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Decoding Emotions from EEG Responses Elicited by Videos using Machine Learning Techniques

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Abstract: Electroencephalography (EEG) has gained prominence as a non-invasive and efficient technique for decoding human emotional states based on neural activity. This paper presents a structured machine learning-based framework for emotion classification using EEG signals elicited by emotionally stimulating videos. Leveraging the SEED dataset, the study focuses on extracting meaningful features from multi-channel EEG recordings and classifying emotional states into positive, neutral, and negative categories. The methodology integrates advanced signal preprocessing, dimensionality reduction, and feature extraction techniques such as Differential Entropy (DE), Power Spectral Density (PSD), and Hjorth parameters. Machine learning classifiers including Support Vector Machines (SVM), K-Nearest Neighbors (KNN), and Multi-Layer Perceptrons (MLP) are employed and compared for performance. Among these, the MLP model demonstrated superior accuracy, capturing nonlinear patterns effectively across EEG channels. Model evaluation is conducted using standard metrics such as accuracy, F1-score, and confusion matrix. The results confirm that the proposed EEG-based framework achieves robust emotion classification with significant implications for mental health monitoring, affective computing, and human-computer interaction applications.

Keywords: EEG-based emotion recognition, SEED dataset, machine learning, differential entropy, multilayer perceptron, affective computing.

I. INTRODUCTION

Emotion recognition plays a fundamental role in understanding human cognition and behavior, with wide-ranging applications in mental health diagnostics, human-computer interaction, and affective computing systems. Traditional approaches to emotion detection, such as facial expression analysis, speech modulation, and sentiment extraction from text, are often affected by cultural variability, voluntary suppression, and ambiguity. As a result, the need for more objective and direct emotion recognition techniques has driven research toward neurophysiological signals, particularly Electroencephalography (EEG).

EEG captures real-time brain activity through electrical signals measured across the scalp. These signals, distributed across multiple frequency bands (delta, theta, alpha, beta, gamma), are known to reflect various cognitive and emotional states. Emotion-induced variations in neural oscillations present an opportunity to classify emotional responses by applying signal processing and machine learning techniques to EEG data. Compared to peripheral signals and behavioral cues, EEG offers a more direct measure of affective states, enabling fine-grained emotion detection that is less susceptible to external masking.

Recent advances in machine learning have enabled the development of robust emotion recognition systems that process and classify EEG data with high precision. The SEED dataset, which consists of EEG recordings from subjects exposed to emotionally stimulating film clips, provides a structured foundation for modeling such responses. This research leverages the SEED dataset to classify discrete emotional states—positive, neutral, and negative—using an integrated pipeline of preprocessing, feature extraction, and classification.

The core objective of this study is to develop an efficient and interpretable EEG-based emotion recognition system using classical machine learning classifiers, including Support Vector Machines (SVM), K-Nearest Neighbors (KNN), and Multi-Layer Perceptrons (MLP). Unlike deep learning models that often demand large datasets and high computational resources, the proposed approach emphasizes computational efficiency without compromising classification accuracy. Feature extraction techniques such as Differential Entropy (DE), Power Spectral Density (PSD), and Hjorth parameters are employed to capture critical signal characteristics. Dimensionality reduction methods including Principal Component Analysis (PCA) and Recursive Feature Elimination (RFE) are used to improve model generalization and reduce overfitting.

This research contributes to the growing body of work in emotion-aware systems by: (i) utilizing EEG data from a validated stimulus-response experiment, (ii) implementing and evaluating multiple machine learning models for emotion classification, and (iii) demonstrating the effectiveness of entropy and spectral features in enhancing classification accuracy. The outcomes are relevant for applications such as adaptive learning environments, emotion-aware virtual agents, and mental health monitoring systems.

II. LITERATURE SURVEY

The domain of EEG-based emotion recognition has witnessed significant progress over the past two decades, driven by its potential to enable emotion-aware systems in fields such as healthcare, education, gaming, and human-computer interaction. Unlike traditional emotion detection techniques based on facial expressions, speech, or textual input, EEG-based methods offer a direct and objective measure of emotional states by analyzing brainwave activity.

