, the focus lies on exploring the utilization of XGBoost for EEG data classification and understanding its potential applications in the broader context of brain signal analysis. While the study by Balli, Osman (2022) highlights the efficacy of XGBoost in EEG signal classification, it's important to note that other researchers have also explored the use of XGBoost in similar contexts [14]. This underscores the growing interest and recognition of XGBoost as a valuable tool in EEG signal analysis.

Parui et al. (2019) propose an innovative approach to enhance the classification of different types of emotions with improved accuracy [15]. Their methodology involves the extraction of several features from EEG brain signals. These features are then optimized using techniques such as correlation matrix analysis, information gain calculation, and recursive feature elimination. The results of the study demonstrate that feature optimization followed by the XGBoost algorithm significantly improves classification accuracy for emotion recognition tasks. Notably, the proposed approach is evaluated using the DEAP dataset, sourced from high-cost laboratory EEG setups. It is essential to highlight that the study does not utilize the MUSE dataset commonly associated with low-cost EEG setups but instead relies on the DEAP dataset, which offers comprehensive EEG data obtained from high-cost lab EEG setups.

In conclusion, the comprehensive exploration of emotion sentiment classification models using both laboratory-grade EEG equipment and Muse EEG wearable devices, alongside the examination of medical and physiological applications beyond emotion analysis, provides a solid foundation for our research endeavors. The integration of XGBoost applications in EEG signal analysis, as evidenced by prior studies, underscores its potential in enhancing emotion recognition accuracy and advancing the field of neuroscience. By leveraging the insights gained from these diverse approaches, we are confident in the success of our project. The utilization of XGBoost specifically for emotion recognition, without reliance on the MUSE dataset but instead leveraging the DEAP dataset from high-cost lab EEG, presents a promising avenue for achieving improved accuracy in emotion classification. This amalgamation of methodologies and datasets not only enriches our understanding of EEG-based emotion analysis but also propels us toward our research goals with optimism and determination.

3 Method

In the methodology section, we present our approach to developing and evaluating the sentiment classification model using EEG data. We introduce the data sources utilized, conduct exploratory data analysis (EDA) to understand the dataset's characteristics, and proceed with the modeling phase.

3.1 Data Source

The EEG brainwave data utilized in this study originates from two seminal research papers [5] [6] led by Bird, J. et al. These papers, recognized for their valuable contributions to EEG-based emotion classification and brain-machine interface research, are titled: "A study on mental state classification using EEG-based brain-machine interface," presented at the 9th International Conference on Intelligent Systems in 2018 and "Mental emotional sentiment classification with an EEG-based brain-machine interface," presented at The International Conference on Digital Image and Signal Processing in 2019.

The EEG data collection process involved human subjects participating in controlled experiments with carefully chosen emotional stimuli. Recorded using a Muse EEG headband equipped with dry electrodes at TP9, AF7, AF8, and TP10 locations, the dataset is publicly available on Kaggle.

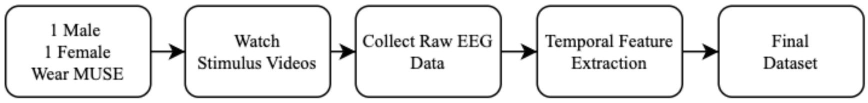

Fig. 4. The diagram illustrates the data collection steps by previous research (Bird, J. et al., 2019). Subjects wear Muse EEG headbands while viewing stimulus videos, and the collected data undergoes raw EEG extraction. Feature extraction techniques, including temporal methods, are then applied to identify pertinent features. These features are compiled into a final dataset for in-depth analysis and emotion classification

The dataset comprises recordings from two participants, one male and one female, each observed for 3 minutes per emotional state (positive, neutral, negative). Using dry electrodes, the Muse EEG headband captured EEG signals from TP9, AF7, AF8, and TP10 locations. In addition to the emotional states, six minutes of resting neutral data were also recorded. The emotional stimuli, as shown in Table 1, included scenes from well-known films and nature timelapse clips.

