DIPARTIMENTO DI
INFORMATICA, SISTEMISTICA E
COMUNICAZIONE

A Flexible Pipeline for Electroencephalographic Signal Processing and Management

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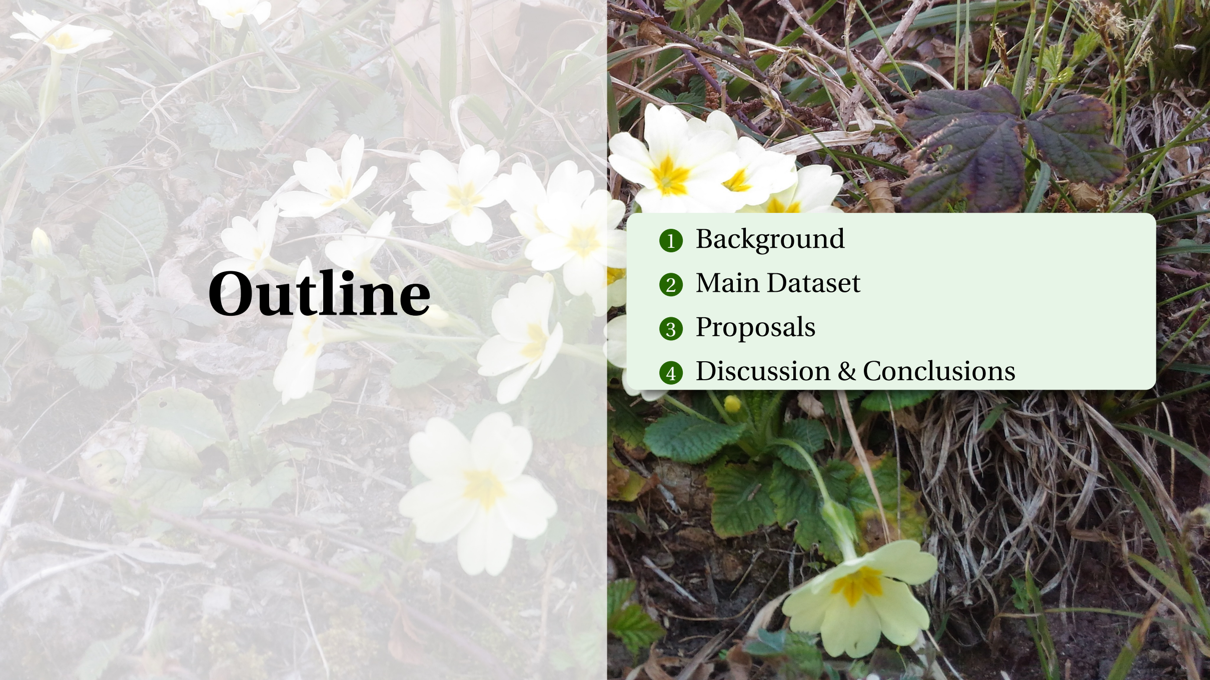
February 9, 2022

Outline

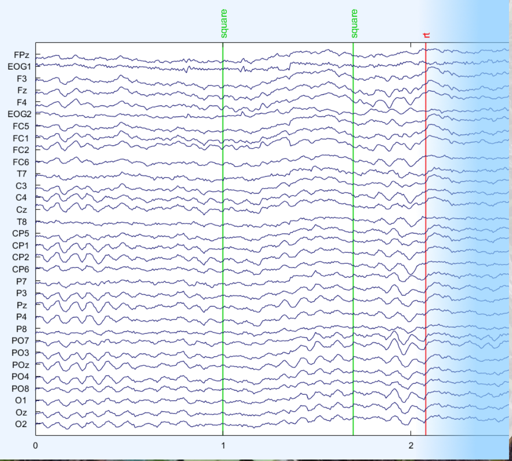
1. Background
2. Main Dataset
3. Proposals
4. Discussion & Conclusions



1. Background

A Flexible Pipeline for Electroencephalographic Signal Processing and Management

- **Electroencephalography** → recording & interpretation of the neural signal
- **Electroencephalogram** → records the brain electric potentials → **electroencephalographic (EEG) signals**



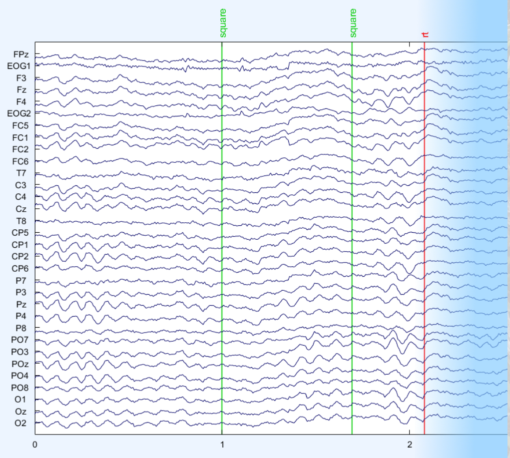
Electroencephalographic (EEG) signal [2/3]

