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Universidad del País Vasco
Euskal Herriko Unibertsitatea

FACULTY OF COMPUTER SCIENCE
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EEG SIGNAL PROCESSING

from Time Series Classification to Emotion Recognition

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OUTLINE
01 MOTIVATION
02 APLICATIONS OF EEG SIGNAL PROCESSING
03 CONTRIBUTIONS
04 DISTRIBUTION OF PUBLICATIONS BY CLINICAL DIAGNOSIS
05 SIGNAL PREPROCESSING
06 EEG SIGNAL CLASSIFICATION
07 NEURAL NETWORKS FOR SIGNAL CLASSIFICATION
08 IMPORTANT CONTRIBUTIONS

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MOTIVATION

EMOTION

Emotions are psychological states comprised of thoughts, feelings, physiological changes, expressive behaviors, and inclinations to act.

DOMAIN

Emotion is a subjective attitude generated by a person's experience of external things, as well as an instinctive coordinated response made by the body, which may include the joint effects of language , behavior, and spirit.

AFFECTIVE COMPUTING

Affective Computing is the study and development of systems and devices that can recognize, interpret, process, and simulate human affects

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Applications of EEG Signal Processing

01 CLINICAL DIAGNOSIS

EEG is widely used to diagnose various neurological disorders such as epilepsy, sleep disorders, and brain injuries.

02 COGNITIVE NEUROSCIENCE

It helps researchers understand cognitive processes, perception, attention, and memory.

03 BRAIN-COMPUTER INTERFACES

EEG signals can be used to control external devices, enabling communication and mobility for individuals with physical disabilities.

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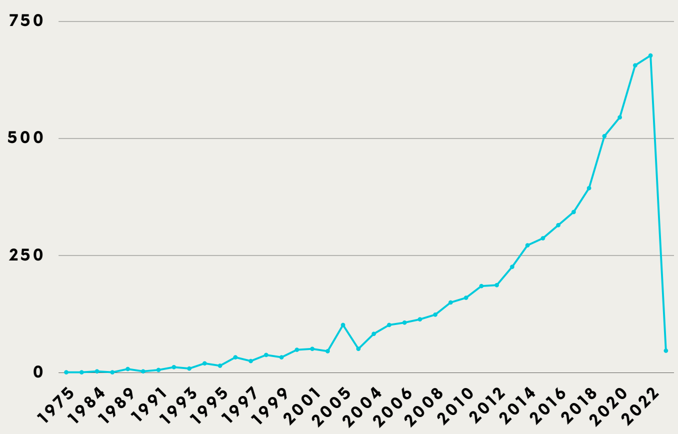
Publications

There has been an evolution in the number of publications in the signal processing area with classical Machine Learning technics, since 1975, the last 2 decades having the most number of contributions in EEG signal processing with Neural Networks



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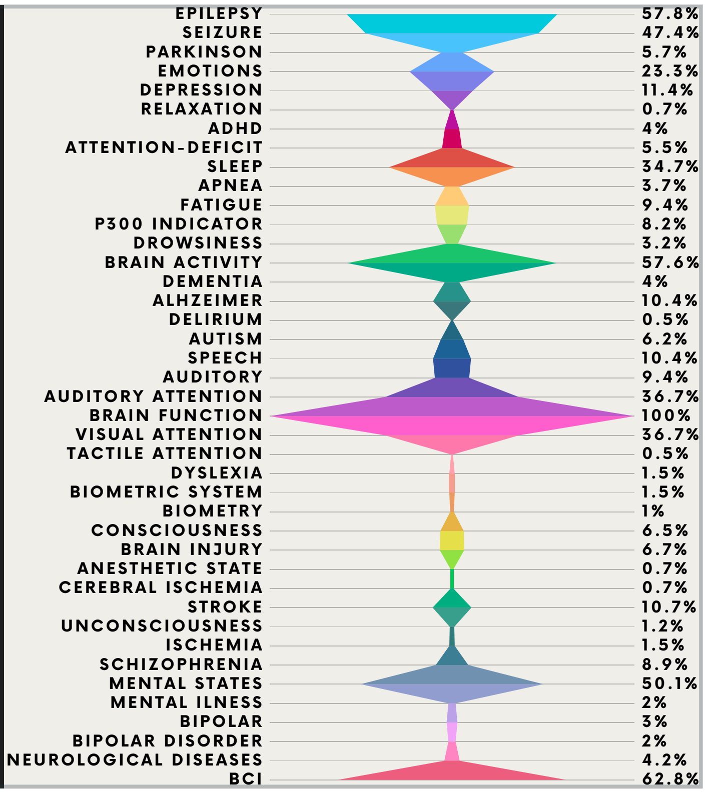
Clinical Diagnosis

According to the contributions seen in the previous chart, there is a distribution of them according to the clinical target, in which depending the area some features or characteristics of the signal may be taken into account in a different way



SIGNAL PREPROCESSING

EEG = True EEG signals + artifacts

Interferences and noise generated by the EEG device or transmission line

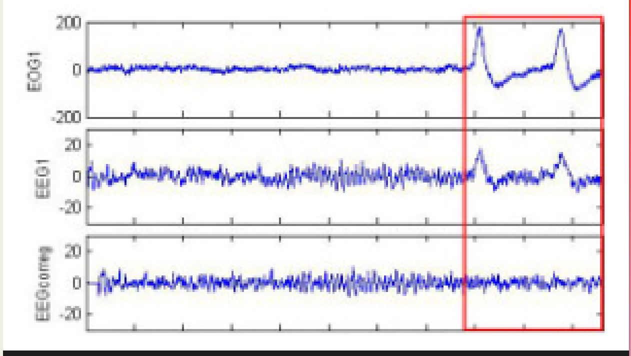
Classification performance affected

Original EEG signal >>> denoised and deinterferenced

Regresion Method

Regresion filter to remove artifacts

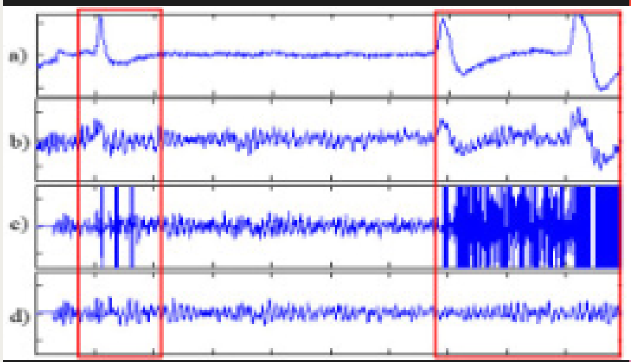
Reference channel (EOG) >>> Proportion of reference signals in a single channel