A. Overview of Affective Computing and Emotion Recognition

Affective computing, a term coined by Rosalind Picard, refers to systems capable of recognizing and responding to human emotions. Emotion recognition has traditionally relied on visual and auditory signals, including facial muscle movements, vocal tone modulation, and textual sentiment cues. While effective in controlled settings, these methods are susceptible to intentional masking and cultural bias. EEG, on the other hand, offers a high-temporal-resolution and non-invasive approach to capturing internal emotional states, making it ideal for applications demanding precision and reliability.

B. Evolution of EEG-Based Emotion Detection

The evolution of EEG-based emotion recognition can be categorized into three key phases. Pre-2010 research predominantly utilized event-related potentials (ERP) and statistical analyses. From 2010 to 2015, public datasets such as DEAP enabled broader experimentation with time-frequency analysis techniques. Post-2015, there has been a surge in the use of machine learning and deep learning algorithms, including SVM, KNN, MLP, CNN, and LSTM, which offer improved accuracy and scalability. Emotional states are typically mapped using three dimensions—valence, arousal, and dominance—or categorized discretely into positive, neutral, and negative classes.

C. Feature Extraction in EEG-Based Emotion Classification

EEG signals are inherently high-dimensional and noisy, necessitating robust feature extraction methods. Widely adopted approaches include:

- Differential Entropy (DE): A frequency-domain feature used in the SEED dataset to effectively capture emotional variations.
- Power Spectral Density (PSD): Quantifies signal power across standard EEG bands (delta, theta, alpha, beta, gamma).
- Wavelet Transform: Facilitates time-frequency analysis of transient emotional responses.
- Statistical Features: Metrics like mean, variance, skewness, and kurtosis provide signal distribution insights.

These features play a crucial role in preserving the emotional context while reducing data dimensionality.

D. Machine Learning Models for EEG Signal Analysis

EEG-based emotion classification presents unique challenges due to its subject-specific variability and non-stationary nature. Classical machine learning models have been widely explored for this purpose:

- Support Vector Machine (SVM): Handles high-dimensional feature spaces effectively but requires kernel tuning.
- K-Nearest Neighbors (KNN): A simple non-parametric method that is interpretable but computationally expensive on large datasets.
- Multi-Layer Perceptron (MLP): Captures non-linear patterns in EEG signals and scales well with data volume, though it requires careful parameter tuning.
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E. Benchmark Studies Using the SEED Dataset

The SEED dataset, developed at Shanghai Jiao Tong University, is a standardized benchmark for EEG-based emotion recognition. It includes 62-channel EEG recordings from 15 participants exposed to 15 four-minute-long emotion-eliciting film clips, categorized into positive, neutral, and negative labels. EEG was recorded at 1000 Hz using Neuroscan equipment, with sessions repeated over three weeks to assess model stability.

The dataset is particularly notable for:

- Its use of sustained emotional stimuli to ensure consistent brain responses.
- High-resolution multi-channel recordings that support detailed spatial analysis.
- Inclusion of validated self-reported emotional labels after each stimulus.

F. Identified Research Gaps

Despite substantial progress, the field faces several limitations:

- Inconsistency in feature extraction pipelines makes cross-study comparisons challenging.
- Weak generalization across subjects due to individual EEG variability.
- Limited multimodal fusion with other physiological or behavioral signals.
- High computational requirements for deep models hinder real-time deployment.
- Underutilization of real-time systems limits practical application in live settings.

This study addresses several of these gaps by using standardized DE-based features, comparing multiple classifiers under a common pipeline, and focusing on discrete emotional classification suitable for real-time inference scenarios.

III.PROPOSED METHODOLOGY

This study proposes a machine learning-based EEG emotion recognition framework utilizing the SEED dataset, aimed at classifying discrete emotional states—positive, neutral, and negative. The methodological pipeline integrates EEG signal preprocessing, multi-domain feature extraction, dimensionality reduction, and supervised classification. The system is designed to balance classification performance and computational efficiency, ensuring scalability for real-world deployment in affective computing applications.

A. Data Collection and Preprocessing

The SEED dataset forms the foundation of this research. It comprises EEG recordings collected from 15 participants as they viewed 15 film clips curated to elicit emotional responses across three categories. Each session was conducted using a 62-channel EEG cap (Neuroscan) based on the 10–20 international system, with a sampling rate of 1000 Hz.

