4/2025

Emotion Recognition Using EEG Signals

Sultanah Al Mutairi
Computer Engineering
Mustaqbal University - Saudi Arabia

Abstract:

This project develops an emotion recognition system using a single-electrode EEG device (TGAM) to classify emotional states such as happiness and sadness. EEG data was processed with filters like Moving Median, Notch Filter, Thresholding, and Band-Pass to isolate relevant frequency bands (Theta, Alpha, Beta, and Gamma). Features like Power Spectral Density (PSD), Mean, Standard Deviation, and Entropic Features such as Permutation Entropy and Spectral Entropy were extracted. These features were used with an SVM classifier. The model achieved 88.64% accuracy, with better performance for happiness (96%) than sadness (84%). The reduced accuracy is a result of the trade-off between the lower cost of the single-channel EEG device and its classification performance.

Note:

This project is a developmental enhancement of a previous project titled “Emotion Recognition using EEG signals”, which was initially conducted as part of a mini-project at Mustaqbal University, Saudi Arabia. I, Sultana Al Mutairi, was part of the original project, alongside my colleagues S. Al Sultan and A. AlAnzy (2024). This version of the project focuses on improving feature extraction methods and enhancing data filtering techniques, with the goal of refining the emotion classification performance.

1 Introduction

Emotions play a vital role in human cognition, influencing behavior, decision-making, and communication. As technology advances, integrating emotional awareness into machines has become a key goal in artificial intelligence, human-computer interaction, and mental health applications.

Various emotion recognition techniques have been developed, each with varying degrees of accuracy. Facial expression analysis typically achieves 60% to 80% accuracy but struggles with subtle or culturally influenced expressions [2]. Voice tone analysis ranges from 55% to 75% but performs poorly in noisy environments or across diverse accents [1]. Self-report surveys, while useful, rely on individuals' subjective responses and are often limited in reliability [1].

In contrast, Electroencephalography (EEG) provides a more objective method by measuring brain activity directly. EEG-based systems typically reach 70% to 90% accuracy using machine learning, though their effectiveness depends on electrode placement, individual variability, and hardware complexity [2].

Emotion recognition also has practical applications in diagnosing mental health conditions such as depression and schizophrenia. It can support clinicians in assessing emotional states and enhance human-computer interaction by enabling more responsive systems [3]. Among various bio-signals used for emotion recognition including ECG, EMG, PPG, and GSR, EEG remains the most commonly applied due to its strong correlation with emotional brain activity [4].

This project presents a cost-effective, real-time emotion recognition system using a single-channel EEG device (TGAM) combined with machine learning techniques. Visual stimuli are used to evoke emotions, and EEG signals are preprocessed using filtering and Fast Fourier Transform (FFT). An SVM classifier is trained to distinguish between happiness and sadness with high accuracy.

2 Literature Review

2.1 Electroencephalography (EEG)

EEG is a well-known method for recognizing emotions because it measures brain activity directly. It records electrical signals from the brain, usually through electrodes placed on the scalp.

These signals are divided into different frequency bands like delta, theta, alpha, beta, and gamma [6], which have been linked to different emotional and mental states.

Unlike other methods like facial expressions or voice tone, EEG gives us a more accurate and real-time look at what's happening inside the brain. Many researchers have used EEG to successfully detect emotions such as happiness, sadness, fear, and relaxation by applying signal processing and machine learning techniques [6].

Even though EEG is non-invasive and fast, it's also sensitive to noise and can vary between people. That's why preprocessing the data and choosing the right features is very important. Because of these challenges, researchers continue to improve machine learning models and filtering methods to make emotion recognition more accurate [5].

2.2 EEG Frequency Bands and Their Relation to Emotion Recognition

EEG signals are divided into different frequency bands, each associated with distinct cognitive and emotional states. The most commonly analyzed bands in emotion recognition studies are Delta, Theta, Alpha, Beta, and Gamma. However, not all of these bands are equally relevant for the recognition of specific emotional states such as happiness and sadness [9].

For this project, we focus primarily on the Theta, Alpha, Beta, and Gamma bands, as they have been shown to correlate with the emotional states of interest.

2.2.1 Delta (0.5 - 4 Hz):

The Delta band is primarily associated with deep sleep and unconscious states. Delta power increases during low alertness and unconscious states and is not related to emotional states such as happiness or sadness. According to Niedermeyer and da Silva (2004), Delta reflects restorative processes during sleep and is not involved in cognitive or emotional processing, making it irrelevant for emotion recognition [9].

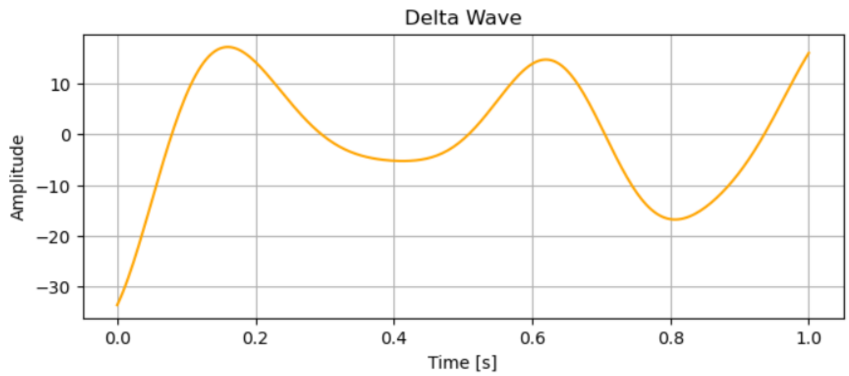


Figure 1: Delta Waveform

2.2.2 Theta (4 - 8 Hz):

The Theta band is linked to relaxed focus, emotional processing, and memory consolidation. It plays a key role in emotion regulation and has been found to increase in response to emotionally arousing stimuli, particularly in states of sadness or relaxation. Niedermeyer and da Silva (2004) explain that Theta activity is involved in emotional processing and memory functions, which makes it relevant for recognizing sadness and other emotional states tied to relaxation and reflection [9].

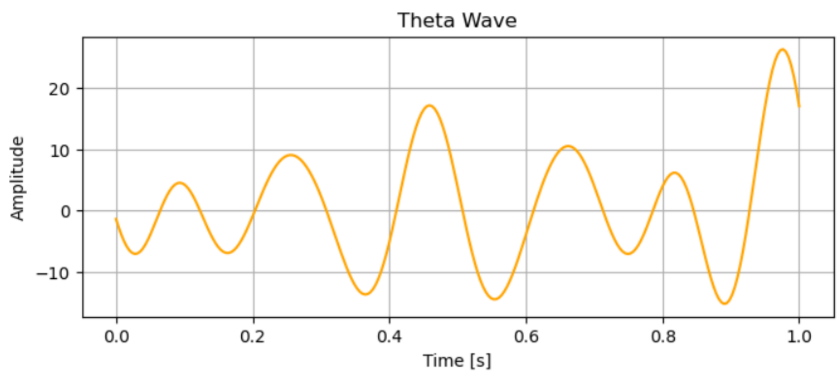


Figure 2: Theta Waveform

2.2.3 Alpha (8 - 13 Hz):

The Alpha band is typically associated with relaxed alertness and calmness. Alpha power increases in states of relaxed wakefulness and is linked to positive emotional states, such as happiness. It is suppressed during tasks that require focus or mental engagement. Niedermeyer and da Silva (2004) note that Alpha waves reflect states of relaxation and are connected to positive emotions like happiness, especially left-frontal Alpha, which has been found to correlate with positive emotional states.[9]