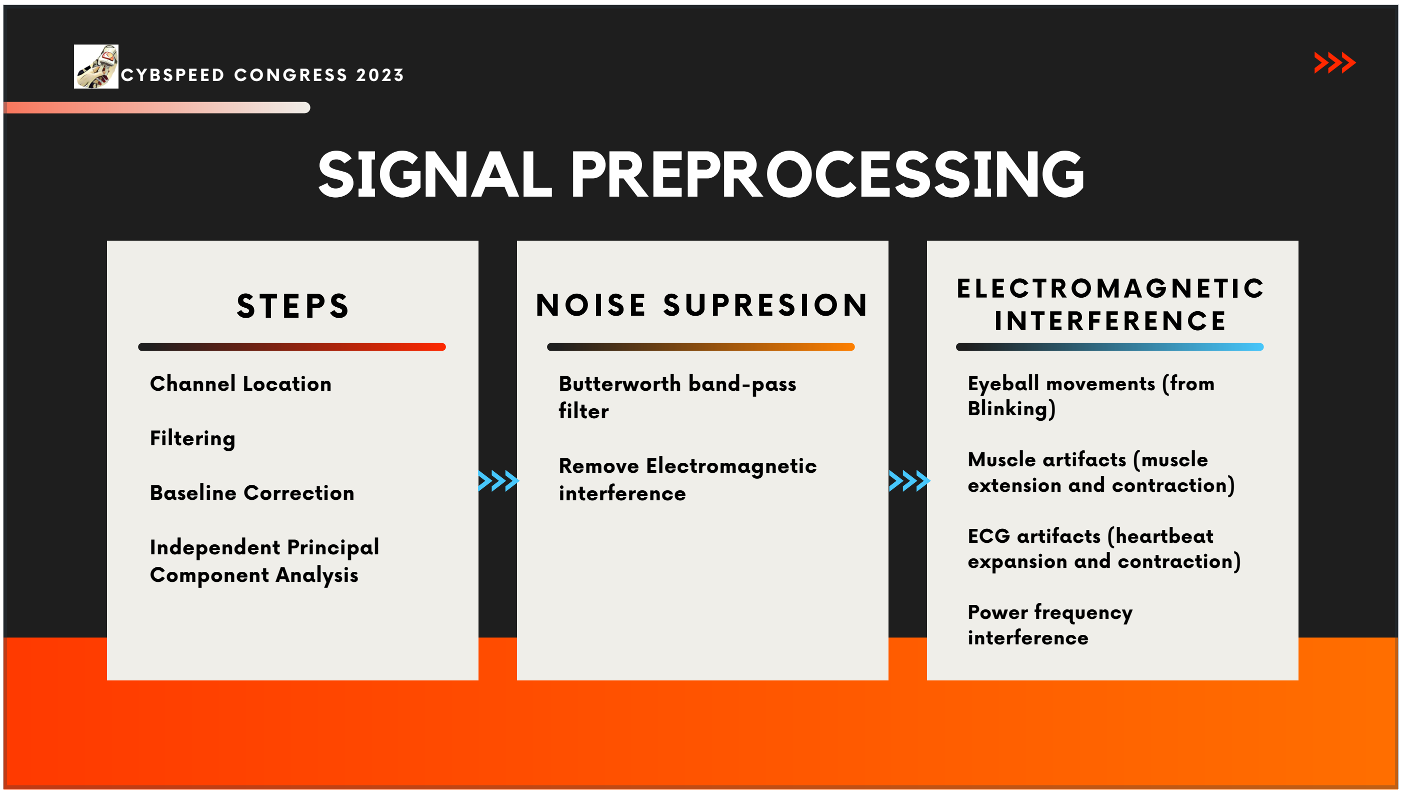


Adaptive Filtering Method

Recursive least-mean-square adaptive filtering to remove (EOG)

Effectively remove multiple EOG artifacts with stability and fast convergence

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SIGNAL PREPROCESSING
STEPS
Channel Location
Filtering
Baseline Correction
Independent Principal Component Analysis
NOISE SUPRESION
Butterworth band-pass filter
Remove Electromagnetic interference
ELECTROMAGNETIC INTERFERENCE
Eyeball movements (from Blinking)
Muscle artifacts (muscle extension and contraction)
ECG artifacts (heartbeat expansion and contraction)
Power frequency interference

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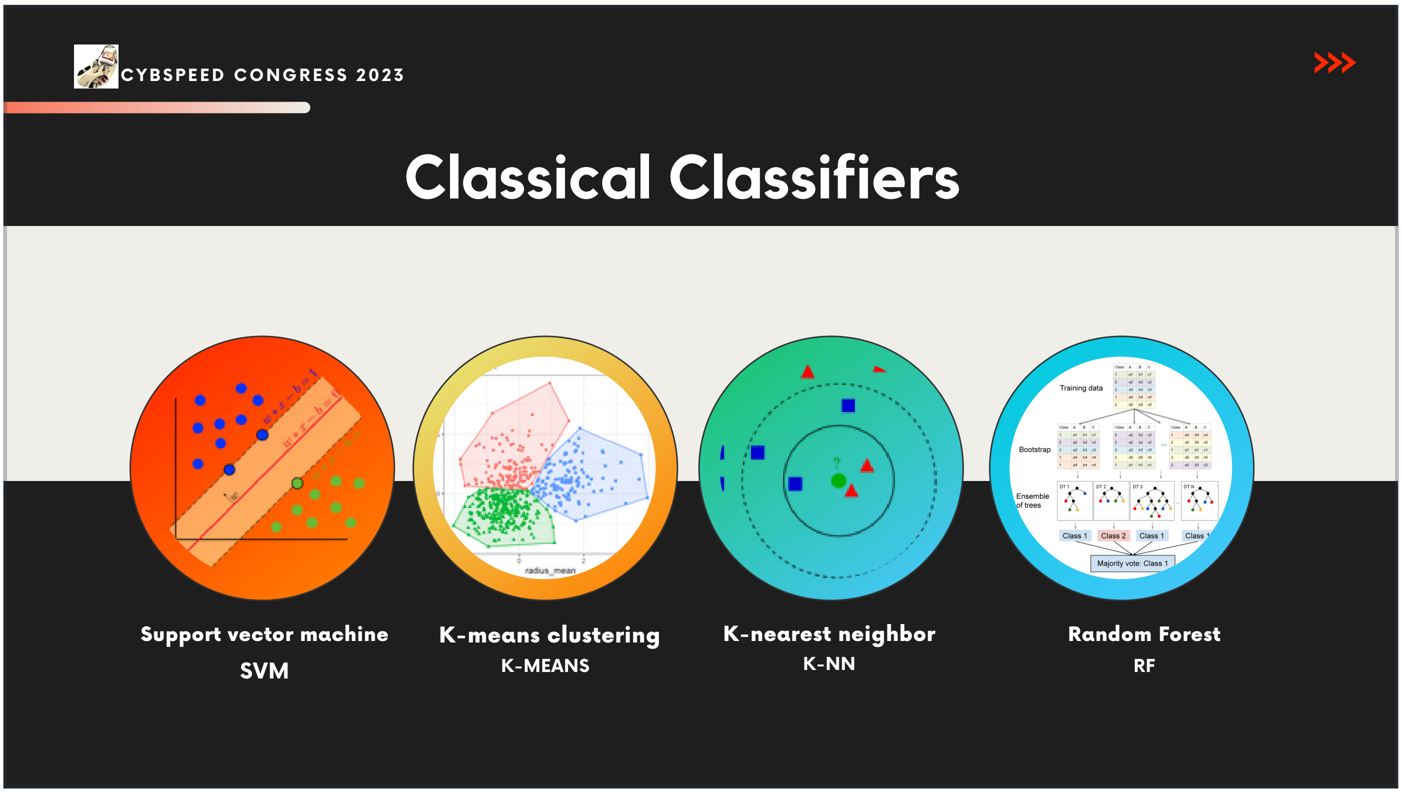
EEG SIGNAL CLASSIFICATION