1. Characteristics

- Time-series

2. Advantages [1, 2, 3, 4, 5]

- High time resolution



Electroencephalographic (EEG) signal [2/3]

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- Relative low-cost
- Wearable devices
- Non-intrusive

Electroencephalographic (EEG) signal [2/3]

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- Spatial resolution

Electroencephalographic (EEG) signal [2/3]

1. Characteristics

- Time-series
- Electrodes/channels
- Frequency bands → **rhythms**

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- High time resolution
- Relative low-cost
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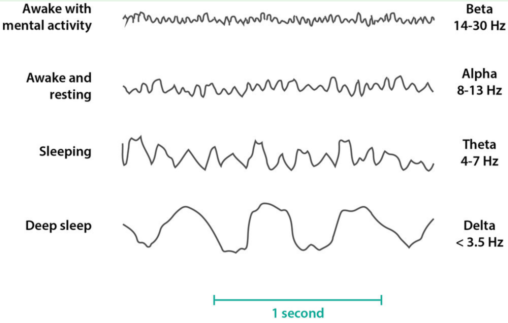
- Spatial resolution
- Intrinsic characteristics



Original pic from:
https://www.firstclassmed.com/articles/2017/eeg-waves

Electroencephalographic (EEG) signal [3/3]

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Awesome, but ...

Electroencephalographic (EEG) signal [3/3]

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- Spatial resolution
- Intrinsic characteristics

3. Issues [6, 7, 8]

- Noise → low signal-to-noise ratio (SNR)
- Heterogeneous
  - Non-stationary
  - Subject specific
  - Varying in a same subject
  - Influenced by protocols and environments
- Data dimensionality

Electroencephalographic (EEG) signal [3/3]

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Open challenges

Open challenges [1/2]

A Flexible Pipeline for Electroencephalographic Signal Processing and Management

Categories

1. **Signal pre-processing** → extraction of neural signal + data dimensionality issue
2. **Normalization** → data heterogeneity
3. **Feature computation and management** → feature types and their selection
4. **Classification** → brain states

Open challenges [1/2]

A Flexible Pipeline for Electroencephalographic Signal Processing and Management

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1. **Signal pre-processing** $\rightarrow$ extraction of neural signal + data dimensionality issue
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3. **Feature computation and management** $\rightarrow$ feature types and their selection
4. **Classification** $\rightarrow$ brain states

Lack of Standards [6, 9]

Open challenges [2/2]

Solve issues + better EEG understanding + application?

Open challenges [2/2]

A Flexible Pipeline for Electroencephalographic Signal Processing and Management

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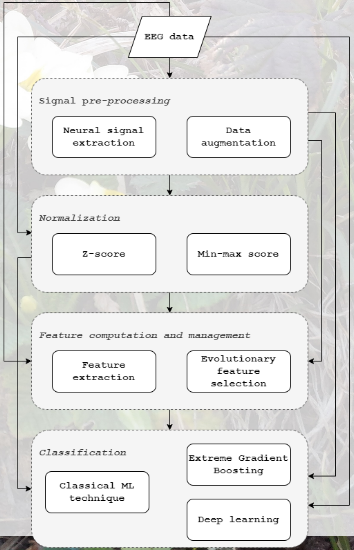
1. Signal pre-processing
2. Normalization
3. Feature computation and management
4. Classification



Open challenges [2/2]

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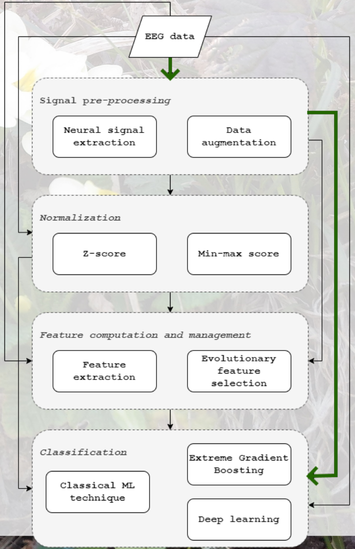

Open challenges [2/2]

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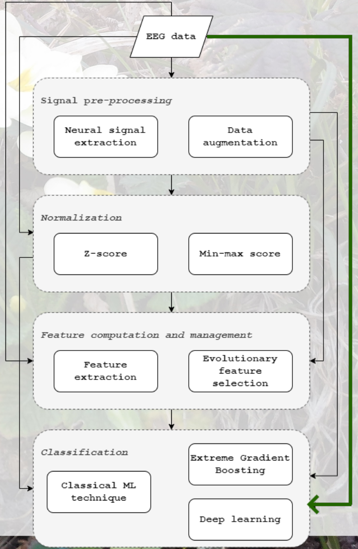

Open challenges [2/2]

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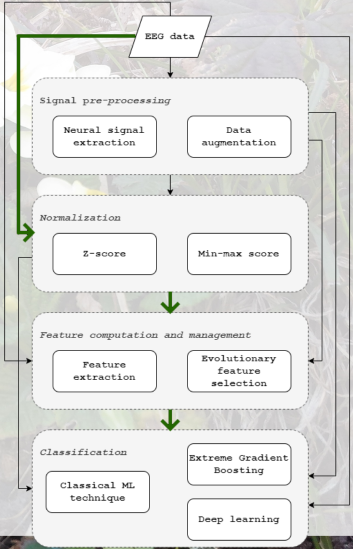

