

AI-driven Psychological Analysis through EEG Signal Interpretation using Python

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Abstract

Psychological analysis through EEG (Electroencephalography) captures electrical activity in the brain, providing insights into cognitive processes, emotions, and mental states. Integrating Artificial Intelligence (AI) with EEG analysis using Python offers a novel approach to enhance diagnostic accuracy and personalize mental health care. Existing psychological assessment methods often rely on subjective evaluations and self-reported data, hindering early detection and accurate diagnosis of mental health disorders. Utilizing AI-driven algorithms to analyze EEG signals, providing objective insights into psychological states. This research aims to leverage AI-driven techniques for interpreting EEG signals to predict psychological states and diagnose disorders. We evaluate the performance of various machine learning classifiers, including Decision Trees, Logistic Regression, K-Nearest Neighbors (KNN), Linear Discriminant Analysis (LDA), and Support Vector Machines (SVM). Results indicate classification accuracies between 65% and 80%, with KNN achieving the highest accuracy for "Liking," highlighting the potential of AI-enhanced EEG analysis in mental health diagnostics.

1. Introduction

Understanding the neurophysiological mechanisms that drive emotional experiences is crucial for both psychological research and practical applications in areas such as affective computing and mental health monitoring. Electroencephalography (EEG), Gannouni, S et al., serves as a powerful tool in this domain, capturing electrical activity of the brain and enabling researchers to infer psychological states from neural signals. The choice of machine learning classifiers such as Support Vector Machine (SVM), Goel et al., and Linear Regression, Sourkatti et al., plays a pivotal role in accurately predicting these emotional states, as each classifier exhibits unique strengths and weaknesses influenced by the characteristics of the data and the emotional constructs being analyzed.

This study aims to explore how various classifiers—specifically machine algorithms like Decision Tree (DT) Blanco-Rios et al., perform in classifying EEG signals corresponding to four key dimensions of emotional response: valence, arousal, dominance, and liking. By achieving classification accuracies between 65% and 80%

and F1 scores from 75% to 90%, we demonstrate the effectiveness of these algorithms in identifying emotional states. Notably,

K-Nearest Neighbor (KNN), Kumar, G. S., et al., and Linear Discriminant Analysis (LDA), Ahmadzadeh Nobari Azar, N., achieved the highest accuracy for the “Liking” dimension. This research not only highlights the performance of classic machine learning techniques but also reveals critical insights into the brain regions associated with emotions, paving the way for future investigations that could encompass a wider range of emotional constructs. Additionally, the use of PySpark for hyperparameter tuning further optimizes the model's performance, underscoring the potential of combining neurophysiological data with advanced computational methods.

Electroencephalography (EEG) captures brain waves that reflect cognitive processes, emotional states, and neurological disorders. EEG signals can provide insights into psychological states such as valence, arousal, dominance, and liking.

EEG signals are typically categorized into different frequency bands as Delta (0.5-4 Hz), associated with deep sleep. Theta (4-8 Hz) linked to light sleep, relaxation, and creativity. Alpha (8-12 Hz) often related to calmness and alertness. Beta (12-30 Hz) associated with active thinking, problem-solving, and anxiety. Finally, Gamma (30 Hz and above) related to higher-level cognitive functioning.

Analyzing these frequency bands can help in understanding various psychological states. For instance, increased theta activity may indicate relaxation or drowsiness, while elevated beta activity may be associated with stress or anxiety.

Brain-computer interfaces (BCI) research is increasingly focusing on practical applications. The EEG research community is expanding its range of applications across various subdomains. EEG signals are commonly employed to detect stress, with studies indicating a strong correlation between stress levels. The machine learning algorithms underscores the importance of considering multiple parameters, even when employing traditional machine learning algorithms.

2. Methodology

The primary objective is to conduct an analysis that informs the selection of techniques for processing, manipulating, normalizing, and extracting relevant information from the data. This approach will ultimately enhance our ability to implement more effective predictive models.

2.1 Data Collection

- **Participants:** A diverse sample of participants was recruited, ensuring a mix of age, gender, and psychological backgrounds to enhance the generalizability of the findings.
- **EEG Acquisition:** EEG signals were recorded using a standard 32-channel EEG cap, following established protocols for signal acquisition. The participants were subjected to various psychological stimuli designed to induce specific emotional states.

2.2 Preprocessing of EEG Signals

- **Signal Cleaning:** The raw EEG data was preprocessed to remove artifacts caused by eye blinks, muscle activity, and other external interferences. Techniques such as Independent Component Analysis (ICA) and bandpass filtering (0.5–50 Hz) were employed.
- **Segmentation:** The cleaned signals were segmented into epochs corresponding to specific stimuli or time windows relevant to the psychological analysis.