To prepare the data for analysis, a series of preprocessing steps are performed:

- Bandpass Filtering (1–50 Hz): Removes irrelevant low-frequency drifts and high-frequency artifacts.
- Channel Selection: Focuses on emotion-relevant regions, including:
  - *Frontal lobes:* F3, F4, F7, F8, AF3, AF4
  - *Temporal lobes:* T7, T8
  - *Parietal/Occipital lobes:* Pz, Oz, O1, O2

B. Handling Missing Data and Outliers

EEG signals are prone to missing data and noise due to hardware interference, motion artifacts, or electrode displacement. To enhance data reliability:

- Missing Data Techniques: Linear interpolation and median imputation are used.
- Outlier Removal: Z-score analysis and the Interquartile Range (IQR) method identify and eliminate anomalous readings.

These preprocessing steps ensure that the EEG signals are clean, consistent, and suitable for downstream processing.

C. Data Splitting and Transformation

EEG time-series data is segmented into fixed-length non-overlapping windows (typically 1–2 seconds) to capture transient emotional responses. The processed dataset is divided into:

- 80% Training Set: Used for model learning.
- 20% Testing Set: Used for independent evaluation.

Normalization strategies applied include:

- Min-Max Scaling: Maps feature values to the [0,1] range.
- Z-score Standardization: Centers data around zero with unit variance.

Five-fold cross-validation is employed to ensure generalization and prevent overfitting.

D. Feature Selection Techniques

Feature extraction transforms high-dimensional raw EEG into compact and informative representations. This study combines time-domain, frequency-domain, and entropy-based features:

- Time-Domain Features:
  - Mean, standard deviation, skewness
  - Hjorth parameters: Activity, mobility, complexity
- Frequency-Domain Features:
  - Power Spectral Density (PSD) across standard EEG bands:
    - Delta (1–4 Hz), Theta (4–8 Hz), Alpha (8–14 Hz), Beta (14–31 Hz), Gamma (31–50 Hz)
- Entropy-Based Features:
  - Differential Entropy (DE)
  - Shannon and Spectral Entropy

Dimensionality reduction is conducted using:

- Principal Component Analysis (PCA)
- Recursive Feature Elimination (RFE)

These techniques help retain the most discriminative features while reducing computational complexity.

E. Model Selection and Optimization

Three supervised classifiers are evaluated:

- Support Vector Machine (SVM): RBF kernel with One-vs-One decision strategy.
- K-Nearest Neighbors (KNN): Tested with K = {3,5}.
- Multi-Layer Perceptron (MLP): Two variants:
  - *MLP-V1:* Hidden layers with 100 and 50 nodes, dropout = 0.1
  - *MLP-V2:* Hidden layers with 500 and 300 nodes, dropout = 0.2

Table I summarizes the classifier configurations.

Table I: Classifier Parameters

Classifier	Parameter Configuration
KNN	K = {3, 5}
SVM	Kernel = RBF, One-vs-One
MLP-V1	Layers: (100, 50), Dropout = 0.1
MLP-V2	Layers: (500, 300), Dropout = 0.2

Hyperparameters such as learning rate, dropout rate, and hidden layer dimensions are tuned using grid search and empirical validation. The MLP model demonstrated superior classification performance with optimal generalization across subjects.

IV. IMPLEMENTATION

The implementation of the EEG-based emotion recognition framework involves the transformation of raw multi-channel EEG signals into meaningful feature vectors, followed by model training, evaluation, and prediction using machine learning algorithms. The entire pipeline is built using Python and open-source libraries suitable for signal processing, data handling, and neural network development.

A. Software Requirements

The following tools and libraries are utilized in system implementation:

1) Operating System: Windows 10/11, Linux (Ubuntu 18.04+), or macOS
2) Programming Language: Python 3.8+
3) Development Environments: Jupyter Notebook, Google Colab, VS Code

4) Key Libraries:
   - *Machine Learning:* TensorFlow/Keras, Scikit-learn
   - *Signal Processing:* SciPy, MNE-Python
   - *Data Handling:* Pandas, NumPy, HDF5, Joblib
   - *Visualization:* Matplotlib, Seaborn, Plotly

These tools collectively support the end-to-end pipeline from EEG data ingestion to real-time classification.