Open challenges [2/2]

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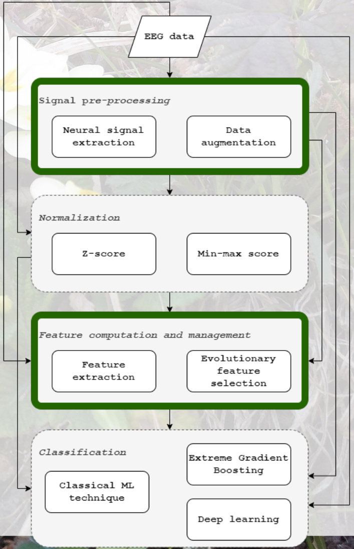
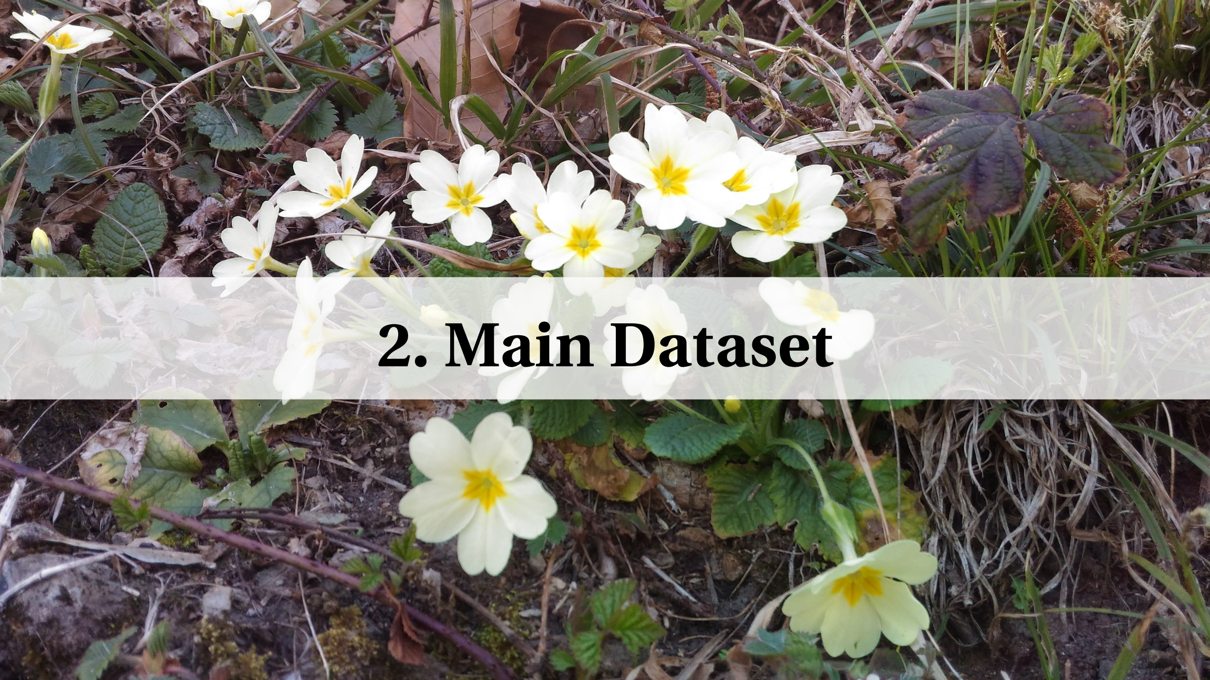


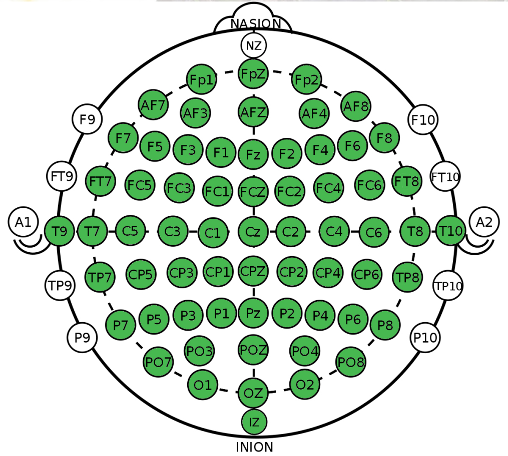
2. Main Dataset



EEG Motor Movement/Imagery Dataset

Why?

