EEG-Based Emotion & Discomfort Detection System for Non-Verbal Patients

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Abstract

This project implements a two-stage machine learning classification system which uses the EEG brain scans that classify emotions underlying that brain signals for detecting the type of emotion and identify physical discomfort locations for patients who are non-verbal patients. This two stage model combines emotion type detection (classification) using the DEAP dataset with type of motor activation detection (classification) using the BCI Competition IV-2a dataset. Two major machine learning architectures which are a multi-scale dynamic CNN with gated transformer architecture, and the other being a compact depthwise separable convolutional network (based on EEGNet) for motor imagery classification the type of model architecture provides health care professionals with real-time insights about patients' emotional states and specific areas of discomfort, significantly improving care for individuals with locked-in syndrome, severe paralysis, and related conditions. Our implementation achieves 64.87% accuracy on 4-class emotion classification and 65.6% accuracy on 4-class motor imagery classification.

1 Introduction

Patients who cannot express either their emotions or discomfort verbally (Non-verbal) patients who are suffering from various conditions like locked-in syndrome, coma, or severe paralysis may not be able communicate their emotional state or physical discomfort, this makes health care professionals a challenging task to better take care of the patients in such situations. Traditional methods like observing patient behavior and monitoring them continuously are mostly inefficient, subjective and time taking, thus creating challenges for effective health and care by healthcare professionals for their emotional support.

This project addresses these limitations by creating a machine learning based detection (classification) system using EEG brain signals detection system that clearly tries to identify both emotional status and specific body locations experiencing discomfort. The major objective lies in the fact of improving patient care by taking care emotionally and quality in clinical and hospital environments such as ICUs, long-term care facilities, and rehabilitation centers. The main challenges include accurately and precisely understanding these complex nature of EEG signals, differentiating emotional states, and precisely identifying motor cortex activation patterns corresponding to specific body regions. The system targets patients with locked-in syndrome, minimally conscious states, severe stroke with complete paralysis, and late-stage ALS.

2 Proposed Project

2.1 Problem Formulation

This project employs a two-stage classification approach, but both models are trained and tested independently (but can be used in culmination during interference). Stage 1 performs multi-class classification (4 classes) for determining the patient's emotional state based on four valence-arousal combinations: LVLA (Low Valence, Low Arousal), LVHA (Low Valence, High Arousal), HVLA (High Valence, Low Arousal), and HVHA (High Valence, High Arousal). Stage 2 implements multi-class classification (4 classes) to identify motor cortex activation patterns corresponding to body parts (left hand, right hand, both feet, tongue), which indicate discomfort location when if they are combined with negative emotional states.

2.2 Datasets

2.2.1 Dataset 1: DEAP (Emotion Detection)

The DEAP dataset [1] contains EEG recordings from 32 subjects from viewing of 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 × 40 channels × 8,064 time points per subject. Labels that includes valence, arousal, dominance, and liking rated 1-9. For 4-class emotion classification, valence and arousal ratings are thresholded at the median. Preprocessing includes segmentation into 2-second windows, Z-score normalization, and stratified train/test split (80%/20%).