Draw a boundary (Separated hyperplane in a multidimensional feature space) between two or more categories

Label the category based on the features it chooses

The better the classifier >>> the better the hyperplane, and the larger the distance from all the categories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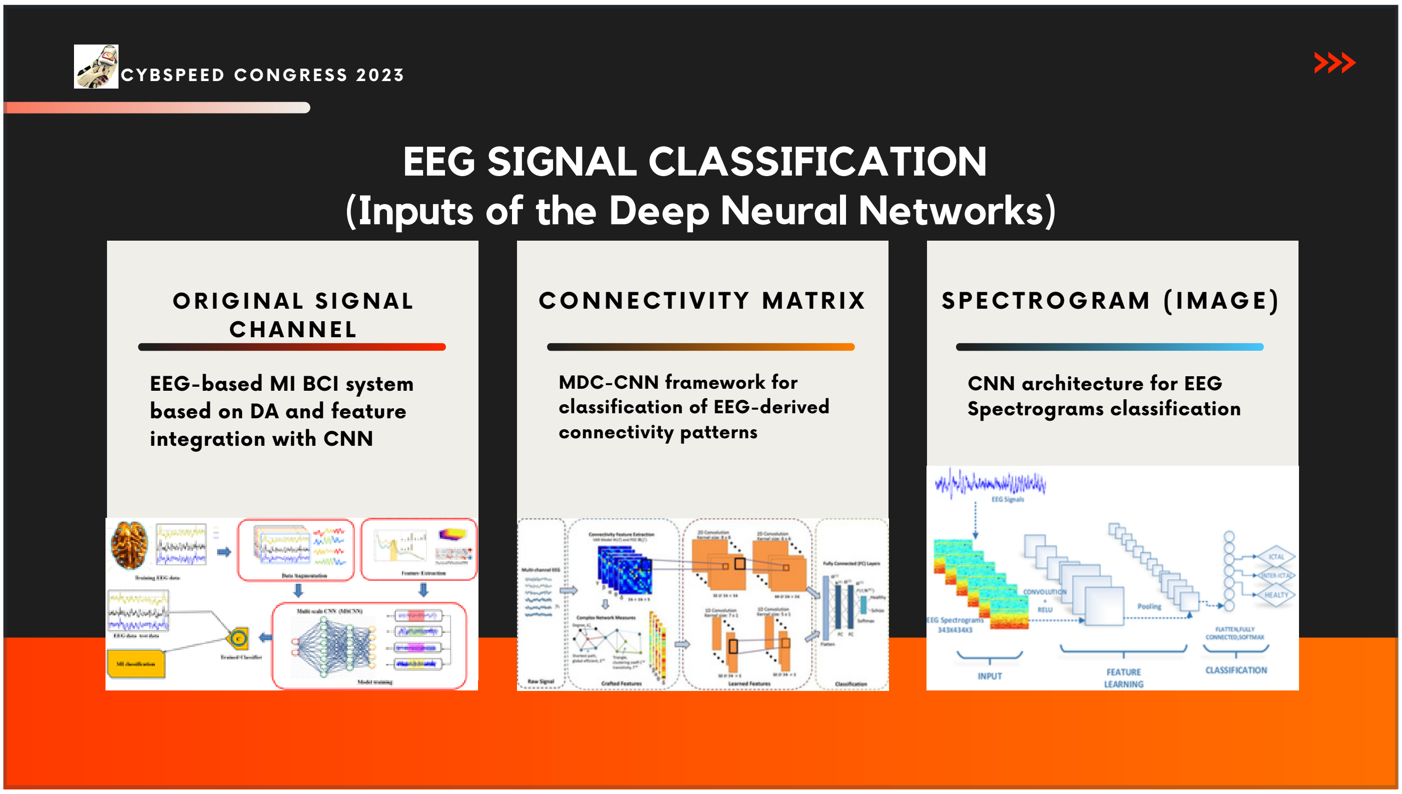
Classical Classifiers
Support vector machine
SVM
K-means clustering
K-MEANS
K-nearest neighbor
K-NN
Random Forest
RF



https://www.biorxiv.org/content/10.1101/2022.01.05.475058v2.full

https://www.researchgate.net/figure/Overview-of-the-proposed-MDC-CNN-framework-for-classification-of-EEG-derived-connectivity_fig1_335800970

https://www.researchgate.net/figure/CNN-architecture-for-EEG-spectrograms-classification_fig5_349336662

CLASSICAL NEURAL NETWORKS

Multi-Layer Perceptron
Fully Convolutional NN (CNN)
Echo-State Networks (based on Recurrent NNs)
Encoder
Multi-Scale Deep CNN
Time CNN

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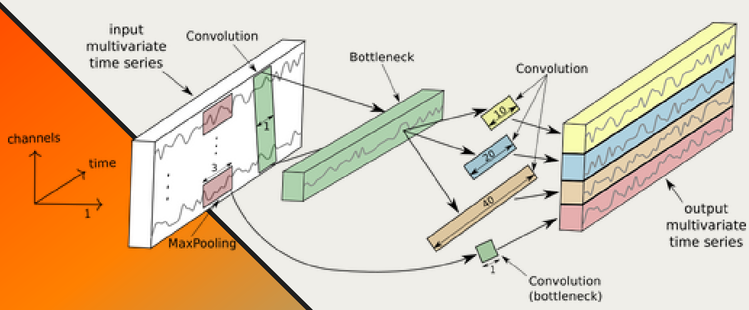
InceptionTime (2020)



Ensemble of five deep learning models, where each one is created by cascading inception modules first proposed by Szegedy et al.