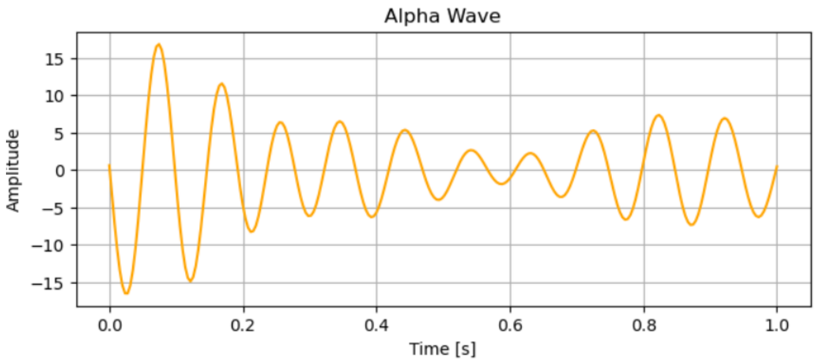


Figure 3: Alpha Waveform

2.2.4 **Beta (13 - 30 Hz):**

The Beta band is associated with active thinking, problem-solving, and cognitive engagement. It also reflects emotional arousal such as stress and anxiety. Beta power increases during mental tasks or in response to negative emotions like sadness. Niedermeyer and da Silva (2004) explain that Beta activity is indicative of mental engagement and emotional arousal, particularly during stress or negative emotional states, which are common in sadness.[9]

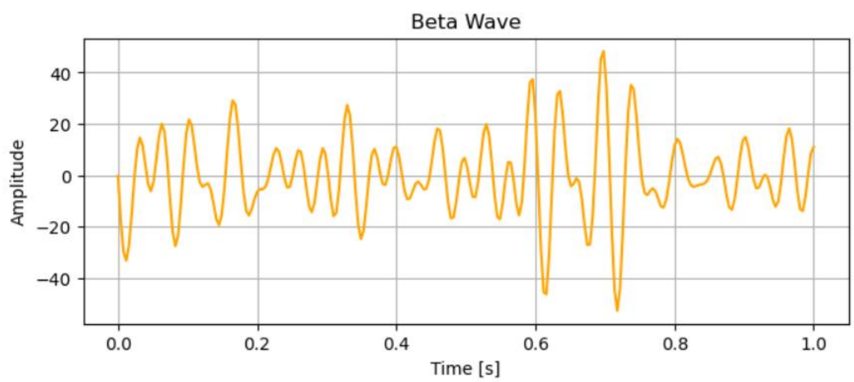


Figure 4: Beta Waveform

2.2.5 **Gamma (30 - 100 Hz):**

The Gamma band is associated with higher-order cognitive functions, sensory processing, and emotional awareness. It reflects emotionally significant stimuli, with increased Gamma activity during emotionally arousing events. Niedermeyer and da Silva (2004) highlight that Gamma-band activity is crucial for cognitive processing and emotional awareness, particularly when responding to emotionally charged stimuli, making it relevant for both positive and negative emotional states like happiness and sadness.[9]

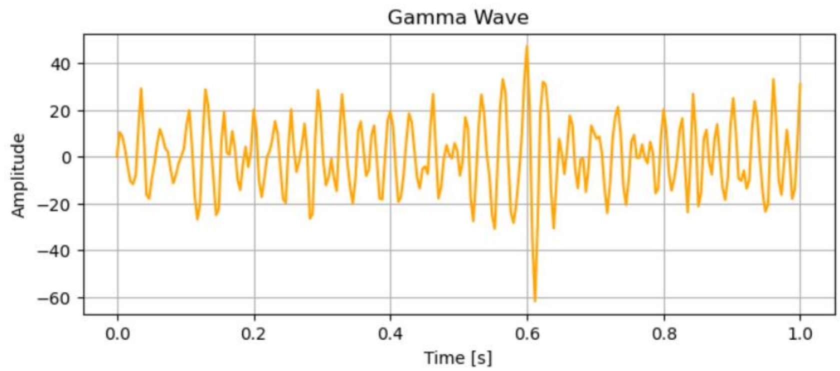


Figure 5: Gamma Waveform

2.3 Welch's method

The Welch method is commonly used to analyze EEG signals, especially to estimate something called Power Spectral Density (PSD). This helps show how the energy in the brainwaves is spread across different frequencies [7].

Compared to older methods like the periodogram, Welch's method works better in reducing noise and gives more stable results by breaking the signal into overlapping parts, applying a window, and averaging them [7]. This is helpful because EEG signals are often messy and change over time.

Studies like the one by Gannouni et al. used PSD features from EEG data and showed that this approach improves the accuracy of emotion classification. That's why the Welch method is still widely used in research today.

2.4 TGAM Module

The TGAM module by NeuroSky is a simple and affordable EEG device with just one channel. It's often used in emotion recognition projects because it's easy to use and doesn't require complicated setup. It collects brain signals from the front of the head (usually FP1) and gives both raw EEG data and values for attention and meditation [8].

Even though it only uses one electrode, TGAM has been shown to work well in research when combined with proper signal processing and machine learning models.

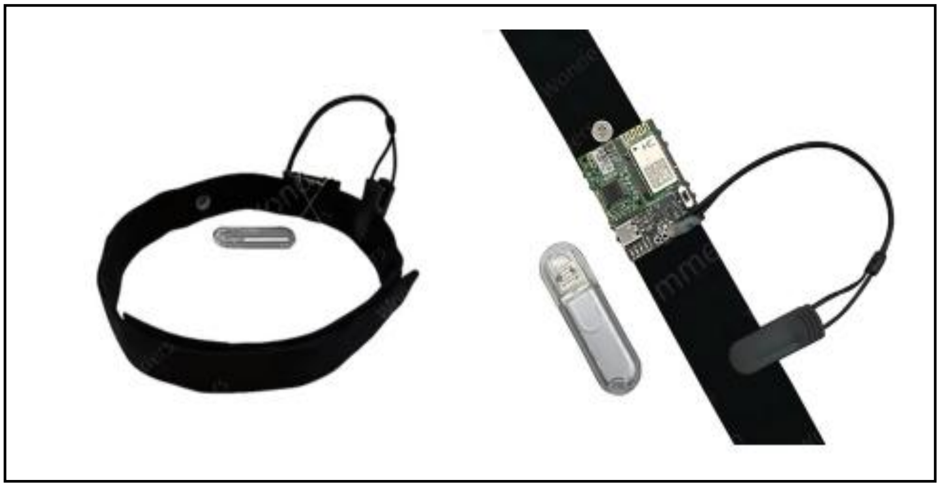


Figure 6: TGAM Kit: Headband, Sensor, Electrode, Ground, Adapter.

3 Methodology and Materials

The proposed project introduces a machine learning-based system for effective emotion recognition utilizing EEG signals. It employs a systematic data processing pipeline comprising key steps: data collection, preprocessing, feature extraction, training and classification. This project aims to recognize emotions such as happiness and sadness using brain signals from a single EEG channel (TGAM). All steps were performed using Python tools and libraries.

Figure 7: Project Methodology.

3.1 Data collection

The data collection process encompasses two key components: the device and the experimental protocol. For this project, EEG signals were recorded using a NeuroSky EEG (TGAM) device. The device captures the electrical activity of the brain through a single-channel sensor placed on the participant's FP1 (frontopolar) location, with the reference electrode positioned at A1 (left earlobe). Along with a buffer size of 512 Hz, the sampling rate was set at 256 Hz to guarantee accurate data collection.

The experimental protocol involved the presentation of emotion-inducing stimuli to evoke specific emotional responses from the participants. For this purpose, FilmStim, a validated database of emotion-eliciting film clips, was utilized (Schaefer et al., 2010)[12]. A combination of happy and sad scenes from this database was selected to effectively stimulate the target emotions during the experiment.