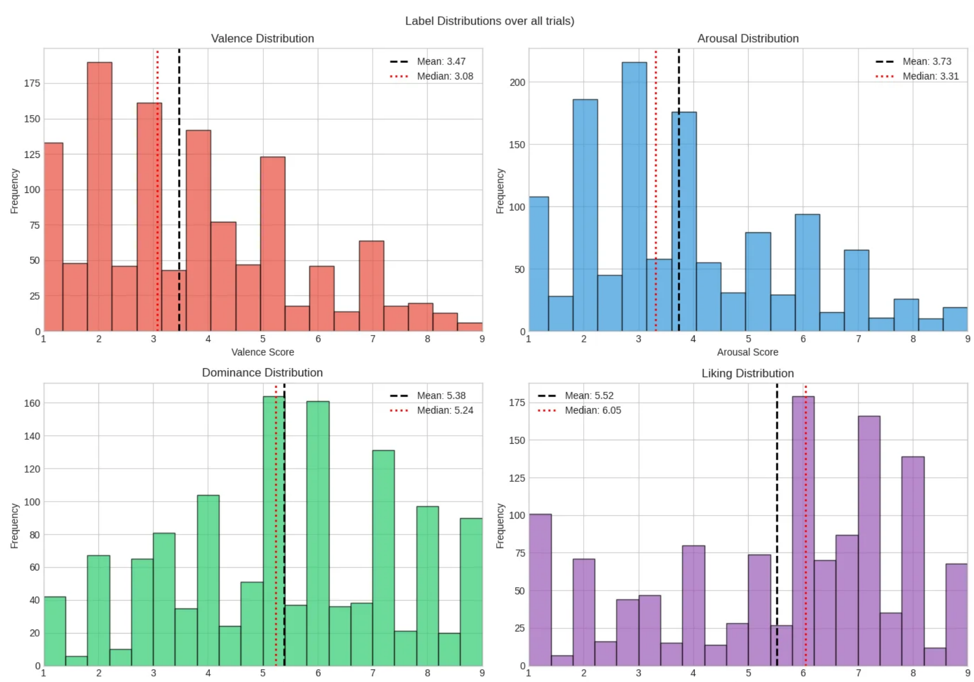

Figure 1: Labeled distribution of over all trials showing Valence (mean: 3.47), Arousal (mean: 3.73), Dominance (mean: 5.38), and Liking (mean: 5.52) scores in the DEAP dataset.

Figure 1 shows the labeled distribution along with the mean score of emotional labels across all trials. The valence and arousal distributions clearly shows that they are slight skew toward lower values (left skewed), while dominance and liking are more centered hence more balanced distribution. The weak correlations that shows between these labeled dimensions (Figure 2) justifies for using independent median thresholds for creating the 4-class labels.

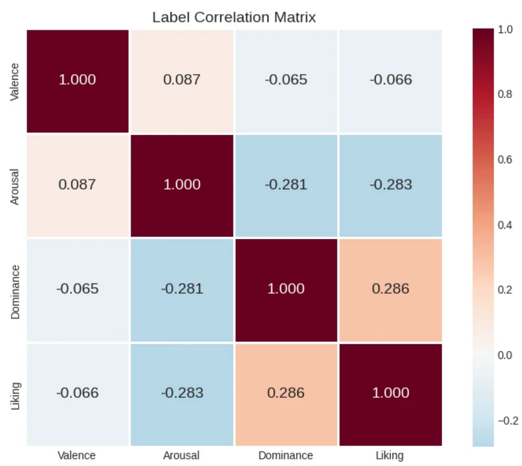

Figure 2: Label correlation matrix showing weak correlations between valence, arousal, dominance, and liking dimensions, justifying independent thresholding for classification.