- Case study: motor related experiment

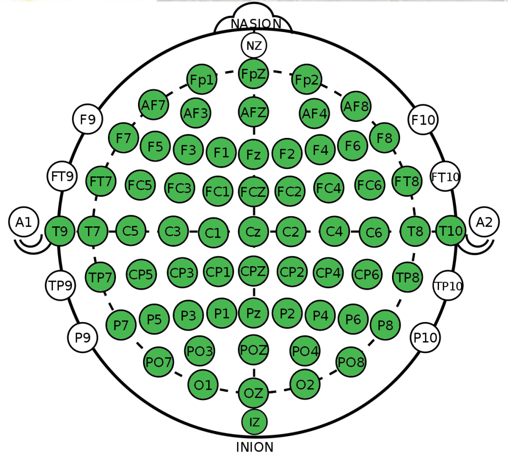


1. Main Dataset [1/2]

EEG Motor Movement/Imagery Dataset

Why?

- Case study: motor related experiment
- Brain computer interfacing & rehabilitation

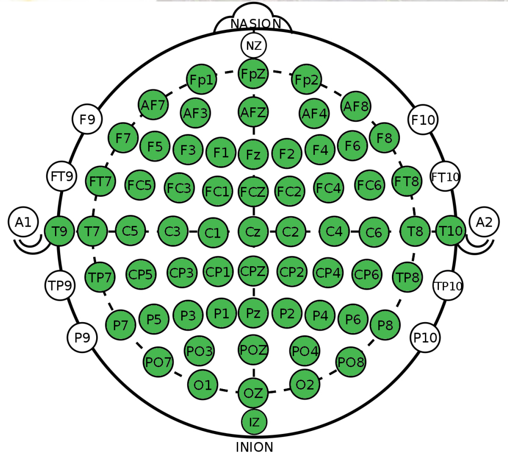


1. Main Dataset [1/2]

EEG Motor Movement/Imagery Dataset

Why?

- Case study: motor related experiment
- Brain computer interfacing & rehabilitation
- Peculiar characteristics:
  - Central cortical area
  - Rhythms $\rightarrow \alpha$ and β
  - Good motor imagery performer $\rightarrow$ 70% task accuracy [8]

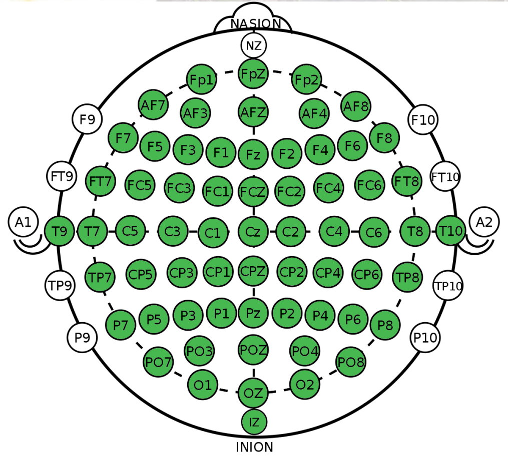


1. Main Dataset [2/2]

EEG Motor Movement/Imagery Dataset

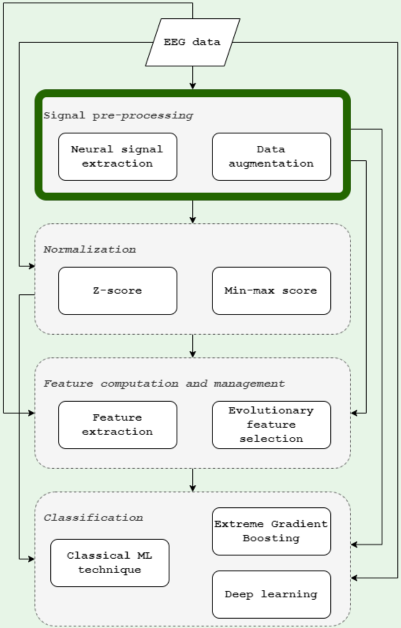
Characteristics

- Available at `https://physionet.org/content/eegmmidb/1.0.0/`
- 109 subjects - 3 (technical issues)
- left/right hand (LH, RH) motor movement (MM) and imagination (MI), eyes closed (CLOSE)
- Instances:
  - MM: 4924 (2469 LH)
  - MI: 4915 (2479 LH)
  - CLOSE: 106



3. Proposals

3.1 Signal Pre-processing



3.1 Signal Pre-processing

Literature

Literature

- Noise removal
- Independent component analysis [10] $\rightarrow$ requires stationary signals, multi-channel
- Discrete wavelet transform [11] $\rightarrow$ spectral properties overlapping, multi-source
- Loss of actual neural signal

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Starting point

- 6 months period abroad at Digital Signal Processing laboratory, Universitat de Vic (Supervisor Jordi Solé-Casals)
- *Dinarès-Ferran et al.* [12]
- Empirical Mode Decomposition (EMD) [13] $\rightarrow$ oscillatory modes = Intrinsic Mode Functions (IMFs)
- Recombine IMFs $\rightarrow$ artificial trials

Proposal

- Change of perspective → find actual neural signal
- EMD → Multivariate Empirical Mode Decomposition (MEMD) [14]
- Intrinsic Mode Functions (IMFs) → most relevant?

