EEG Emotions

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Abstract

Emotion recognition using electroencephalography (EEG) has emerged as a promising avenue for applications in mental health, human-computer interaction, and adaptive learning due to its capacity to provide direct insights into emotional states, unlike potentially manipulated facial or vocal cues. This project introduces a novel hybrid machine learning approach to classify emotions from EEG signals by integrating supervised learning for the detection of predefined emotional states (e.g., calm, stressed, happy, sad) with unsupervised learning to discover underlying emotional patterns and transitions. The proposed methodology employs a comprehensive feature extraction process encompassing frequency-based, statistical, and dynamic signal characteristics, followed by dimensionality reduction, to build a robust system capable of both classifying known emotions and exploring the dynamic landscape of emotional experiences.

1 Introduction

In recent years, emotion recognition using electroencephalography (EEG) has gained substantial traction due to its potential in addressing critical real-world challenges across mental health, human-computer interaction, and adaptive learning technologies. Traditional emotion recognition systems often rely on facial expressions or speech, which can be consciously manipulated or obscured. In contrast, EEG offers a more direct and involuntary insight into a user's cognitive and emotional state, making it an invaluable tool in applications such as early stress detection, personalized learning environments, and mental health diagnostics.

This project proposes a hybrid machine learning approach to detect and classify emotional states from EEG signals. The goal is twofold: (1) to build a robust supervised learning model capable of classifying known emotional states (such as calm, stressed, happy, or sad), and (2) to utilize unsupervised learning methods to uncover latent or transitional emotional patterns that may not be immediately labeled in traditional datasets.

The novelty of this approach lies in its dual-layered strategy. By combining supervised classification with unsupervised clustering, the system aims to go beyond static emotion labeling and explore the dynamic nature of emotional shifts. Moreover, the project integrates a feature-rich pipeline including frequency-based characteristics (e.g., band power), statistical descriptors (e.g., variance, RMS), and signal dynamics (e.g., line length, zero-crossings), followed by dimensionality reduction techniques like PCA for optimal performance.

2 About our models

3.1 Supervised Learning

In our study, we implemented two supervised learning models—Support Vector Machine (SVM) and Multi-Layer Perceptron (MLP)—to classify emotional states based on EEG data. The SVM utilizes kernel methods to find optimal decision boundaries by maximizing the margin between classes, making it particularly effective for high-dimensional data with clear separation. Our MLP implementation features a feed-forward architecture with two hidden layers, leveraging backpropagation to learn complex patterns in the feature space. All models were trained on identical datasets. As a baseline, with PCA analysis, and then with hyperparameters optimized through grid search and cross-validation to ensure fair comparison. We evaluated performance using accuracy metrics and confusion matrices to reveal classification patterns across emotional categories.

$$\textbf{DE} = -\int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi\sigma}} \exp \frac{(x-\mu)^2}{2\sigma^2} \ln\left(\frac{1}{\sqrt{2\pi\sigma}} \exp \frac{(x-\mu)^2}{2\sigma^2}\right) dx = \frac{1}{2} \ln 2\pi e\sigma^2$$

$$\textbf{LDS} \qquad \frac{d}{dt}\mathbf{x}(t) = \mathbf{A}\mathbf{x}(t)$$

Fig. 1: Differential Entropy and Linear Dynamic System features from on raw data.

To enhance our feature engineering process, we incorporated Principal Component Analysis (PCA) as a dimensionality reduction technique. As demonstrated by our explained variance curve, we could capture over 90% of the variance using approximately 30-50 components, significantly reducing our feature space from the original hundreds of dimensions. This approach allowed us to investigate whether the essential emotional signal patterns could be preserved in a more compact representation. We trained each model in three configurations: without PCA, with standard PCA implementation, and with optimized PCA parameters selected through validation performance. The integration of PCA was particularly important given our focus on Differential Entropy features processed through Linear Dynamic System smoothing, which we selected for their ability to categorize emotional states based on EEG variability while tracking evolving temporal states in the data.

3.1.1 Unsupervised Learning

In addition to our supervised classification models, we explored unsupervised learning methods to uncover inherent structure in the EEG data without relying on labeled emotional categories. This approach allowed us to analyze how emotional states naturally group based on neural signal patterns alone.