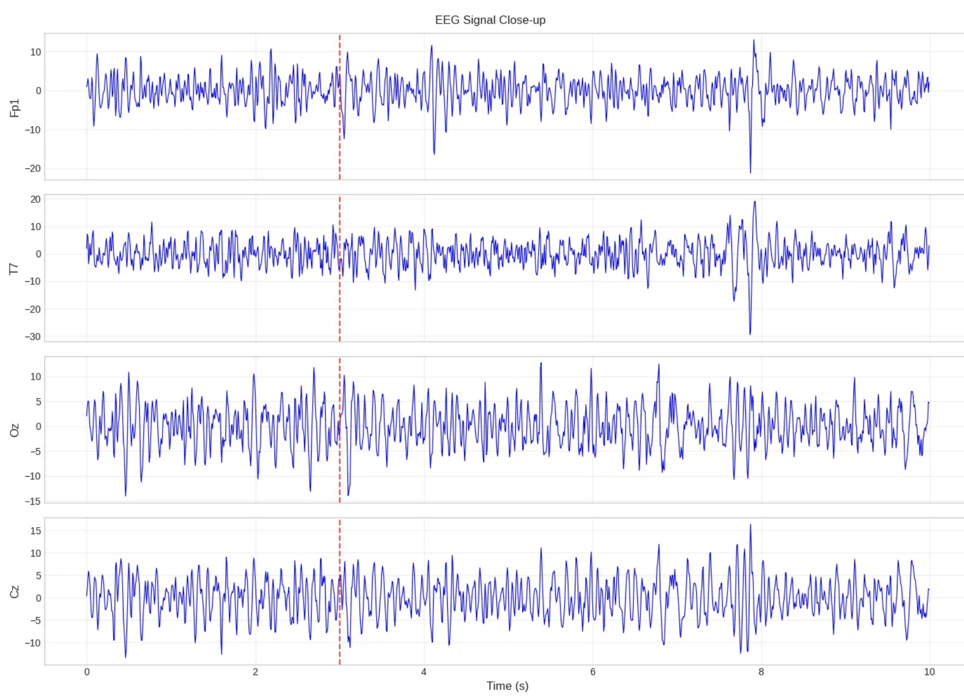

Figure 3: EEG signal close-up showing 10 seconds of preprocessed data from channels Fp1, T7, Oz, and Cz. The red dashed line indicates stimulus onset at 3 seconds.

2.2.2 Dataset 2: BCI Competition IV-2a (Motor Imagery)

The second dataset which is the BCI Competition IV-2a dataset [2] contains motor imagery data from 9 subjects performing various body parts (mainly four which are the labels too) movement imagination. Key specifications: 22 EEG + 3 EOG channels (25 total), 250 Hz sampling rate, 4-second motor imagery trials, 2,328 total valid trials extracted (2 sessions $\times$ 288 trials per subject). Four classes: left hand, right hand, both feet, and tongue motor imagery. Preprocessing includes bandpass filtering (4-38 Hz) to capture mu (8-12 Hz) and beta (13-30 Hz) rhythms, extraction of motor imagery period (2-6 seconds after cue), Z-score normalization, and temporal windowing focused on motor cortex regions (C3, Cz, C4).

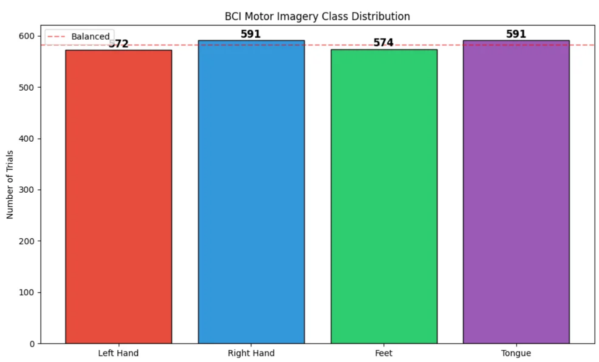

Figure 4: BCI Motor Imagery class distribution showing balanced classes: Left Hand (572), Right Hand (591), Feet (574), Tongue (591).

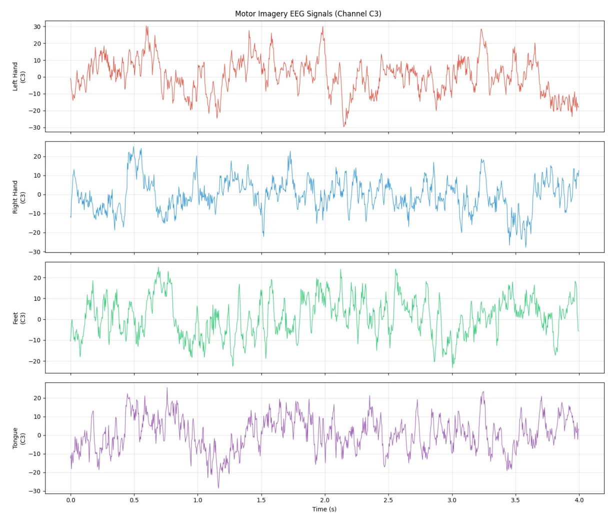

Figure 5: Motor Imagery EEG signals from channel C3 showing 4-second trials for each class.