Table 1. List of emotional stimuli videos sourced from previous research (Bird, J. et al., 2019)

Scene	Studio	Stimuli Emotion
Marley and Me (2008)	Twentieth Century Fox	Negative
Up (2009)	Wal Disney Pictures	Negative
My Girl (1991)	Imagine Entertainment	Negative
La La Land (2016)	Summit Entertainment	Positive
Slow Life (2014)	BigQuest Studios	Positive
Funny Dogs (2015	MashupZone	Positive

Following the collection of EEG signals in each emotional state, a comprehensive set of features was extracted for analysis. The dataset encompasses 2548 features extracted statistically from each sliding time window, employing temporal extraction techniques such as mean, median, standard deviation, and more. This extensive feature set aims to capture the diverse aspects of brainwave activity associated with different emotional states.

3.2 Exploratory Data Analysis (EDA)

This section will delve into the Exploratory Data Analysis phase, providing insights into the characteristics of the EEG dataset. Descriptive statistics, visualizations, and key observations will be presented to offer a comprehensive understanding of the data's distribution, patterns, and potential challenges.

	# mean_0_a	mean_1_a	mean_2_a	mean_3_a	...	fft_747_b	fft_748_b	fft_749_b	label
0	4.620	30.300	-356.000	15.600	...	-162.000	-162.000	280.000	NEGATIVE
1	28.800	33.100	32.000	25.800	...	-31.600	-31.600	2.570	NEUTRAL
2	8.900	29.400	-416.000	16.700	...	-148.000	-148.000	281.000	POSITIVE
3	14.900	31.600	-143.000	19.800	...	9.530	9.530	-12.400	POSITIVE
4	28.300	31.300	45.200	27.300	...	23.900	23.900	-17.600	NEUTRAL
...	...	...	...	...	...	...	...	...	...
2127	32.400	32.200	32.200	30.800	...	47.200	47.200	-19.900	NEUTRAL
2128	16.300	31.300	-284.000	14.300	...	-59.800	-59.800	142.000	POSITIVE
2129	-0.547	28.300	-259.000	15.800	...	-10.500	-10.500	-169.000	NEGATIVE
2130	16.800	19.900	-288.000	8.340	...	-271.000	-271.000	552.000	NEGATIVE
2131	27.000	32.000	31.800	25.000	...	22.800	22.800	-6.710	NEUTRAL

2132 rows × 2549 columns

Fig. 5. Dataset Overview: Statistical Features Extracted from EEG Signals, with 2548 Features, 1 Target Label, and 2132 Records

The dataset under consideration, containing 2132 rows and 2549 columns, presents a comprehensive tabular structure for analysis. Each row signifies an individual observation, while columns encompass a range of features, such as 'mean_0_a,' 'mean_1_a,' ..., 'fft_749_b,' and the 'label' column, designating the emotional sentiment category (NEGATIVE, NEUTRAL, POSITIVE) associated with each observation. One notable advantage in this dataset is the absence of missing values, streamlining the preprocessing stage and ensuring a complete dataset for analysis. The features within the dataset exhibit a numerical nature, reflecting statistical attributes like mean values ('mean_0_a,' 'mean_1_a') and Fast Fourier Transform (FFT) coefficients ('fft_0_a,' 'fft_1_a'). Given the structure, it is evident that these features are likely derived from EEG brainwave data, capturing both statistical characteristics and frequency-related components.

In Figure 6, we observe the distribution of sentiment labels across the dataset, revealing a well-balanced distribution among the three categories. Approximately 33.6% of the instances are labeled as neutral, while positive and negative sentiments each constitute 33.2% of the dataset. This equal distribution is highly beneficial for the development of machine learning models, as it fosters a scenario where the model is exposed to a representative and diverse set of sentiment instances. This balance minimizes the risk of bias and ensures that the model can effectively learn from instances of each sentiment category. Such equilibrium in label distribution forms a solid foundation for training sentiment classification models, contributing to their ability to generalize and accurately predict emotions across a spectrum of positive, negative, and neutral states.

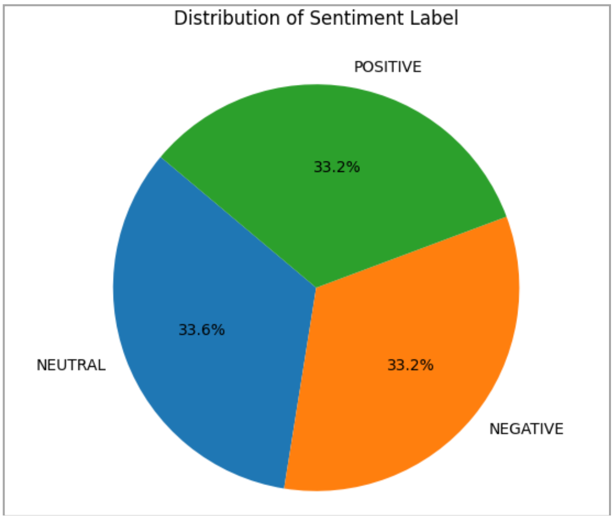

Fig. 6. Distribution of Labels: The balanced distribution among positive (33.2%), negative (33.2%), and neutral (33.6%) labels forms a solid foundation for training sentiment classification models.