These inception modules apply multiple filters of various lengths simultaneously to a time series while extracting relevant features and information from shorter, as well as longer, subsequences of the time series

It could consist of multiple inception modules stacked in a feedforward manner and additionally connected with residual connections

Finally, global average pooling combined with a simple fully connected NN produces the predictions

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EEG Emotion Recognition Using DynamicalGraph Convolutional Neural Networks

Journal: IEEE Transactions of affective computing

year of publication: September 2020

Authors: Tengfei Song, Wenming Zheng

Index terms: EEG emotion recognition, adjacency matrix, graph convolutional neural networks (GCNN), dynamical convolutional neuralnetworks (DGCNN)

EEG Emotion Recognition Using Dynamical Graph Convolutional Neural Networks

Tengfei Song, Wenming Zheng, Member, IEEE, Peng Song, Member, IEEE, and Zhen Cui

Abstract—In this paper, a multichannel EEG emotion recognition method based on a novel dynamical graph convolutional neural networks (DGCNN) is proposed. The basic idea of the proposed EEG emotion recognition method is to use a graph to model the multichannel EEG features and then perform EEG emotion classification based on this model. Different from the traditional graph convolutional neural networks (GCNN) methods, the proposed DGCNN method can dynamically learn the intrinsic relationship between different electroencephalogram (EEG) channels, represented by an adjacency matrix, via training a neural network so as to benefit for more discriminative EEG feature extraction. Then, the learned adjacency matrix is used to learn more discriminative features for improving the EEG emotion recognition. We conduct extensive experiments on the SJTU emotion EEG dataset (SEED) and DREAMER dataset. The experimental results demonstrate that the proposed method achieves better recognition performance than the state-of-the-art methods, in which the average recognition accuracy of 90.4 percent is achieved for subject dependent experiment while 79.95 percent for subject independent cross-validation one on the SEED database, and the average accuracies of 86.23, 84.54 and 85.02 percent are respectively obtained for valence, arousal and dominance classifications on the DREAMER database.

Index Terms—EEG emotion recognition, adjacency matrix, graph convolutional neural networks (GCNN), dynamical convolutional neural networks (DGCNN)

1 INTRODUCTION

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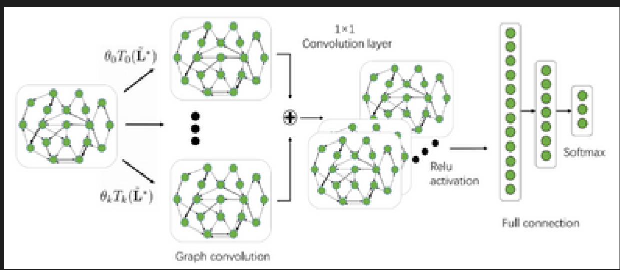
DGCNN Framework

Model for EEG emotion recognition, which consists of the dynamical graph convolutional operation via thelearned graph connections, convolution layer with11kernel, Relu activation and the full connection. The inputs of the model are the EEG featuresextracted from multiple frequency bands, e.g., five frequency bands (dband,uband,aband,bband, andgband), in which each EEG channel is rep-resented as a node of the graph. The outputs are the predicted labels through softmax



01 DREAMER DATABASE

EEG data via 14 EEG electrodes of 23 subjects (14 males and 9 females). To build this database, 18 film clips are used for eliciting 9 different emotions, i.e., amusement, excitement, happiness, calmness, anger, disgust, fear, sadness, and surprise. Each film clip lasts for a period time between 65 to 393s, which is thought to be sufficient for eliciting single emotions.

02 SEED DATABASE

EEG data of 15 subjects(7 males and 8 females) are collected via 62 EEG electrodes from the subjects when they watch fifteen Chinese film clips with three types of emotions, i.e., negative, positive, and neutral.

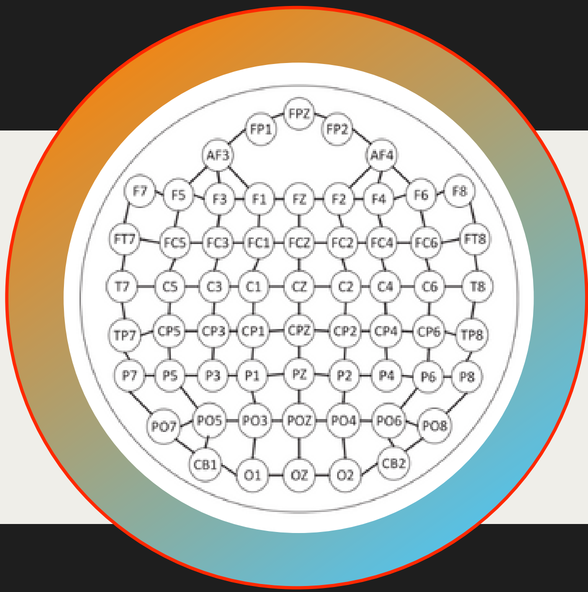
03 FEATURES EXTRACTED: SEED DATABASE

Number of the Five Types of EEG Features Extracted from Each Frequency Band on SEED Database

Feature type	Number of EEG features per sample				
	δ	θ	α	β	γ
PSD	62	62	62	62	62
DE	62	62	62	62	62
DASM	27	27	27	27	27
RASM	27	27	27	27	27
DCAU	23	23	23	23	23

DYNAMICAL GRAPH CONNECTIONS

Illustration of the connections among the 62 EEG channels, whichis used for constructing the adjacency matrix of GCNN.



