Enhancing EEG-Based Emotion Recognition using Multi-Domain Features and Genetic Algorithm based Feature Selection

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Introduction

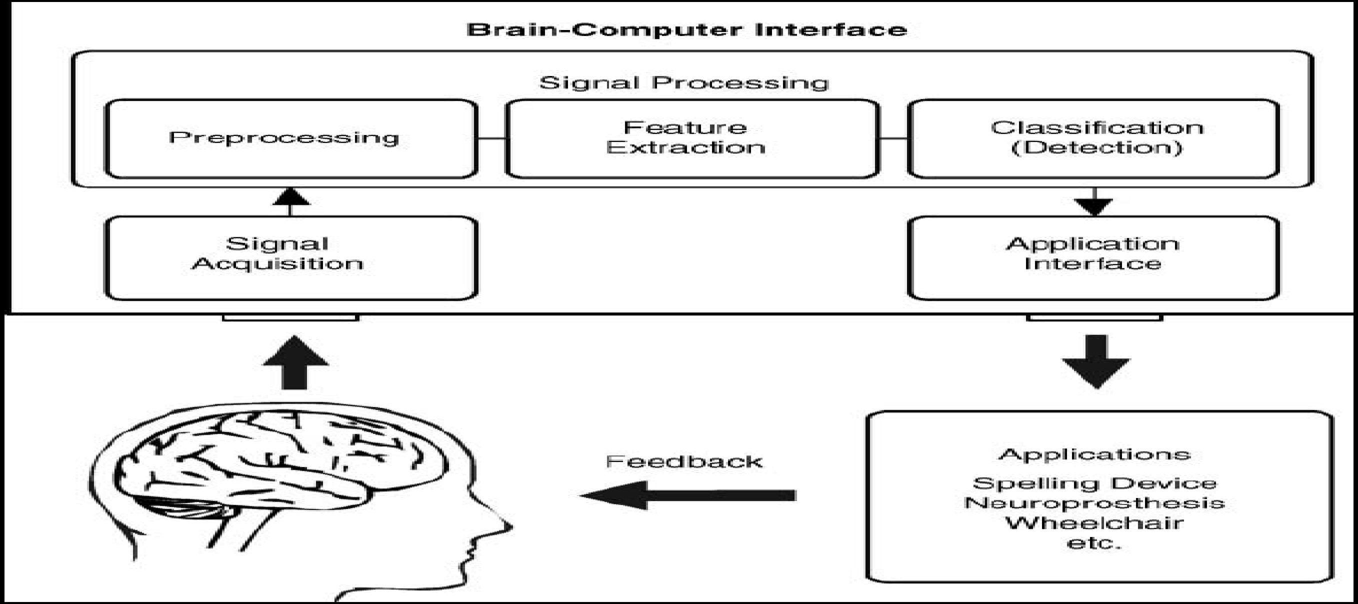

Figure 1. **Brain-Computer Interface (BCI)**

(Image from https://www.researchgate.net/figure/Components-of-a-BCI-system-signals-from-the-users-brain-are-acquired-and-processed-to_fig1_267792090dd text)