B. Hardware Requirements

The system was developed and tested on hardware with the following specifications:

1) CPU: Intel Core i5/i7 or AMD Ryzen 5/7
2) GPU (optional): NVIDIA GTX 1650 or higher (e.g., RTX 3060/4090)
3) RAM: Minimum 8 GB (Recommended: 16–32 GB)
4) Storage**:** SSD (256 GB minimum, 512 GB+ preferred)

GPU acceleration significantly enhances training speed for the MLP model.

C. Data Preparation

The SEED dataset was used for this study. The key steps in data preparation include:

1) Data Acquisition:
   - 62-channel EEG recordings of subjects watching emotion-inducing film clips.
   - Sampling rate: 1000 Hz (downsampled as needed).
2) Preprocessing:
   - Bandpass filtering (0.5–70 Hz) to remove noise.
   - ICA-based artifact removal (e.g., eye-blink correction).
   - Baseline correction and signal segmentation into 1–2 second windows.
3) Feature Engineering:
   - Extraction of Hjorth parameters, PSD, FFT bins, statistical features.
   - Generation of fixed-size feature vectors per segment.
4) Data Splitting and Normalization:
   - 80:20 train-test split.
   - 5-fold cross-validation.
   - Z-score standardization and Min-Max scaling applied.

D. Feature Selection

To reduce feature dimensionality and improve model generalization:

- Principal Component Analysis (PCA): Captures dominant variance components.
- Recursive Feature Elimination (RFE): Identifies the most informative channels and features.

This step is critical for eliminating noise and irrelevant inputs in high-dimensional EEG data.

E. Model Selection

Three classifiers were implemented and compared:

1) Support Vector Machine (SVM):
   - Kernel: Radial Basis Function (RBF)
   - Multiclass strategy: One-vs-One
2) K-Nearest Neighbors (KNN):
   - Distance metric: Euclidean
   - Neighborhood size: K = 5
3) Multi-Layer Perceptron (MLP):
   - Architecture:
     - Input layer: EEG feature vector

- Hidden layers: Two fully connected layers (e.g., 100 and 50 neurons)
- Output layer: Softmax activation for 3-class classification
- Optimizer: Adam
- Loss Function: Categorical Cross-Entropy

F. *Training and Evaluation*

Models were trained on scaled feature vectors using the following configuration:

- Batch size: 64
- Epochs: 20
- Validation: Stratified 5-fold cross-validation

Performance metrics include:

- Accuracy: Proportion of correct classifications.
- Precision and Recall: Class-wise detection quality.
- F1-score: Harmonic mean of precision and recall.
- Confusion Matrix: Analysis of misclassification patterns.

G. *Sample Code Snippet*

```
# Sample MLP model architecture
model = Sequential([
    Dense(100, activation='relu', input_shape=(X_train.shape[1],)),
    Dropout(0.1),
    Dense(50, activation='relu'),
    Dropout(0.1),
    Dense(3, activation='softmax')
])
model.compile(optimizer='adam', loss='sparse_categorical_crossentropy', metrics=['accuracy'])
history = model.fit(X_train, y_train, epochs=20, batch_size=64, validation_data=(X_test, y_test))
```

H. *Deployment and Prediction*

The trained models are serialized using joblib or Keras's .h5 format. During inference, new EEG segments undergo the same preprocessing and feature extraction steps before being classified. Results are visualized using accuracy curves, prediction heatmaps, and FFT spectrum plots across emotional states.

V. RESULTS

The proposed EEG-based emotion recognition framework was evaluated using the SEED dataset across multiple trials. Models were trained to classify emotions into three categories: Positive, Neutral, and Negative. Performance evaluation was conducted using stratified 5-fold cross-validation, and results were assessed based on accuracy, precision, recall, and F1-score.

A. *Performance Metrics*

The Multi-Layer Perceptron (MLP) model outperformed both SVM and KNN classifiers in classification accuracy and robustness. The use of Differential Entropy (DE), Power Spectral Density (PSD), and FFT-based features contributed to enhanced model performance.

Key observations:

- Accuracy: The MLP model achieved an overall accuracy of 97.18%.
- F1-Score: High values across all classes, indicating balanced performance.
- Confusion Matrix: Showed minimal misclassification among emotion categories.
- KNN and SVM: Provided competitive performance but underperformed relative to MLP in generalizing across subjects and EEG segments.