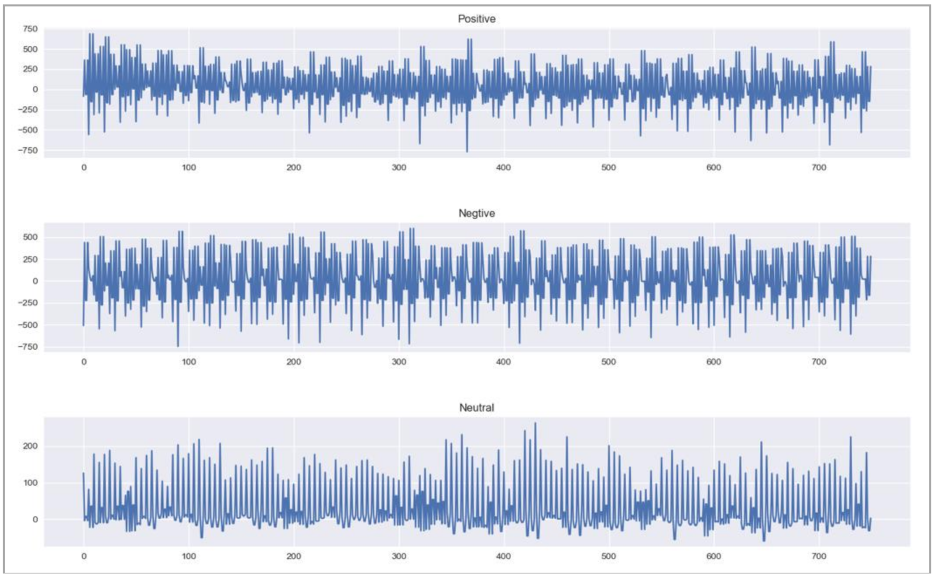

Fig. 7. EEG Signal Patterns illustrate show the distinctive EEG signal patterns corresponding to positive, negative, and neutral emotional states

As shown in figure 7, The plot illustrates the distinct signal patterns of EEG data corresponding to positive, negative, and neutral sentiments. Each subplot represents a sentiment category, with the x-axis denoting the sample index and the y-axis indicating the signal amplitude. Notably, positive and negative signals predominantly exhibit amplitudes greater than 600 and less than -600, suggesting pronounced variations. In contrast, neutral signals cluster within the range of -50 to 250, showcasing a comparatively narrower amplitude distribution. It's important to note that these patterns emerge from a subset of features, specifically filtered to focus on relevant information. The EEG data has 2548 features, and this analysis specifically considers the range from 'fft_0_b' to 'fft_749_b,' narrowing down the features for a more targeted exploration. This separation highlights the potential discriminatory features present in the EEG data, laying the groundwork for further analysis and model development in sentiment classification tasks.

In Summary, The Exploratory Data Analysis (EDA) of the EEG-based emotion classification dataset, comprising 2132 observations and 2549 features, revealed a well-distributed label distribution with approximately 33.6% for neutral sentiments and 33.2% each for positive and negative sentiments. The absence of missing values and the wide span of numerical representations contribute to the dataset's complexity. EDA plots, such as Figure 6, highlighted distinct patterns in positive, negative, and neutral signals, laying a robust foundation for subsequent model development with a balanced dataset conducive to effective sentiment classification based on EEG data.

3.3 XGBoost Model Algorithm

This section explores the utilization of the XGBoost algorithm for EEG-based sentiment classification. XGBoost, also known as Extreme Gradient Boosting, is renowned for its versatility and effectiveness in diverse machine learning tasks, including sentiment analysis based on EEG signals.

XGBoost operates on a boosting ensemble learning technique, sequentially constructing multiple weak models to rectify errors made by its predecessors. Through iterative refinement, XGBoost achieves exceptional predictive performance, making it an appealing choice for sentiment classification tasks [22].