2.3 Methodology

The two independent architectures proposed here are one a multi-scale dynamic CNN for spatial feature extraction, a gated transformer for temporal dependency modeling [3], and a temporal convolutional network for sequence processing. And the second is a compact depthwise separable convolutional network (based on EEGNet) for motor imagery classification. The system processes patient EEG input through two parallel branches through 2 different architectures as mentioned above: Branch 1 analyzes 40 channels from DEAP for emotion classification (4 classes: LVLA, LVHA, HVLA, HVHA), while Branch 2 with architecture processes 22 channels from BCI-IV 2a for motor cortex activation detection (4 classes: left hand, right hand, feet, tongue).

2.3.1 MSDCGTNet for Emotion Classification

The Multi-Scale Dynamic CNN with Gated Transformer Network consists of three main components:

Multi-Scale CNN Block: Three parallel branches with different temporal kernel sizes (16, 8, 4 samples) capture multi-resolution temporal features. Each branch applies temporal convolution followed by spatial convolution across all 32 EEG channels, with batch normalization, ELU activation, average pooling, and dropout (0.4). The outputs are concatenated to form a rich multi-scale representation.

Gated Transformer Block: Multi-head self-attention mechanism (8 heads) captures global temporal dependencies across the entire sequence. Layer normalization with residual connections ensures stable training, and an MLP with GELU activation transforms the attended features.

Temporal Convolutional Network (TCN): Two dilated convolutional layers with dilation rates 1 and 2 capture hierarchical temporal patterns at different scales. Global average pooling reduces the temporal dimension before the final linear classifier for 4-class output. Total model parameters: 17,468.

2.3.2 MotorImageryNet for Motor Imagery Classification

Based on the EEGNet architecture [4], this compact network is optimized for the BCI IV-2a dataset:

Block 1 - Temporal and Spatial Filtering: Temporal convolution with F1=8 filters and kernel length=125 (half the sampling rate) learns frequency-specific features corresponding to mu and beta rhythms. Depthwise spatial convolution with D=2 filters per temporal filter learns spatial patterns across the 22 EEG channels, similar to Common Spatial Patterns (CSP) but learned end-to-end.

Block 2 - Separable Convolution: Depthwise temporal convolution (kernel=16) followed by pointwise convolution (F2=16 filters) efficiently combines temporal and channel features with minimal parameters.

Classifier: Global average pooling followed by a linear layer produces 4-class output. Total model parameters: 3,932.

2.3.3 Decision Logic/ Inference Logic

The integrated system architecture operates as follows: If emotion detection indicates a positive state (HVLA or HVHA), the system reports the patient's positive emotional condition. If negative emotion is detected with high confidence (LVLA or LVHA), the motor detection branch identifies the active body part and reports the specific discomfort location. This two-stage approach provides clinically actionable information to care takers of the patients.

2.4 Evaluation

This project evaluated these two different classification models using subject-mixed validation with stratified train/test splits (80%/20%). And the Performance metrics includes accuracy, precision, recall, and F1-score for both tasks. Training was performed on NVIDIA GPU A100 with mixed precision for efficiency.

3 Experimental Results

3.1 Emotion Classification Results

The MSDCGTNet model achieved **64.87% accuracy** on 4-class emotion classification. Training configuration: AdamW optimizer (lr=3e-4, weight decay=0.01), OneCycleLR scheduler (max_lr=3e-3), batch size 128, 350 epochs with mixed precision training (FP16).