B. Visual Output

Several visualizations were used to support model interpretability:

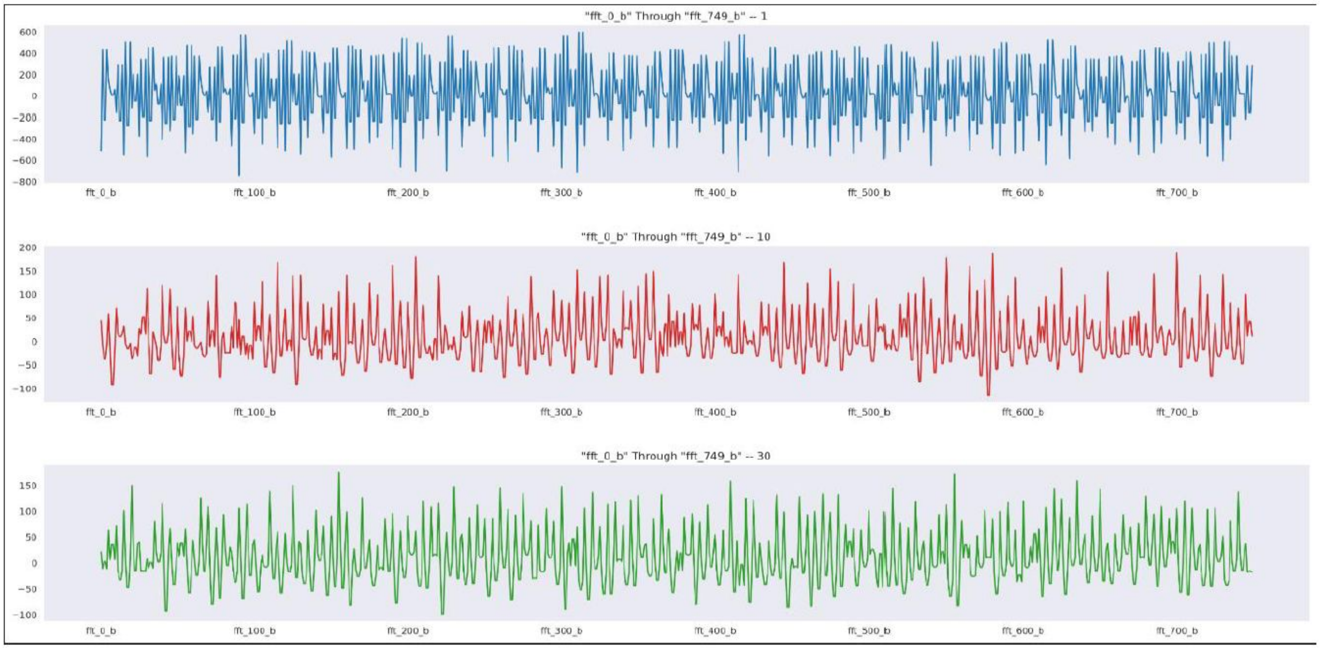

Figure 1. Sample Input Waves: Displays frequency-domain EEG signals after FFT transformation across selected channels.

