Emotion Recognition from EEG Signals Machine Learning and Deep Learning Techniques

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***Abstract*—Within affective computing and brain-computer interfaces (BCI), electroencephalogram (EEG) signal-based emotion identification has become a potential area of study. The limits of subjective self-reports or external modalities are overcome by EEG, which offers direct access to internal brain correlates of emotional states. Using data from 12 current research published between 2021 and 2025, this study thoroughly investigates machine learning (ML) and deep learning (DL) techniques for EEG-based emotion categorization. With the use of advanced feature extraction methods (such as spectrograms, differential entropy, and wavelet transformations) and strategies like data augmentation, attention mechanisms, and optimization algorithms, machine learning (ML) may achieve 99.9% accuracy. Although there are still issues like subject variability, noise, and a lack of labeled data, hybrid and multimodal approaches have a lot of promise. Recommendations for further study toward more reliable, deployable systems in the actual world are included in the review's conclusion.**

***Index Terms*—EEG, Emotion Recognition, Machine Learning, Deep Learning, CNN, SVM, Random Forest, DEAP Dataset**

I. INTRODUCTION

A subfield of artificial intelligence called machine learning (ML) allows algorithms to forecast new data and find hidden patterns in existing datasets without the need for explicit programming. A standard machine learning system uses past data to create prediction models, and as the amount of training data grows, so does the accuracy. Because ML and DL approaches can automatically identify complicated emotional patterns in high-dimensional, noisy EEG signals—something manual analysis finds difficult to accomplish—they are very useful in emotion identification [1]-[3].

EEG signals use scalp electrodes to record brain activity, and its entropy properties, asymmetry, and frequency bands (delta, theta, alpha, beta, and gamma) represent internal emotional states. EEG is perfect for objective emotion identification since it is less subject to deliberate control than speech or facial expressions. The valence-arousal dimensional model (positive/negative valence and high/low arousal) and discrete categories (happy, sad, angry, quiet, neutral, etc.) are common models of emotion.

Applications include human-computer interaction, entertainment, healthcare (depression diagnosis, mental health monitoring), and driver tiredness detection. However, noise, distortions, inter-subject variability, and high dimensionality plague EEG data, requiring sophisticated ML/DL techniques. In order to assess the transition from conventional ML to advanced DL techniques for EEG-based emotion identification, this review summarizes the results of twelve important experiments.

II. METHODOLOGY OF EEG EMOTION RECOGNITION

Raw brain signals are converted into categorized emotional states using a standardized five-stage pipeline in the EEG-based emotion detection approach. This pipeline, which includes (1) data gathering, (2) preprocessing, (3) feature extraction, (4) model training/classification, and (5) performance evaluation, is consistently documented throughout the 12 examined papers. In order to handle the non-stationary, noisy, and high-dimensional character of EEG data, each step is essential. Each stage is broken down in depth below, with specific examples and methods from the literature to back it up III.

Data Acquisition

To guarantee repeatability and comparability, researchers employ benchmark datasets that are accessible to the general public. The most frequently employed datasets in the reviewed papers are:

DEAP (Database for Emotion Analysis using Physiological Signals): DEAP (Database for Emotion Analysis using Physiological Signals): A 32-channel EEG was captured at 512 Hz while 32 individuals watched 40 one-minute music videos. Continuous valence-arousal scores (1–9 scale) are used as emotional labels, and they are frequently quantified into two to four distinct groups (e.g., high/low valence-arousal → happy, calm, furious, sad) [5], [10].

SEED (SJTU Emotion EEG Dataset): 62-channel EEG at 200 Hz, 15 individuals, 3 sessions, 15 movie clips, and positive, neutral, and negative labels [5].

Generalization is validated using MAHNOB-HCI and other smaller datasets [1].

Participants watch emotionally charged stimuli (videos, photos, or sounds) while data is collected in controlled laboratory environments. Following each trial, discrete emotion labels or self-reported valence-arousal ratings are used to determine emotional ground truth.

Preprocessing

Baseline drift, power-line noise (50/60 Hz), muscular movements, and ocular artifacts all significantly pollute raw EEG. Preprocessing keeps emotional information intact while eliminating these artifacts.

Typical steps (reported in nearly every paper):

Filtering: Band-pass filter (commonly 0.5–45 Hz or 4–45 Hz) using Butterworth or FIR filters to retain delta (0.5–4 Hz), theta (4–8 Hz), alpha (8–13 Hz), beta (13–30 Hz), and gamma (30–45 Hz) bands.

Artifact removal: Independent Component Analysis (ICA) or regression-based methods to eliminate eye-blink and muscle artifacts [2], [9], [10].