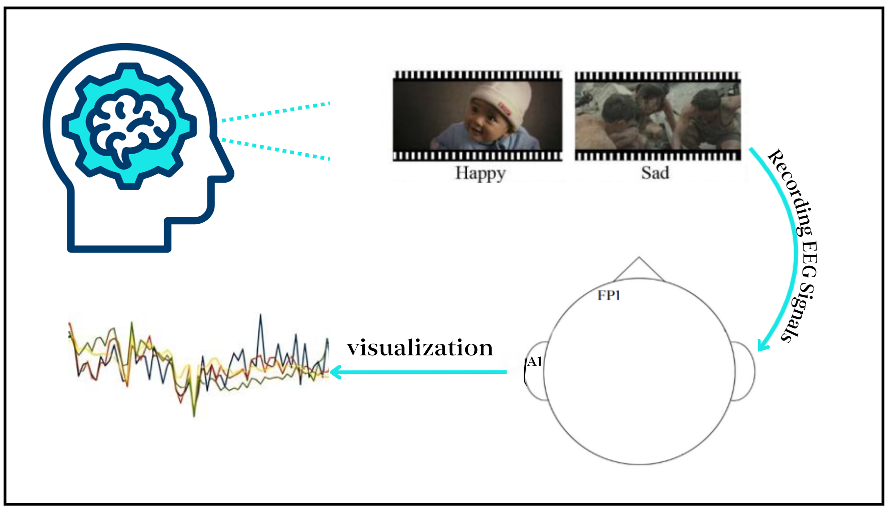


Figure 8: EEG Data collection Experimental Process.

3.2 Preprocessing

During EEG signal collection, artifacts are a common issue. These artifacts can be of two types: psychological and non-psychological. Non-psychological artifacts originate from external sources such as electrode malfunctions, the movement of cables, or poor connections in channels.

On the other hand, physiological artifacts are caused by internal electrical signals within the body. It is necessary to remove these unwanted signals [13].

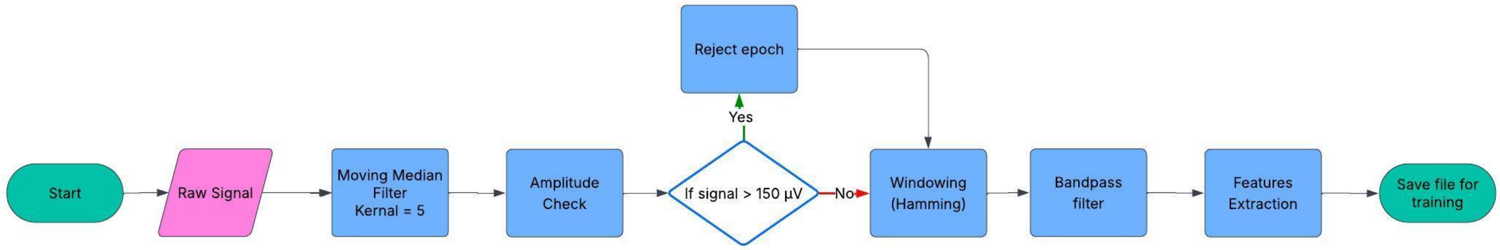


Figure 9: Flowchart of the Preprocessing Step.

3.2.1 Moving Median:

The first step in preprocessing is median filtering, which is used to remove spikes and other sudden changes in the signal. This technique works by replacing each value in the signal with the median value of its surrounding points. The kernel size used for median filtering is 5, meaning the filter considers 5 data points around each value to calculate the median.

3.2.2 Notch Filter:

After median filtering, a notch filter is applied to remove power line interference (60 Hz). This technique attenuates the 60 Hz frequency band, eliminating any unwanted components that could distort the EEG data.

3.2.3 Thresholding:

Next, a thresholding step is applied with a limit of ±150 µV. This is done to remove large artifacts, such as muscle movements or high-amplitude noise, that might still remain after the previous steps. Any values exceeding this threshold are considered outliers and are replaced or discarded.

3.2.4 Bandpass Filtering:

Finally, a bandpass filter is applied to isolate the relevant brainwave frequencies. The filter is applied to each frequency band individually, excluding the delta band (0.5–4 Hz). The relevant frequency bands for emotion recognition are:

- Theta band: 4–8 Hz
- Alpha band: 8–13 Hz
- Beta band: 13–30 Hz

- Gamma band: 30–100 Hz

This filtering helps isolate the relevant brainwave frequencies associated with emotional states, while excluding unwanted signals like delta, which can overlap with physiological artifacts (e.g., eye movements).

The **Hamming window** function is used to design the band-pass filter. It helps reduce leakage, which can occur when signals spread into adjacent frequencies, especially during Fourier transforms. This windowing function minimizes noise and improves the quality of the extracted spectral data by reducing unwanted frequency components [13].

3.3 Features extraction

The process involves extracting features from noise and artifacts removed from signals to create data sets for machine learning tools. Electroencephalography (EEG) signals provide rich data for analysis, with features extracted from both time and frequency domains.

3.3.1 Frequency-Domain features

Frequency domain features such as Power Spectral Density (PSD [Theta, Alpha, Beta, Gamma]) and Band-power across alpha, beta, theta, and gamma waves, spectral entropy, and permutation entropy provide insights into brain rhythms [10].

Power Spectral Density (PSD):

FFT (Fast Fourier Transform) is used to convert the EEG signal from the time domain to the frequency domain. The Power Spectral Density (PSD) of the artifact-free EEG signal is estimated using the FFT algorithm. To calculate PSD, Welch's method is applied, which averages the periodograms over overlapping segments. In this method, the signal is split into segments with 50% overlap. The PSD is then computed for each overlapping segment and averaged, yielding more stable results. This process is repeated for all frequency bands (Theta, Alpha, Beta, and Gamma) to obtain the final PSD values.

The PSD according to Welch is expressed by [7]:

$$P_d(f) = \frac{1}{MU}\left|\sum\nolimits_{n=0}^{M-1} x_d(n)w(n)e^{-j2\pi fn}\right|^2$$

Where $x_d(n)$ is the sequence, and d = L,…,3,2,1 are the signal intervals. While each interval length is M. U is the normalization factor for the power in the window function, while $w(n)$ is the windowed data.

The Welch power spectrum is the average over these modified periodograms, and represented as [7]:

$$Pw_{elch}(f) = \frac{1}{L}\sum_{i=0}^{L-1} P_d(f)$$

However, to obtain a clearer overall picture of the signal's energy distribution across time, we use mean PSD. The mean PSD is calculated by averaging the PSD values across all segments for each frequency band (Theta, Alpha, Beta, Gamma). This helps in understanding the average power within each frequency band over the entire EEG signal.

Power Bands and Power Ratio:

In the frequency domain, the EEG signal is analyzed by dividing it into different frequency bands (Alpha, Beta, etc.). For each of these bands, the power is calculated by averaging the Power Spectral Density (PSD) values within each frequency range. These power values are then used as features to analyze emotional states, specifically happiness and sadness.

To further analyze the relationship between brainwave activities, the Power Ratio is computed by dividing the power of one frequency band by the power of another [10]. In this project, the Alpha/Beta ratio is calculated, where the PSD of Alpha is divided by the PSD of Beta. The Alpha/Beta ratio helps in distinguishing between emotional states, with changes in this ratio being associated with different emotional conditions such as happiness and sadness.

3.3.2 Time-Domain features

Time Domain: Time-domain analysis is a fundamental approach for extracting features from EEG signals. It focuses on characterizing the signal's behavior directly over time, offering insights into its amplitude, variability, and rhythmicity [14].

Standard Deviation:

Standard deviation shows how much variation or 'dispersion' exists from the mean. A low standard deviation indicates that the data points tend to be very close to the mean, whereas the high standard deviation indicates that the data points are spread out over a large range of values [14].

