Human emotion recognition from EEG signals: model evaluation in DEAP and SEED datasets.

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Introduction

1. Emotion is considered an important factor in human life
2. Human can decipher the emotional states of others
3. HMI can be improved if the machines can infer the human emotional states.
4. EEG-based methods are more reliable as they are less susceptible to counterfeit.

Dataset description

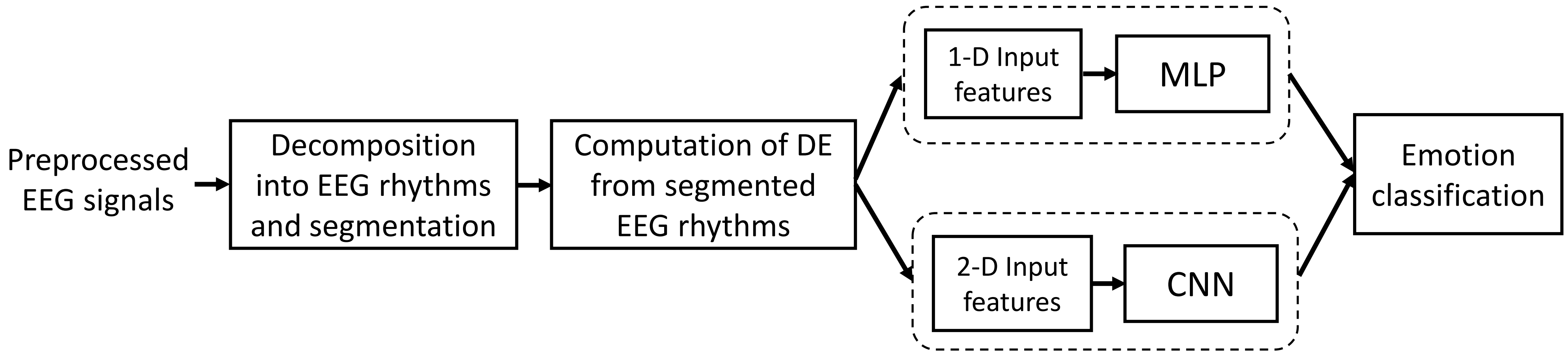
DEAP dataset:

1. No. of subjects: **32**
2. No. of trial for each subject: **40**
3. Trial length= **60 sec.**
4. Sampling Frequency: **128** Hz
5. Total Channels: **32**
6. BPF: **4-45 Hz**
7. Baseline signal: **3 sec.**
8. Classes: Valance/Arousal

SEED dataset:

1. No. of subjects **15.**
2. **15 trials** for each subject and 3 sessions (Total **45 trials**).
3. Trial length: **4 min.**
4. Sampling rate: **200 Hz**.
5. Total channels: **62**
6. BPF: **0-70 Hz**
7. Classes: **Negative, Neutral, and Positive**

Methodology



Decomposition and segmentation

- SEED dataset are decomposed into five EEG rhythms, **delta (1- 4Hz), theta (4-8Hz), alpha (8-14Hz), beta (14-31Hz), and gamma (31- 51Hz).**
- EEG signals of the DEAP dataset are decomposed into four rhythms namely, **theta (4-8Hz), alpha (8-14Hz), beta (14-31Hz), and gamma (31-45Hz).**
- 1 sec. Segment **length is used [1].**
- Total epochs for each subject are **3394** and **2400** for SEED and DEAP datasets

1. X.-W. Wang, D. Nie, B.-L. Lu, Emotional state classification from EEG data using machine learning approach, Neurocomputing 129 (2014) 94–106.

Feature extraction

- **Differential Entropy** (DE) is used as a feature.
- Sub-band EEG signals can meet the Gaussian distribution criterion [2].
- Hence, De can be computed as:

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

2. L.-C. Shi, Y.-Y. Jiao, B.-L. Lu, Differential entropy feature for EEG-based vigilance estimation, in: 35th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), 2013, pp. 6627–6630.