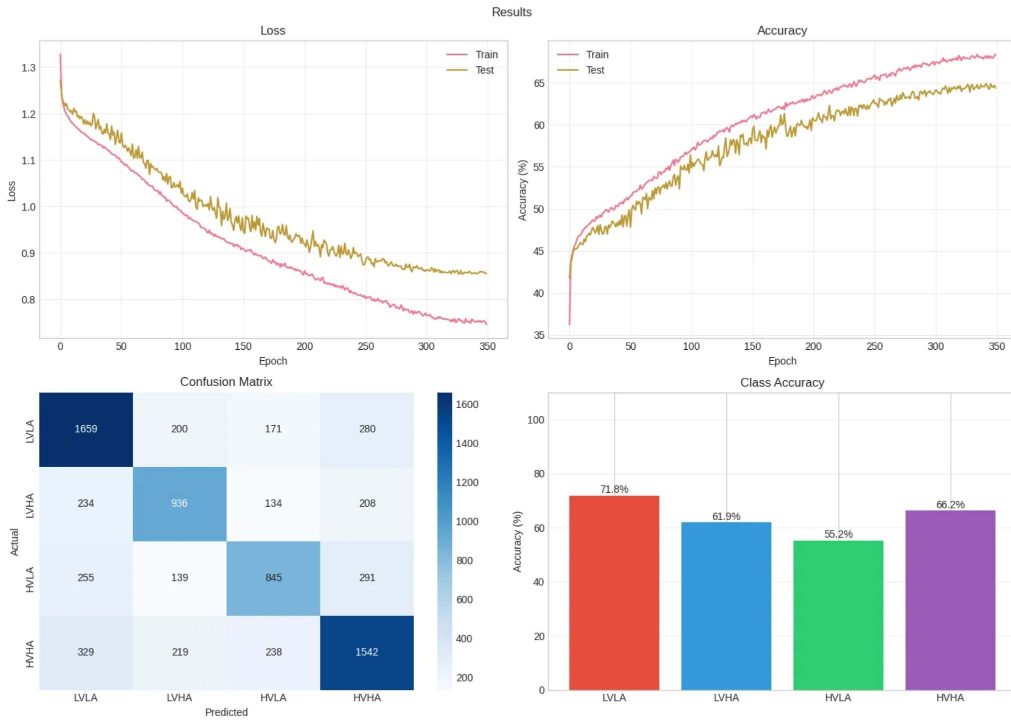

Figure 6: Emotion classification results: (Top-Left) Training and test loss curves showing stable convergence over 350 epochs. (Top-Right) Accuracy curves reaching 64.87%. (Bottom-Left) Confusion matrix showing class-wise predictions. (Bottom-Right) Per-class accuracy: LVLA (71.8%), LVHA (61.9%), HVLA (55.2%), HVHA (66.2%).

Table 1: Emotion Classification Performance Metrics

Class	Precision	Recall	F1-Score	Support
LVLA	0.67	0.72	0.69	2,310
LVHA	0.63	0.62	0.62	1,512
HVLA	0.55	0.55	0.55	1,530
HVHA	0.72	0.66	0.69	2,328
Weighted Avg	**0.65**	**0.65**	**0.65**	**7,680**

The confusion matrix reveals that LVLA (negative-calm) and HVHA (positive-excited) are most reliably classified, while HVLA (positive-calm) shows the most confusion with other classes. This pattern is consistent with literature showing that high-arousal states produce more distinctive EEG signatures than low-arousal states.

3.2 Motor Imagery Classification Results

The MotorImageryNet model achieved **65.6% accuracy** on 4-class motor imagery classification. Training configuration: AdamW optimizer (lr=1e-3, weight decay=0.01), CosineAnnealingLR scheduler (T_max=200, eta_min=1e-5), batch size 32, 200 epochs with early stopping (patience=30) and Gaussian noise augmentation (σ=0.1).