Introduction

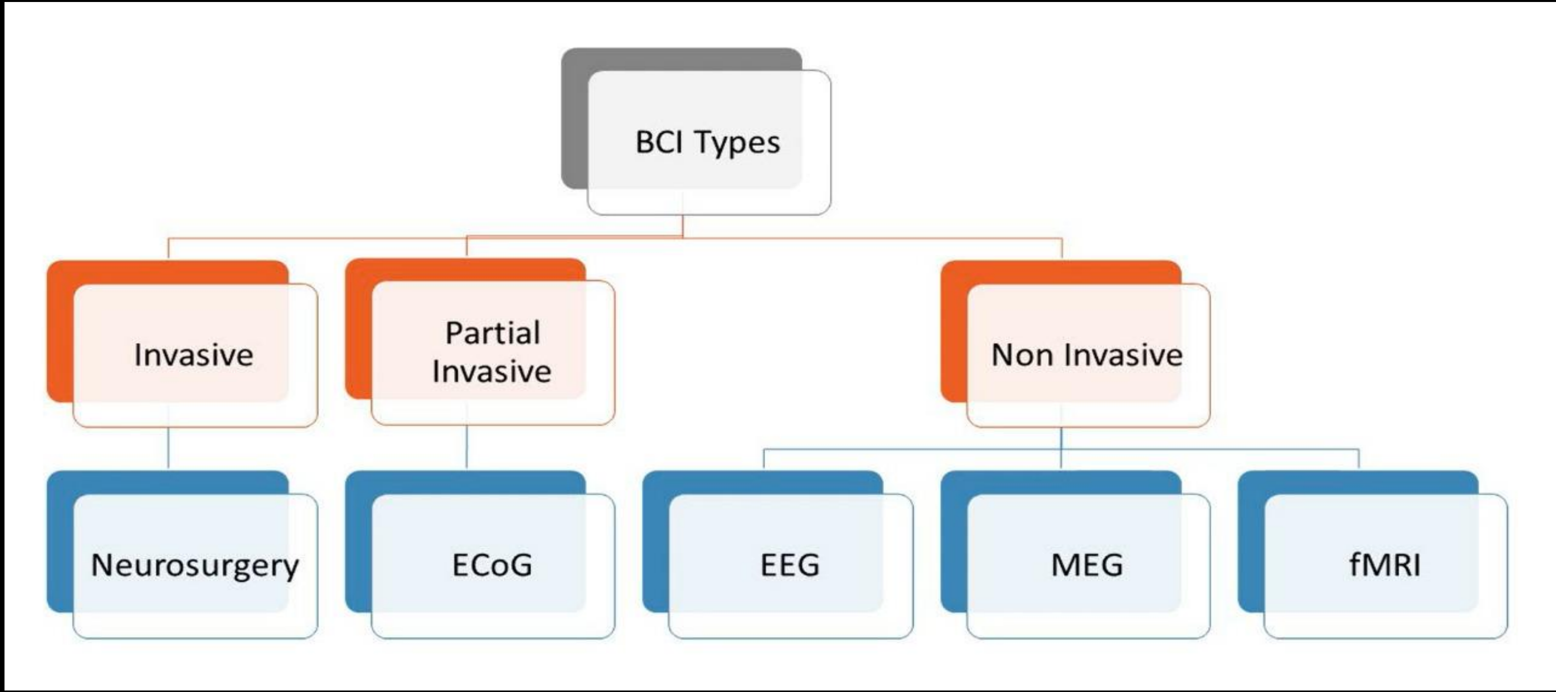

Figure 2. **BCI Signals**

Introduction

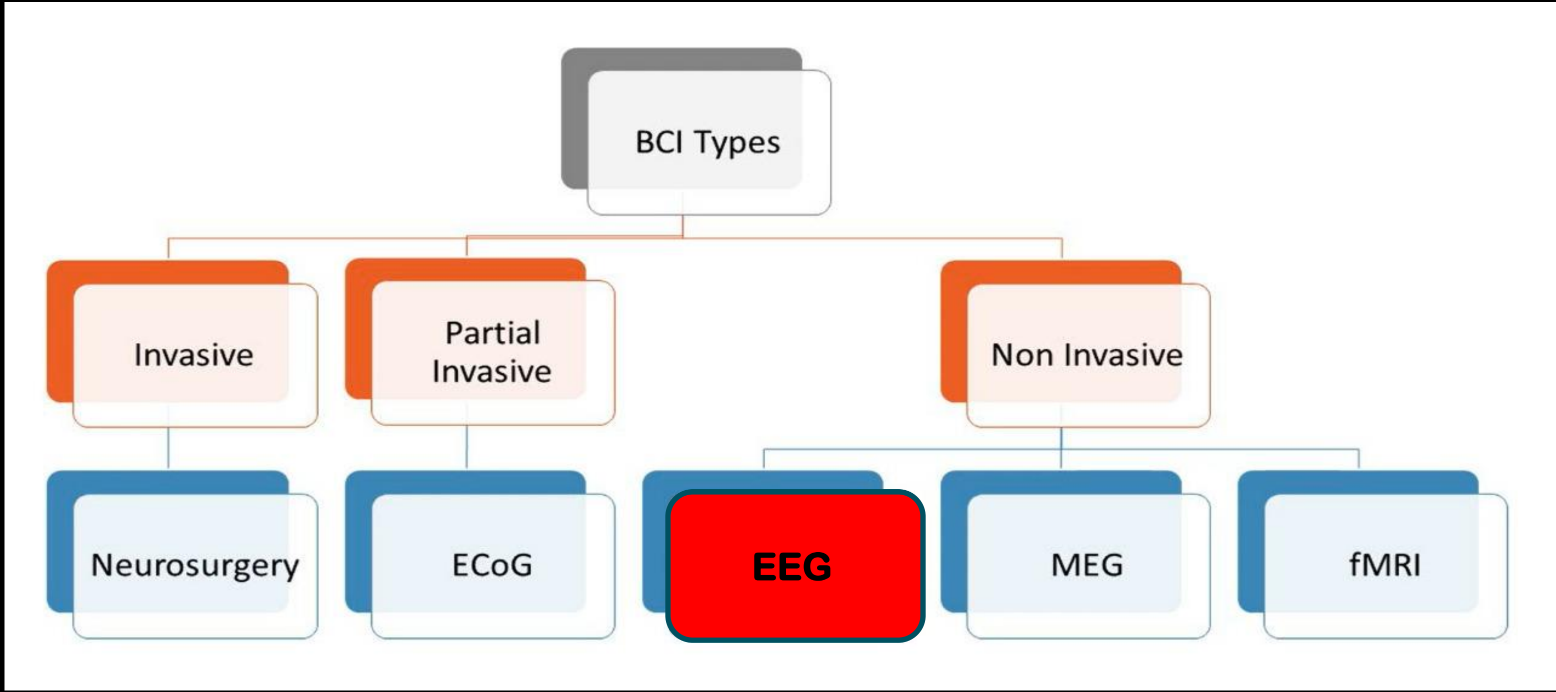

Figure 3. **BCI Signals**

Introduction

EEG based BCI

1. **Why EEG based BCI ?**
   - Functionally fast.
   - High precision time measurements.
   - Low cost and portability.
   - Minimum setup requirement .
   - Extremely Non-invasive.
   - EEG does not involve exposure to high-intensity

2. **Challenges:**
   - Non-stationary
   - Non-linearity
   - High Dimensionality
   - Noisy

3. **Applications:** Seizure Detection, Motor Imagery Classification, Mental Task Classification, Emotion Recognition, Sleep Rate Classification etc.

Introduction

EEG based BCI

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Introduction

- Emotions play an indispensable role in day-to-day life activities. Thus emotion recognition within Human-Computer Interaction caters more natural interactions in the elds of personalized recommender systems, rehabilitation robotics, etc. [1].
- Research within human-computer interaction has focused on Brain-Computer Interfaces (BCI), a communication methodology based on brain signals, to monitor and detect emotions of human beings.

Aim

- To propose an EEG based emotion recognition methodology based on a hybrid feature extraction combined with Genetic Algorithm (GA) based feature selection.

The proposed work is evaluated on DEAP Dataset[1] (a dataset for emotion analysis using EEG, physiological and video signals [2]) to recognize different emotions via the Valence and Arousal category.