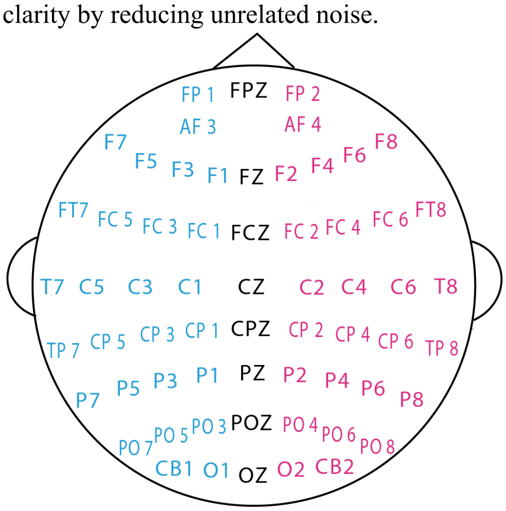
We applied **k-means clustering** to the EEG-derived feature set, focusing particularly on features such as **Differential Entropy (DE)** and smoothed representations generated by the **Linear Dynamic System (LDS)**. Prior to clustering, we performed **Principal Component Analysis (PCA)** to reduce dimensionality while preserving the variance crucial for emotional discrimination. This transformation improved clustering stability and interpretability by compressing the feature space from hundreds of dimensions to a compact, information-rich subset.

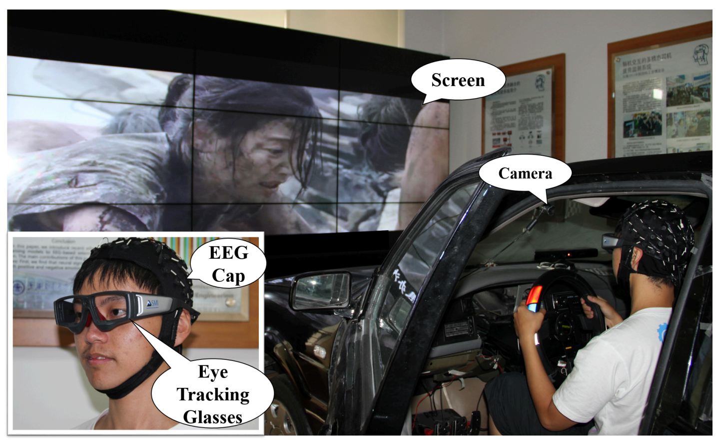
To visualize the clustering results, we used **t-distributed Stochastic Neighbor Embedding (t-SNE)**, which projects the high-dimensional EEG features into two dimensions. This allowed us to assess whether meaningful emotion-related groupings emerged without supervision. Each point in the 2D space represents a time window or sample, and similar emotional responses tend to form visually discernible clusters. We colored the points based on their assigned cluster and, in some cases, by known labels to qualitatively assess overlap.

The consistency between the unsupervised clusters and known emotional labels provided insight into how distinguishable the emotional states were in the EEG space, even without explicit training. This also helped validate the effectiveness of our feature extraction pipeline, indicating that the signals carried enough emotional information for grouping to occur naturally.

3 Data gathering and preprocessing

The EEG data utilized in this project originates from a publicly available dataset (see acknowledgements), which was generated from an experiment where participants watched a curated selection of 72 film clips. These clips were carefully chosen in a preliminary study specifically for their propensity to induce four distinct target emotions: happiness, sadness, fear, or a neutral state. The experiment involved fifteen healthy subjects, each participating in three separate experimental sessions conducted on different days to ensure varied physiological and psychological states. Each of these sessions comprised 24 trials, with each trial corresponding to the viewing of one of the 24 unique video clips assigned to that session. Throughout every trial, continuous 62-channel electroencephalography (EEG) signals were meticulously recorded across the scalp using the ESI NeuroScan System. This project specifically leveraged two forms of the acquired EEG data: the minimally processed raw EEG signals, and the more refined pre-calculated "feature smooth" data. The latter "feature smooth" dataset represents EEG signals that have undergone a comprehensive preprocessing pipeline; this involved downsampling the raw data to 200 Hz, applying a bandpass filter between 1 Hz and 75 Hz to mitigate noise and artifacts, and then segmenting the data into non-overlapping 4-second epochs. From each of these segments, Power Spectral Density (PSD) and Differential Entropy (DE) features were extracted across five critical frequency bands: delta (1-4 Hz), theta (4-8 Hz), alpha (8-14 Hz), beta (14-31 Hz), and gamma (31-50 Hz). Furthermore, this extracted feature data underwent an additional smoothing process using either a moving average or a Linear Dynamic System (LDS) to further enhance signal clarity by reducing unrelated noise.