One of the notable strengths of XGBoost lies in its ability to handle complex datasets effectively. By incorporating regularization techniques, it prevents overfitting and enhances generalization. Additionally, XGBoost demonstrates robustness in handling missing values, ensuring efficient utilization of incomplete data [22].

Furthermore, XGBoost is highly scalable and adaptable, facilitating parallel processing even with large datasets. Its flexibility and robustness contribute to its widespread adoption in various machine learning tasks.

In the context of EEG-based sentiment classification, XGBoost excels in capturing subtle patterns within EEG signals. With EEG data often exhibiting non-linear relationships, XGBoost's gradient boosting approach effectively captures complex interactions and dependencies, enabling accurate classification of emotional states [22].

XGBoost is typically employed in supervised learning scenarios, where training data denoted by (x, y) is utilized to predict a target variable y. The model's formulation can be expressed as follows:

$$\hat{y}_i = \sum_{k=0}^{K} f_k(x_i), f_k \in U \tag{1}$$

This equation represents the aggregation process in XGBoost, where K denotes the total number of trees. Each tree's prediction, denoted by f_k belongs to the function space U. The equation iterates over all K trees in the ensemble, summing up their individual predictions for the input data point x_i, yielding the final prediction y_i as aggregated outcome [22].

Overall, XGBoost's versatility, scalability, and capability to handle non-linear relationships make it a powerful tool for EEG-based sentiment classification, enabling precise inference of emotional states from EEG data.

3.4 Model Development Process

In the initial step, the categorical sentiment labels ('NEGATIVE', 'NEUTRAL', 'POSITIVE') are transformed into numerical representations (0, 1, 2) using a predefined dictionary called label_mapping. This conversion is crucial for ensuring compatibility with machine learning algorithms. Subsequently, the preprocess_inputs function is utilized to partition the dataset into input features (X) and target labels (y), where the 'label' column serves as the target variable. By employing the train_test_split function, the dataset is further divided into training and testing sets, with 70% of the data allocated for training and 30% for testing. This preprocessing pipeline prepares the data for subsequent modeling steps, facilitating the development and evaluation of sentiment classification models.

Upon inspection, the training set comprises 1492 samples, each associated with a corresponding label, while the testing set consists of 640 samples, also aligned with their respective labels. This verification ensures the consistency and integrity of the dataset, guaranteeing that each observation is appropriately paired with its corresponding label for accurate model training and evaluation.

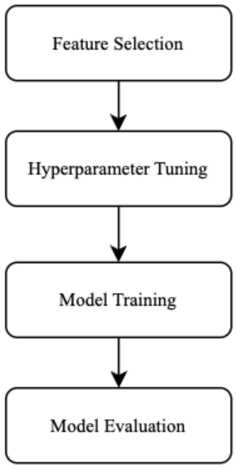

Fig. 8. The diagram illustrates the sequential workflow involved in preparing and developing a machine learning model. It consists of four main stages, each contributing to the refinement and optimization of the model for optimal performance.

The sequential workflow outlined in the diagram (Fig. 7) presents the systematic progression of tasks involved in preparing and refining a machine learning model. Beginning with feature selection, the process identifies and prioritizes the most influential attributes crucial for effective classification. This initial stage streamlines the dataset, enhancing the model's efficiency by focusing on key features. Moving to hyperparameter tuning, the model's parameters undergo optimization to maximize performance, ensuring alignment with the dataset and task requirements. Once parameters are fine-tuned, the model proceeds to training, utilizing the selected features and optimized parameters to learn predictive patterns from the provided data. Finally, model evaluation rigorously assesses the trained model's performance using metrics such as accuracy, precision, recall, and F1-score, offering invaluable insights into its effectiveness and areas for potential refinement. This systematic approach to model preparation, as depicted in Fig. 7, guarantees the resulting model is not only robust and accurate but also meticulously optimized for its intended purpose.

3.5 Model Feature Selection

Feature selection techniques were utilized to identify the most informative and relevant features for the classification task. This step involved analyzing the importance of each feature and selecting a subset of features that contributed the most to the predictive power of the model.

Following initial model training, we computed feature importance scores using the trained XGBoost classifier. These scores quantified the contribution of each feature to the predictive capability of the model. Subsequently, we sorted the features based on their importance scores in descending order.