[1] http://www.eecs.qmul.ac.uk/mmv/datasets/deap/download.html

Our Contributions

- **Multi-domain Feature Extraction:** Emotions are complex brain activities and are induced by neural activities in various brain areas. From the viewpoint of machine learning, computing noticeable information from EEG data necessitates suitable extraction of features. In this regard, the features are extracted from various domain viz. **frequency**, **time**, and **wavelet** to well represent the underlying EEG data.
- **GA Based Feature Selection:** GA has been implemented to reduce the dimensionality of the feature space by removing redundant and irrelevant feature vectors and to select the subset of optimal feature vectors from the higher dimensional feature space that carries the most discriminative information.

Related Works

- **Interpretation of Emotions:** Emotions can be interpreted and recognized in two taxonomy models i.e. **discrete model** and **dimensional model** [3]. The discrete taxonomy represents six key emotions viz. surprise, fear, sadness, joy, disgust and anger. The dimensional model describes emotions in terms of two principal dimensions: **valence** and **arousal**.
    - The valence illustrates the level of pleasant or unpleasant feeling while arousal is the intensity of associated emotional state.
    - The dimensional model based on valence and arousal recognizes various emotional states [4].

Related Works

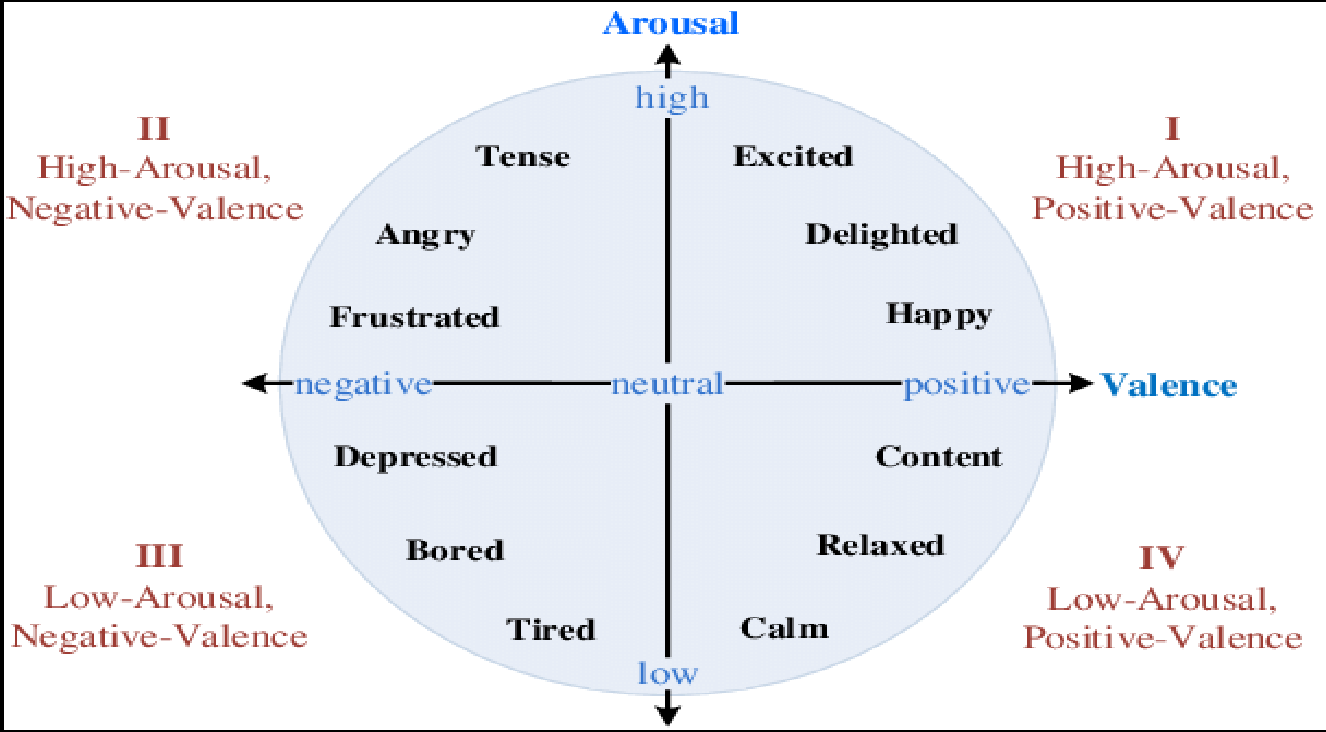

Figure 4: Emotion states based on the valance-arousal score level [https://www.researchgate.net/figure/Two-dimensional-valence-arousal-space_fig1_304124018]