The raw EEG signals were preprocessed first by applying a referential montage to standardize the comparison across electrodes and reduced spatial noise. Then a band-pass filter was applied to isolate the frequency range most relevant to brain activity associated with emotional processing and to reduce noise and artifacts. The raw EEG data was then organized into label folders for each specific emotion the EEG was associated with. Finally extended features were extracted such as mean, variance, fano_factor, etc.

For the "feature smooth" data, the raw EEG signals underwent a preprocessing pipeline. This involved downsampling to 200 Hz and applying a bandpass filter between 1 Hz and 75 Hz to reduce noise and artifacts. Following this, the data was segmented into non-overlapping 4-second epochs. Within each segment, Power Spectral Density (PSD) and Differential Entropy (DE) features were extracted across five frequency bands: delta (1-4 Hz), theta (4-8 Hz), alpha (8-14 Hz), beta (14-31 Hz), and gamma (31-50 Hz). The "feature smooth" data further included the application of either a moving average or a Linear Dynamic System (LDS) for additional noise reduction. Both the raw EEG data and these pre-calculated, smoothed features were utilized in this project for analysis.

4 Experiments

3.1 Supervised Learning

Figure 1 shows the variance explained using Principal Component Analysis (PCA) The original feature dimension was 310 in Table 1 and reduced to 133 components in 1a/1b which explained 99.9% of the Variance.

Table 1-1b: Comparative analysis of classification performance across Support Vector Machine (SVM) and Multi-Layer Perceptron (MLP) models under varying conditions: without preprocessing, with PCA, and with both PCA and hyperparameter optimization via GridSearchCV.

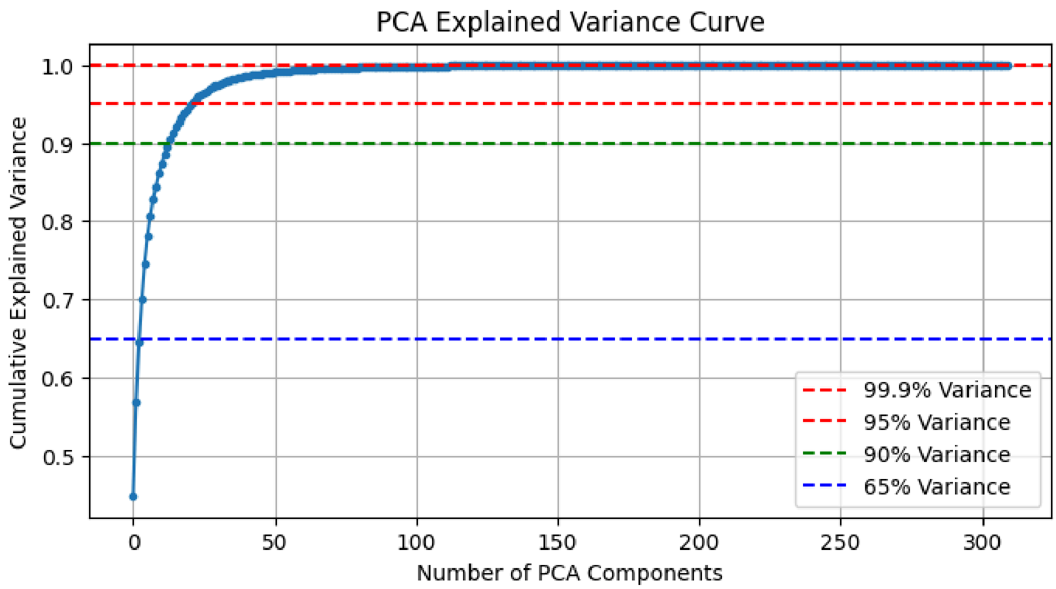


Fig. 1: PCA Explained variance curve

Table 1: Support Vector Machine and Multi-Layer Perceptron

SVM	Precision	Recall	F1-Score
Neutral	0.67	0.86	0.73
Sad	0.56	0.49	0.59
Fear	0.64	0.58	0.66
Happy	0.73	0.65	0.62
Accuracy		0.65	