3.4 Signal pre-processing

Changing Perspective

Proposal

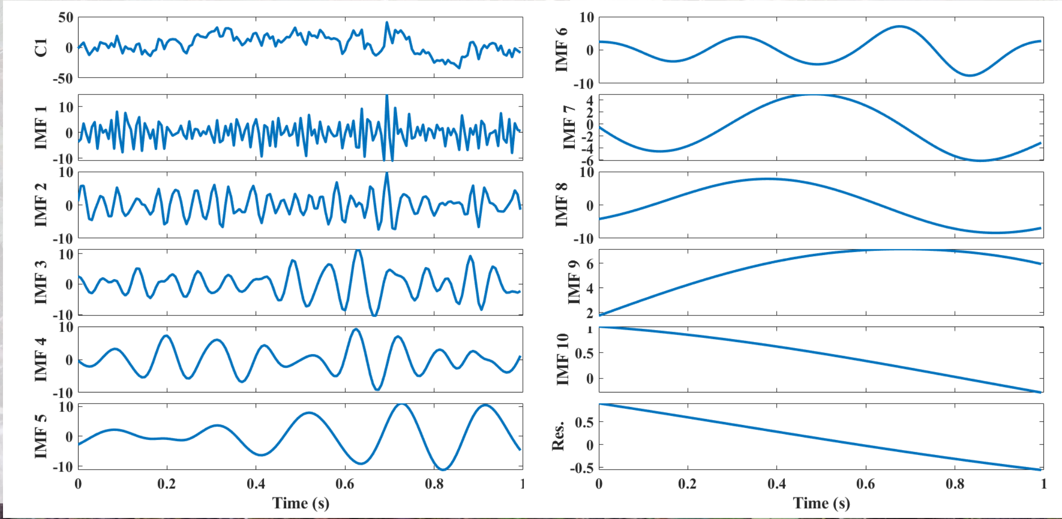
- Change of perspective → find actual neural signal
- EMD → Multivariate Empirical Mode Decomposition (MEMD) [14]
- Intrinsic Mode Functions (IMFs) → most relevant?

Research questions

1. How does the selection of relevant oscillatory modes of the EEG signals affect the neural dynamics of these data as well as their analyses?
2. What is the impact of the recombination of relevant IMFs extracted from different experimental trials, i.e., recording blocks, on physiological signals?

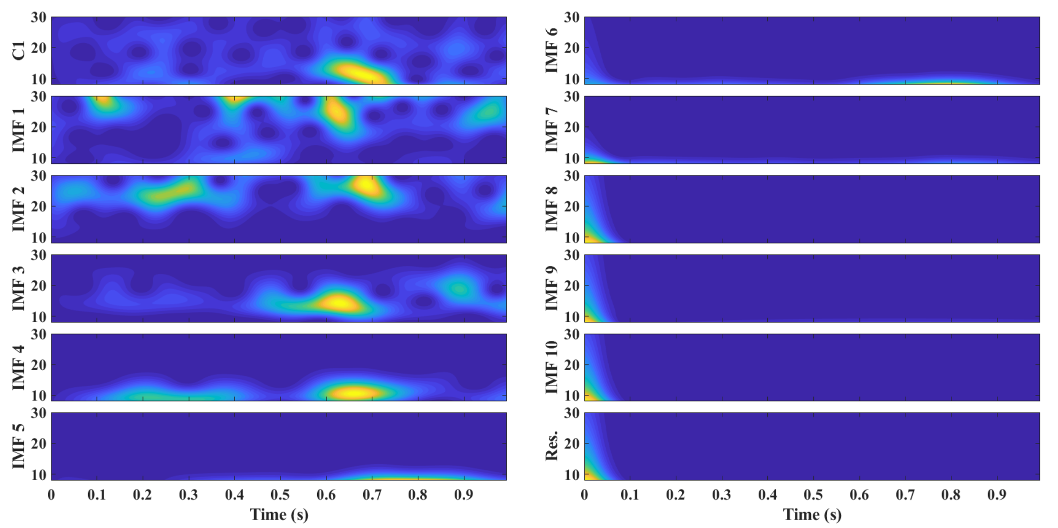
3.1 Signal Pre-processing

Multivariate Empirical Mode Decomposition



3.1 Signal Pre-processing

Multivariate Empirical Mode Decomposition



3.1. Signal Pre-processing

Relevance & Recombination

Relevance

- Entropy $\rightarrow$ selection criterion
- Reliability of signal reconstruction using only the relevant IMFs
  - Simulated dataset [15]
  - Pearson correlation coefficient
  - Signal similarity
- Maintains brain dynamics

3.1. Signal Pre-processing

Relevance & Recombination

Relevance

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Recombination

- *Dinarés-Ferran et al.* $\rightarrow$ recombine IMFs $\rightarrow$ artificial trials
- Trial substitution
- Relevant IMFs
- Tested on the same dataset
- Coherence $\rightarrow$ double median absolute deviation

3.1 Signal Pre-processing

Data Augmentation [1/2]

Steps

1. Original data: 45 LH and RH MI per subject
2. Bandpass (0.5 - 100 Hz) and notch (50 Hz) filtering
3. MEMD for each subject and trial
4. Time-frequency images in the 8 - 30 Hz range (α and β)
5. 100 combinations for data augmentation with different percentages