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Algorithm for DGCNN

optimize the optimal network parameters, we adopt the back propagation (BP) method to iteratively update the network parameters until the optimal or suboptimal solutions are achieved. For this purpose, we define a loss function based on cross entropy cost, which is expressed as the following form:

$$Loss = cross\_entropy(\mathbf{l}, \mathbf{l}^{\mathbf{P}}) + \alpha\|\Theta\|,$$

Algorithm 1. Procedures of Training Optimal DGCNN Model for EEG Emotion Recognition

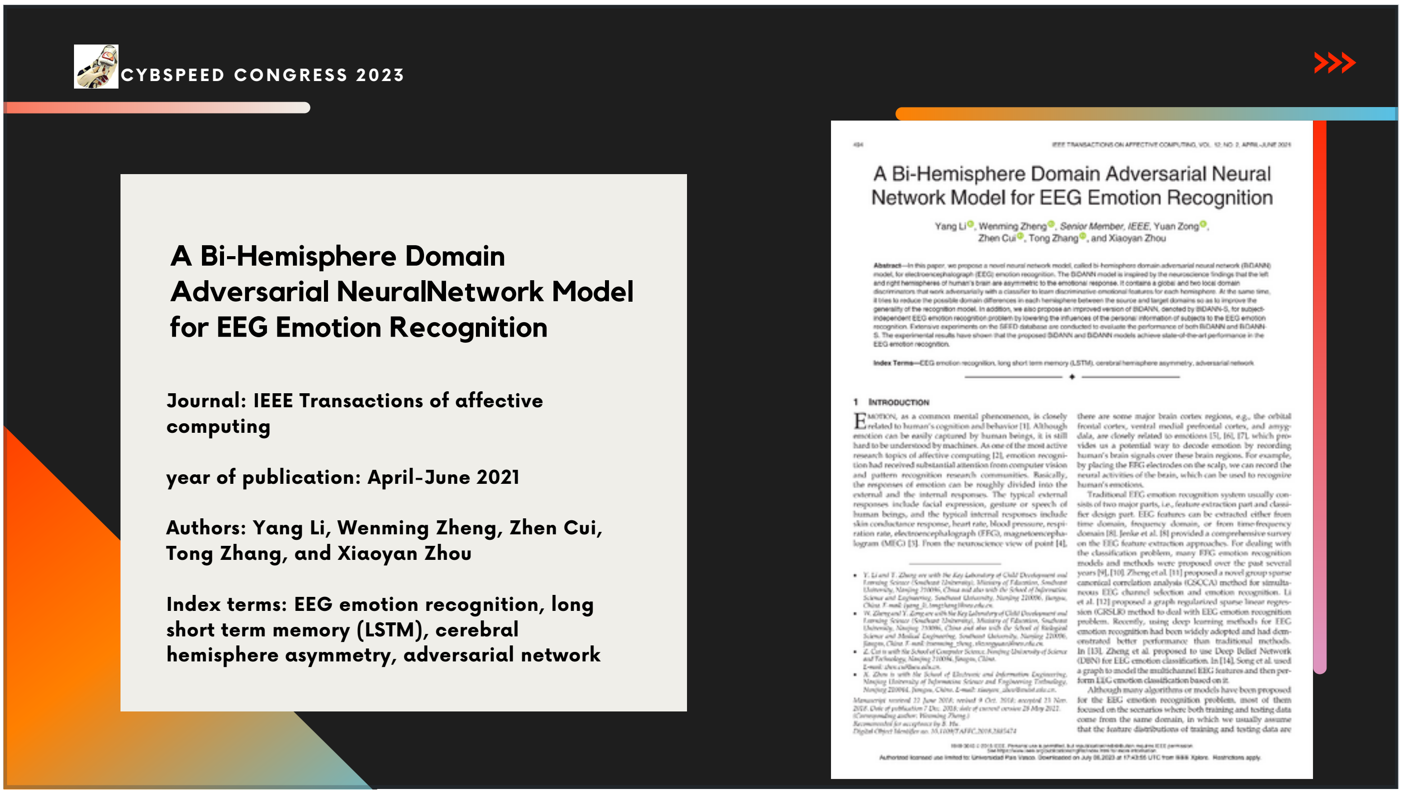
Require: Multichannel EEG features associated with multiple frequency bands, the class labels corresponding to the EEG features, the number of Chebyshev polynomial order K, the learning rate ρ;
Ensure: The desired adjacency matrix $\mathbf{W}^*$ and model parameters of DGCNN;
Initialize the adjacency matrix $\mathbf{W}^*$ and other model parameters;
repeat
    Regularizing the elements of the matrix $\mathbf{W}^*$ using Relu operation such that the elements are non-negative;
    Calculating the Laplacian matrix $\mathbf{L}^*$;
    Calculating the normalized Laplacian matrix $\tilde{\mathbf{L}}^*$;
    Calculating the Chebyshev polynomial items $T_k(\tilde{\mathbf{L}}^*)$ $(k = 0, 1, \ldots, K-1)$;
    Calculating $\sum_{k=0}^{K-1} \theta_k T_k(\tilde{\mathbf{L}}^*)\mathbf{x}$;
    Calculating the 1×1 convolution results and regularizing the results using the Relu operation;
    Calculating the results of the full connection layer;
    Calculating the loss function using (14);
    Updating the adjacency matrix

$$\mathbf{W}^* = (1-\rho)\mathbf{W}^* + \rho\frac{\partial Loss}{\partial \mathbf{W}^*}$$

    and other model parameters;
until the iterations satisfy the predefined algorithm convergence condition.