MLP	Precision	Recall	F1-Score
Neutral	0.69	0.77	0.73
Sad	0.65	0.54	0.59
Fear	0.64	0.69	0.66
Happy	0.64	0.61	0.62
Accuracy		0.65	

Table 1a: SVM and MLP, with PCA

SVMa	Precision	Recall	F1-Score
Neutral	0.67	0.85	0.75
Sad	0.55	0.49	0.52
Fear	0.63	0.57	0.60
Happy	0.73	0.66	0.69
Accuracy		0.64	

MLPa	Precision	Recall	F1-Score
Neutral	0.71	0.87	0.78
Sad	0.66	0.52	0.58
Fear	0.68	0.70	0.69
Happy	0.73	0.68	0.70
Accuracy		0.69	

Table 1b: SVM and MLP, with PCA and GridsearchCV

SVMb	Precision	Recall	F1-Score
Neutral	0.66	0.87	0.75
Sad	0.62	0.52	0.57
Fear	0.64	0.58	0.61
Happy	0.72	0.65	0.68
Accuracy		0.64	

MLPb	Precision	Recall	F1-Score
Neutral	0.65	0.80	0.72
Sad	0.61	0.53	0.57
Fear	0.65	0.62	0.63
Happy	0.66	0.61	0.63
Accuracy		0.64	

