EEG-Based Emotion Detection System for Non-Verbal Patients

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Abstract

This project proposes a machine learning system that uses EEG brain signals to detect and classify emotions in non-verbal patients. The system performs multi-class emotion classification using the DEAP dataset, employing a multi-scale dynamic CNN with gated transformer architecture. By categorizing emotional states into four classes based on valence and arousal dimensions, the system aims to provide healthcare professionals with real-time, granular insights into patients' emotional states, significantly improving care for individuals with locked-in syndrome, severe paralysis, and related conditions.

1 GitHub Repository

The project code and documentation are available at: `https://github.com/2025-F-CS6220/project-eeg-based-emotion-detection-system`

2 Introduction

Non-verbal patients suffering from conditions such as locked-in syndrome, coma, or severe paralysis cannot communicate their emotional state, making their care challenging for healthcare professionals. Traditional behavioral observation methods are often insufficient and subjective, creating barriers to effective emotional support and patient care.

This project addresses these limitations by developing an automated EEG-based classification system that identifies emotional states across multiple categories. The importance lies in improving patient care quality in clinical settings such as ICUs, long-term care facilities, and rehabilitation centers. Key challenges include accurately interpreting complex EEG signals and distinguishing between different emotional states using valence and arousal dimensions. The system targets patients with locked-in syndrome, minimally conscious states, severe stroke with complete paralysis, and late-stage ALS.

3 Proposed Project

3.1 Problem Formulation

This is a multi-class emotion classification problem that categorizes a patient's emotional state into distinct emotion classes based on EEG signals. The classification uses ***valence and arousal dimensions*** from the DEAP dataset to create emotion categories. Using the circumplex model of emotion, valence scores (positive/negative feelings) and arousal scores (activation level) rated 1-9 are thresholded at their medians to form ***four emotion classes***: (1) High Valence-High Arousal (HVHA: excited, happy), (2) High Valence-Low Arousal (HVLA: calm, relaxed), (3) Low Valence-High Arousal (LVHA: angry, nervous), and (4) Low Valence-Low Arousal (LVLA: sad, bored). The system analyzes brain activity patterns to provide real-time emotional state detection for non-verbal patients.

3.2 Datasets

Dataset: DEAP (Emotion Detection) [1, 2] - Contains EEG recordings from 32 subjects viewing 40 videos each. Key specifications: 32 EEG + 8 peripheral channels (40 total), 128 Hz sampling rate, 63-second trials, total 1,280 trials. Data dimensions: 40 trials $\times$ 40 channels $\times$ 8,064 time points per subject. Labels include valence, arousal, dominance, and liking rated 1-9. For multi-class emotion classification, valence and arousal ratings are thresholded at their medians to create four emotion classes based on the circumplex model. Preprocessing includes bandpass filtering (0.5-45 Hz), artifact removal, and normalization.

3.2.1 Dataset Structure Example

Tables 1 through 5 show a representative sample of the DEAP dataset with 4 trials, displaying emotion labels and sample EEG signals from 4 channels with 8 time points each.

Trial	**Valence**	**Arousal**	**Dominance**	**Liking**
1	1.29	1.40	6.90	7.83
2	0.90	1.69	7.28	8.47
3	0.42	1.46	9.00	7.08
4	4.94	6.01	6.12	8.06

Table 1: Emotion labels for 4 sample trials from DEAP dataset

Trial	**T1**	**T2**	**T3**	**T4**	**T5**	**T6**	**T7**	**T8**
1	0.95	1.65	3.01	1.50	-1.26	-1.97	-2.17	-0.22
2	10.26	12.80	10.43	8.23	3.75	-3.48	-8.57	-15.00
3	1.01	-1.07	3.91	6.09	4.15	0.65	-5.82	-6.77
4	-7.66	-3.27	0.70	2.96	3.46	5.10	6.64	6.60

Table 2: Channel 1 EEG signals (8 time points) for 4 trials

Trial	T1	T2	T3	T4	T5	T6	T7	T8
1	0.12	1.39	1.84	-1.11	-2.59	-1.84	-0.74	2.40
2	9.49	12.59	10.57	6.41	3.92	-1.53	-10.42	-15.80
3	0.03	-1.52	4.82	5.65	2.50	-0.82	-5.21	-5.31
4	-9.48	-6.13	-1.12	1.14	2.37	4.81	6.48	7.42

Table 3: Channel 2 EEG signals (8 time points) for 4 trials

Trial	T1	T2	T3	T4	T5	T6	T7	T8
1	-2.22	2.29	2.75	-2.36	-2.31	-0.67	-0.84	3.65
2	7.13	12.21	9.50	4.64	5.17	1.97	-6.77	-12.70
3	0.72	0.51	8.04	8.20	5.21	-0.63	-4.83	-2.29
4	-5.08	-5.19	-2.71	-0.43	0.81	3.58	6.68	7.46

Table 4: Channel 3 EEG signals (8 time points) for 4 trials

Trial	T1	T2	T3	T4	T5	T6	T7	T8
1	1.01	1.30	2.37	-0.23	-1.66	-0.01	0.74	1.42
2	10.48	14.65	13.24	11.32	5.63	-2.78	-8.97	-15.71
3	9.76	3.35	10.45	17.00	5.92	0.11	-3.71	-13.92
4	-5.73	-7.77	-10.33	-6.13	0.01	4.69	11.34	15.79

Table 5: Channel 4 EEG signals (8 time points) for 4 trials

3.3 Methodology

The proposed architecture integrates a multi-scale dynamic CNN for spatial feature extraction, a gated transformer for temporal dependency modeling, and a temporal convolutional network for sequence processing. The system processes patient EEG input by analyzing 40 channels from DEAP for multi-class emotion classification into four categories: HVHA (excited/happy), HVLA (calm/relaxed), LVHA (angry/nervous), and LVLA (sad/bored).

The system operates by continuously monitoring the patient's EEG signals and classifying their emotional state in real-time. The four-class output provides caregivers with granular information about both the valence (positive/negative) and arousal (activated/calm) dimensions of the patient's emotional state. When negative emotions (LVHA or LVLA) are detected, the system alerts caregivers to provide appropriate emotional support and investigate potential sources of distress. This approach provides clinically actionable information to caregivers, enabling timely intervention and improved patient care tailored to the specific emotional state.

3.4 Evaluation

We will evaluate using both subject-dependent and subject-independent validation with 5-fold cross-validation. Performance metrics include accuracy, precision, recall, and F1-score. Expected baseline accuracy is approximately 60-70% for four-class emotion classification based on benchmark results.

To ensure the results are meaningful, we will: (1) analyze the confusion matrix to verify balanced performance across all four emotion classes (HVHA, HVLA, LVHA, LVLA), (2) examine prediction consistency by comparing results across different cross-validation folds, (3) conduct subject-independent testing to assess generalization to unseen patients, and (4) inspect correctly and incorrectly classified samples to identify systematic patterns or biases in the model's predictions. The system performance will be evaluated on scenarios matching real clinical use cases to ensure practical applicability in healthcare settings.

References

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