TABLE 2
Comparisons of the Average Accuracies and Standard Deviations (%) of Subject Dependent EEG-Based Emotion Recognition Experiments on SEED Database Among the Various Methods

Feature	Method	δ band	θ band	α band	β band	γ band	all ($\delta, \theta, \alpha, \beta, \gamma$)
DE	DBN [19]	64.32 / 12.45	60.77 / 10.42	64.01 / 15.97	78.92 / 12.48	79.19 / 14.58	86.08 / 8.34
	SVM [19]	60.50 / 14.14	60.95 / 10.20	66.64 / 14.41	80.76 /11.56	79.56 / 11.38	83.99 / 9.72
	GCNN	72.75 / 10.85	**74.40 / 8.23**	73.46 / 12.17	83.24 / 9.93	83.36 / 9.43	87.40 /9.20
	DGCNN	**74.25 / 11.42**	71.52 / 5.99	**74.43 / 12.16**	**83.65 / 10.17**	**85.73 / 10.64**	**90.40 / 8.49**
PSD	DBN [19]	60.05 / 16.66	55.03 / 13.88	52.79 / 15.38	60.68 / 21.31	63.42 / 19.66	61.90 / 16.65
	SVM [19]	58.03 / 15.39	57.26 / 15.09	59.04 / 15.75	73.34 /15.20	71.24 / 16.38	59.60 / 15.93
	GCNN	69.89 / 13.83	70.92 / 9.18	73.18 / 12.74	76.21 / 10.76	76.15 / 10.09	81.31 / 11.26
	DGCNN	**71.23 / 11.42**	**71.20 / 8.99**	**73.45 / 12.25**	**77.45 / 10.81**	**76.60 / 11.83**	**81.73 / 9.94**
DASM	DBN [19]	48.79 / 9.62	51.59 / 13.98	54.03 / 17.05	69.51 / 15.22	70.06 / 18.14	72.73 / 15.93
	SVM [19]	48.87 / 10.49	53.02 / 12.76	59.81 / 14.67	**75.03 / 15.72**	**73.59/16.57**	72.81 / 16.57
	GCNN	**57.07 / 6.75**	54.80 / 9.09	62.97 / 13.43	74.97 / 13.40	73.28 / 13.67	76.00 / 13.32
	DGCNN	55.93 / 9.14	**56.12 / 7.86**	**64.27 / 12.72**	73.61 / 14.35	73.50 / 16.6	**78.45 / 11.84**
RASM	DBN [19]	48.05 / 10.37	50.62 / 14.02	56.15 / 15.28	70.31 / 15.62	68.22 / 18.09	71.30 / 16.16
	SVM [19]	47.75 / 10.59	51.40 / 12.53	60.71 / 14.57	74.59 /16.18	74.61 / 15.57	74.74 / 14.79
	GCNN	**59.70 / 5.65**	**55.91 / 8.82**	59.97 / 14.27	**79.45 / 13.32**	79.73 / 13.22	84.06 / 12.86
	DGCNN	57.79 / 6.90	55.79 / 8.10	**61.58 / 12.63**	75.79 / 13.07	**82.32 / 11.54**	**85.00 / 12.47**
DCAU	DBN [19]	54.58 / 12.81	56.94 / 12.54	57.62 / 13.58	70.70 / 16.33	72.27 / 16.12	77.20 / 14.24
	SVM [19]	55.92 / 14.62	57.16 / 10.77	61.37 / 15.97	75.17 / 15.58	76.44 / 15.41	77.38 / 11.98
	GCNN	62.60 / 12.88	**65.05 / 8.35**	66.41 / 11.06	77.28 / 11.55	78.68 / 13.00	79.02 / 11.27
	DGCNN	**63.18 / 13.48**	62.55 / 7.96	**67.71 / 10.74**	**78.68 / 10.81**	**80.05 / 13.03**	**81.91 / 10.06**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A Bi-Hemisphere Domain Adversarial NeuralNetwork Model for EEG Emotion Recognition
Journal: IEEE Transactions of affective computing
year of publication: April-June 2021
Authors: Yang Li, Wenming Zheng, Zhen Cui, Tong Zhang, and Xiaoyan Zhou
Index terms: EEG emotion recognition, long short term memory (LSTM), cerebral hemisphere asymmetry, adversarial network
A Bi-Hemisphere Domain Adversarial Neural Network Model for EEG Emotion Recognition
Yang Li, Wenming Zheng, Senior Member, IEEE, Yuan Zong, Zhen Cui, Tong Zhang, and Xiaoyan Zhou
1 INTRODUCTION

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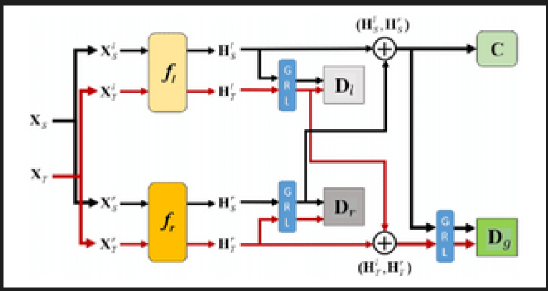
BiDANN Framework

The target of BiDANN is to alleviate the possible feature distribution difference between source and target domains, either in each hemisphere or the whole brain cortex area. To achieve this goal, we borrow the basic idea of the DANNmethod by leveraging the adversarial operation between the source and the target domains into the discriminative EEG feature learning module and also make use of the neuroscience findings that the left and right hemispheres of the human brain are asymmetric to the emotional response to further enhance the discriminative ability of the EEG features