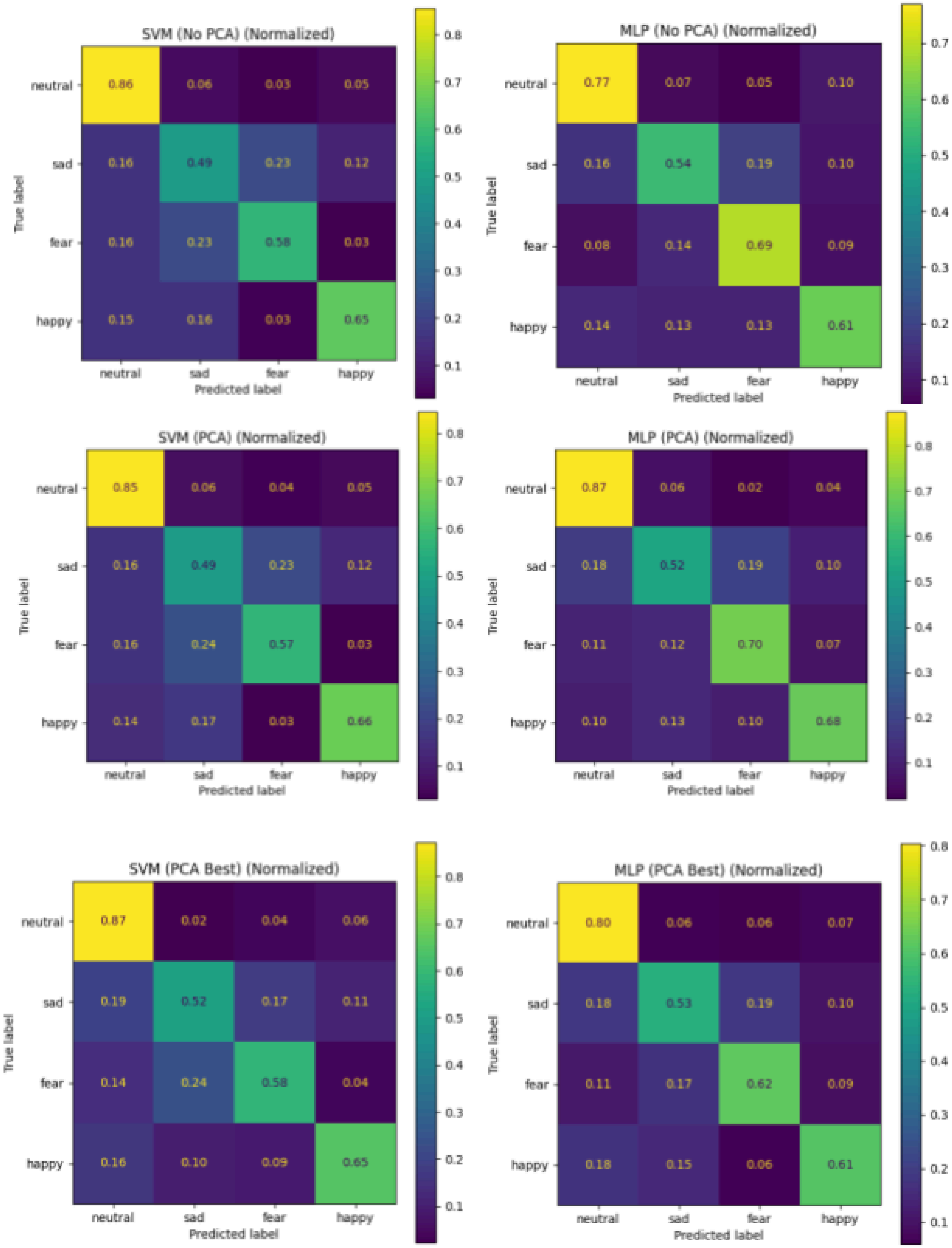


Fig. 2: confusion matrices for different machine learning models

3.1.1 Unsupervised Learning Analysis on EEG Data

In addition to the supervised classification models, an unsupervised learning component was incorporated to explore whether natural groupings in the EEG data aligned with known emotional categories. This was achieved using a combination of Principal Component Analysis (PCA) for dimensionality reduction, t-distributed Stochastic Neighbor Embedding (t-SNE) for visualization, and K-Means clustering to detect latent structure.

