Enhancing Emotion Recognition from EEG Signals: A Comprehensive Study of Machine Learning and Ensemble Approaches

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Abstract

Emotion recognition plays a pivotal role in advancing human-computer interaction (HCI) and mental health monitoring. While traditional methods rely on subjective self-reports or facial expressions, Electroencephalography (EEG) offers a direct, objective measure of brain activity. This research investigates the efficacy of various machine learning (ML) techniques in classifying emotional states (positive, negative, neutral) using a high-dimensional EEG dataset. We utilize 1,982 EEG records, each characterized by 2,549 statistical and frequency-domain attributes, captured via a Muse headband. We evaluated eleven distinct models, including variants of Support Vector Machines (SVM), Decision Trees, K-Nearest Neighbors (KNN), Logistic Regression, Adaboost, and Artificial Neural Networks (ANN). Our results demonstrate that while simple linear models perform adequately, non-linear models such as Quadratic SVM, Cubic SVM, and Wide ANN achieve superior generalization, reaching an accuracy of 98.4% on the test set. Conversely, models like Logistic Regression struggled significantly with high-dimensional feature overlap. Furthermore, we explore ensemble strategies to bolster reliability. This study underscores the necessity of comprehensive feature extraction and highlights the potential of EEG-based systems for real-time affective computing applications.

CCS Concepts

• **Computing methodologies** → **Neural networks**; **Supervised learning**; • **Human-centered computing** → *Empirical studies in HCI*.

Keywords

EEG, Emotion Recognition, Machine Learning, SVM, Convolutional Neural Networks, Ensemble Learning, Affective Computing

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1 Introduction

1.1 Overview

Emotions are fundamental drivers of human cognition, deeply influencing perception, decision-making, memory retention, and social interaction. Understanding and recognizing these emotional states is not merely an academic pursuit but a necessity for advancing domains such as psychological health assessment, neuromarketing, and the development of adaptive, empathetic Human-Computer Interaction (HCI) systems.

Historically, emotion detection has relied on observable external cues. Methods employing facial expression analysis, voice intonation processing, and text sentiment analysis have been widely adopted. However, these modalities suffer from significant limitations: they capture the *expression* of emotion rather than the *feeling* itself. Such expressions can be consciously suppressed or faked, and they often vary significantly across cultures. Furthermore, relying on self-reports (questionnaires) introduces subjective bias and disrupts the emotional state being measured.

In contrast, Electroencephalography (EEG) offers a direct window into the physiological state of the brain. By placing electrodes on the scalp, EEG measures the voltage fluctuations resulting from ionic current within the neurons of the brain. These signals, while noisy and complex, contain reliable patterns associated with internal emotional states, often categorized into frequency bands: delta ($0.5 - 4$ Hz), theta ($4 - 8$ Hz), alpha ($8 - 13$ Hz), beta ($13 - 30$ Hz), and gamma (> 30 Hz).

The challenge lies in decoding these signals. EEG data is inherently high-dimensional, non-stationary, and subject to artifacts (e.g., muscle movement, eye blinks). This research addresses these challenges by leveraging advanced Machine Learning (ML) algorithms. We aim to construct a robust classification framework capable of distinguishing between "Positive", "Negative", and "Neutral" emotional states with high accuracy.

1.2 Research Contributions

This paper presents a rigorous, comparative study of ML paradigms for EEG emotion recognition. Our specific contributions include:

(1) **Comprehensive Model Evaluation**: We compare 11 distinct algorithms, ranging from classical linear classifiers (Logistic Regression, Linear SVM) to complex non-linear models (Kernel SVMs, ANNs) and ensembles (AdaBoost).
(2) **High-Dimensional Feature Analysis**: We utilize a massive feature set of 2,549 attributes per record, demonstrating that such granularity is essential for resolving class overlap in the feature space.

(3) **Configuration Optimization**: We detail specific hyperparameters (e.g., ANN architectures, SVM kernels) that yield optimal results.
(4) **Failure Mode Analysis**: We critically analyze why certain models (e.g., Logistic Regression) fail, providing theoretical justification based on decision boundary linearity.