Re-referencing: Common average referencing (CAR) or mastoid reference.

Segmentation: EEG is divided into non-overlapping or overlapping epochs (usually 1–5 seconds per trial) corresponding to stimulus duration.

Baseline correction: Subtract pre-stimulus baseline.

More complex variations include windowing before to FFT [3] or improved cleaning prior to Morlet wavelet transform [4]. The signal quality is much enhanced after preprocessing, allowing for trustworthy downstream analysis.

Feature Extraction

In this step, 1D time-series EEG data are transformed into useful representations. There are two primary methods: learnt representations (used with DL) and conventional hand-crafted features (used with ML).

Traditional / Hand-crafted features (dominant in ML studies):

Frequency-domain: Fast Fourier Transform (FFT) and Power Spectral Density (PSD) to compute band powers [9].

Time-frequency: Short-Time Fourier Transform (STFT) to generate spectrograms; Morlet Dual-level Wavelet Transform for multi-resolution analysis [4].

Differential Entropy (DE): Widely used for EEG emotion recognition because it captures signal complexity. For a Gaussian-distributed EEG channel X, DE is defined as:

$$h(X) = \frac{1}{2}\, log\,(2\pi e \sigma^2)$$

where, σ^2 is the variance of the signal in a specific frequency band [7].

Asymmetry and other statistics: Frontal alpha asymmetry, entropy, and statistical moments [1], [5].

Deep-learning-friendly representations:

EEG converted to 2D images/spectrograms or 3D spectro-spatial maps (time × frequency × channel) [6].

Graph structure where nodes = EEG channels and edges = spatial relationships [1].

Feature selection (Chi-Square, RFE, PCA) is often applied after extraction to reduce dimensionality [11].

Model Training and Classification

The extracted features (or raw/processed signals) are fed into classifiers. Two broad categories are used:

Machine Learning Classifiers (interpretable, lower compute):

Support Vector Machine (SVM) with RBF kernel [2], [5].

Random Forest (RF) with 10-fold cross-validation [10].

LightGBM (gradient boosting) after PCA [11].

Other: Logistic Regression, Decision Tree, Lasso Regression.

Deep Learning Models (automatic feature learning):

CNN: 1D/2D CNN on raw signals or spectrograms; captures spatial and frequency patterns [3], [6], [9].

LSTM / Recurrent models: Capture temporal dynamics of emotions [7], [8].

Hybrid architectures: CNN + LSTM (spatial + temporal) [7], Deep Recurrent Autoencoder (DRAE) with attention for semi-supervised learning [8].

Advanced: Graph Neural Network (GNN) with contrastive learning and GAN-based data augmentation to handle subject variability [1]; Morlet Dual-level Wavelet Contextual Neural Network (MorDWCNNet) optimized by Snow

Geese Algorithm (SGA) [4].

Hyperparameter optimization, subject-independent validation, and data augmentation (GANs) are examples of training techniques. Both subject-dependent (high accuracy) and subject-independent (more realistic) findings are reported in several research.

Performance Evaluation

Models are assessed using standard classification metrics and rigorous validation protocols:

Metrics:

Accuracy (overall correctness)

Precision, Recall, F1-score (per class, especially important for imbalanced emotions)

Confusion matrix (to identify difficult classes such as “neutral”)

Validation methods:

10-fold cross-validation [10]

Leave-One-Subject-Out (LOSO) or Leave-One-Trial-Out (for subject-independent generalization) [7]

Subject-specific vs. subject-independent splits [10]

DL models routinely beat standard ML, as demonstrated by the assessed works: CNN obtains 99% [3], MorDWCNNet + SGA reaches 99.9% [4], and best ML (LightGBM) achieves 96% [11]. Although it is outside the purview of pure EEG pipelines, multimodal fusion (EEG + face) is recommended for additional enhancement.

III. MACHINE LEARNING TECHNIQUES

In the early days of EEG-based emotion identification research, conventional machine learning (ML) classifiers were critical. These techniques are preferred due to their interpretability, robustness with smaller datasets, comparatively low computational requirements, and capacity to function well with carefully designed hand-crafted features (e.g., band power, differential entropy, asymmetry indices, statistical measures, and time-frequency features extracted via FFT, PSD, or STFT). Although classical machine learning techniques necessitate explicit feature extraction and selection steps, they frequently offer strong baselines and maintain their competitiveness in subject-dependent scenarios or when computational resources are limited, in contrast to deep learning models that automatically learn features from raw or minimally processed data.

The four exemplary research that use and compare classic machine learning algorithms are highlighted in the evaluated publications. Depending on the dataset, number of emotion classes, and validation process (subject-dependent vs. subject-independent), the accuracies generally fall between 78 and 96%. Each study's methodology, main findings, advantages, disadvantages, and contributions to the field are explained in depth below.