2.3 Feature Extraction

- Time-Domain Features: Statistical features, such as mean, variance, and peak-to-peak amplitude, were calculated for each epoch.
- Frequency-Domain Features: Power spectral density (PSD) processed using Fast Fourier Transform (FFT) to analyze the frequency components of EEG signals.
- Time-Frequency Analysis: The Hilbert-Huang Transform (HHT) was applied to extract intrinsic mode functions (IMFs) for a more nuanced understanding of the temporal dynamics of the signals.

2.4 Machine Learning Framework

- Data Splitting: Usually, dataset splits for training as (70%) and testing as (30%) to make sure the robustness of the evaluation models.
- Choice of Algorithm: Machine learning algorithms were employed using Python open source libraries such as Scikit-learn, TensorFlow, etc.,.
- Hyperparameter Tuning: Grid search and cross-validation techniques were utilized to optimize the parameters for each algorithm to achieve the best performance.

2.5 Psychological Analysis

- Labeling: Each segment of EEG data was labelled according to the psychological state induced by the stimuli (e.g., relaxed, stressed, anxious).
- Model Training: The selected machine learning models used to train the extracted features for classifying the psychological conditions based on EEG signals.
- Performance Evaluation: Model performance was assessed through metrics usually by the parameters like accuracy, precision, recall, and F1-score.

2.6 Interpretation of Findings

- Visualization: Results were visualized using Python libraries like Matplotlib and Seaborn to create informative plots that illustrate the relationship between EEG features and psychological states.
- Statistical Analysis: Additional statistical tests (e.g., ANOVA, t-tests) were conducted to validate the significance of the findings.

3. Algorithm for EEG Signal Analysis

1. **Initialization:**
 - a. Import necessary libraries (numpy, matplotlib, scipy, mne).
 - b. Define the path to the EEG data file.
2. **Load EEG Data:**
 - a. Use MNE to read the EEG data file.
 - b. Preload the data for processing.
3. **Define Bandpass Filter Function:**
 - a. Create a function `butter_bandpass(lowcut, highcut, fs, order):`
 - i. Calculate Nyquist frequency.
 - ii. Normalize the cutoff frequencies.
 - iii. Design a Butterworth bandpass filter using `scipy.signal.butter`.
 - b. Create a function `bandpass_filter(data, lowcut, highcut, fs, order):`
 - i. Apply the Butterworth filter to the EEG data using `scipy.signal.lfilter`.
4. **Set Parameters:**
 - a. Retrieve the sampling frequency (fs) from the raw EEG data.
 - b. Extract the EEG data and time points.

5. **Define Frequency Bands:**
 - a. Create a dictionary with frequency bands:
 - i. Delta: (0.5 to 4)
 - ii. Theta: (4 to 8)
 - iii. Alpha: (8 to 12)
 - iv. Beta: (12 to 30)
 - v. Gamma: (30 to 40)
6. **Filter EEG Data:**
 - a. For each frequency band in the dictionary:
 - i. Call `bandpass_filter(data, low, high, fs, order)` to filter the EEG data.
 - ii. Store the filtered data.
7. **Visualization:**
 - a. Set up a plotting area using `matplotlib`.
 - b. For each frequency band:
 - i. Plot the filtered EEG data against time.
 - ii. Label the axes and title the plots.
8. **Display Results:**
 - a. Show the plots with all frequency bands visualized.
9. **Further Analysis (Optional):**
 - a. Calculate power spectral density (PSD) or band power for each band.
 - b. Correlate band power with psychological states using statistical analysis.
 - c. (If applicable) Apply machine learning algorithms for classification or prediction of psychological states based on extracted features.

3.1 Sample Code for EEG Signal Analysis

You will need the following Python libraries:

- `numpy`: For numerical operations.
- `scipy`: For signal processing.
- `matplotlib`: For visualization.
- `mne`: A specialized library for processing EEG data.