Classification

1. Subject-based (24)
2. Electrodes: C{1,2,3,4,z}
3. Rhythms: α and β
4. Power Spectral Density (PSD) $\rightarrow$ Morlet wavelet convolution
5. Total features: 10

3.1 Signal Pre-processing

Data Augmentation [2/2]

	Number of trials per condition																	
	0		*0 - rec*		*3*		*6*		*9*		*12*		*15*		*18*		*21*	
Subject	*RH*	*LH*	*RH*	*LH*	*RH*	*LH*	*RH*	*LH*	*RH*	*LH*	*RH*	*LH*	*RH*	*LH*	*RH*	*LH*	*RH*	*LH*
S001	34.09	47.83	31.82	47.83	32.00	46.15	32.14	44.83	29.03	43.75	26.47	42.86	24.32	42.11	25.00	41.46	23.26	40.91
S002	36.36	30.43	36.36	32.61	36.00	30.77	35.71	31.03	35.48	31.25	35.29	31.43	35.14	28.95	32.50	26.83	30.23	27.27
S004	27.27	26.09	27.27	26.09	24.00	23.08	21.43	20.69	19.35	21.88	17.65	20.00	16.22	19.74	15.00	19.51	13.95	18.18
S007	18.18	13.04	18.18	13.04	16.00	11.54	14.29	8.62	16.13	6.25	11.76	5.71	13.51	5.26	12.50	4.88	11.63	6.82
S010	38.10	20.83	38.10	20.83	35.42	18.52	37.04	16.67	30.00	18.18	30.30	16.67	30.56	15.38	28.21	14.29	28.57	14.44
S011	45.45	39.13	43.18	39.13	44.00	38.46	42.86	37.93	41.94	37.50	41.18	37.14	37.84	34.21	40.00	36.59	37.21	34.09
S012	29.17	42.86	31.25	42.86	31.48	39.58	31.67	37.04	30.30	35.00	27.78	33.33	28.21	33.33	26.19	30.77	24.44	30.95
S013	31.82	26.09	31.82	26.09	32.00	26.92	28.57	24.14	25.81	25.00	26.47	21.43	24.32	21.05	25.00	21.95	23.26	20.45

Error rate $\rightarrow$ the percentage of predicted values that have been wrongly classified for each class
Bold subjects $\rightarrow$ good MI performers

Research questions

1. How does the selection of relevant oscillatory modes of the EEG signals affect the neural dynamics of these data as well as their analyses?
2. What is the impact of the recombination of relevant IMFs extracted from different experimental trials, i.e., recording blocks, on physiological signals?

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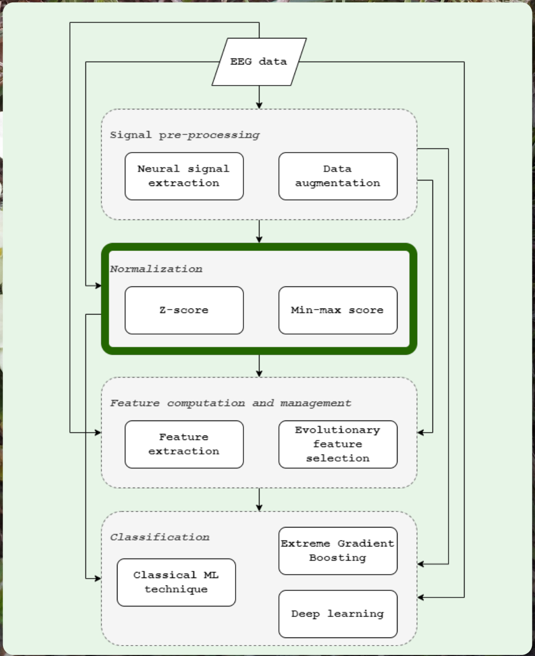
Future works

- Test on other paradigms
- Detect noisy/faulty trials
- On-line procedure

3.2 Normalization



3.2 Normalization

At a glance

Literature [16, 17, 18]

- Little to no information
- Lack of standard procedures
- Subject-based analyses

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Research question

1. What is the impact of the application of normalization strategies on EEG data?

Proposal

- Mitigate heterogeneity
- Min-max and Z-score normalization

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At a glance

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Research question

1. What is the impact of the application of normalization strategies on EEG data?

Proposal

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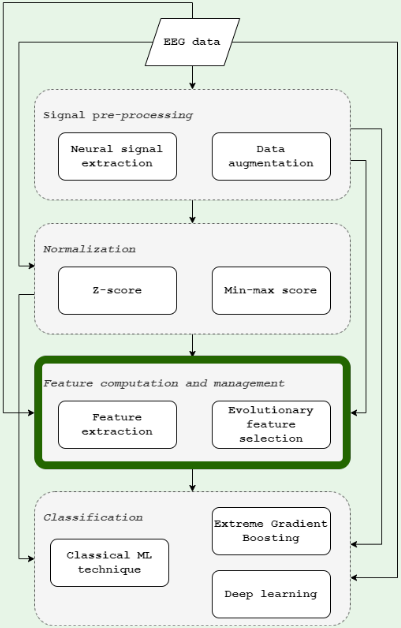
Preliminary results