Related Works

- Feature Extraction and Selection for EEG-based Emotion Recognition:
  - Diah et al. [5] employed nine types of time frequency domains features combined with feature selection and achieved 60.68% accuracy rate.
  - Liu et al. [6] used hybrid feature extraction method which is further amalgamated with optimal sequence backward feature selection and obtained an accuracy rate of 84.90% and 86.46% for valence and arousal respectively.
  - Different variants of feature selection can also be employed, viz. mRMR [7], KPLS-mRMR [8], etc. Various machine learning algorithms have also been employed [9, 10].

Related Works

Reference	Year	Features	Feature Selection
Nitin et al. [1]	2016	Bispectrum	Yes (Backward sequential)
Atkinson et al. [11]	2016	Statistical features, Band power for different frequencies, Hjorth parameters, Fractal dimension	Yes (mRMR)
Alhagry et al. [12]	2017	LSTM	No
Soroush et al. [13]	2018	Correlation Dimension, Fractal dimension, Largest Lyapunov exponent, Sample entropy, Recurrence rate, Determinism, Average diagonal line length, Entropy,Differential entropy, Fractal dimension, Largest Lyapunov exponent, Sample entropy	Yes (Local subset feature selection along with channel selection) \
Hao Chao et al. [14]	2019	Multiband Feature Matrix by CapsNet	No
Asghar et al. [15]	2020	Analytic Wavelet Transform	Yes (Deep Feature Clustering)
Liu et al. [16]	2020	Multi-level features by CapsNet	No
Li et al. [17]	2020	Frequency, time, time-frequency	Yes (Particle Swarm Optimization)
Yin et al. [18]	2020	Power Spectral	Yes (Locally Robust)
Li et al. [19]	2021	Spectrogram Representation	No

Table 1: **Background Research**

Materials and Methods

Dataset Description

- **DEAP Dataset[1]**: A Database for Emotion Analysis using Physiological Signals [2].
  - Subjects : Individual (32), 16 males and 16 females.
  - Number of Videos : 40 (Each length 60 sec)
  - Sampling Rate : 128Hz
  - Rating Scale: Arousal and Valence
  - Rating Values: Continuous scale of 1-9
- The rating in the range of 1-5 was categorized as Low Valence/Arousal state and rating in the range of 5-9 was categorized as High Valence/Arousal state.

Array Name	Array Shape	Array Contents
Data	40x40x8064	Video/TrialxChannelxData
Labels	40x4	Video/TrialxLabel

Array Name	Array Shape	Array Contents
Data	40x32x7680	Video/TrialxChannelxData
Labels	40x2	Video/TrialxLabel

