BCI S2024 Project –Submission of Part-1

**Group No**. 35

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**Manuscript Title:**  Emotion Recognition Using Multimodal Deep Learning

**Focus Application:** Emotion

**Methodology used:** Restricted Boltzmann Machines, Multimodal Deep Learning

**Dataset Available:** Yes, Link: <https://www.eecs.qmul.ac.uk/mmv/datasets/deap/>

**Our understanding/ summary of the manuscript:**

This Paper utilizes the SEED dataset, capturing EEG and eye movements of 15 subjects reacting to emotional movie clips, and the DEAP dataset, monitoring EEG and physiological signals from 32 participants viewing music videos. Emotional states were evaluated without considering familiarity, with trials categorized for valence, arousal, dominance, and liking, and a 90/10 split for training and testing data.  
  
This paper employs a multimodal deep learning approach using SEED and DEAP datasets to recognize emotions efficiently. Utilizing the Bimodal Deep Auto Encoder (BDAE), it achieves high accuracy rates on SEED and DEAP datasets, respectively, outperforming existing methods. The BDAE effectively leverages complementary information from EEG and eye features for enhanced emotion recognition.

Here it implements Restricted Boltzmann Machines (RBMs) in emotion recognition through multimodal deep learning. RBMs, with visible and hidden layers lacking within-layer connections, facilitate modeling joint distributions of binary variables. Training RBMs involves optimizing parameters via algorithms like Contrastive Divergence (CD), specifically using the Bernoulli RBM model. Through CD, RBMs capture complex inter-modal relationships for robust emotion recognition, offering insights into their effectiveness in multimodal contexts and advancing emotion recognition via deep learning.  
  
The proposed multimodal emotion recognition framework involves three main steps:

* Bimodal Deep Auto-Encoder (BDAE) training
* Supervised training with high-level features using a linear SVM classifier
* Testing for recognition results

During BDAE training, separate encoding and decoding are done for EEG and eye movement features. Hidden layers from RBMs for each modality are concatenated, forming the visual layer for an upper RBM. Stacked RBMs reconstruct input features, and unsupervised back-propagation refines weights and biases. This integration of modalities enhances emotion recognition accuracy, leveraging BDAE's feature extraction capabilities.  
  
For the SEED dataset, EEG data yielded Power Spectral Density (PSD) and Differential Entropy (DE) features across five frequency bands. Eye movement data used features from previous research, totalling 41 dimensions. All features were rescaled to [0, 1] for input into the BDAE network. The DEAP dataset utilized pre-processed EEG and physiological data directly for shared representation extraction

The study compares single and multimodal emotion recognition models on the SEED and DEAP datasets. In SEED, the BDAE model achieves the highest accuracy (91.01%) and lowest standard deviation. For DEAP, BDAE outperforms existing methods, improving recognition accuracies across all tasks.

The experimental findings highlight the effectiveness of the BDAE network in extracting shared representations from different modalities, outperforming other feature extraction methods. EEG features excel in positive emotion recognition, while eye features are advantageous for negative emotions. Combining both modalities with BDAE yields superior results across all emotion types.

The paper demonstrates the effectiveness of the BDAE model in extracting shared representations for emotion recognition, achieving superior accuracy on both SEED and DEAP datasets. EEG and eye features complement each other, enhancing recognition accuracy. Future research will explore the synergies between EEG and eye movement features for improved multimodal emotion recognition.