Classification methods

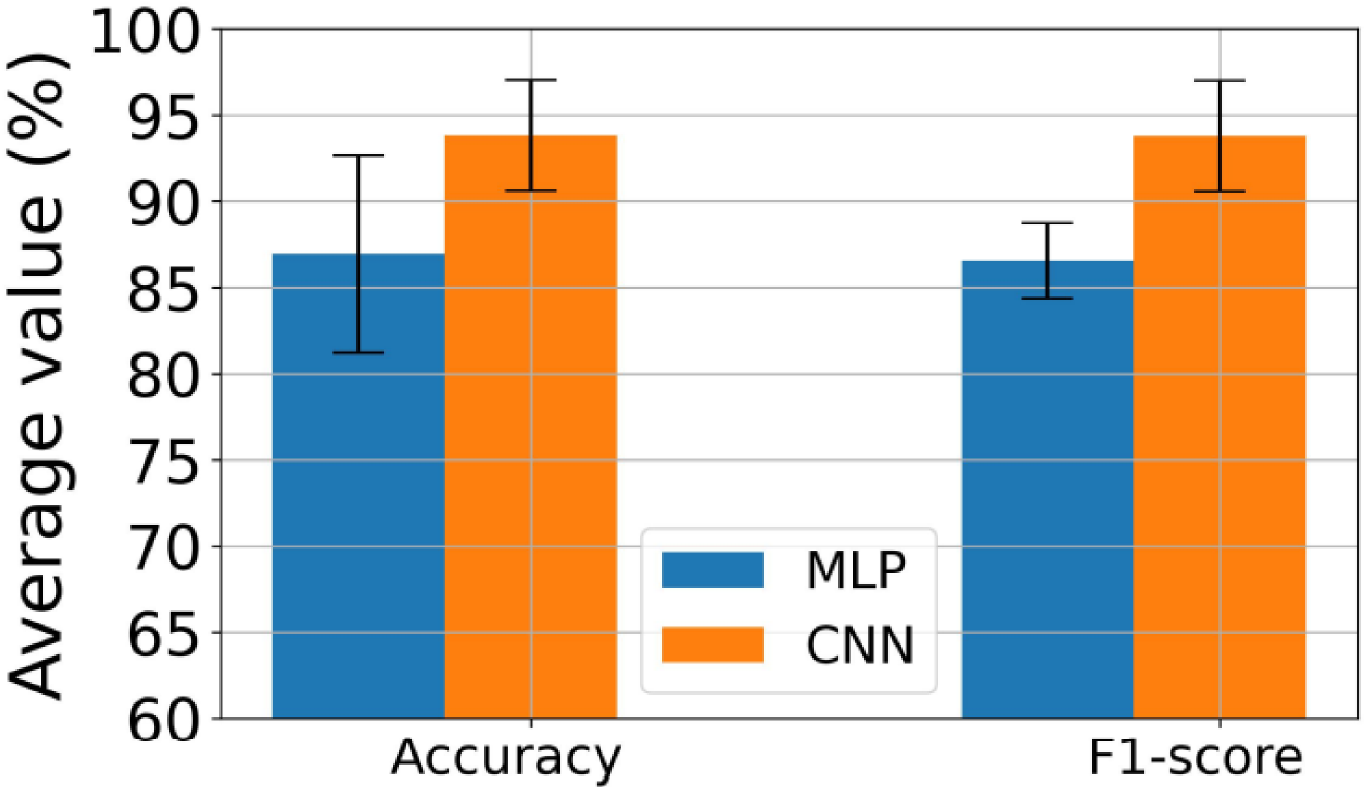
- **MLP:** 4 hidden layers. The hidden layers consist of 256, 256, 128, and 64 units corresponding to hidden layer 1 to hidden layer 4.
- SEED dataset:(3394,310)
- DEAP dataset:(2400,128)

- **CNN:** SEED dataset: (3394, 8, 9, 5)
- DEAP data: (2400, 8, 9, 4).
- It has two convolution blocks CB-1 and CB-2.
- CB-1 consists of 2 CLrs and one maxpooling layer.
- Each CLr of CB-1 has 256 units with a filter size of 5X5.
- CB-2 contains one CLr having 128 units with a filter size of 4x4 and one maxpooling layer.
- The filter size of maxpooling layer for CB-1 and CB-2 is 2x2 with a stride of 2.