Materials and Methods

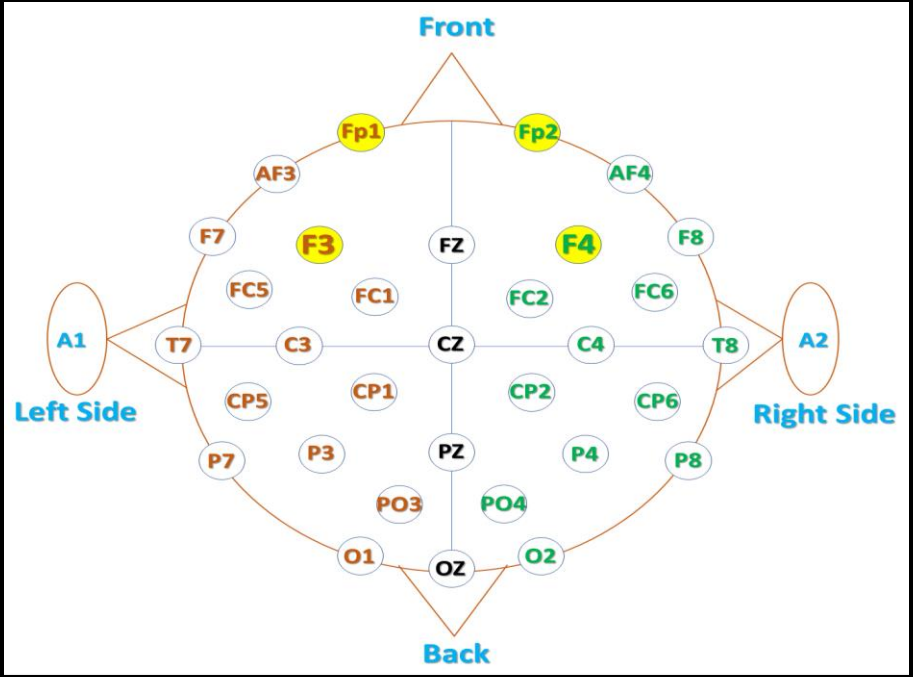

Figure 5: EEG electrode locations according to the 10-20 International system used for recording EEG data in DEAP Dataset. The yellow marked electrodes were used for our experiments.