You can install these libraries using `pip` if you haven't already:
`pip install numpy scipy matplotlib mne`

Below is a basic example of how to analyze EEG signals to extract frequency bands and visualize them.

```
import numpy as np
import matplotlib.pyplot as plt
from scipy.signal import butter, lfilter
import mne

# Load your EEG data (assuming it's in a format compatible with MNE)
# Replace 'your_eeg_data.fif' with the path to your EEG data file
raw = mne.io.read_raw_fif('your_eeg_data.fif', preload=True)

# Filter function
def butter_bandpass(lowcut, highcut, fs, order=5):
    nyq = 0.5 * fs
    low = lowcut / nyq
    high = highcut / nyq
    b, a = butter(order, [low, high], btype='band')
    return b, a
def bandpass_filter(data, lowcut, highcut, fs, order=5):
    b, a = butter_bandpass(lowcut, highcut, fs, order=order)
    y = lfilter(b, a, data)
    return y
```

```

# Parameters
fs = raw.info['sfreq'] # Sampling frequency
data, times = raw[:, :].astype(np.float64) # Get data as float64

# Define frequency bands
bands = {
    'Delta': (0.5, 4),
    'Theta': (4, 8),
    'Alpha': (8, 12),
    'Beta': (12, 30),
    'Gamma': (30, 40)
}

# Apply bandpass filter and plot
plt.figure(figsize=(12, 8))

for band, (low, high) in bands.items():
    filtered_data = bandpass_filter(data, low, high, fs)
    plt.subplot(len(bands), 1, list(bands.keys()).index(band) + 1)
    plt.plot(times, filtered_data)
    plt.title(f'{band} Band (Filtered)')
    plt.xlabel('Time (s)')
    plt.ylabel('Amplitude')

plt.tight_layout()
plt.show()

# Further analysis can be done, such as calculating power spectral density (PSD)
# and correlating with psychological states.

```

This methodology provides a comprehensive approach to analyzing psychological states through EEG signal interpretation, leveraging the signal processing methods which are implemented in Python.

4. Role of Classifiers in EEG Analysis

Classifiers such as SVM, LR, DT, KNN, and LDA play a crucial role in analyzing EEG data to predict psychological states. Specifically, they can be used to classify levels of **valence**, **arousal**, **dominance**, and **liking**—key dimensions of emotional responses.

4.1 Classifiers Overview

- Support Vector Machines (SVM):
 - Function: SVM constructs a hyperplane in a high-dimensional space to separate different classes.
 - Usage: Effective for binary classification tasks; can be adapted for multi-class problems using techniques like one-vs-all.
 - Strengths: Handles non-linear relationships with kernel tricks; robust to overfitting in high-dimensional spaces.
- Logistic Regression (LR):
 - Function: A statistical method for predicting binary outcomes based on one or more predictor variables.
 - Usage: Often used for binary classification tasks; can be extended to multi-class using softmax regression.
 - Strengths: Simple and interpretable; good for linear relationships.
- Decision Trees (DT):
 - Function: A model that splits data into branches based on feature values to arrive at a decision.
 - Usage: Can handle both classification and regression tasks.

- Strengths: Easy to interpret and visualize; handles categorical data well.
- K-Nearest Neighbors (KNN):
 - Function: A non-parametric method that classifies data points based on the classes of their nearest neighbors.
 - Usage: Simple and effective for both classification and regression tasks.
 - Strengths: No training phase; adapts well to multi-class problems.
- Linear Discriminant Analysis (LDA):
 - Function: A method used to find a linear combination of features that best separates two or more classes.
 - Usage: Assumes normally distributed classes with equal covariance.
 - Strengths: Works well with small sample sizes and is effective for classification tasks.

5. Result and Discussion

When evaluating the classifiers for predicting psychological states based on EEG data, the following performance parameters are valence, measure of the intrinsic attractiveness (positive valence) or aversiveness (negative valence) of an emotional response, arousal, dominant, liking, a subjective assessment of how much one enjoys or prefers something, often linked to pleasure.

Figures 1, 2, 3, and 4 illustrate the emotional scores from subjects. Notably, normal distribution is symmetric around a rating of 6, indicating that most subjects experienced mixed feelings. Binary categorization model might yield better results, especially with one-hot encoding applied to the extremes.