Results

- 5-fold cross-validation
- The Adam optimizer is used with the default learning rate provided in the Keras library.
- The RELU activation function is used

Results on SEED dataset



- CNN takes tensor (2D) as input so it can understand spatial relation between EEG channels

Results on SEED dataset

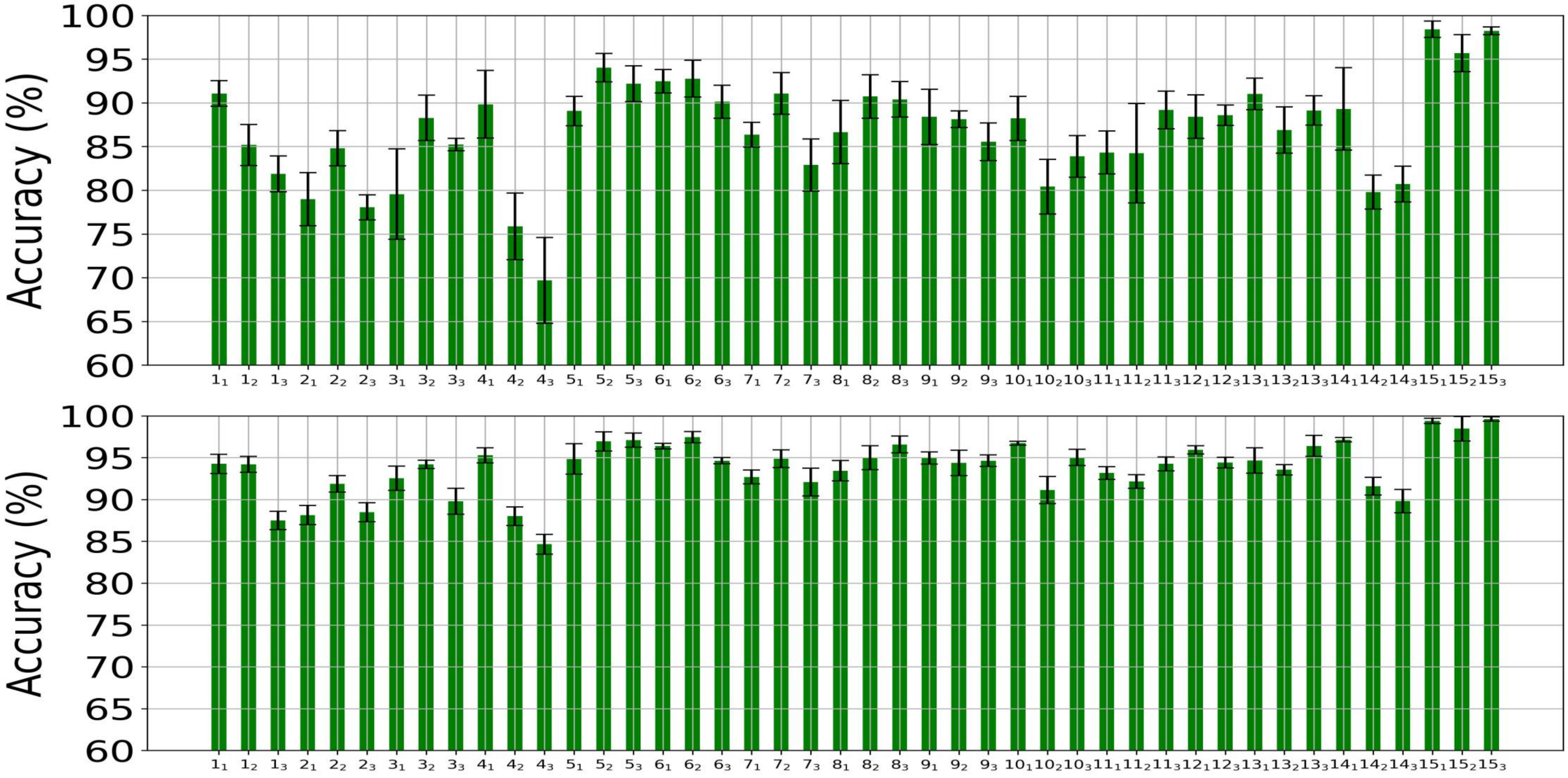
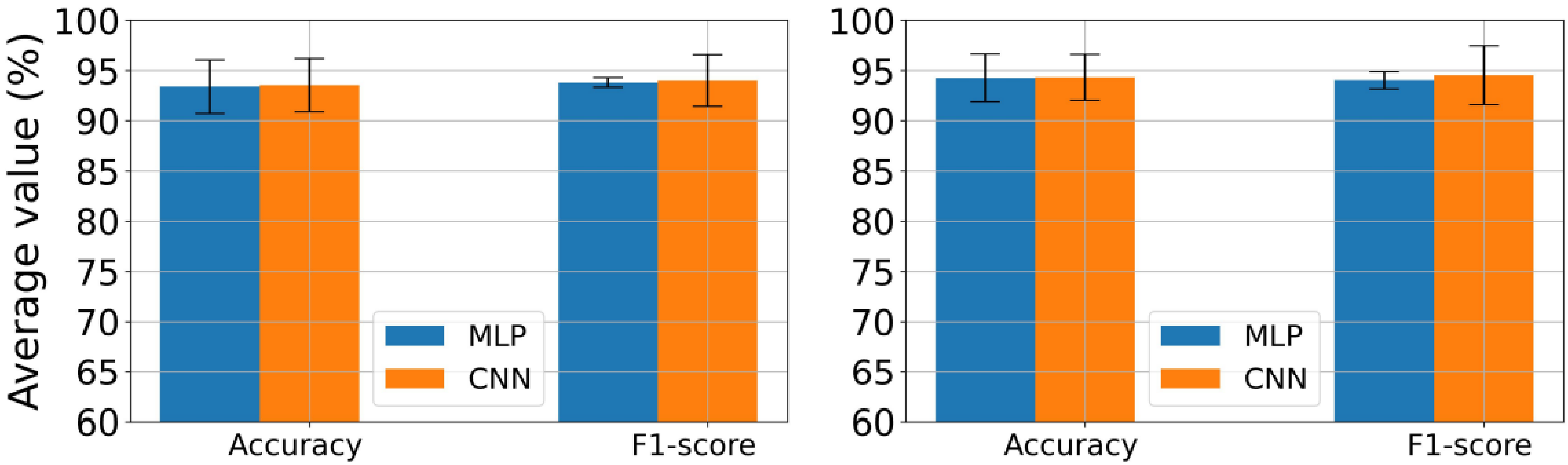