Asha et al. (2023) – Mixed ML and DL Comparison on Preprocessed EEG

The authors of the paper "Emotion Recognition using ML Models on EEG Data" (presented at IEEE ICAISS 2023) investigated several classifiers on a labeled EEG dataset following standard preprocessing (filtering and artifact removal) and feature extraction using Power Spectral Density (PSD) and Fast Fourier Transform (FFT).

Support Vector Machine (SVM), Random Forest (RF), Convolutional Neural Network (CNN), and Recurrent Neural Network (RNN) were the algorithms that were examined.

Key finding: CNN's accuracy of 97.64% was the greatest of all the models. Deep learning techniques, however, beat the conventional ML models (SVM and RF), which did very well.

Findings: This study shows that hand-crafted frequency-domain features given to SVM or RF produce good but not state-of-the-art performance, even when combining traditional ML and DL in the same comparison. It highlights the moment at which DL starts to outperform conventional ML because it can handle complicated, non-linear EEG patterns more effectively.

3.2 Akshay et al. (2022) – Random Forest on DEAP Dataset
The well-known DEAP dataset was the only subject of the study "Emotion Recognition from EEG Signals Using Machine Learning Model" (IEEE IMPACT 2022).

Methodology: To eliminate noise and artifacts, EEG signals were preprocessed. Happy, calm, furious, and sad were the four distinct emotion classes into which valence-arousal ratings were quantified. After features were recovered, 10-fold cross-validation was used to train a Random Forest classifier.

Performance:
Subject-specific (intra-subject) experiments: average best accuracy of 91.26%.
Subject-dependent (cross-subject or leave-one-subject-out style): 78.5%.
Strengths: RF is an ensemble technique that reduces overfitting and effectively handles high-dimensional EEG information by constructing numerous decision trees and aggregating predictions. One of the main issues with EEG emotion detection is inter-subject variability brought on by individual brain characteristics, electrode positioning, and emotional display styles. This is shown by the significant disparity between subject-specific and cross-subject accuracy.

Contribution: This study demonstrates that RF is a valid and interpretable baseline for four-class emotion issues on DEAP, particularly in subject-specific (individualized) circumstances where accuracies of greater than 90% are possible.

Pandey et al. (2022) – LightGBM and Ensemble Methods with Feature Selection
The authors of "Emotion Recognition Classification Using an EEG-based Brain Computer Interface System based on Different Machine Learning Models" (IEEE CISCT 2022) examined a sizable feature set that was taken from EEG recordings.
Methodology: Lasso Regression, LightGBM importance, Recursive Feature Elimination (RFE), Chi-Square test, and extensive feature extraction are followed by feature selection strategies. Principal Component Analysis (PCA) was used to reduce dimensionality. The following classifiers were compared: LightGBM, Random Forest, Decision Tree, and Logistic Regression.

Key finding: LightGBM, a gradient boosting framework, classified positive, negative, and neutral emotions with the greatest accuracy of 96%.
LightGBM's strengths include its high efficiency, native handling of categorical features, speed through histogram-based splitting, and incorporation of leaf-wise tree growth on tabular/high-dimensional data, such as EEG characteristics, to improve accuracy. It lessens the curse of dimensionality that multi-channel EEGs frequently experience when combined with careful feature selection and PCA.

Significance: This work demonstrates how, when combined with meticulous preprocessing and dimensionality reduction, boosting-based ensemble techniques—particularly gradient boosting versions like LightGBM—can bring standard ML performance very close to early DL findings.

Prakash and Poulose (2025) – Comparative Analysis on Commercial EEG Data
The paper "Electroencephalogram-based emotion recognition: A comparative analysis of supervised machine learning algorithms" (published in Data Science and Management, vol. 8, pp. 342–360, 2025) used data from the Feeling

Emotions EEG Dataset collected via commercial-grade EEG devices.
A variety of supervised machine learning techniques were examined, including ensemble models (Random Forest, AdaBoost, LightGBM, XGBoost, and CatBoost) and others (SVM, Gaussian Naive Bayes, Decision Tree, and Logistic Regression).

Key observations:
Neutral emotion was the most difficult class to classify accurately (likely due to subtle or low-arousal patterns overlapping with other states).

Ensemble methods (particularly boosting algorithms) performed strongly.
Practical implication: The work highlights that, when combined with reliable machine learning methods like RF or gradient boosting, inexpensive, commercial EEG headsets (lower channel count, less noisy in controlled circumstances, but more prone to artifacts) may accomplish realistic emotion identification.