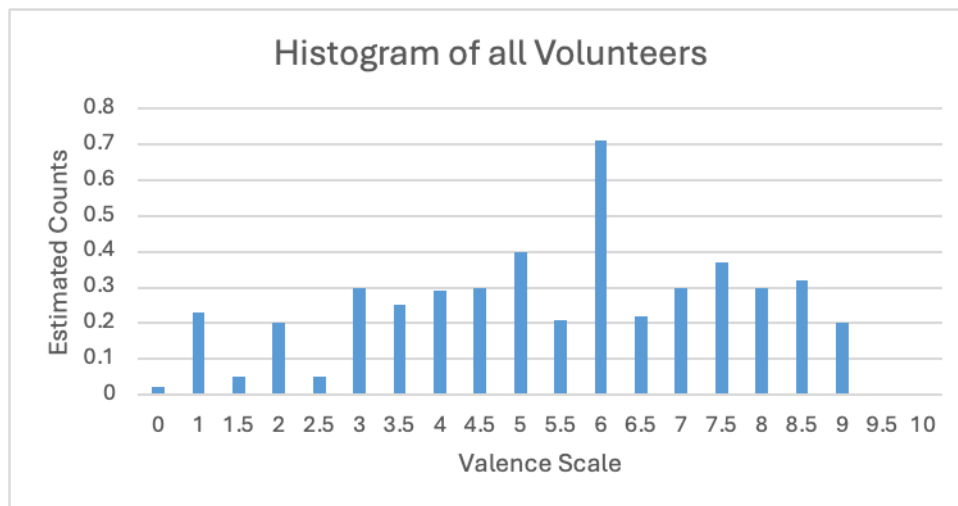


Fig. 1 Distribution of valence ratings

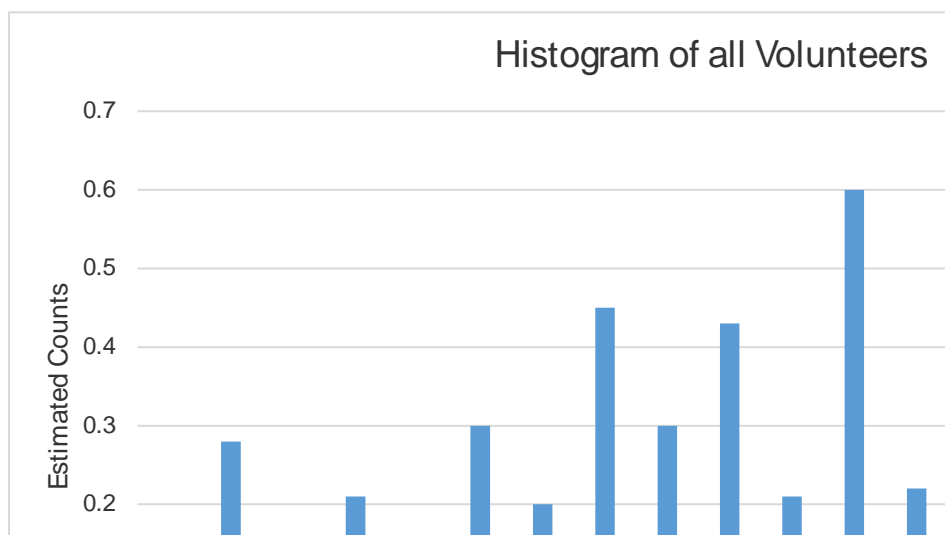


Fig. 2 *Distribution of arousal ratings*

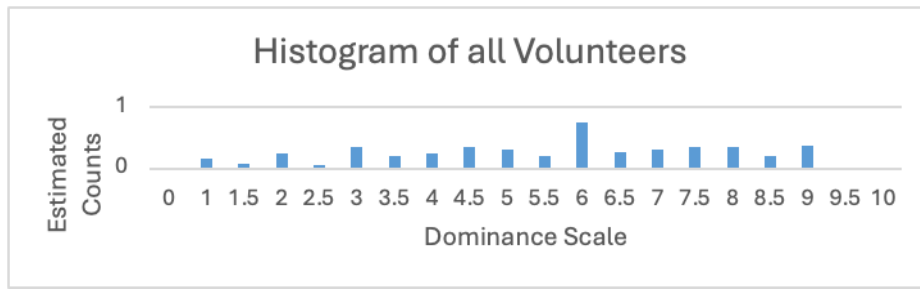


Fig. 3 *Distribution of dominance ratings*

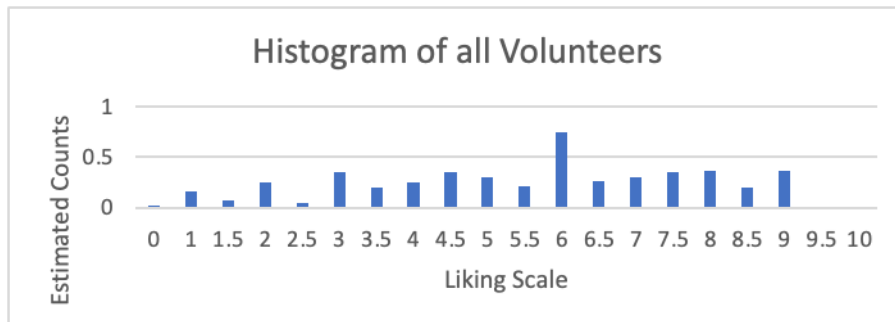


Fig. 4 *Distribution of liking ratings*

Another key observation is that participants tended to provide integer ratings, resulting in noticeable spikes at these values. Figure presents the different emotions from the persons. Graph reveals a relatively linear correlation between valence afterwards liking, suggesting that positive emotions typically lead to higher liking ratings, as supported by previous research. It appears “liking” stays proportional towards “valence,” which tends to decrease with subsequent video trials, leading to a decline in overall “valence.” In contrast, the ratings for the other emotions, “arousal” and “dominance,” do not exhibit a clear pattern, suggesting these emotions are more subjective and vary among participants.