Let X be a random variable with mean value μ and N is the total number of data points (sample size), then the Standard deviation of X is [14]:

$$\sigma_x = \left(\frac{1}{N-1}\right)\sum_{n=1}^{N}(X_n - \mu_x)$$

Mean:

An Arithmetic Mean is a mathematical representation of the typical value of a set of data, computed as the sum of all the numbers in the dataset divided by the size of the dataset. Suppose we have the sample space $\{x_1, x_2, x_3, \ldots.., x_n\}$ then the arithmetic mean μx is defined as the mean of the raw signals [14]:

$$\mu_x = \frac{1}{N}\sum_{n=1}^{N} X_n$$

3.3.3 Entropic Feature

The entropic features that were calculated, Permutation Entropy and Spectral Entropy, provide valuable insights into the complexity and randomness of EEG signals, which can be particularly useful for distinguishing emotional states like happiness and sadness [15].

Permutation Entropy:

Permutation Entropy (PE) measures the complexity or unpredictability of a time series. It is based on the idea that a signal can be thought of as a series of ordered sequences (or permutations) of consecutive data points. The entropy of these permutations reflects the amount of randomness or order within the signal. The higher the entropy, the more complex and less predictable the signal is. The equation for Permutation Entropy is [16]:

$$H_{PE} = -\sum_{i} p(i)\log\big(p(i)\big)$$

Where $p(i)$ is the probability of the occurrence of the i-th permutation.

Spectral Entropy:

Spectral Entropy (SE) quantifies the complexity of a signal in the frequency domain. It is based on the idea that the energy distribution across different frequency bands can reflect the degree of disorder or randomness in the signal. High spectral entropy indicates a more evenly distributed spectrum, implying greater unpredictability, while lower spectral entropy suggests that the signal has dominant frequencies, implying more regularity.

The equation for Spectral Entropy is [15]:

$$H_{SE} = -\sum_{i} \frac{P(f_i)}{P_{total}}\log\left(\frac{P(f_i)}{P_{total}}\right)$$

Where $P(f_i)$ is the power at frequency f_i, and P_{total} is the total power across all frequencies.

3.4 Training and Classification

The objective of this project is to develop an emotion recognition model to classify emotional states, specifically happiness and sadness, using EEG signals. A Support Vector

Machine (SVM) classifier was chosen for its efficacy in handling high-dimensional data, such as the EEG features utilized in this project.

3.4.1 Data Preparation and splitting

The datasets for Happy State and Sad State were combined and labeled with values of 1 for happiness and 0 for sadness. The data was then divided into a training set comprising 80% of the data and a test set comprising the remaining 20%.

To enhance the model's generalization capabilities and minimize bias, K-Fold Cross-Validation was implemented for 5 folds. This method partitions the data into K equally-sized subsets, with the model being trained on K-1 subsets and tested on the remaining subset. This process is repeated K times, ensuring a more reliable and robust evaluation of the model's performance. [17]

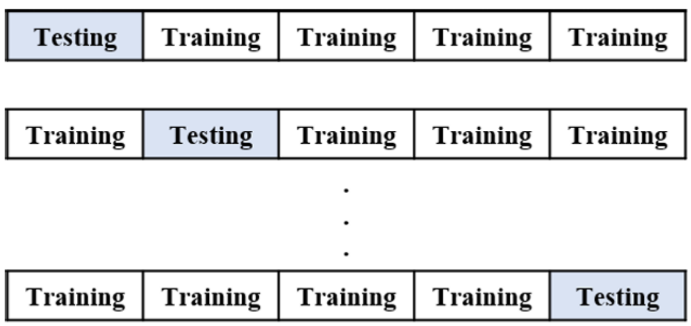


Figure 10: K Fold cross-validation of data set

3.4.2 Feature processing

Power Spectral Density (PSD) values were extracted across several frequency bands, including Theta, Alpha, Beta, and Gamma. However, due to the inability of the SVM classifier to handle list-type features, the analysis was simplified by retaining only the mean PSD for each frequency band. This reduction ensured the data remained compatible with the SVM model, while preserving essential information for classification.

3.4.3 Model training

To optimize the model's performance, GridSearchCV was utilized to fine-tune the hyperparameters, including C, gamma, and the RBF kernel. The C parameter governs the trade-off between maximizing the margin and minimizing classification errors, while gamma controls the influence of each training example on the decision boundary. The RBF kernel was selected for its ability to map the data into higher dimensions, facilitating non-linear classification.

Following the training phase, the model was applied to the test set, and its performance was assessed using multiple metrics. These included accuracy, which reflects the proportion of correct classifications. Precision and Recall, which measure the model's ability to correctly identify true positive and false positive instances. The F1-score, which provides a balanced evaluation of precision and recall. A confusion matrix was also generated to provide a detailed breakdown of true positives, true negatives, false positives, and false negatives.

Additionally, a learning curve was created to evaluate how the model's performance varied with different training set sizes, offering insights into the potential benefits of additional data for improving generalization.

4 Result and discussion

4.1 Data Representation

Before proceeding with the classification, the raw signals for both emotional states (happiness and sadness) were represented and compared to the filtered signals. As shown in the figures, the raw signals exhibit significant fluctuations and irregularities in amplitude over the sample index. In contrast, the filtered signals are smoother and more stable, with much less noise, which enhances the clarity and precision of the data.

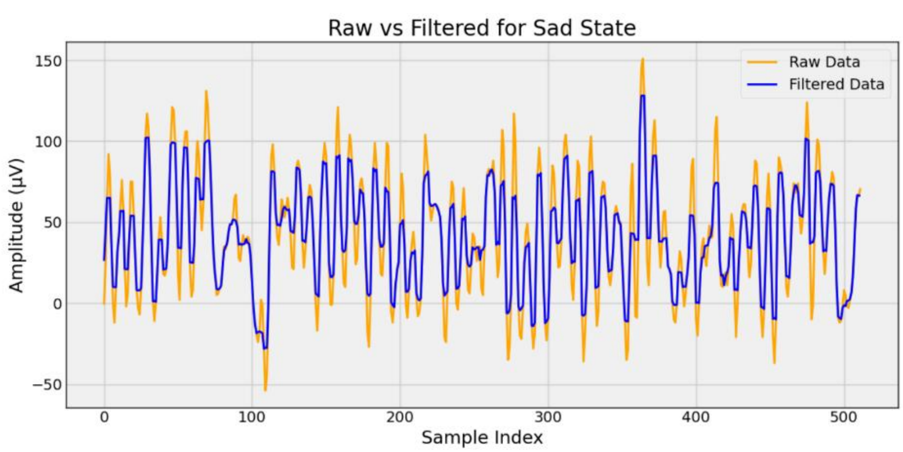


Figure 11: Raw vs Filtered Data for Sad State.