Figure: (a) MLP classifier, **(b)** CNN classifier

Baseline correction on DEAP dataset

- A 3 sec. baseline signal is available with DEAP dataset.
- we also computed DE feature from the baseline.
- First, we have divided the 3 secs. baseline into 3 segments of 1 sec. duration.
- Then, we computed the DE from all 3 segments and marked it as DE_{base}.
- Finally, we consider the average value of the three DE_{base} as the baseline DE features.
- The baseline DE feature matrix has a dimension of (40, 4) for each subject, where, 40 represents the number of trials and 4 features correspond to the four subbands.
- The baseline DE feature is subtracted from the main DE feature before applying it to the input of the classifiers

Results on DEAP dataset



(a)

(b)

- DEAP dataset has 32 channels EEG recording.
- CNN does not benefit much from only 32 channels compared to 62 channels.

Results on DEAP dataset

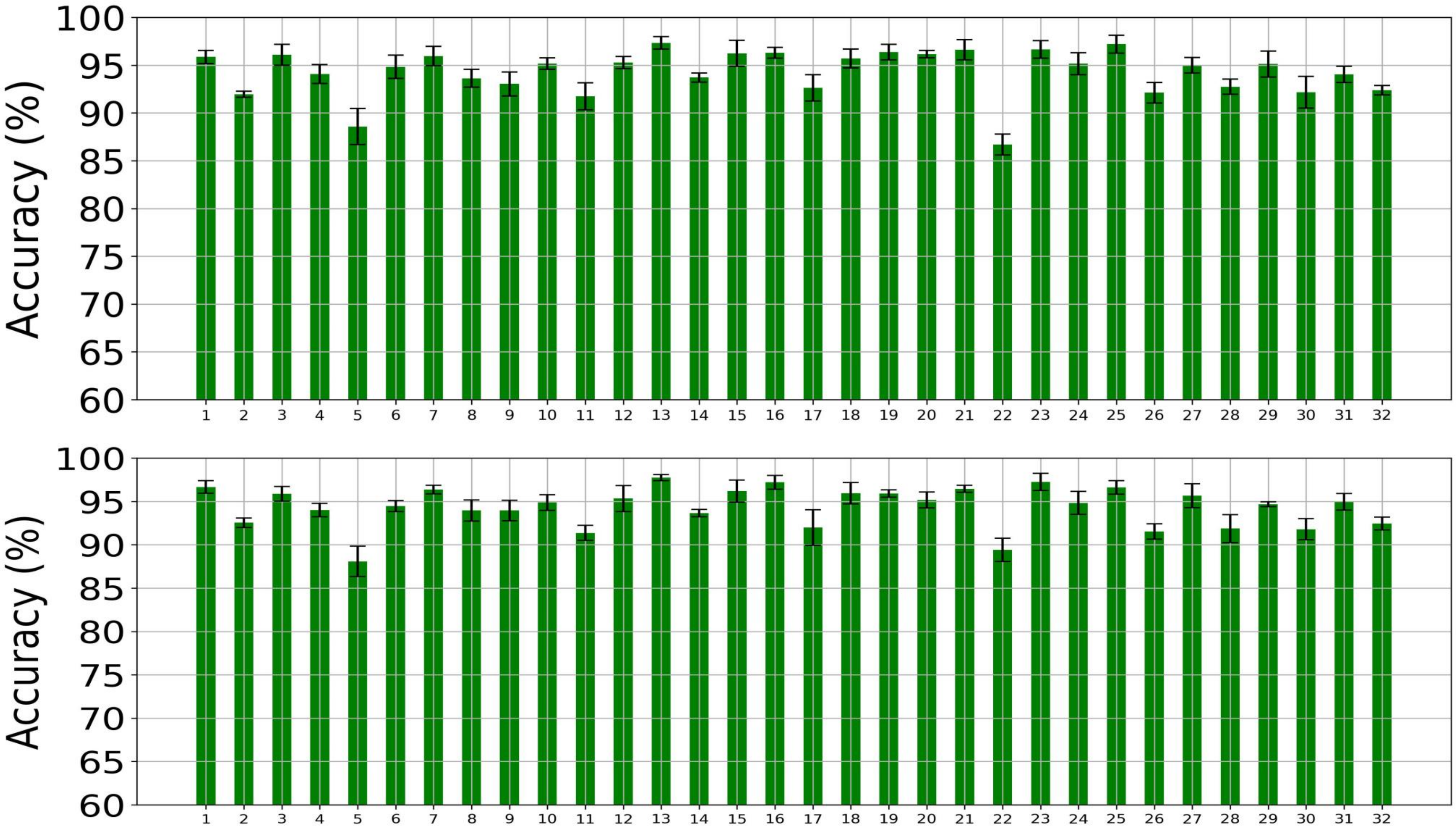


Figure: High and low arousal classes. **(a)** MLP classifier, **(b)** CNN classifier