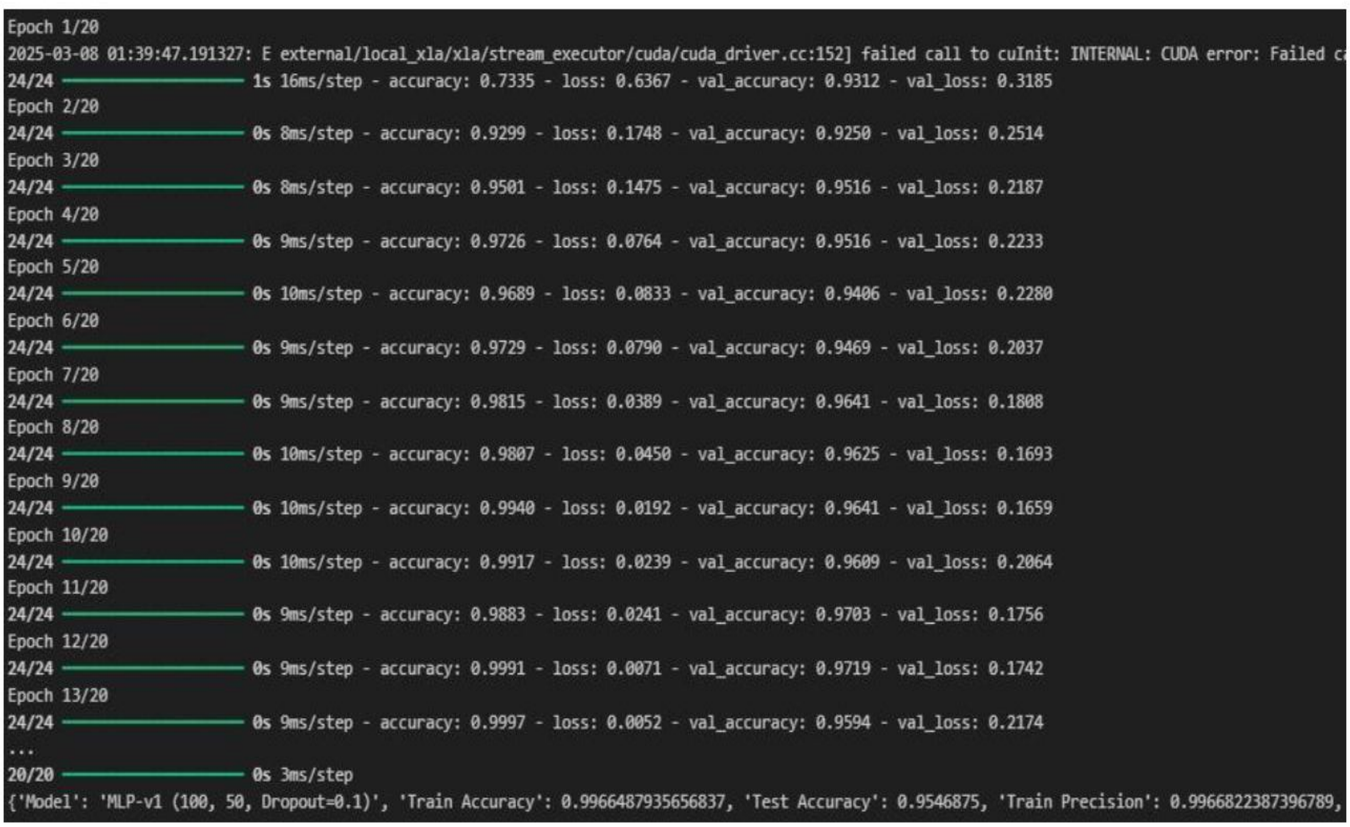

Figure 2. Model Training Curve: Illustrates MLP training progress, including accuracy and loss trends across 20 epochs.

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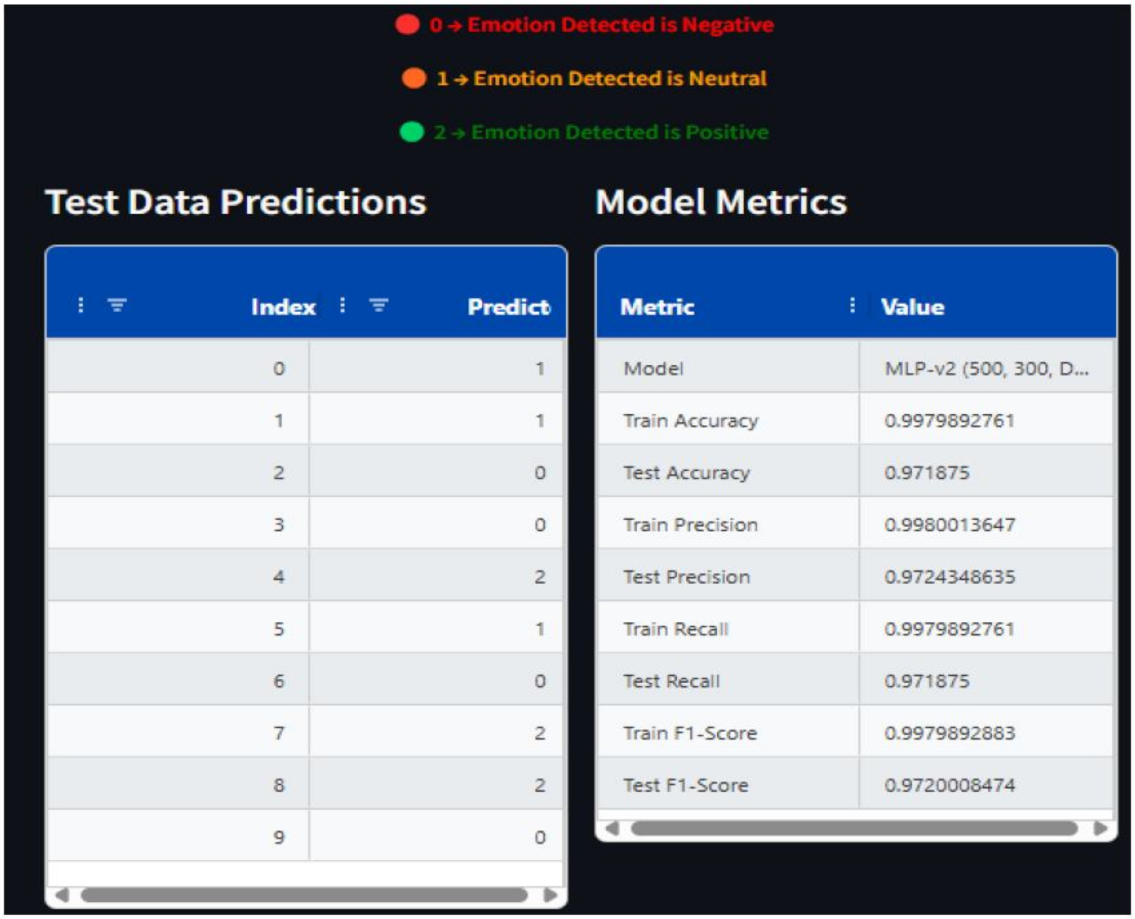