Materials and Methods

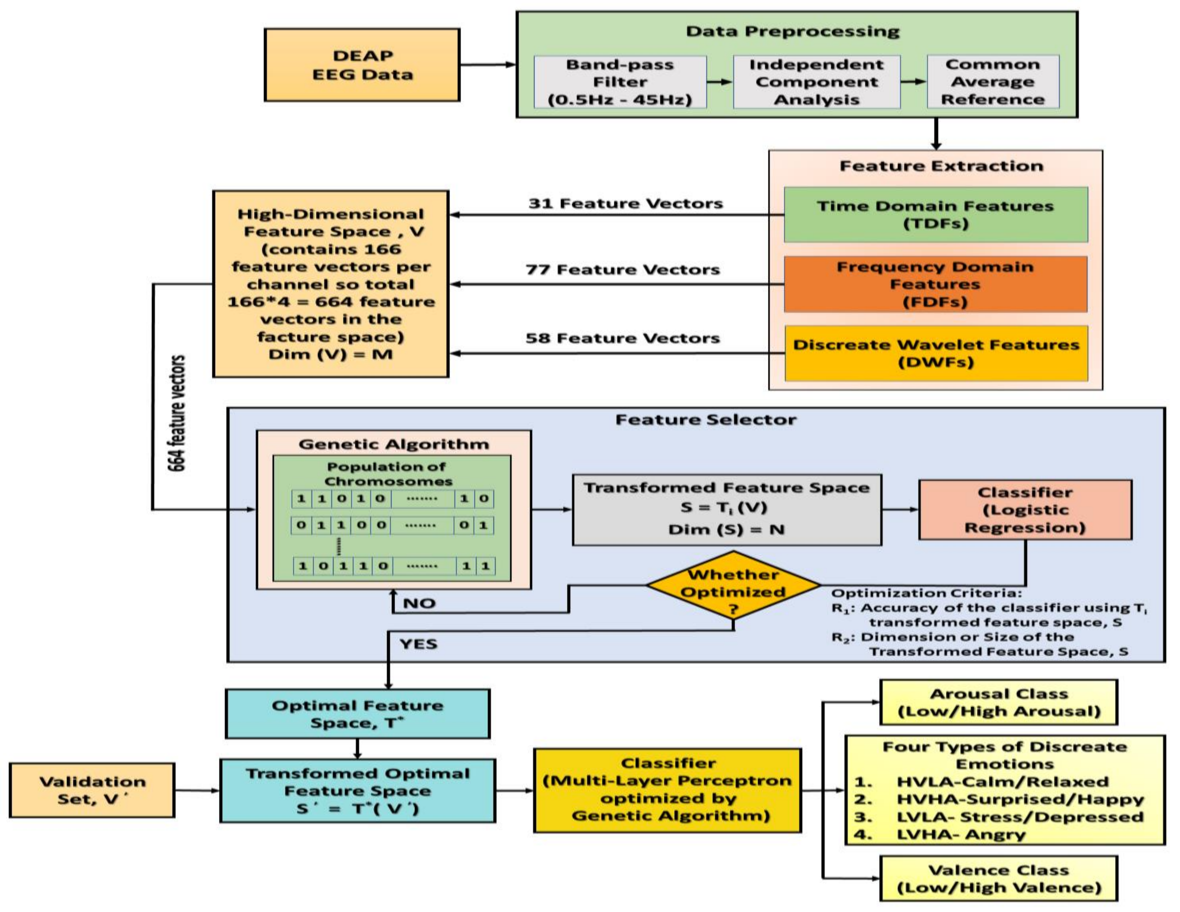

Figure 6. **Steps in our emotion recognition framework**

Materials and Methods

Feature Extraction

Domain	Features	Included in
Time Domain	Mean, Variance, Mode, Median, Skew, Standard Deviation, Kurtosis, Energy, Average Power, RMS, Katz fractal dimension, Nonlinear Energy, Approximate Entropy, Shannon Entropy, Permutation Entropy, Sample Entropy, Weighted Permutation Entropy, Singular Value, Decomposition, Hurst Exponent, Higuchi fractal dimension, Hjorth activity, mobility, complexity, Detrended Fluctuation Analysis, Number of local extrema, Number of zero-crossings, Petrosian fractal dimension	[20]
	First Difference, Second Difference, Normalized First Difference, Normalized Second Difference	[21]
Frequency Domain	Mean, Variance, Mode, Median, Skew, Standard, Deviation, Kurtosis, Energy, Average Power, RMS for 5, frequency bands(0.5-4 Hz, 4-7 Hz, 8-13 Hz, 13-30 Hz, 30-40 Hz) after applying PSD on raw data, Spectral Edge Frequency, Intensity weighted mean frequency, Spectral Entropy, Intensity weighted bandwidth, Mean of Peak Frequency after applying PSD on the raw data.	[20]
	First Difference, Second Difference, Normalized First Difference, Normalized Second Difference after applying PSD on raw data	[21]
	Rational Asymmetry, Differential Asymmetry	[22]
Wavelet	Mean, Variance, Mode, Median, Skew, Standard deviation, Kurtosis, Energy, Average Power, RMS, Shannon Entropy, Approximate Entropy, Permutation Entropy, Weighted Permutation Entropy, Hurst Exponent, Higuchi Fractal Dimension, Petrosian Fractal Dimension, Spectral Entropy, Mean of Peak Frequency, Auto Regressive and Auto Regressive, moving Average model parameters computed on decomposition coefficients	[20]

Table 2. **Features extracted in this study from time, frequency and wavelet domain**

Materials and Methods

GA based Feature Selection

- GA is implemented to select the most relevant features.
  - Each chromosome in the individual is represented as a bit-string of 0's and 1's.
  - Size of the individual is the no of features presented in the feature space i.e. 664.
  - Presence of a feature vector is represented by the following rules: If we have '0' bit in a gene position then we are not taking that feature and if we have '1' in a gene position then we are taking that feature for our classification problem.
- Steps in GA includes :
  - calculation of fitness value : accuracy of the logistic regression model.
  - selection of the individuals based on the fitness value: 7-way tournament selection.
  - cross-over and mutation: One-point cross over is used.
- GA Parameters:
  - Hence, for our classification problem we have taken number of generations as 50 (as stated in [23]), size of the population as 100 (as stated in [24]), crossover and mutation probability as 0.65 and 0.001 respectively (as stated in [23, 24]).