Results on DEAP dataset

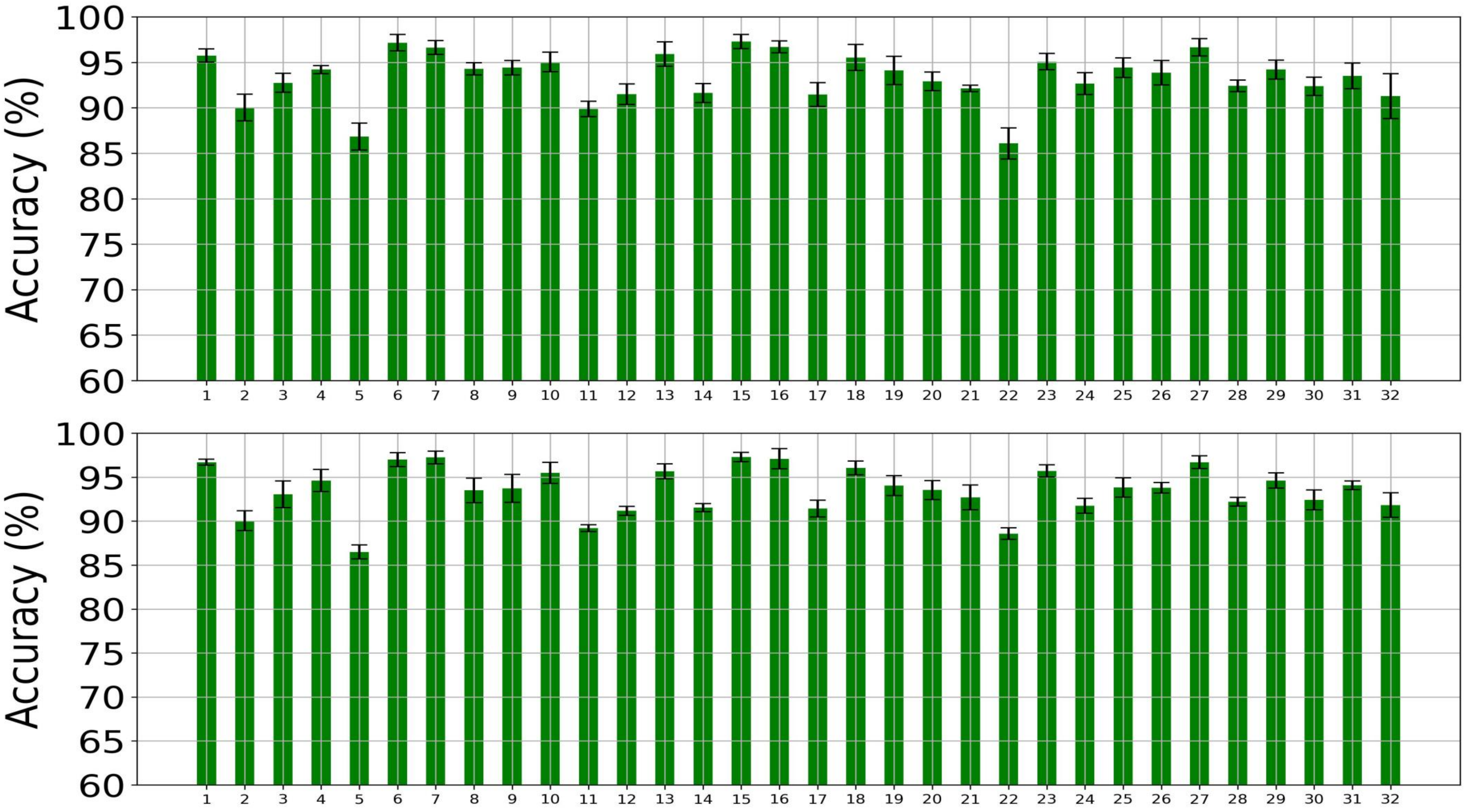


Figure: High and low valence classes. **(a)** MLP classifier, **(b)** CNN classifier

Comparison with other works

Comparision of the results (average accuracy (ACC) and standard deviation (STD)) of the present work with other works.

Authors	Method	Cross-validation	DEAP (32 channels) High and low valence	DEAP (32 channels) High and low arousal	SEED (62 channels)
			ACC/STD	ACC/STD	ACC/STD
Yang et al. [14]	PCRNN	10-fold	90.8/3.08	91.03/2.99	
Yang et al. [21]	CCNN	10-fold	89.45	90.24	
Shen et al. [15]	4D-CRNN	5-fold	94.22/2.61	94.58/3.69	94.74/2.32
Present work	MLP	5-fold	93.39/2.66	94.25/2.37	86.8/6.4
	CNN	5-fold	93.53/2.65	94.33/2.29	93.81/3.21

Conclusion

- CNN-based method outperforms the MLP-based method for the SEED dataset.
- No significant difference is observed in the performance of MLP and CNN-based approaches for DEAP dataset.
- The obtained results show that it is possible to achieve state-of-the-art performance with less complex models.
- In future, our aim is to implement a channel selection approach to select the channels which are more relevant for emotion detection.