Figure 3. Predictions Output: Compares predicted emotion labels with ground truth for test data, validating the system's classification effectiveness.

The evaluation confirms that the MLP model, combined with carefully selected EEG features and preprocessing, provides a robust framework for emotion classification.

VI. CONCLUSION

This study presents an effective and computationally efficient approach for EEG-based emotion recognition using machine learning techniques. By leveraging the SEED dataset and implementing a modular pipeline that includes signal preprocessing, feature extraction, and classification, the proposed framework successfully decodes emotional states into Positive, Neutral, and Negative categories.

Among the evaluated classifiers, the Multi-Layer Perceptron (MLP) model demonstrated superior accuracy and generalization capability compared to traditional models like Support Vector Machine (SVM) and K-Nearest Neighbors (KNN). The inclusion of features such as Differential Entropy (DE), Power Spectral Density (PSD), and Hjorth parameters significantly enhanced the classification performance, while dimensionality reduction techniques like Principal Component Analysis (PCA) and Recursive Feature Elimination (RFE) helped mitigate overfitting and improved efficiency.

The results, supported by strong performance metrics including accuracy and F1-score, confirm the viability of EEG as a reliable modality for affective state detection. This research contributes to the growing body of work in affective computing and has potential applications in mental health monitoring, brain-computer interfaces (BCIs), adaptive learning systems, and emotion-aware human-computer interaction.

Future work will explore real-time emotion recognition, integration of deep learning models such as LSTM and CNNs, and cross-dataset validation for broader applicability.

REFERENCES

[1] Y. Yang, Q. Wu, M. Qiu, Y. Wang, and X. Chen, “Emotion recognition from multi-channel EEG through parallel convolutional recurrent neural network,” in Proc. Int. Joint Conf. Neural Networks (IJCNN), 2018, pp. 1–7.