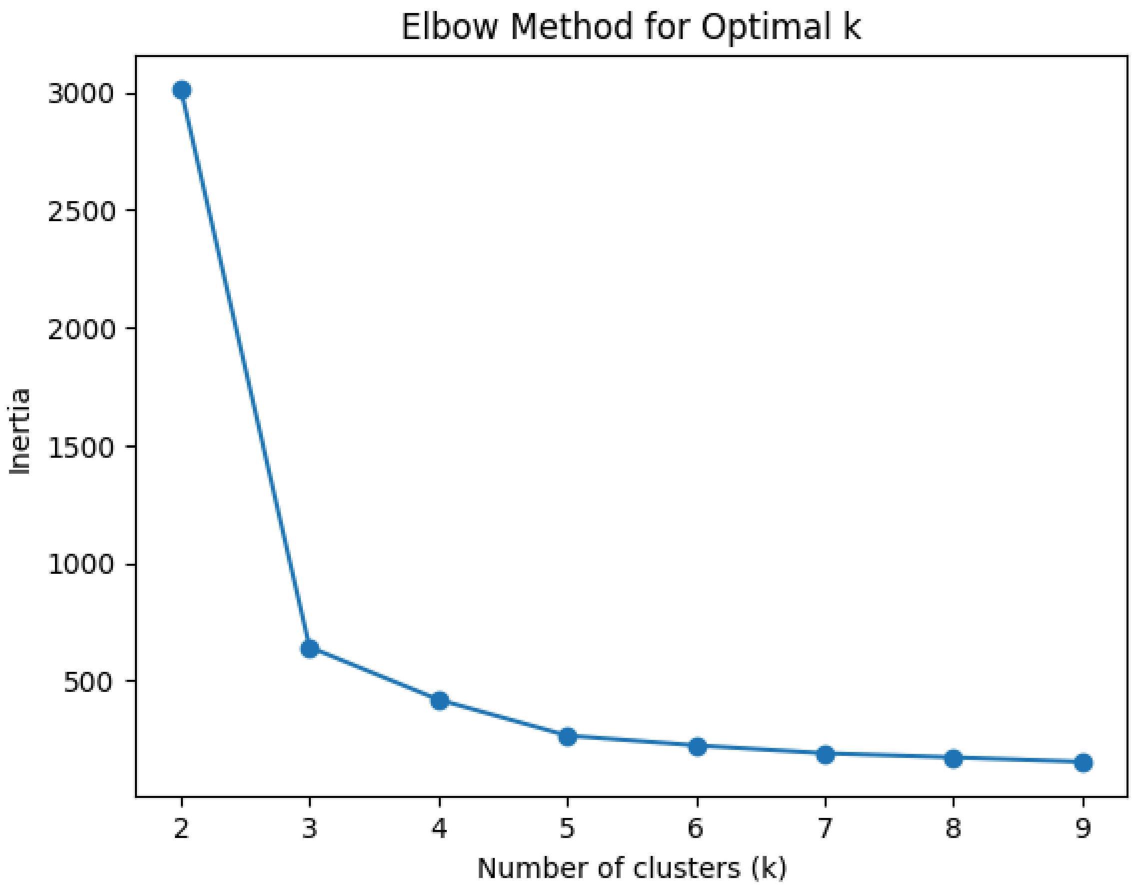


Fig. 3: The Elbow Method used to obtain K

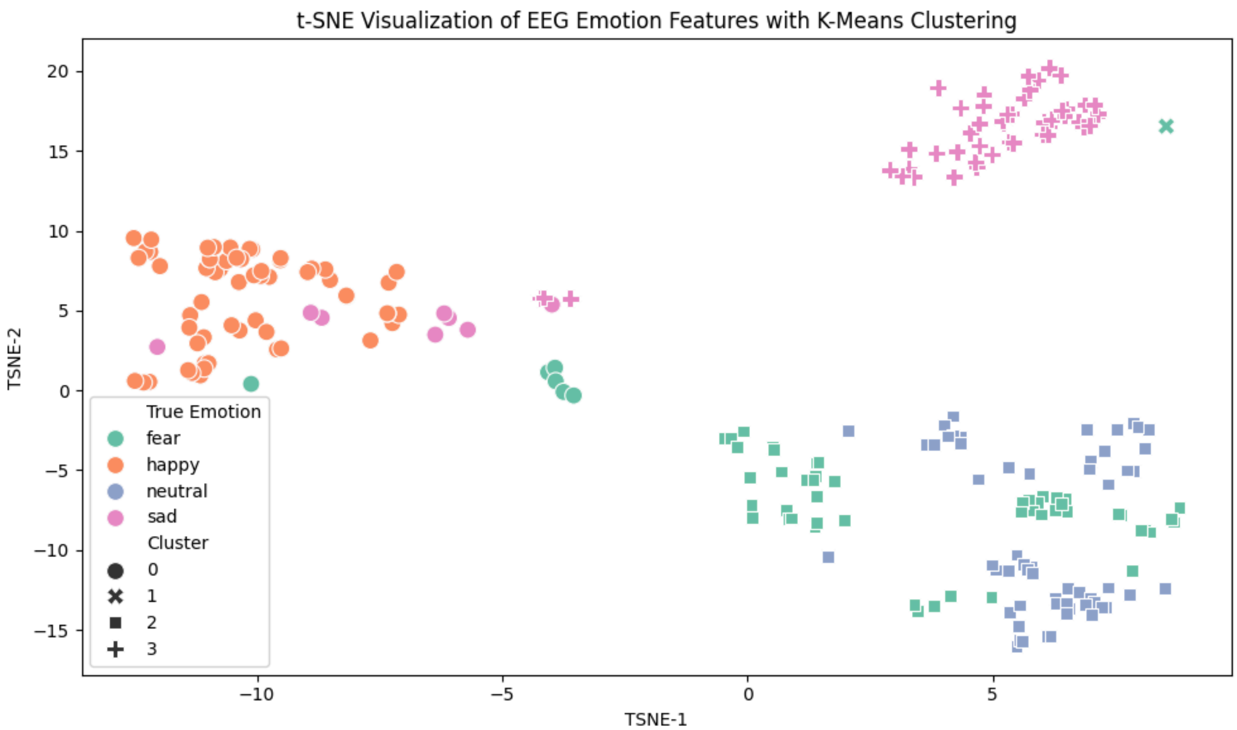


Fig. 4: The Visualization of t-SNE with K-Means Clustering

Observations:

- The t-SNE projection of extended EEG features revealed **visually separable clusters** that loosely corresponded to the four emotion labels (fear(0), happy(1), sad(2), neutral(3)), suggesting the presence of **intrinsic structure** within the data.
- K-Means clustering (with k=4) produced cluster groupings that exhibited partial alignment with emotion labels.
- This alignment reinforces the idea that the feature engineering pipeline—consisting of time-domain statistics, power spectral features, and signal dynamics—**effectively captures emotion-relevant patterns** in EEG signals.

5 Results and discussion

3.1 SVM vs. MLP, PCA Analysis, GridsearchCV

At the baseline, SVM showed stronger recall for Neutral and Happy classes while MLP slightly outperformed when classifying Fear, suggesting a better fit for nuanced emotional features. With PCA, SVM maintained similar performance. While MLP saw a significant gain in accuracy (to 69%) with overall improved precision and recall especially for the Neutral and Fear classes. PCA with hyper parameterization (via Gridsearch) led to marginal performance shifts that were slightly lower than their PCA-only counterparts. However, class-level metrics remained fairly consistent, indicating that grid search may have overfitted to cross-validation folds or was unable to generalize improvements to the test set.

Overall, MLP with PCA (MLPa) produced the best results in this experiment, achieving 69% accuracy and the most balanced performance across emotion categories. This accuracy is comparable to the 70.33% score found in the referenced experiment using SVM on EEG data with differential entropy features and smoothed with rolling averages.[1]

Unlike Power Spectral Density, which focuses on the distribution of power over frequency bands, differential entropy captures the complexity and variability in the raw amplitude distribution of EEG channels. Overall the models were very sensitive to variance. We observed that applying PCA while retaining less than 99.9% of the variance led to a noticeable drop in classification accuracy for both models. This suggests that even small components of variance contained meaningful information in the EEG data.

Overall, our findings highlight the importance of preprocessing (like PCA) and model-specific tuning strategies in optimizing classifier performance for emotion recognition tasks.

3.2 Supervised Learning

The unsupervised results support the hypothesis that emotional states are naturally embedded in the EEG signal space, even without explicit label supervision. The presence of coherent clusters indicates that EEG signals encode sufficient discriminative information for emotion differentiation, likely stemming from the neural dynamics evoked by the emotion-eliciting film stimuli.

These findings validate the quality of the extracted features and also suggest that unsupervised learning could be used for emotion discovery in real-world applications where emotion labels are unavailable or unreliable (e.g., in-the-wild recordings, continuous monitoring systems).

3.3 Interpretation

- Each point's true emotion label is shown via color, revealing the emotional ground truth from the EEG data.
- Each point's **K-Means cluster label** is visualized by its shape, allowing us to assess how well unsupervised clustering aligns with known emotional states.
- Visually, some clusters (e.g., Cluster 3 with + shapes, corresponding mostly to pink/sad points) show **strong consistency** with a specific emotion, indicating successful separation.
- Other clusters may show **overlap** between multiple emotions (e.g., Cluster 2 with ■ squares includes both blue/neutral and green/fear), suggesting less distinct boundaries in those features.

Acknowledgements

The dataset used in this project was obtained from `https://bcmi.sjtu.edu.cn/~seed/seed-iv.html.` This dataset was created in BCMI (Brain-like Computing & Machine Intelligence) under Shanghai Jiao Tong University.

References

[1] Wei-Long Zheng, Wei Liu, Yifei Lu, Bao-Liang Lu, and Andrzej Cichocki, EmotionMeter: A Multimodal Framework for Recognizing Human Emotions. IEEE Transactions on Cybernetics, Volume: 49, Issue: 3, March 2019, Pages: 1110-1122, DOI: 10.1109/TCYB.2018.2797176.