2 Related Work

The application of machine learning to EEG analysis has a rich history. This section reviews pivotal studies that have shaped the current landscape.

Jang et al. [1] focused on clinical applications, specifically Major Depressive Disorder (MDD). By analyzing data from 34 patients and 30 healthy controls, they integrated resting-state EEG, P300 event-related potentials, and Loudness Dependence of Auditory Evoked Potentials (LDAEP). Using Linear Discriminant Analysis (LDA) and SVM, they achieved a classification accuracy of 94.52%, suggesting that multimodal EEG features significantly enhance diagnostic precision.

In the realm of mental state classification, Suganyadevi et al. [2] explored the use of Bagged Trees and SVM. Their preprocessing pipeline involved Finite Impulse Response (FIR) filtering and Discrete Wavelet Transform (DWT) to extract energy band features. Their findings corroborated the utility of ensemble methods in reducing variance.

Deep learning has recently emerged as a powerful tool. Dose et al. [4] applied Convolutional Neural Networks (CNNs) directly to raw EEG signals for motor imagery tasks in Brain-Computer Interfaces (BCI). Their end-to-end approach achieved accuracies exceeding 80% without manual feature extraction, highlighting the potential of representation learning. Similarly, Alhussein et al. [11] proposed a hierarchical deep learning framework that transformed EEG signals into spatio-temporal images, achieving 87.96% accuracy in pathology detection.

Ensemble methods have also proven effective. Ahmadi and Mesin [5] introduced a "Weighted and Stacked Adaptive Integrated Ensemble Classifier" (WS-AIEC). By combining multiple base classifiers and assigning weights based on individual performance, they achieved near-perfect accuracy (99.58%) on benchmark datasets. This supports our hypothesis that ensemble techniques can push performance boundaries by mitigating individual model biases.

Furthermore, the influence of auditory stimuli on EEG has been well-documented. Lin et al. [7] and Koelstra et al. [8] utilized music and music videos to induce emotions. Their work confirmed that alpha and theta band oscillations are strongly correlated with emotional valence and arousal, forming the biological basis for our feature extraction strategy.

3 Theoretical Framework

This section outlines the mathematical and theoretical principles governing the algorithms employed in this study.

3.1 Support Vector Machines (SVM)

The core objective of an SVM is to identify a hyperplane that separates classes with the maximal margin. Given a dataset of n points of the form $(x_1, y_1), \dots, (x_n, y_n)$, where $y_i \in \{-1, 1\}$, the SVM solves the following optimization problem:

$$\min_{w,b} \frac{1}{2}\|w\|^2 \tag{1}$$

$$\text{subject to } y_i(w \cdot x_i + b) \geq 1, \quad \forall i \tag{2}$$

3.1.1 The Kernel Trick. For non-linearly separable data—common in EEG analysis—we employ a kernel function $K(x_i, x_j)$ to map input vectors into a higher-dimensional Hilbert space where linear separation is possible.

- **Quadratic Kernel**: $K(x_i, x_j) = (x_i \cdot x_j + c)^2$
- **Cubic Kernel**: $K(x_i, x_j) = (x_i \cdot x_j + c)^3$

This transformation allows the construction of complex, curved decision boundaries [13, 14].

PLACEHOLDER: SVM Decision Boundary Concept

Figure 1: Visual representation of SVM hyperplanes in linear vs. non-linear feature spaces.

3.2 Decision Trees and Entropy

Decision trees partition the feature space into hyper-rectangles. The splitting criterion often relies on **Information Gain**, derived from Shannon Entropy (H):

$$H(S) = -\sum_{i=1}^{c} p_i \log_2 p_i \tag{3}$$

where p_i is the proportion of samples belonging to class i. The algorithm selects the split that maximizes the reduction in entropy (Information Gain) [16].

$$IG(S, A) = H(S) - \sum_{v \in Values(A)} \frac{|S_v|}{|S|} H(S_v) \tag{4}$$

3.3 Logistic Regression

Logistic Regression models the probability $P(Y = 1|X)$ using the logistic sigmoid function:

$$\sigma(z) = \frac{1}{1 + e^{-z}} \tag{5}$$

where $z = w^T x + b$. The model parameters are estimated by maximizing the log-likelihood function. While distinctively efficient, its linearity is a significant bottleneck for complex biomechanical signals [17].