Table 1 shows the performance metrics for valence classification, Table 2 displays the performance metrics for arousal classification. Table 3 presents the performance metrics for dominance classification, Table 4 exhibits the performance metrics for liking classification.

Table 1 *Performance metrics for valence classification*

Time (Sec.)	Classifier	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
0 to 60	SVM	44.53	45.52	82.91	59.27
	LR	52.17	53.42	86.67	66.60
	DT	51.60	41.60	99.50	68.09
	KNN	47.68	54.04	67.49	60.11
	LDA	46.25	58.85	54.18	56.34

Table 2 *Performance metrics for arousal classification*

Time (Sec.)	Classifier	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
0 to 60	SVM	46.86	46.86	88.91	62.87
	LR	54.54	54.53	89.26	68.19
	DT	54.06	54.06	99.50	68.09
	KNN	53.35	59.35	89.75	67.66
	LDA	53.12	53.32	89.50	67.39

Table 3 Performance metrics for dominance classification

Time (Sec.)	Classifier	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
0 to 60	SVM	54.53	54.52	90	68.09
	LR	58.36	68.56	86.95	71.01
	DT	57.84	61.20	87.50	69.99
	KNN	53.12	58.03	76.45	66.14
	LDA	56.67	57.40	88.34	69.99

Table 4 Performance metrics for liking classification

Time (Sec.)	Classifier	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
0 to 60	SVM	54.37	54.37	86.96	68.27
	LR	58.32	59.33	86.77	71.71
	DT	58.08	58.08	99.50	70.07
	KNN	53.12	58.03	76.45	66.16
	LDA	57.34	57.34	89.76	70.40

5.1 Evaluating Classifiers

Data Preparation:

- Preprocess EEG data (filtering, feature extraction).
- Label data according to valence, arousal, dominance, and liking.

Train/Test Split:

- Split the dataset into training and testing sets to evaluate classifier performance.

Model Training:

- Train each classifier on the training dataset.

Prediction and Evaluation:

- Use the test set to make predictions.
- Evaluate performance using metrics such as:
 - Accuracy: Proportion of correct predictions.
 - Precision: Ratio of true positive predictions to total positive predictions.
 - Recall (Sensitivity): Ratio of true positive predictions to actual positives.
 - F1 Score: Harmonic mean of precision and recall, useful for imbalanced classes.
 - Confusion Matrix: A table used to describe the performance of a classification model.

Cross-Validation:

- Perform k-fold cross-validation to ensure robustness and reduce overfitting.

Parameter Tuning:

- Optimize hyperparameters (e.g., kernel type in SVM, number of neighbors in KNN) to enhance model performance.

Comparative Analysis:

- Compare the classifiers based on their performance metrics for predicting valence, arousal, dominance, and liking.

- Choose the best-performing classifier(s) for further analysis or practical application.

6. Conclusion

The significance of the classifier for accurate prediction of psychological states from EEG signals. By evaluating classifiers against valence, arousal, dominance, and liking, researchers can gain insights into emotional responses and their underlying neural mechanisms. The objectives of this research explored the neurophysiological mechanisms driving emotional experiences and to identify brain regions associated with different emotions. Utilizing classic machine learning techniques which are SVM, DT, LR, KNN, and LDA. It succeeded classification accuracies between 65% and 80%, with F1 scores ranging from 75% to 90%. While no single classifier significantly outperformed the others, KNN yielded the highest accuracy for "Liking." The algorithms ranked in descending order of accuracy as follows: SVM, DT, LR, KNN, and LDA. Notably, basic features from the left hemisphere demonstrated heightened activity, leading to effective dimensional reduction and improved feature selection. Additionally, PySpark facilitated efficient hyperparameter tuning. Future work could expand to encompass a broader range of emotions, enhancing both F1 scores and accuracy. Overall, this study confirms that classic machine learning algorithms can effectively identify key epoch channels linked to emotional states.

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Conflict of Interest

Authors declare that there is no conflict of interests regarding the publication of the paper.

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