	Feature	Importance Score									
0	# mean_0_a	0.147733	25	correlate_46_b	0.00476093	50	covmat_26_a	0.00259433	75	fft_630_a	0.00143578
1	max_q_8_a	0.136296	26	mean_d_46_b	0.00469457	51	mean_d_16_a	0.00244271	76	min_q_15_b	0.00142767
2	mean_2_b	0.0863283	27	mean_4_b	0.00466118	52	covmat_83_a	0.00240615	77	min_q_27_a	0.00141243
3	fft_46_a	0.0745661	28	min_1_b	0.00461457	53	correlate_35_b	0.002392	78	covmat_5_a	0.00138375
4	max_q_3_a	0.0455134	29	min_q_5_a	0.00417607	54	fft_727_b	0.00237526	79	min_q_13_b	0.00134087
5	mean_0_b	0.0420689	30	mean_d_11_b	0.00399224	55	covmat_3_a	0.00235361	80	min_3_a	0.00130581
6	fft_541_a	0.0342774	31	eigen_4_a	0.00373378	56	fft_360_b	0.00234111	81	max_2_b	0.00127283
7	mean_d_17_a	0.0329787	32	fft_195_a	0.00367514	57	min_1_a	0.00233023	82	min_q_15_a	0.00123909
8	stddev_1_b	0.0279176	33	eigen_0_b	0.00363403	58	covmat_105_b	0.00229079	83	stddev_3_b	0.0012104
9	correlate_45_b	0.0191893	34	mean_d_13_b	0.00363313	59	covmat_10_a	0.00223479	84	correlate_66_a	0.00119152
10	eigen_0_a	0.0179322	35	min_q_18_b	0.00362116	60	logm_3_b	0.00202112	85	logm_8_b	0.00118253
11	max_q_3_b	0.0175949	36	stddev_0_a	0.0035276	61	mean_d_8_a	0.00200364	86	min_q_11_b	0.00108927
12	moments_16_a	0.0166319	37	covmat_4_b	0.0035244	62	fft_525_a	0.00198827	87	fft_586_a	0.00107622
13	covmat_20_a	0.0158568	38	min_q_10_b	0.00339884	63	mean_d_45_a	0.00195292	88	moments_6_a	0.00106819
14	covmat_130_a	0.0152731	39	covmat_21_a	0.00330735	64	fft_720_a	0.00194965	89	min_q_46_b	0.00104367
15	covmat_8_a	0.00961654	40	mean_d_12_b	0.00329556	65	mean_2_a	0.00188514	90	mean_1_a	0.00104035
16	covmat_16_b	0.00946087	41	min_q_10_a	0.00317975	66	mean_4_a	0.00186258	91	fft_661_a	0.00102583
17	stddev_0_b	0.0079095	42	fft_181_a	0.00315893	67	max_3_a	0.00181767	92	moments_0_b	0.00100741
18	min_q_5_b	0.00761345	43	max_q_13_a	0.00315008	68	min_q_8_a	0.00173347	93	covmat_52_a	0.000958895
19	stddev_1_a	0.00620887	44	covmat_0_a	0.00281668	69	mean_3_a	0.00167573	94	logm_25_a	0.000958187
20	max_q_13_b	0.00590344	45	logm_66_a	0.0028085	70	mean_d_31_a	0.00166796	95	stddev_d_0_a	0.000951208
21	covmat_56_a	0.00524604	46	min_q_0_a	0.00280809	71	fft_410_b	0.00163312	96	mean_d_2_a2	0.000924085
22	min_q_3_a	0.00512193	47	mean_d_15_b	0.00280167	72	mean_3_b	0.00153463	97	mean_d_4_a2	0.000922574
23	correlate_21_b	0.00505931	48	fft_440_b	0.00273429	73	fft_165_a	0.0015247	98	fft_662_b	0.000900541
24	eigen_3_b	0.00477383	49	fft_696_a	0.0026884	74	correlate_49_a	0.0014712	99	covmat_44_b	0.000880963

Fig. 9. The top 100 features ranked according to their feature importance scores, highlighting the most influential factors identified by the XGBoost model in EEG-based sentiment classification

To streamline the feature set and focus on the most influential attributes, we selected the top N features with the highest importance scores. In our case, we opted for the top 100 features for further analysis and model refinement. These selected features were deemed to carry the most discriminative information for the task of emotional sentiment classification

3.6 Model Hyperparameter Tuning

In the model hyperparameter tuning phase, we meticulously defined a parameter grid that encapsulated various hyperparameter values pivotal for exploring the tuning process. The grid encompassed key parameters such as max_depth, min_child_weight, subsample, colsample_bytree, learning_rate, n_estimators, and gamma. Each parameter was assigned multiple values, ensuring a thorough exploration of the parameter space.