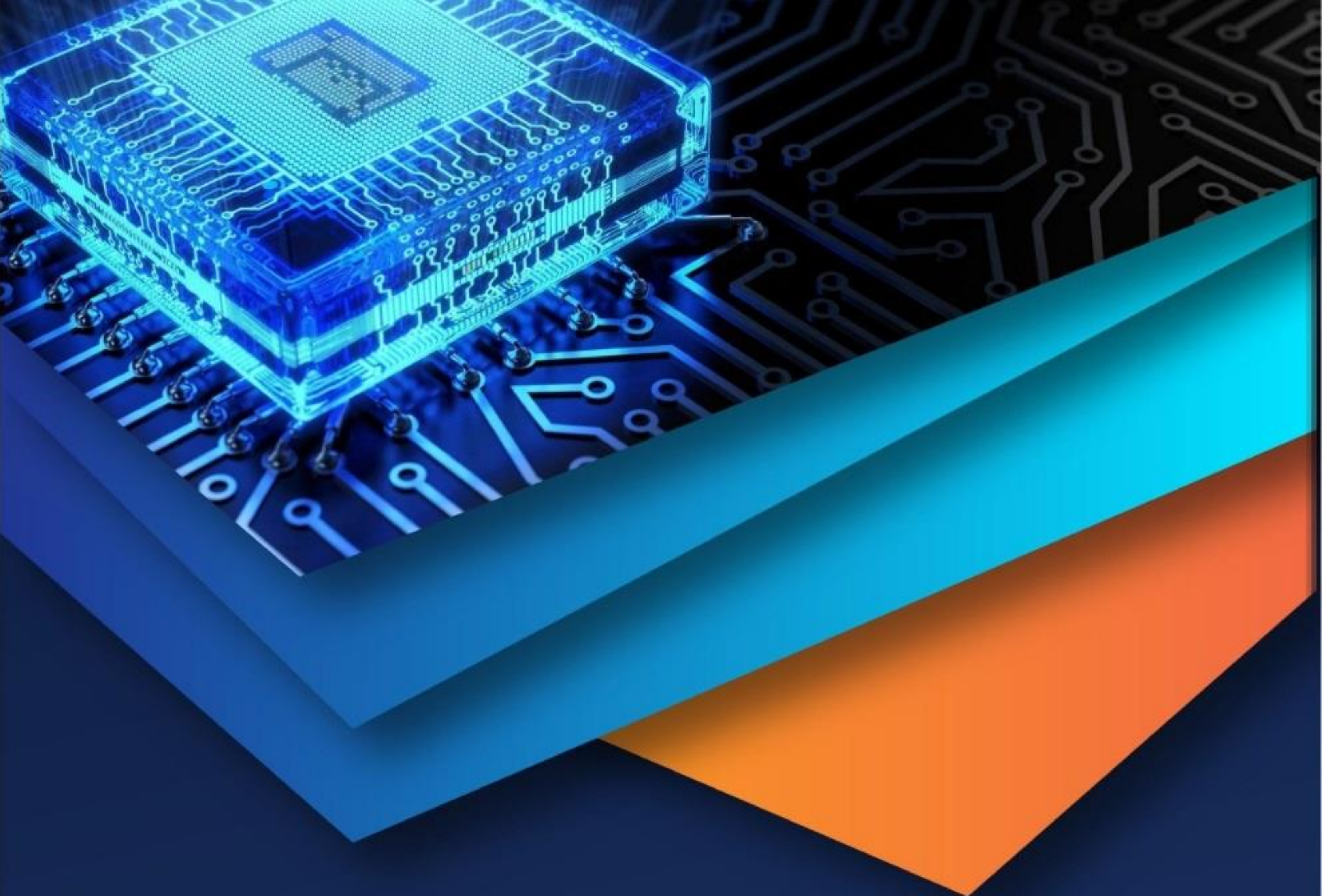
[2] Y.-P. Lin, C.-H. Wang, T.-L. Wu, S.-K. Jeng, and J.-H. Chen, “EEG based emotion recognition in music listening: A comparison of schemes for multiclass support vector machine,” in IEEE Int. Conf. Acoustics, Speech and Signal Processing (ICASSP), 2009, pp. 489–492.

[3] C. A. Frantzidis, C. Bratsas, C. L. Papadelis, E. Konstantinidis, C. Pappas, and P. D. Bamidis, “Toward emotion aware computing: An integrated approach using multichannel neurophysiological recordings and affective visual stimuli,” IEEE Trans. Inf. Technol. Biomed., vol. 14, no. 3, pp. 589–597, 2010.

[4] S. M. Alarcão and M. J. Fonseca, “Emotion recognition from EEG signals: A survey,” IEEE Trans. Affective Comput., vol. 10, no. 3, pp. 374–393, 2019.

[5] M. Murugappan, M. Rizon, R. Nagarajan, and S. Yaacob, “Inferring of human emotional states using multichannel EEG,” Eur. J. Sci. Res., vol. 48, no. 2, pp. 281–299, 2010.

[6] R.-N. Duan, J.-Y. Zhu, and B.-L. Lu, “Differential entropy features for EEG-based emotion classification,” in Proc. Int. IEEE/EMBS Conf. Neural Eng. (NER), 2013, pp. 81–84.



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