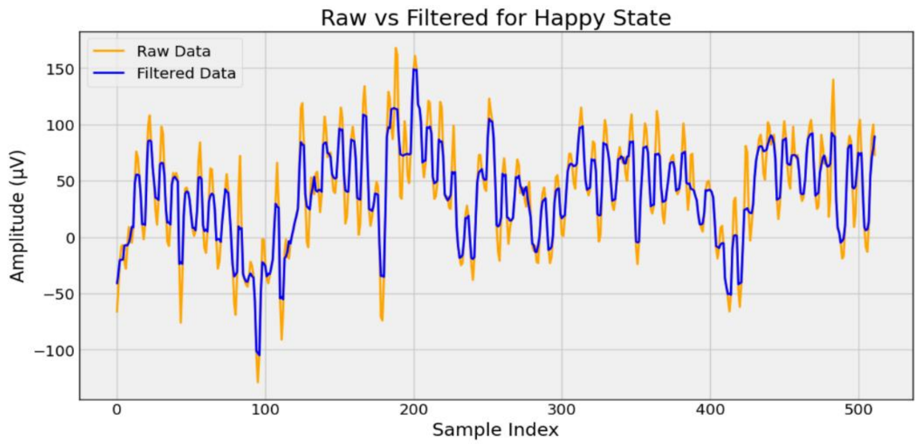
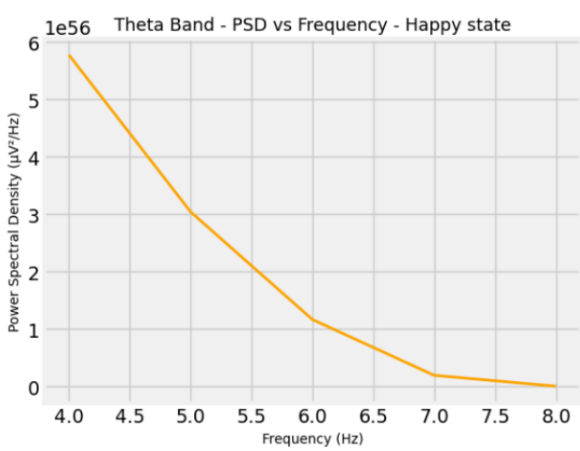


Figure 12: Raw vs Filtered Data for Happy State.

These representations corresponds to a subset of 512 samples from each emotional state. The filtered signals show a more consistent pattern, making it easier to extract meaningful features from the EEG data. These observations highlight the importance of signal filtering in improving data quality, particularly when dealing with EEG signals that are prone to noise and artifacts.

Now, to identify the most dominant frequency band, we examine the power of each band across different frequencies. As shown in the figures below, each frequency band—Theta, Alpha, Beta, and Gamma—has distinct characteristics. Below are the Power Spectral Density (PSD) plots for each frequency band for both happy and sad emotional states:



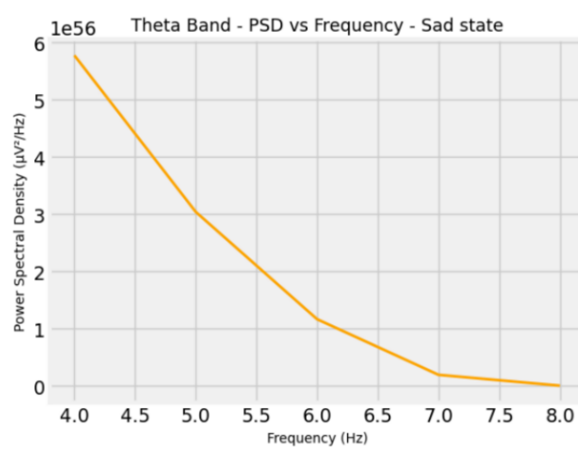


Figure 13: PSD over Frequency for Theta Band.

The Theta Band shows a significant drop in power spectral density as the frequency increases, with the highest power concentrated in the lower frequencies (around 4-5 Hz) as shown in figure 13.

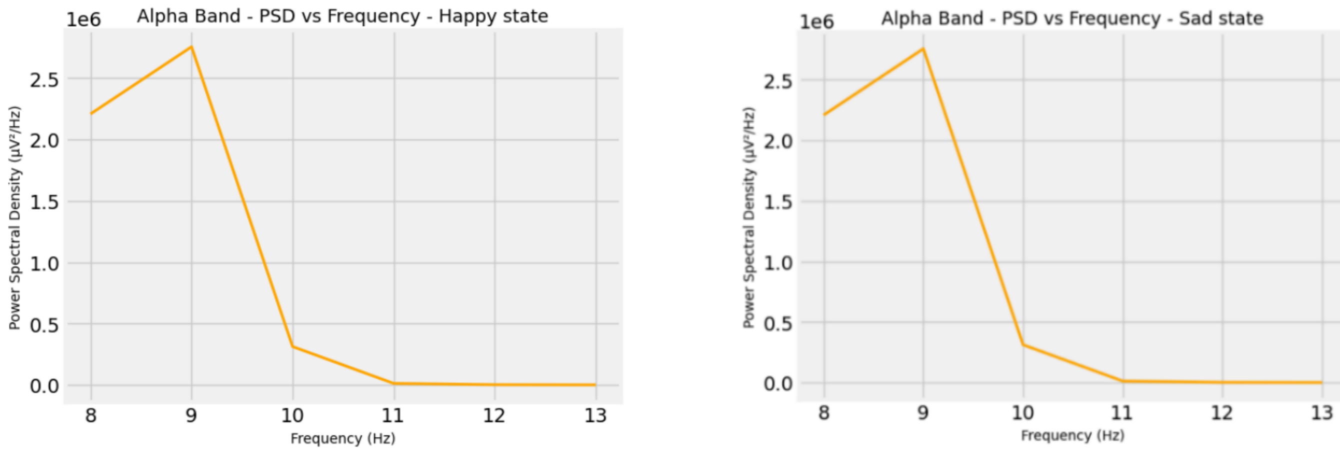


Figure 14: PSD over Frequency for Alpha Band.

As shown in the figure above, the Alpha Band shows a peak in power spectral density around 8-9 Hz, followed by a rapid decrease in power as the frequency increases.

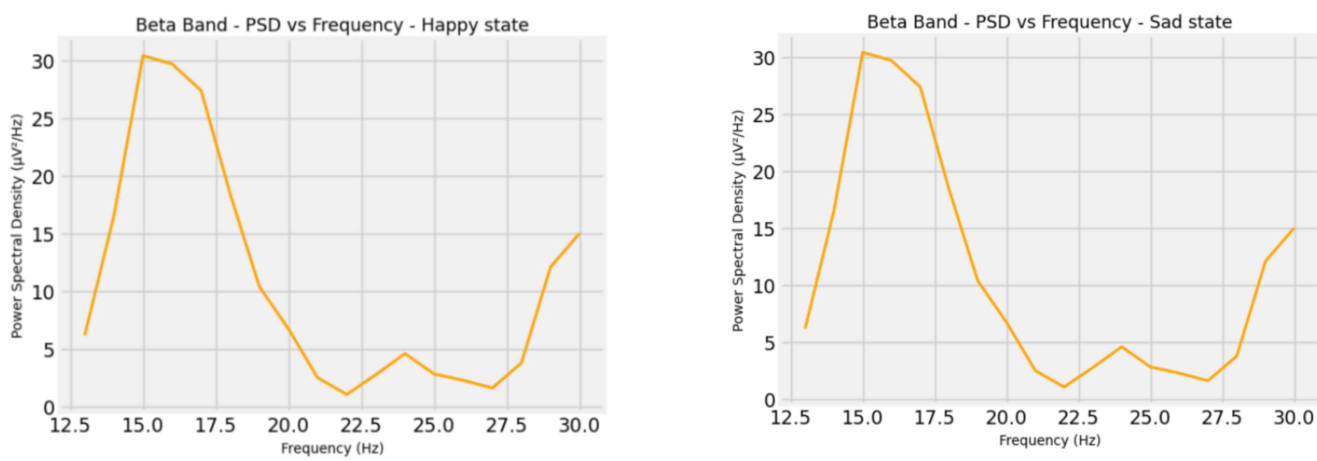


Figure 15: PSD over Frequency for Beta Band.

As shown in the figure above, the Beta Band shows a fluctuating pattern with higher values between 15-20 Hz, reflecting areas of brain activity associated with cognitive tasks.