Table 2. Hyperparameter Grid for XGBoost Model Tuning

Parameter Name	Value to search	Optimal value
max_depth	3, 5, 7	7
min_child_weight	1, 3, 5	1
subsample	0.6, 0.8, 1	1
colsample_bytree	0.6, 0.8, 1	1
learning_rate	0.01, 0.1, 0.2	0.2
n_estimators	100, 200, 300	100
gamma	0, 0.1, 0.2	0

Table 2 illustrates the parameter grid utilized for hyperparameter tuning through grid search in the XGBoost model. It encompasses various hyperparameters, including max_depth, min_child_weight, subsample, colsample_bytree, learning_rate, n_estimators, and gamma, each with specific values aimed at optimizing the model's performance."

To rigorously evaluate the model's performance, Stratified K-Fold cross-validation with 5 folds was implemented. This method enabled assessment across diverse dataset subsets while maintaining class distribution integrity, mitigating overfitting risks, and yielding reliable estimates of model generalization.

The hyperparameter tuning approach relied on the robust GridSearchCV function from the scikit-learn library. This tool facilitated exhaustive exploration of the parameter grid, systematically evaluating each combination through cross-validation. To enhance efficiency and prevent overfitting, early stopping mechanisms were integrated, capping the maximum number of rounds at 10 during the grid search.

Post grid search, the optimal hyperparameter combination was determined based on the highest accuracy score from cross-validation. This meticulous selection ensured the final XGBoost model was trained using the most effective hyperparameters obtained from the grid search, thereby bolstering its predictive performance and generalization capabilities.

3.7 Model Training

In the phase of model retraining, we undertook a meticulous approach by combining the top 100 features selected through the feature selection process with the optimal hyperparameters obtained from the grid search procedure. This integration aimed to refine the model's predictive capacity by prioritizing the most influential features while fine-tuning the model's parameters for optimal performance.

Through this integrated approach, we aimed to achieve a balance between model complexity and predictive accuracy, thereby ensuring that the final model is well-suited for real-world applications and capable of delivering reliable insights from the data. To evaluate the model's performance robustly, we implemented Stratified K-Fold cross-validation with 5 folds. This approach allowed us to assess the model across diverse subsets of the dataset while preserving the distribution of classes. By employing Stratified K-Fold, we mitigated the risk of overfitting and attained reliable estimates of the model's generalization performance.

3.8 Model Evaluation

In evaluating the performance of our trained XGBoost model, we will employ two key evaluation metrics: the classification report and the confusion matrix.

Firstly, we will generate a classification report, which provides detailed metrics for each class, including precision, recall, and F1-score. This report allows us to assess the model's performance across different classes and identify any potential imbalances or biases in its predictions.

Secondly, we will construct a confusion matrix to visually represent the model's performance. By comparing predicted labels against true labels, the confusion matrix helps us understand the distribution of correct and incorrect predictions across different classes. This analysis enables us to identify patterns of misclassification and assess the overall accuracy of the model.

By utilizing both the classification report and the confusion matrix, we aim to gain comprehensive insights into the strengths and weaknesses of our XGBoost model, thereby making informed decisions regarding its deployment in real-world applications.

4 Results

The XGBoost model exhibited exceptional performance, achieving an accuracy of 99.1% when trained with selected features, underscoring its effectiveness in sentiment classification across the dataset.

A detailed analysis of the model's classification capabilities is presented in the classification report as shown in figure 11. Precision, recall, and F1-score metrics are provided for each sentiment category (negative, neutral, and positive), showcasing the model's ability to accurately classify instances within each class. The macro and weighted average F1-scores, both at 0.99, indicate high overall model performance across all sentiment categories.

Furthermore, the confusion matrix offers valuable insights into the model's classification outcomes as shown in figure 12. The high diagonal values in the confusion matrix signify correct predictions, while off-diagonal elements highlight instances of misclassification. Specifically, the model demonstrates strong performance in accurately classifying instances across all sentiment categories, as evidenced by the distribution of values in the confusion matrix.