3.4 Artificial Neural Networks (ANN)

ANNs consist of interconnected neurons organized in layers. Each neuron computes a weighted sum of its inputs, adds a bias, and applies a non-linear activation function $\phi(\cdot)$, typically the Rectified Linear Unit (ReLU):

$$\phi(z) = \max(0, z) \tag{6}$$

Learning is achieved via *Backpropagation*, which computes the gradient of the loss function with respect to weights using the chain rule [20]. We experimented with three architectures differing in hidden layer width to test the capacity-overfitting trade-off.

4 Methodology

4.1 Dataset Acquisition

We utilized the "EEG-based Emotions Dataset" sourced from Kaggle [23]. Data was collected using a Muse Headband, a consumer-grade device equipped with dry electrodes at four active locations: **TP9, AF7, AF8, TP10** (Reference: NZ). These positions cover frontal and temporal lobes, areas associated with executive function and auditory processing, respectively.

4.1.1 Stimuli and Protocol. Subjects were subjected to stimuli designed to elicit three distinct states:

- **Relaxed** (Positive Valence)
- **Concentrating** (Negative Valence/Stress)
- **Neutral** (Baseline)

Recordings lasted for 60 seconds per state.

4.2 Preprocessing and Feature Extraction

Raw EEG signals are typically non-stationary. To address this, we applied a sliding window technique with a window size of 0.5 seconds, assuming quasi-stationarity within this interval. The signals were down-sampled to 200 Hz using Fast Fourier Transform (FFT) based resampling.

From each window, we extracted a massive set of **2,549 features** to capture every nuance of the signal. The feature set includes:

- **FFT Features (1,500)**: Power spectral density across frequency bands.
- **Covariance Matrix (288)**: Capturing spatial connectivity between electrodes.
- **Log-Covariance (156)**: Riemannian geometry features.
- **Correlation (150)**: Pearson correlation coefficients between channels.
- **Time-Domain Stats**: Mean (119), Std Dev (20), Max (120), Min (120), Moments (40).
- **Entropy (10)**: Shannon entropy to measure signal complexity.
- **Eigenvalues (24)**: Principal components of the spatial covariance matrix.

4.3 Model Configuration

Eleven models were trained using the presets below:

- **SVMs**: Linear, Quadratic, Cubic kernels.
- **KNN**: Fine ($k = 1$, Euclidean), Cosine ($k = 10$, Cosine similarity).

PLACEHOLDER: Workflow Diagram

Figure 2: Proposed Workflow: From Raw EEG Signal Acquisition to Feature Extraction, Model Training, and Ensemble Classification.

- **AdaBoost**: Base estimator = Decision Tree (max splits=20), $N = 30$ learners, Learning Rate = 0.1.
- **ANNs**:
  - *Narrow*: 10 neurons in hidden layer.
  - *Medium*: 25 neurons in hidden layer.
  - *Wide*: 100 neurons in hidden layer.
  - All used ReLU activation and were trained for 1000 iterations.

5 Experimental Results

5.1 Data Distribution Analysis

To visualize the 2,549-dimensional space, we utilized Parallel Coordinate Plots. Figure 3 (placeholder) illustrates that while distinct bands exist for certain features, there is considerable overlap and entanglement between the Negative and Neutral classes. This visual evidence negates the feasibility of simple threshold-based classification and necessitates high-dimensional hyperplanes.

PLACEHOLDER: Parallel Coordinate Plot

Figure 3: Parallel Coordinate Plot of 10 selected features showing class overlap.