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02 SEED DATABASE

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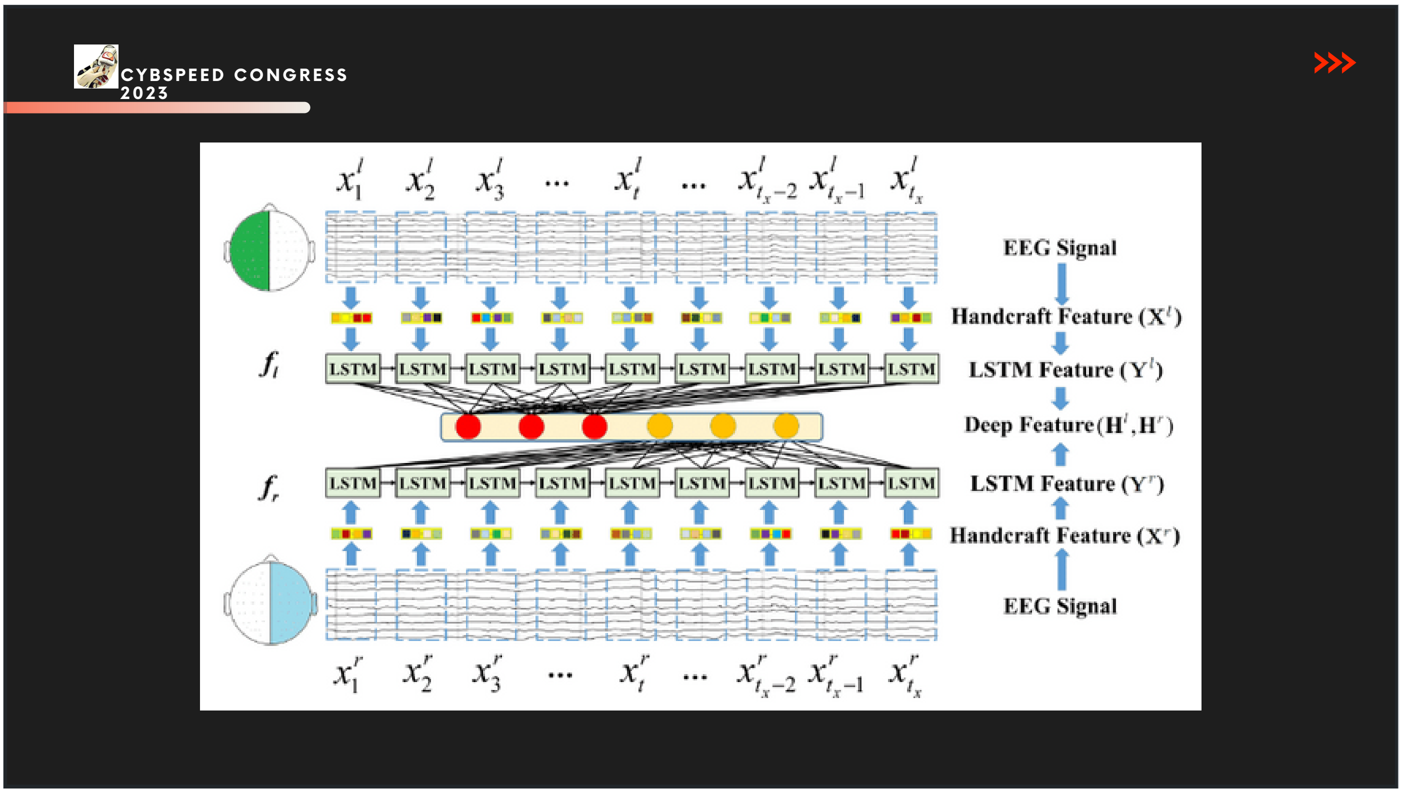
03 FEATURES EXTRACTED: SEED DATABASE

Extract more discriminativefeatures from handcraft EEG features to improve theEEG classification performance. The whole feature extraction, which consists of thehandcraft EEG feature extraction part and the discriminativedeep feature learning part.



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EEG Signal
Handcraft Feature (X^l)
LSTM Feature (Y^l)
Deep Feature (H^l, H^r)
LSTM Feature (Y^r)
Handcraft Feature (X^r)
EEG Signal
LSTM

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Algorithm for BiDANN

We can iteratively train the classifier and three discrimina-tors and update the parameters with the similar approach ofstandard deep learning methods by chain rule. Specifically,to solve the optimal solution of BiDANN, we adopt thestochastic gradient descent (SGD) algorithm [35] to find opti-mal model parameters (ulf,urf,uc)

$$(\hat{\theta}_f^l, \hat{\theta}_f^r, \hat{\theta}_c) = \arg \min_{\theta_f^l, \theta_f^r, \theta_c} L(\mathbf{X}_{S,T}; (\theta_f^l, \theta_f^r, \theta_c), \hat{\theta}_d^g, \hat{\theta}_d^l, \hat{\theta}_d^r).$$

Algorithm 1. Procedures of Training BiDANN Model

Input: Source data set $\{\mathbf{X}_S\}$ and Target data set $\{\mathbf{X}_T\}$;
Ground-truth label set $\mathbf{L}_S = \{y\}$ of source data set;
Source domain label set $\mathcal{D}_S = [\mathcal{D}_S^l, \mathcal{D}_S^r] = \{0\}$ and target domain label set $\mathcal{D}_T = [\mathcal{D}_T^l, \mathcal{D}_T^r] = \{1\}$;

1: Initialize model parameters and learning rate α;
2: **repeat**
3: Update the parameters of the classifier:
$\theta_c \leftarrow \theta_c - \alpha \frac{\partial L_c}{\partial \theta_c}$, $\theta_f^l \leftarrow \theta_f^l - \alpha \frac{\partial L_c}{\partial \theta_f^l}$, and
$\theta_f^r \leftarrow \theta_f^r - \alpha \frac{\partial L_c}{\partial \theta_f^r}$;
4: Update the parameters of the global discriminator:
$\theta_d^g \leftarrow \theta_d^g - \alpha \frac{\partial L_d^g}{\partial \theta_d^g}$, $\theta_f^l \leftarrow \theta_f^l + \alpha \frac{\partial L_d^g}{\partial \theta_f^l}$, and
$\theta_f^r \leftarrow \theta_f^r + \alpha \frac{\partial L_d^g}{\partial \theta_f^r}$;
5: Update the parameters of the local discriminator corresponding to the left hemisphere:
$\theta_d^l \leftarrow \theta_d^l - \alpha \frac{\partial L_d^l}{\partial \theta_d^l}$, $\theta_f^l \leftarrow \theta_f^l + \alpha \frac{\partial L_d^l}{\partial \theta_f^l}$;
6: Update the parameters of the local discriminator corresponding to the right hemisphere:
$\theta_d^r \leftarrow \theta_d^r - \alpha \frac{\partial L_d^r}{\partial \theta_d^r}$, $\theta_f^r \leftarrow \theta_f^r + \alpha \frac{\partial L_d^r}{\partial \theta_f^r}$;
7: If the model has been trained for 100 epochs, then $\alpha \leftarrow 0.9 \times \alpha$ and goto step 3;
8: **until** The iterations satisfies the predefined condition, i.e., the loss function satisfies:

$$L(\theta_f^l, \theta_f^r, \theta_c, \theta_d^l, \theta_d^r, \theta_d^g) < 10^{-3}.$$

Output:
9: Parameters: $\hat{\theta}_f^l, \hat{\theta}_f^r, \hat{\theta}_c, \hat{\theta}_d^l, \hat{\theta}_d^r, \hat{\theta}_d^g$.