- Intra-subject heterogeneity
- Inter-subject heterogeneity
- Best: Z-score

3.3 Feature Computation and Management



Literature

- A priori selection
- Principal Component Analysis (PCA) [19]
- Evolutionary Feature Selection (EFS) [20]
  - Supervised
  - External measures

3.3 Feature Computation and Management

Changing Perspective

Proposal

- Feature variety
- Relevant features
- Evolutionary Feature Selection (EFS): Particle Swarm Optimization (PSO), Genetic Algorithm (GA), Simulated Annealing (SA)
- Modified GA
- Novel stopping criteria and fitness functions

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Research questions

1. What effect does a variety of feature types present in the characterization of the EEG signals?
2. How do evolutionary algorithms provide a data-driven feature selection?
3. When conducting the evolutionary feature selection optimization problem, what is the effect of using both supervised and unsupervised learning strategies and a set of stopping criteria?

3.3 Feature Computation and Management

Contributions

Proposals	EFS comparison [21]	GA heterogeneous [22]
Heterogeneous feature set	Time, frequency, time-frequency domain, statistical measures	Time, frequency, time-frequency domain
Feature selection	PSO, GA, SA	GA
Learning model	SVM	SVM, K-means
Fitness functions	accuracy, number of features	accuracy, silhouette, number of features
Stopping criteria	Number of generations	Number of generations, maximum time, performance
Normalization	Min-max, Z-score	Z-score
Datasets	Motor movement/imagery	Motor movement, cognitive workload, mix

Evidences

- Efficacy of a variety of features (1280) computed on each channel (64)

Domain	**Features**
Time	Hjorth activity, mobility and complexity parameters
Frequency	Power Spectral Density (PSD) estimated through Welch's method
Time-frequency	PSD extracted through Morlet wavelet convolution
Statistical	Mean, standard deviation, skewness, excess kurtosis, median, low/high percentile and trimmed mean/standard deviation

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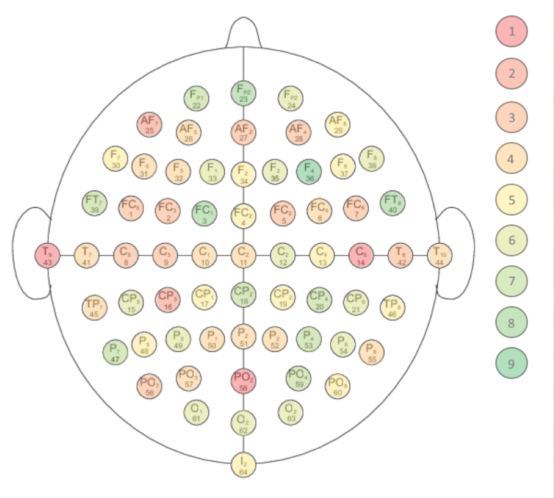
- Comparison



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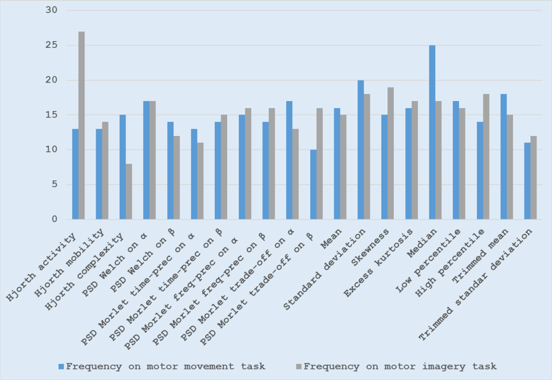
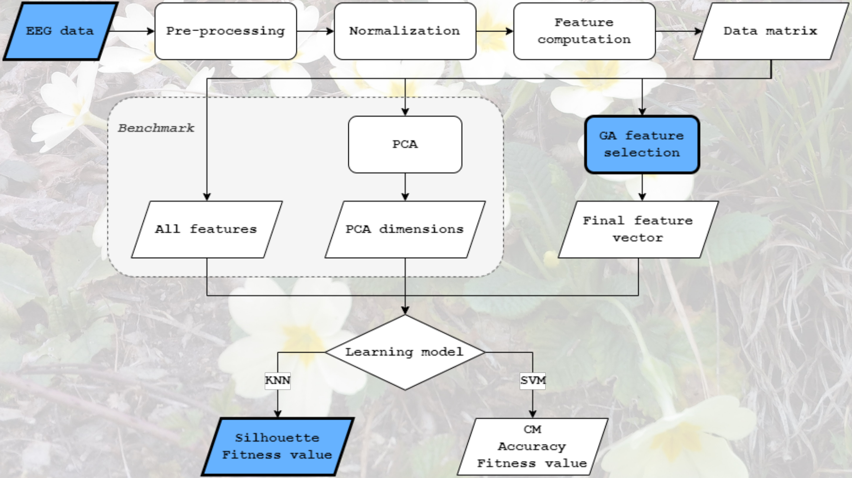