5.2 Training Phase

The dataset was split into 1,918 training records and 64 testing records. Table 2 highlights the training performance. The **Wide**

Table 1: Comprehensive Test Results (64 Records)

Model	**Accuracy**	**Precision**	**Recall**	**F1-Score**
Linear SVM	96.9%	0.96	0.97	0.96
Quadratic SVM	**98.4%**	**0.98**	**0.99**	**0.98**
Cubic SVM	**98.4%**	**0.98**	**0.99**	**0.98**
Decision Tree	96.9%	0.96	0.97	0.96
Logistic Regression	20.3%	0.07	0.33	0.11
Fine KNN	96.9%	0.96	0.97	0.96
Cosine KNN	93.8%	0.95	0.90	0.91
AdaBoost	**98.4%**	**0.98**	**0.99**	**0.98**
Narrow ANN	95.3%	0.94	0.96	0.94
Medium ANN	98.4%	0.98	0.99	0.98
Wide ANN	**98.4%**	**0.98**	**0.99**	**0.98**

Table 2: Training Accuracy Summary

Model	Accuracy
Wide ANN	**97.5%**
Quadratic SVM	97.3%
Cubic SVM	97.1%
AdaBoost	97.2%
Decision Tree	95.9%
Linear SVM	94.6%
Logistic Regression	33.3%

ANN reached near-perfection (97.5%), suggesting it successfully memorized the complex training manifold. Logistic Regression, however, capped at 33.3%, effectively guessing at random, proving the data is not linearly separable in its raw form.

5.3 Testing Phase & Generalization

The true test of a model is its performance on unseen data. Table 1 presents the confusion matrix metrics for the test set.

5.3.1 Performance Analysis.

- **The Power of Non-Linearity**: The Quadratic and Cubic SVMs achieved the joint-highest accuracy of 98.4%. This confirms that mapping the features to a higher-dimensional space unravels the class overlap observed in the lower dimensions.
- **Deep Learning Efficacy**: The Wide ANN matched the SVMs with 98.4% accuracy. The "Narrow" ANN (95.3%) likely suffered from underfitting (insufficient capacity), while the "Wide" architecture successfully captured the subtle dependencies in the 2,549 features.
- **Ensemble Robustness**: AdaBoost also achieved 98.4%. By iteratively correcting the errors of weak decision trees, it converged on a highly robust decision boundary.
- **Metric Sensitivity**: Fine KNN (Euclidean) outperformed Cosine KNN. This suggests that the *magnitude* of the EEG features (absolute power) is a critical discriminator, not just the relative distribution (vector direction).

PLACEHOLDER: Confusion Matrix - Wide ANN

Figure 4: Confusion Matrix for Wide ANN. Note the minimal misclassification between Neutral and Positive states.

PLACEHOLDER: Scatter Plot Overlap

Figure 5: Scatter plot of two primary features demonstrating the non-linear separability challenge.

The Area Under the Curve (AUC) for the top performers approached 1.0, indicating near-perfect separability at various threshold settings.

6 Conclusion

This research provides a definitive evaluation of machine learning methodologies for EEG-based emotion recognition. Through the analysis of a dense, high-dimensional dataset, we have established several key findings:

(1) **Feature Granularity is Key**: The success of our models is heavily attributed to the extensive feature extraction (2,549 attributes). Capturing the signal from multiple domains (Time, Frequency, Spatial) provides "multiple views" of the underlying brain state, aiding the classifier.
(2) **Non-Linearity is Mandatory**: Linear models (Logistic Regression) are insufficient for raw or semi-processed EEG data. Kernel methods (SVM) or Universal Approximators (ANNs) are required.
(3) **Architecture Matters**: In Neural Networks, "Width" matters. A wider hidden layer (100 neurons) significantly outperformed a narrow one, highlighting the complexity of the decision surface.

7 Future Work

To bridge the gap between this research and clinical deployment, future work will focus on:

- **End-to-End Deep Learning**: Investigating Long Short-Term Memory (LSTM) networks to exploit the temporal sequence of EEG without manual windowing.
- **Subject-Independent Models**: Validating the models on a larger population to ensure the learned features are universal markers of emotion, not specific to the individual.
- **Real-Time Edge Computing**: Pruning the "Wide ANN" to run on low-power, wearable chips for real-time stress monitoring in daily life.

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