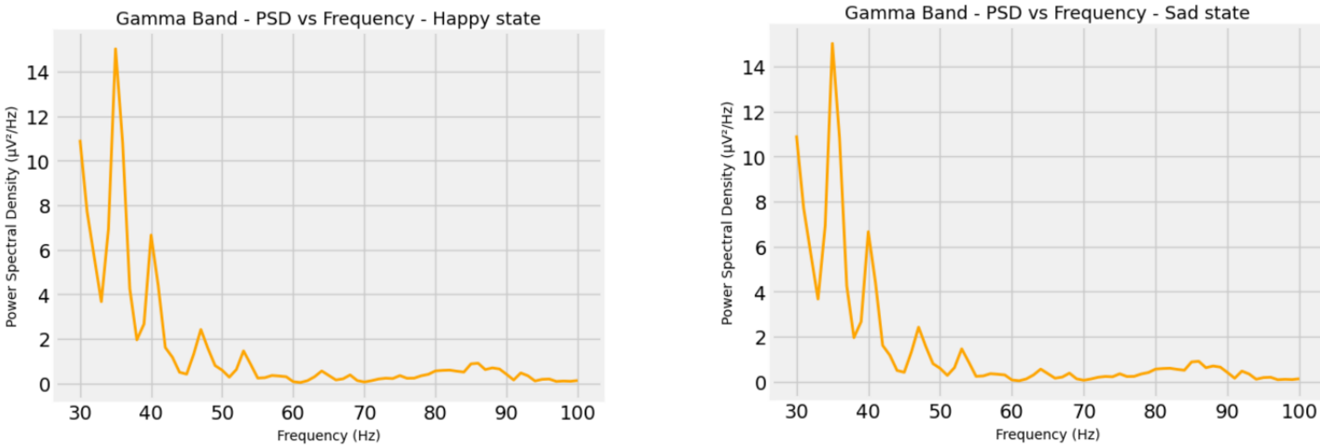


Figure 16: PSD over Frequency for Gamma Band.

The Gamma Band has a sharp peak around 30 Hz, but its power quickly declines, indicating that higher frequencies have less power compared to the lower ones as shown in figure 16.

These plots clearly show that the Alpha Band exhibits the most noticeable peak, particularly in the range of 8-9 Hz, suggesting its significant role in emotional state recognition. The other bands, while still informative, show less pronounced peaks.

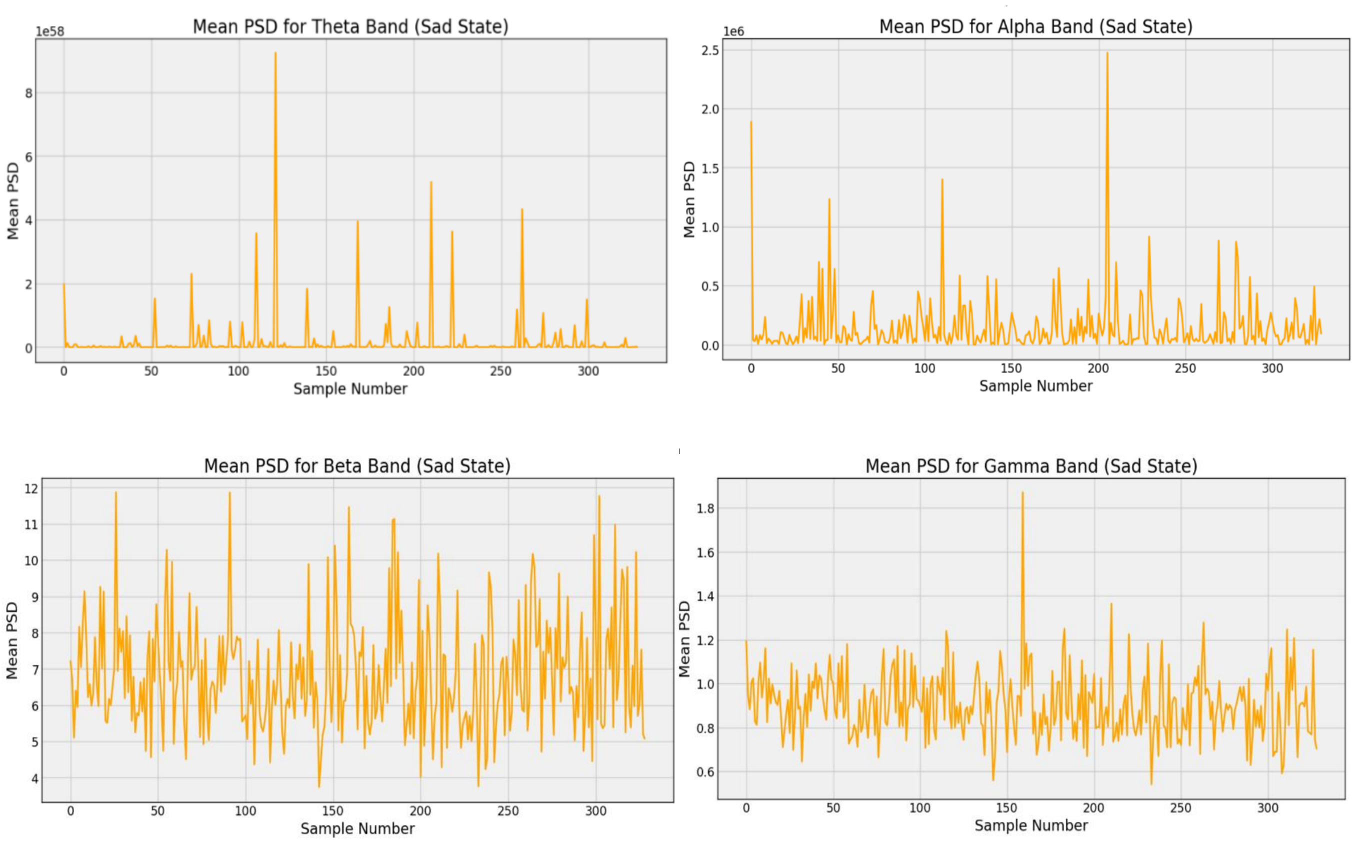


Figure 17: Mean PSD over Sample Number for Sad State.

The plots of the Mean PSD for each frequency band in the Sad State provide a clear representation of the power distribution across different sample numbers. As shown in the figures below, the Mean PSD for each frequency band (Theta, Alpha, Beta, and Gamma) reflects the power variations, which are indicative of brain activity specific to the sad emotional state.

These plots demonstrate how the power within each frequency band changes throughout the recorded samples, which can be used to extract features for classification tasks in identifying emotional states.