Classification Report for XGBoost Model:

	precision	recall	f1-score	support
0	0.99	0.99	0.99	201
1	1.00	0.99	1.00	231
2	0.98	0.99	0.98	208
accuracy			0.99	640
macro avg	0.99	0.99	0.99	640
weighted avg	0.99	0.99	0.99	640

Fig. 11. The classification report for XGBoost model provides detailed metrics on the XGBoost model's performance across different sentiment categories.

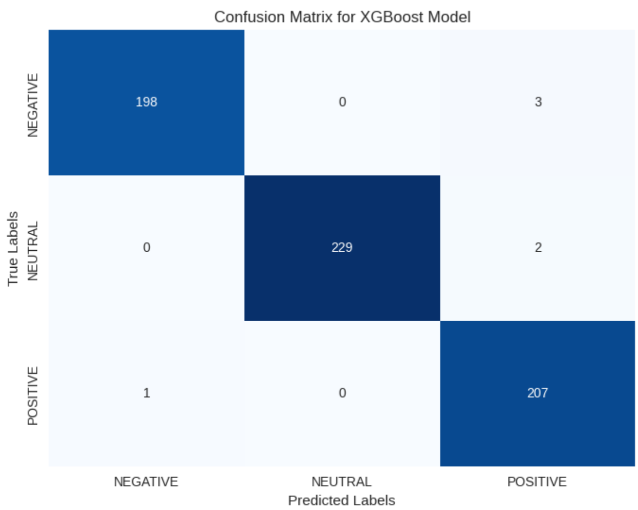

Fig. 12. The confusion matrix for XGBoost model provides classification performance across sentiment categories.

Overall, these results underscore the robustness and efficacy of the XGBoost model in sentiment classification, validating its potential for real-world applications in sentiment analysis and beyond.

5 Discussion

The utilization of XGBoost in EEG-based classification has demonstrated remarkable accuracy compared to conventional methods. Our model achieved higher accuracy rates than most research efforts in this domain. This suggests the efficacy of XGBoost in extracting meaningful patterns from EEG signals, contributing to enhanced sentiment classification performance.

While achieving high accuracy is commendable for predictive tasks, it may not necessarily translate to interpretability. In our study, prioritizing accuracy enabled us to develop a robust predictive model for sentiment classification. However, the trade-off between accuracy and interpretability is crucial, especially in contexts where understanding the underlying factors driving predictions is essential for decision-making processes.

It's imperative to acknowledge the limitations of our study, particularly regarding the dataset's scope and generalizability. The data collection process involved a small sample size comprising only two individuals (1 male, 1 female), each monitored for 3 minutes per state while watching specific video scenes. Such a limited dataset may not fully represent the broader population, thereby potentially constraining the model's generalization to diverse demographic groups. Additionally, gender differences in emotional processing and response patterns could influence the interpretation of the EEG signals [19] [20] and should be considered in future studies aiming for broader applicability.

In future research, it is imperative to extend the applicability of the model to real-time settings and larger participant cohorts, integrating EEG signals and an attention mechanism into deep learning models. By deploying the model in real-time scenarios where participants engage with various video stimuli, we can evaluate its performance across a more extensive range of emotional states and demographic profiles. Additionally, incorporating EEG data collected from devices like the MUSE EEG headband could enhance the model's scalability and applicability to real-world emotion prediction applications, paving the way for innovative solutions in affective computing and human-computer interaction, as well as consumer sentiment analysis in e-commerce [21].

6 Conclusion

This research represents a significant milestone in EEG-based sentiment classification, leveraging data obtained from the MUSE EEG wearable device to achieve an outstanding accuracy rate of 99.1%. Through the implementation of advanced machine learning techniques, particularly XGBoost, the study successfully decoded emotional states based on EEG signals recorded during participants' engagement with video stimuli. The approach adopted in this research underscores the effectiveness of employing ensemble learning algorithms like XGBoost to discern intricate patterns within EEG signals, thereby enabling precise inference of emotional states. By demonstrating the potential of machine learning models to decipher subtle nuances in human emotions, this study contributes substantially to the fields of affective computing and human-computer interaction.

Moving forward, future research endeavors may explore avenues to expand the dataset, incorporating a more diverse sample of participants and scenarios. Furthermore, integrating real-time EEG monitoring devices like the MUSE EEG wearable device opens avenues for creating practical applications capable of accurately predicting and responding to users' emotional states in real-time settings.

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