Experimental Results

Feature Selection	Valence				Arousal				4−types of emotions			
	Precision	Recall	F1-Score	Accuracy	Precision	Recall	F1-Score	Accuracy	Precision	Recall	F1-Score	Accuracy
No (664 features)	78.25	86.71	82.26	93.13	76.12	84.667	80.17	92.34	73.91	80	76.83	85.625
Yes (320 features)	83.33	91.67	86.71	95.96	84.57	90.00	87.20	95.39	78.57	86.67	82.42	91.875

Table 3: Comparison of the performance of with and without GA based feature selection

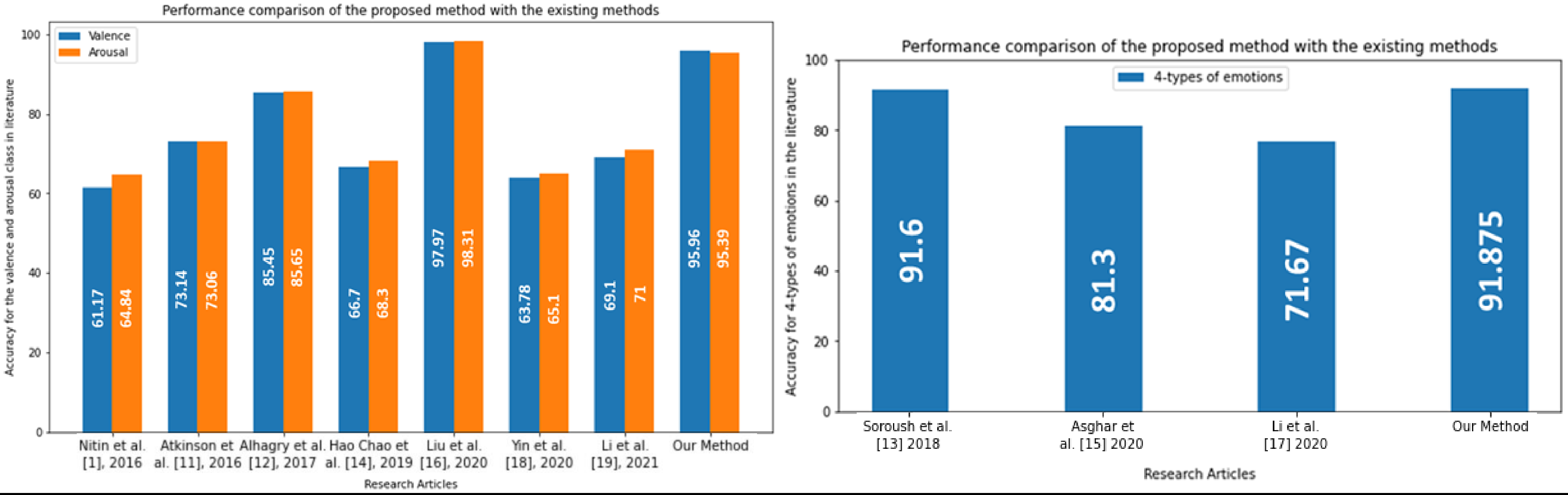

Figure 7: Performance comparison of the proposed method with the existing methods

Conclusion and Future Works

- The proposed framework uses features extracted from **time**, **frequency** and **wavelet domain** from four selected electrodes namely, **Fp1**, **Fp2**, **F3** and **F4**.
- The paper proposes an emotion recognition paradigm that encompass a **feature selection method using GA**.
- The experimental results reveal that the reduced feature sets obtained through GA yields better performance in comparison to the state-of-the art approaches.
- Future works will include testing with **different bandpass filters and validating on additional datasets**. It will also include to put forward an **effective channel selection strategy**.

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Questions?

Thank You!