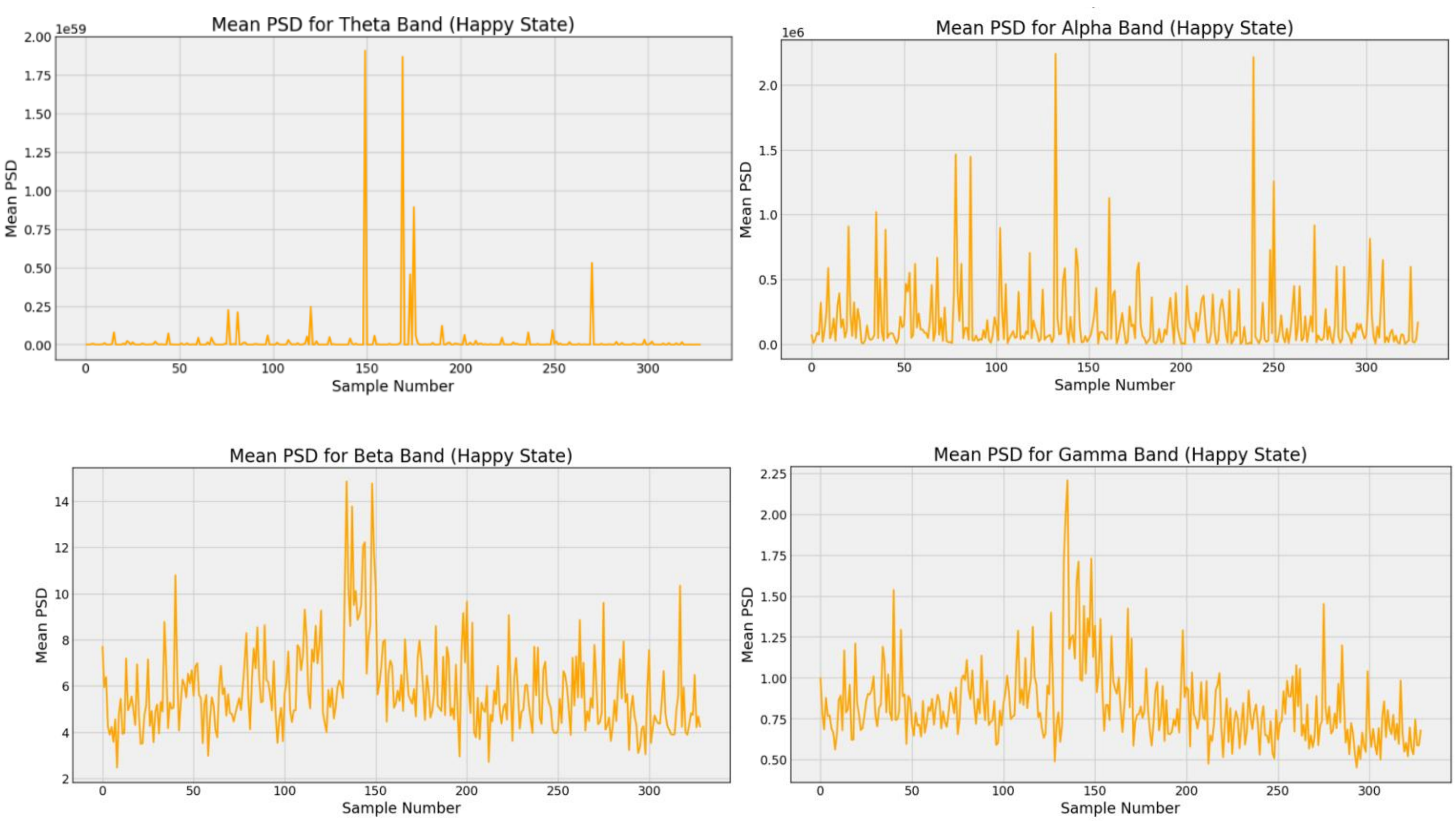


Figure 18: Mean PSD over Sample Number for Happy State.

Similarly, the plots of the Mean PSD for each frequency band in the Happy State reveal the power distribution across different sample numbers. As shown in the figures below, these plots represent the variations in power within the Theta, Alpha, Beta, and Gamma bands, providing insight into brain activity specific to the happy emotional state.

The Mean PSD for the happy state shows the aggregated power within each frequency band, offering a clear understanding of how the power in these bands fluctuates over the sample numbers.

4.2 Training Result

After the data representation and comparison of raw and filtered signals, the support vector machine model (SVM) was trained to classify the emotional states (happiness vs. sadness). The classification model achieved an accuracy of 88.64%. As shown in the classification report in Figure 19, the model's precision and recall for both emotional states (happy and sad) are quite good, but there is still some imbalance in the classification, particularly for sad emotions.

Accuracy: 0.8863636363636364

	precision	recall	f1-score	support
0	0.84	0.97	0.90	68
1	0.96	0.80	0.87	64
accuracy			0.89	132
macro avg	0.90	0.88	0.88	132
weighted avg	0.90	0.89	0.89	132

Figure 19: The Classification Model Report.

The precision and recall scores reflect the balance between minimizing errors and maximizing classification accuracy. The model performed better at classifying happy emotions (precision = 0.96) compared to sad emotions (precision = 0.84). The trade-off between the single-channel EEG device's cost and the resulting classification performance is evident in the overall accuracy.

The confusion matrix in Figure 20 further illustrates the model’s classification performance. It shows the number of true positives, false positives, true negatives, and false negatives. The matrix highlights that the model is generally successful in classifying the happy state, but some errors are made in classifying sad emotions, with 13 misclassified as happy.

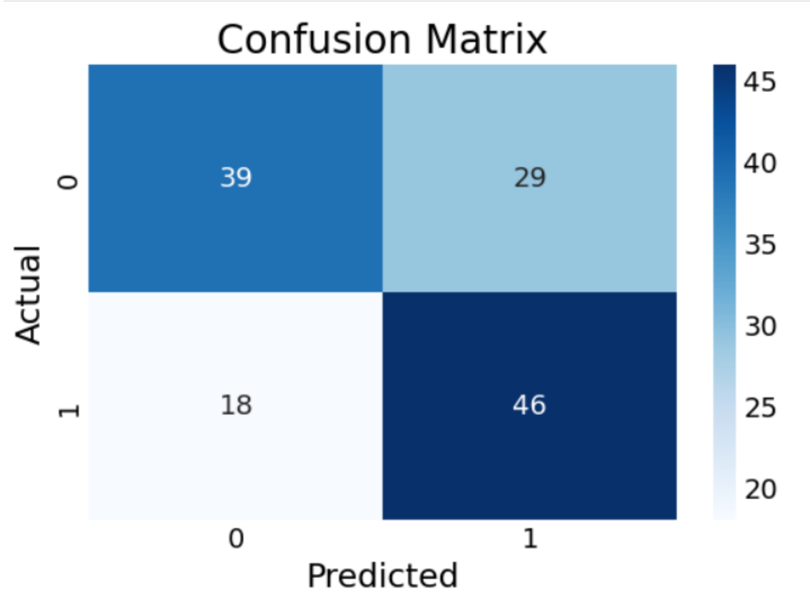


Figure 20: The Confusion Matrix of the Model performance.

The learning curve in Figure 21 demonstrates that as the training set size increases, both the training score and validation score improve. However, the gap between the two suggests that the model might still be overfitting at smaller sample sizes, though it stabilizes as more data is used.

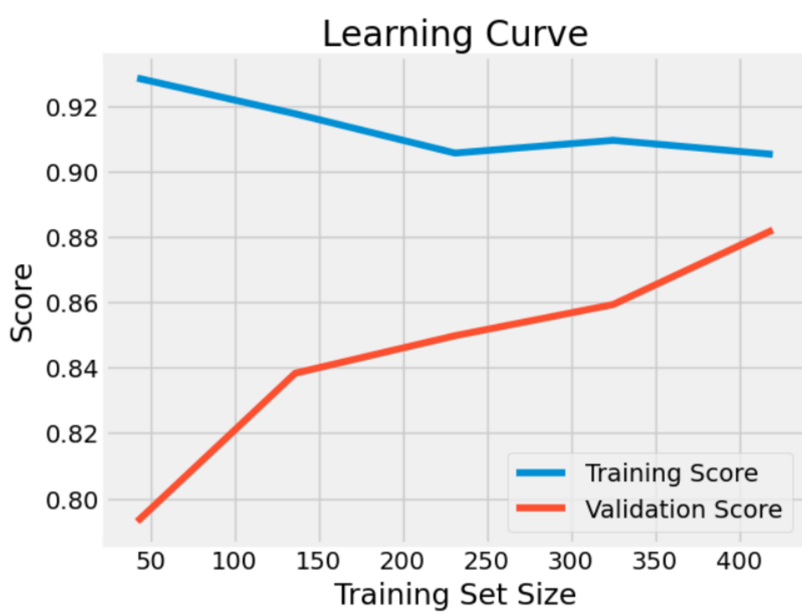


Figure 21: The learning Curve of the model.