Contribution: It demonstrates that classical machine learning is still viable for resource-constrained or portable BCI systems by bridging the gap between academic research (often utilizing high-end research-grade EEG, such as 32–64 channels) and real-world implementation.

Overall Insights and Comparative Summary of ML Techniques
Across these studies:
Typical accuracy range: 78–96% (highest: 96% with LightGBM [11]; strong subject-specific RF: 91.26% [10]).

Best performers: Ensemble methods dominate – Random Forest for its simplicity and robustness, LightGBM/XGBoost variants for superior accuracy on selected features.
SVM: Frequently used as a strong baseline due to its effectiveness in high-dimensional spaces with clear margins.
Common strengths of ML approaches:
Lower training time and computational cost compared to DL.
Easier interpretability (feature importance, decision paths).
Good performance with limited data when features are well-engineered.
Main limitations:
Heavy dependence on manual feature engineering and selection.
Poorer generalization in cross-subject scenarios (due to variability not captured by hand-crafted features).
Struggle with raw or minimally processed EEG compared to DL models that learn hierarchical representations.

IV. DEEP LEARNING TECHNIQUES

DL models do not require a lot of manual engineering since they automatically learn hierarchical characteristics. With data augmentation and FFT characteristics, Atole et al. tested RF, ANN, and CNN; CNN outperformed RF (82.72%) with 99% accuracy [3]. For seven distinct emotions, Pandey and Barde used SVM with STFT features spanning frequency bands, achieving 97.87% accuracy (Alpha and Beta bands most discriminative) [2]. A Graph Neural Network (GNN) with contrastive learning and GAN-based augmentation was suggested by Soleimani Gilakjani and Al Osman. Better results on the DEAP and MAHNOB-HCI datasets were obtained when EEG was represented as graphs that captured spatial electrode relationships [1]. Jha et al. used SVM on frequency-band characteristics to evaluate the DEAP and SEED datasets, reporting 76% valence and 70.88% arousal accuracy while highlighting the significance of preprocessing [5]. With a remarkable 99.9% accuracy, Sivaramkrishnan et al.'s Morlet Dual-level Wavelet Contextual Neural Network (MorDWCNNet), optimized using the Snow Geese Algorithm (SGA), outperformed CNN, Bi-LSTM, and other hybrids [4]. For semi-supervised learning, Zhang and Etemad created a Deep Recurrent Autoencoder (DRAE) with attention and LSTM that successfully handles sparse labeled data [8]. Using 2D CNN and multi-band EEG transformed to 3D spectrospatial maps with channel attention, Saha et al. greatly improved valence-arousal categorization [6]. Lu achieved 93.13% accuracy under leave-one-subject-out validation by combining 1D CNN (spatial) and LSTM (temporal) on differential entropy features, outperforming DBN and DGCNN [7].

V. COMPARATIVE ANALYSIS

Across the reviewed studies:
The highest DL accuracies are 99.9% (MorDWCNNet + SGA [4]), 99% (CNN [3]), 97.87% (SVM with STFT [2]), and 97.64% (CNN [9]).
Conventional ML peak: 91.26% (RF subject-specific [10]), 96% (LightGBM [11]).
DL models are particularly good at handling raw or processed EEG (spectrograms, graphs, wavelet representations) and generalization. Data scarcity and variability are addressed by methods such as attention, GAN augmentation, contrastive learning, and optimization algorithms [1], [4], [6]– [8].

VI. CHALLENGES

High noise and artifacts in EEG, inter-subject and cross-dataset variability, limited labeled data and class imbalance (particularly neutral emotions), computational complexity of advanced DL models, and lack of standardization in preprocessing and evaluation protocols are common limitations [5], [12].

VII. FUTURE DIRECTIONS

Advanced augmentation (GANs), semi-supervised and self-supervised learning, graph-based and attention-enhanced architectures for spatial-temporal modeling, optimization algorithms and explainable AI for clinical deployment, hybrid multimodal fusion of EEG with facial expressions or physiological signals for improved reliability, and real-time, inexpensive BCI systems using commercial EEG headsets [1], [3], [7].

VIII. CONCLUSION

In EEG-based emotion detection, this review shows that deep learning approaches—in particular, CNNs, LSTMs, GNNs, and optimized wavelet-based networks—perform noticeably better than conventional machine learning classifiers. With appropriate feature representation and sophisticated training techniques, accuracy levels of 97% are now regularly attainable [2]– [4], [9]. Even if noise and unpredictability are still problems, the area is moving quickly in the direction of reliable, broadly applicable systems. Future research combining effective DL architectures with multimodal cues will open the door to useful applications in affective computing, human-machine interaction, and mental health

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