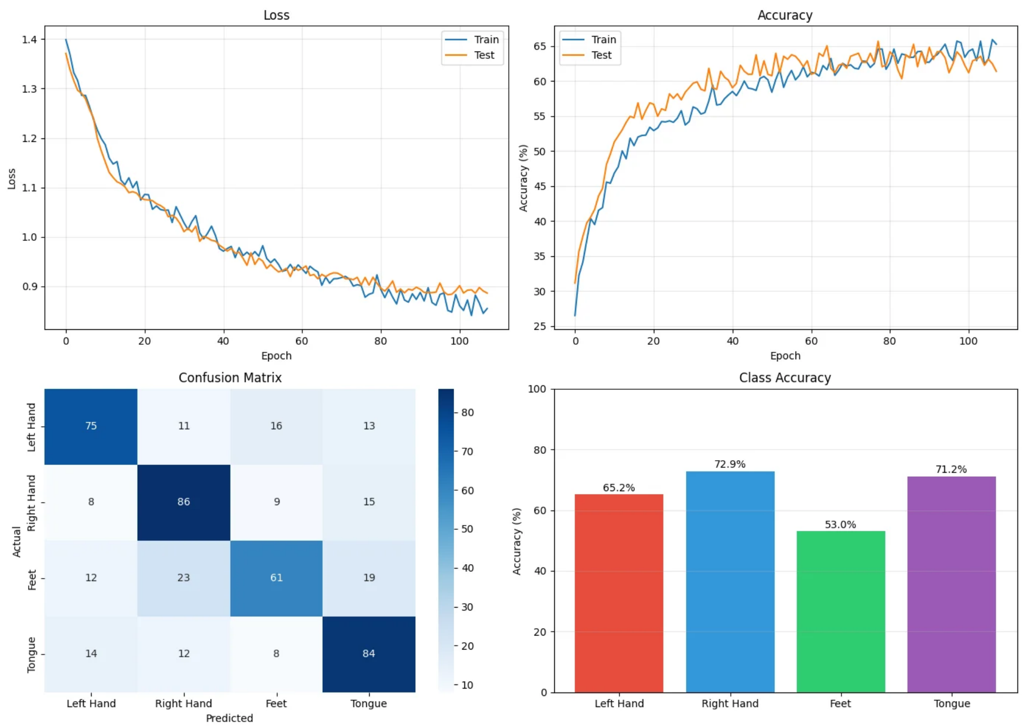

Figure 7: Motor imagery classification results: (Top-Left) Training and test loss curves with early stopping triggered at epoch 107. (Top-Right) Accuracy curves reaching 65.6%. (Bottom-Left) Confusion matrix showing class-wise predictions. (Bottom-Right) Per-class accuracy: Left Hand (65.2%), Right Hand (72.9%), Feet (53.0%), Tongue (71.2%).

Table 2: Motor Imagery Classification Performance Metrics

Class	**Precision**	**Recall**	**F1-Score**	**Support**
Left Hand	0.69	0.65	0.67	115
Right Hand	0.65	0.73	0.69	118
Feet	0.65	0.53	0.58	115
Tongue	0.64	0.71	0.67	118
Weighted Avg	**0.66**	**0.66**	**0.65**	**466**

Right Hand imagery achieved the highest recall (72.9%), consistent with stronger contralateral motor cortex activation patterns. Feet imagery showed the lowest accuracy (53.0%), likely due to overlapping cortical representations in the central sulcus region. Tongue imagery performed well (71.2%) due to its distinct cortical representation in the lateral motor areas.

3.3 Interpretation of accuracies

Table 3: Comparison with State-of-the-Art Methods

Method	**DEAP (4-class)**	**BCI IV-2a (4-class)**
Our Method	**64.87%**	**65.6%**

Our emotion classification achieves 64.87%, which is in because of the implementation decisions of using transformer clubbed with CNN. The motor imagery accuracy of 65.6% is within expected ranges for subject-mixed evaluation; subject-specific calibration typically adds 5-10% improvement but requires per-patient training data that may not be available in clinical settings. Also these accuracies are closely in relation with each other which is both around 65 percent tells us this combined architecture while interference gives a combined accuracy of 65%.

4 Discussion

Strengths: Both models learned complete end-to-end from raw EEG signals without requiring to create manual handcrafted features such as power spectral density or wavelet coefficients that are usually done with some deterministic methods. The compact architectures (combined <22K parameters) are suitable for final edge device deployment in clinical monitoring devices. Regularization techniques including dropout, weight decay, and early stopping effectively prevented overfitting despite limited training data. The balanced performance across emotion classes enables reliable multi-class detection for clinical decision support.