These results highlight that while the model performs well, there is a clear trade-off between the lower cost of the single-channel EEG device and the accuracy of the classification. This affects the model's ability to classify both emotional states with the highest possible accuracy, particularly the sad emotion.

5 Challenges

There are various challenges associated with this project, which can be classified into technical challenges and user-related challenges. The technical challenges include the limitations of using a single-channel EEG device, which, while cost-effective, impacts the accuracy of the model. This limitation results in less detailed brain signal data compared to multi-channel EEG systems, thus influencing the quality of classification.

Additionally, dealing with EEG signal noise presents another challenge. Artifacts caused by eye movements or muscle activity interfere with the brain signals, especially in the Delta band, which is often influenced by such artifacts.

The Delta band has been excluded from the analysis due to its interference with the EOG signal, which has a frequency range of 4 Hz and below, potentially leading to misinterpretation of emotional states. This is because the Delta band primarily reflects deep sleep and unconscious states. Instead, focus has been directed toward the frequency bands more directly related to emotions, such as Theta, Alpha, Beta, and Gamma, which are more reflective of conscious states and emotional processing.

When dealing with the technical side of the project, there are other factors to consider, such as the sensor placement and the real-time processing of the EEG signals. Achieving accurate classification in real-time adds another layer of complexity, as it requires balancing processing time with high accuracy.

On the user side, each individual has their own unique perception of what constitutes happiness or sadness, making it difficult to consistently evoke these emotions across all participants during data collection. This variability leads to challenges in accurately capturing the emotional states, which in turn affects the overall model performance, resulting in lower accuracy.

To sum up, several challenges were encountered throughout the project, including technical limitations and user-related factors. Each obstacle provided valuable insights that guided the approach taken. From dealing with signal artifacts to the difficulty of eliciting consistent emotional states, these challenges ultimately strengthened the understanding and improved the methods. By focusing on relevant frequency bands and fine-tuning the model, meaningful steps were taken toward overcoming these hurdles.

6 Conclusion

This work concludes by showing how machine learning approaches, specifically using SVM as the classifier, can identify emotional reactions from EEG data. The project employed a single-channel EEG device to extract key features and analyzed emotional states such as happiness and sadness. Despite the constraints imposed by the cost and limitations of the device, the project achieved a classification accuracy of 88%.

Key improvements were made in the feature extraction methods and filtering processes, enhancing the system's performance. Moreover, the analysis of EEG bands revealed crucial insights, particularly within the Theta, Alpha, Beta, and Gamma bands, each contributing uniquely to emotion recognition. Future efforts will focus on refining these methods and addressing the challenges of real-time processing and individual variability to further improve the model's accuracy.

References

[1] IEEE Xplore. "Research Document." Available at: https://ieeexplore.ieee.org/document/6890301 . Last visited on October 23, 2024.

[2] Alfaisal University. "Review and Classification of Emotion Recognition Based on EEG Brain-Computer Interface System Research: A Systematic Review." Available at: https://faculty.alfaisal.edu/awabil/publications/review-and-classification-of-emotion-recognition-based-on-eeg-brain-computer-interface-system-research%3A-a-systematic-review . Last visited on October 22, 2024.

[3] Frontiers in Computational Neuroscience. Research Article. Available at: https://www.frontiersin.org/journals/computational-neuroscience/articles/10.3389/fncom.2021.758212/full . Accessed: October 17, 2024.

[4] Choi, G.-Y., Shin, J.-G., Lee, J.-Y., Lee, J.-S., Heo, I.-S., Yoon, H.-Y., Lim, W., Jeong, J.-W., Kim, S.-H., & Hwang, H.-J. (2024). EEG dataset for the recognition of different emotions induced in voice-user interaction. *Scientific Data*, 11(1084). Browse Articles | Nature

[5] Taran, S., Krishna, A. H., Sri, A. B., Priyanka, K. Y. V. S., & Bajaj, V. (2019). Emotion classification using EEG signals based on tunable-Q wavelet transform. IET Science, Measurement & Technology. https://doi.org/10.1049/iet-smt.2018.5237

[6] Gannouni, S., Aledaily, A., Belwafi, K., & Aboalsamh, H. (2021). Emotion detection using electroencephalography signals and a zero-time windowing-based epoch estimation and relevant electrode identification. Scientific Reports, 11, 7071. https://doi.org/10.1038/s41598-021-86345-5

[7] Rahi, P. K., & Mehra, R. (2014). Analysis of power spectrum estimation using Welch method for various window techniques. International Journal of Emerging Technologies and Engineering, 2(6), 106-109. ICRTIET-2014 Conference Proceeding, 30th-31st August 2014welch method. https://citeseerx.ist.psu.edu/document?repid=rep1&type=pdf&doi=5cbf8c2e646aa0f74c5f3cda1f0407e72b27ac5d

[8] NeuroSky. *ThinkGear Module (TGAM) Datasheet*. https://store.neurosky.com/pages/tgam

[9] Niedermeyer, E., & da Silva, F. L. (2004). Electroencephalography: Basic Principles, Clinical Applications, and Related Fields. Lippincott Williams & Wilkins.

[10] Wen, T. Y., & Aris, S. A. M. (2020). Electroencephalogram (EEG) stress analysis on alpha/beta ratio and theta/beta ratio. Indonesian Journal of Electrical Engineering and Computer Science, 17(1), 175-182. (PDF) Electroencephalogram (EEG) stress analysis on alpha/beta ratio and theta/beta ratio

[11] Patel, P., Raghunandan, R., & Annavarapu, R. N. (2021). EEG-based human emotion recognition using entropy as a feature extraction measure. Brain Informatics, 8(1), 20. https://link.springer.com/article/10.1186/s40708-021-00141-5

[12] Schaefer, A., Nils, F., Sanchez, X., & Philippot, P. (2010). Assessing the effectiveness of a large database of emotion-eliciting films: A new tool for emotion induction research. *Cognition and Emotion*, **24**(7), 1153–1172. https://doi.org/10.1080/02699930903274322

[13] Murad, S. A., & Rahimi, N. (2024). *Unveiling Thoughts: A Review of Advancements in EEG Brain Signal Decoding into Text*. IEEE. Unveiling Thoughts: A Review of Advancements in EEG Brain Signal Decoding Into Text | IEEE Journals & Magazine | IEEE Xplore

[14] Ashish Panat, Anita Patil, Gayatri Deshmukh. (2014). *Feature Extraction of EEG Signals in Different Emotional States*. Proceedings of 8th IRF International Conference, 04th May-2014, Pune, India. ISBN: 978-93-84209-12-4. https://digitalxplore.org/up_proc/pdf/70-139928877263-67.pdf#:~:text=Abstract-%20This%20paper%20aims%20to%20analyze%20real%20life,is%20captured%20in%20the%20suitable%20environment%20and%20processed.

[15] Patel, P., Raghunandan, R., & Annavarapu, R. N. (2021). *EEG-based human emotion recognition using entropy as a feature extraction measure*. *Brain Informatics*, 8(20). EEG-based human emotion recognition using entropy as a feature extraction measure | Brain Informatics

[16] Bandt, C., & Pompe, B. (2001). *Permutation entropy: A natural complexity measure for time series*. *Physical Review Letters*, 88(17), 174102. Permutation Entropy: A Natural Complexity Measure for Time Series | Phys. Rev. Lett.

[17] Suwanto, S., Bisri, M., Novitasari, D., & Asyhar, A. (2019). Classification of EEG Signals using Fast Fourier Transform (FFT) and Adaptive Neuro Fuzzy Inference System (ANFIS). *Jurnal Matematika MANTIK*, 5(1), 35-44. Classification of EEG Signals using Fast Fourier Transform (FFT) and Adaptive Neuro Fuzzy Inference System (ANFIS) | Jurnal Matematika MANTIK