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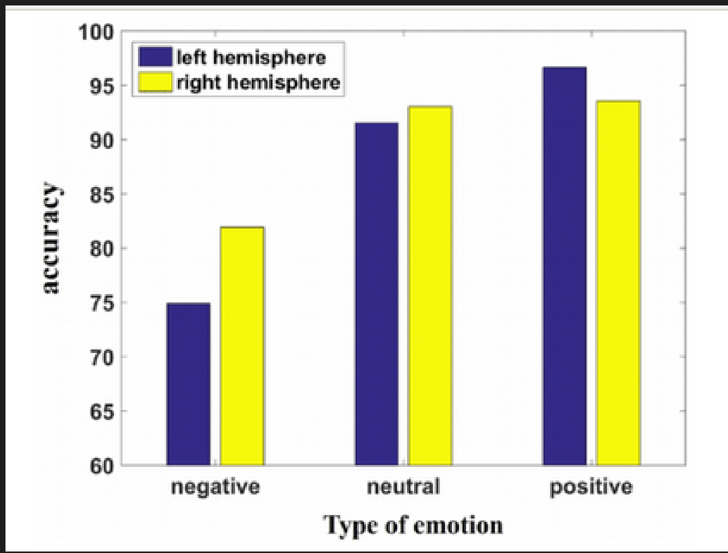
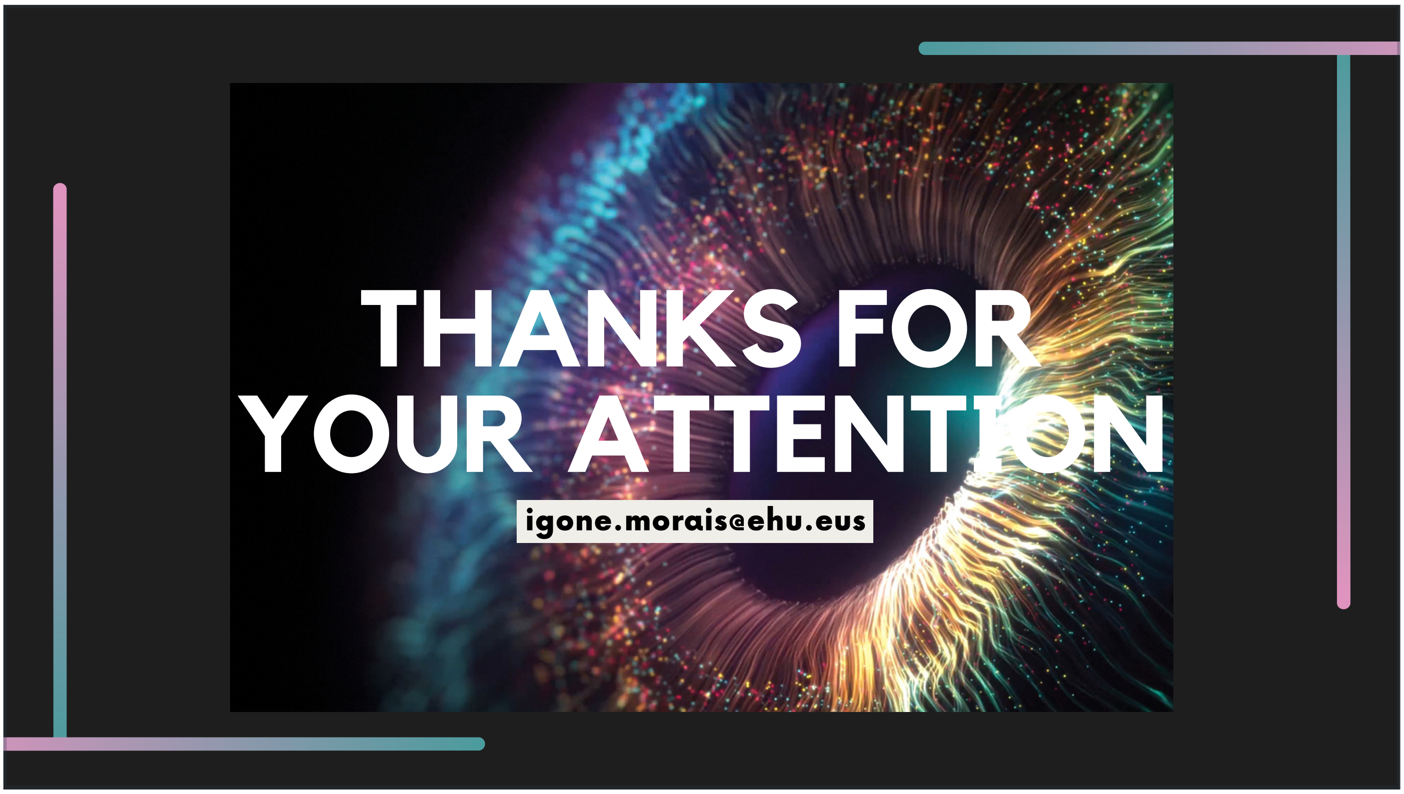
TABLE 3
The Mean Accuracies (and Standard Deviations) Using Different Frequency Bands for Subject-Dependent EEG Emotion Recognition Experiment on SEED Database

Methods	Frequency bands				
	δ	θ	α	β	γ
SVM [37]	60.50 (14.14)	60.95 (10.20)	66.64 (14.41)	80.76 (11.56)	79.56 (11.38)
RF* [38]	64.56 (08.32)	65.27 (11.64)	65.67 (13.94)	73.35 (14.35)	74.48 (12.80)
CCA* [39]	55.30 (12.02)	55.75 (10.99)	64.96 (12.05)	69.16 (11.45)	70.67 (14.06)
GSCCA* [11]	63.92 (11.16)	64.64 (10.33)	70.10 (14.76)	76.93 (11.00)	77.98 (10.72)
DBN [13]	64.32 (12.45)	60.77 (10.42)	64.01 (15.97)	78.92 (12.48)	79.19 (14.58)
GRSLR* [12]	63.90 (11.83)	62.61 (10.73)	71.11 (09.04)	81.18 (10.74)	81.91 (10.36)
GCNN [40]	72.75 (10.85)	74.40 (08.23)	73.46 (12.17)	83.24 (09.93)	83.36 (09.43)
DGCNN [14]	74.25 (11.42)	71.52 (05.99)	74.43 (12.16)	83.65 (10.17)	85.73 (10.64)
DANN* [17]	72.13 (11.22)	68.75 (07.40)	70.27 (10.84)	83.35 (11.46)	87.89 (11.35)
BiDANN-R1	71.63 (10.69)	66.79 (08.96)	67.71 (12.49)	85.68 (10.13)	86.93 (09.56)
BiDANN-R2	75.26 (10.95)	71.20 (07.73)	75.40 (14.26)	87.73 (10.58)	86.80 (10.78)
BiDANN	**76.97 (10.95)**	**75.56 (07.88)**	**81.03 (11.74)**	**89.65 (09.59)**	**88.64 (09.46)**

* *Denotes the experiment results obtained are based on our own implementation.*




THANKS FOR
YOUR ATTENTION
igone.morais@ehu.eus