Limitations: Performance varies significantly across subjects due to inter-individual differences in EEG patterns, which we did not evaluate separately. Motor imagery accuracy of 65.6% may require confirmation mechanisms (e.g., repeated queries) for reliable clinical deployment. The system was evaluated offline using recorded datasets; real-time performance with streaming EEG data needs validation. The BCI IV-2a dataset's limited size (2,328 trials) constrains deep learning potential compared to larger datasets.

Clinical Applicability: This two architecture integrated system demonstrates the applicability and feasibility for edge clinical deployment with appropriate safeguards. Emotion detection at 64.87% accuracy can provide useful state assessment when combined with clinician judgment and other physiological indicators. Motor imagery detection can guide the clinical care takers by giving attention to specific body regions, with continuous repeated queries and retrainings improving confidence. Combined confidence thresholding can improve reliability at the cost of temporal coverage.

5 Conclusion

This project successfully architected, developed and implemented a two step or stage EEG-based system for emotion and discomfort detection in non-verbal patients. The MSDCGT architecture achieved 64.87% accuracy on 4-class emotion classification using the DEAP dataset, while the MotorImagery architecture achieved 65.6% accuracy on 4-class motor imagery classification using the BCI Competition IV-2a dataset. These results demonstrate the applicability of using deep learning approaches specially transformer in combination with convolution neural networks for real-time EEG analysis in clinical settings.

Future Work: In future these are the main key directions to proceed further with the project that is including implementing subject specific fine tuning approaches to improve individual accuracy, exploring and implementing transfer learning or finetuned approaches similar to what has been there in language modelling like pretrained models and finetuning between emotion and motor imagery tasks to leverage shared representations, developing confidence calibration methods for clinical decision support, and conducting real-time evaluation with actual patient populations in clinical environments.

Code Repository: `https://github.com/PavanchytanyaD/EEG-Based-Emotion-Discomfort-Detection-System-for-Non-Verbal-Patients`

References

[1] Koelstra, S., Muhl, C., Soleymani, M., Lee, J.S., Yazdani, A., Ebrahimi, T., Pun, T., Nijholt, A., and Patras, I. DEAP: A Database for Emotion Analysis using Physiological Signals. IEEE Transactions on Affective Computing, 3(1):18-31, 2012.

[2] Tangermann, M., Müller, K.R., Aertsen, A., Birbaumer, N., Braun, C., Brunner, C., Leeb, R., Mehring, C., Miller, K.J., Müller-Putz, G.R., Nolte, G., Pfurtscheller, G., Preissl, H., Schalk, G., Schlögl, A., Vidaurre, C., Waldert, S., and Blankertz, B. Review of the BCI Competition IV. Frontiers in Neuroscience, 6:55, 2012.

[3] Zhang, H., et al. EEG-based emotion recognition using multi-scale dynamic CNN and gated transformer. Scientific Reports, 14:82705, 2024. DOI: 10.1038/s41598-024-82705-z

[4] Lawhern, V.J., Solon, A.J., Waytowich, N.R., Gordon, S.M., Hung, C.P., and Lance, B.J. EEGNet: A compact convolutional neural network for EEG-based brain-computer interfaces. Journal of Neural Engineering, 15(5):056013, 2018.

[5] Hybrid CNN-transformer architecture for enhanced EEG-based emotion recognition: capturing local and global dependencies with self-attention mechanisms. Discover Computing, 2025. DOI: 10.1007/s10791-025-09596-0

[6] CTNet: a convolutional transformer network for EEG-based motor imagery classification. Scientific Reports, 14, 2024. DOI: 10.1038/s41598-024-71118-7

[7] Transformers in EEG Analysis: A Review of Architectures and Applications in Motor Imagery, Seizure, and Emotion Classification. Sensors, 25(5):1293, 2025.

[8] Effectiveness of multi-task deep learning framework for EEG-based emotion and context recognition. Expert Systems with Applications, 2023.

[9] Wang, F., Tian, Y.C., and Zhou, X. Cross-dataset EEG emotion recognition based on pretrained Vision Transformer considering emotional sensitivity diversity. Expert Systems with Applications, 2025.