3.3 Feature Computation and Management

GA heterogeneous [1/5]



3.3 Feature Computation and Management

GA heterogeneous [2/5]

Characteristic	*dataset A [23, 25]*	*dataset B [24, 25]*
resource	`https://physionet.org/content/eegmat/1.0.0/`	`https://physionet.org/content/eegmmidb/1.0.0/`
experiment	cognitive workload	motor/imagery
# participants	36	109
# recordings per subject	2	14
conditions	REST, MAT	CLOSE, LH, RH
electrode positioning	10/20 international system	modified 10/10 international system
recording sampling rate	500 Hz	160 Hz
pre-processing	bandpass (0.5 - 45 Hz) and notch (50 Hz) filtering	none

$$\textit{dataset GEN}^{(170x135)} = \text{mix}(\text{dataset A}^{(68x209)}, \text{dataset B}^{(5033x576)})$$

Conditions: REST = resting state with eyes opened, MAT = arithmetic calculation, CLOSE = resting state with closed eyes, LH = movement of left hand, RH = movement of right hand.

Fitness function

1. $f_{S1}(c) = \text{accuracy}$, $f_{U1}(c) = \text{silhouette}$
2. $f_{S2}(c) = \lambda(1 - f_{S1}(c))\ (1 - \lambda)\,(1 - \frac{N_{sf}}{N_{if}})$, $f_{U2}(c) = \lambda(1 - f_{U1}(c))\ (1 - \lambda)\,(1 - \frac{N_{sf}}{N_{if}})$
3. $f_{S3}(c) = f_{S1}(c)\,(1 - \frac{N_{sf}}{N_{if}})$, $f_{U3}(c) = f_{U1}(c)\,(1 - \frac{N_{sf}}{N_{if}})$

Stopping criteria

- Maximum time parameter
- Dynamic maximum generations based on fitness check value
- 80% generation, global best = local best
- Maximum number of generations ≥ 1000

Dataset

- GEN dataset (170x135)
- Channels: Fp{1, 2}, F{3,4,7,8,z}, C{3,4,z}, P{3,4,z}, O{1,2}
- Frequency: θ, α, β
- Features: 15 electrodes x (3 Hjorth parameters + 3 frequency bands x (1 PSD Welch + 1 PSD Morlet))

3.3 Feature Computation and Management

GA heterogeneous [4/5]

ID	N_{sf}	Acc					gAcc	waF1
		MAT	REST	CLOSE	RH	LH		
GEN-ALL	135	1.00	1.00	1.00	0.81	0.81	0.82	0.81
GEN-PCA	5	0.89	0.98	0.90	0.78	0.78	0.66	0.64
GEN-$f_{S1}(c)$	77	1.00	1.00	1.00	0.86	0.86	0.86	0.86
GEN-$f_{S2}(c)$	51	1.00	1.00	1.00	0.75	0.75	0.75	0.75
GEN-$f_{S3}(c)$	19	1.00	1.00	1.00	0.92	0.92	**0.92**	**0.92**

Consider GEN dataset with the supervised approach.

gACC = global accuracy, waF1 = weighted average F1-score, N_{sf} = number of selected features

3.3 Feature Computation and Management

GA heterogeneous [5/5]

ID	N_{sf}	Silhouette
GEN-ALL	135	0.51
GEN-PCA	5	0.50
GEN-$f_{U1}(c)$	32	0.60
GEN-$f_{U2}(c)$	44	0.26
GEN-$f_{U3}(c)$	14	**0.61**

Consider GEN dataset with the unsupervised approach.

N_{sf} = number of selected features

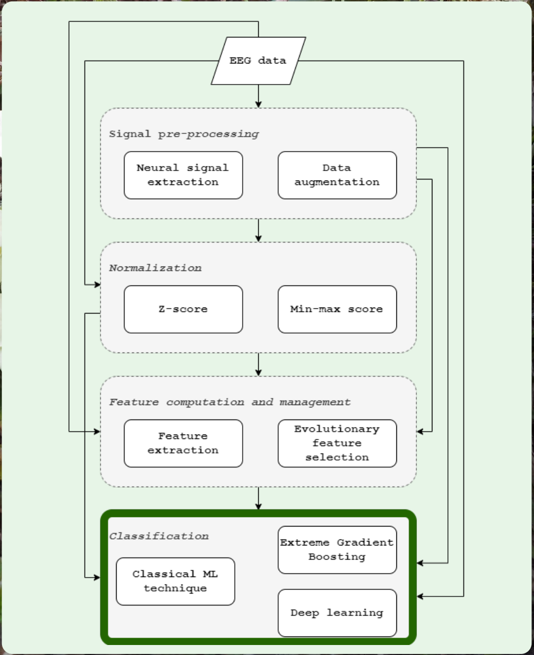
Research questions

1. What effect does a variety of feature types present in the characterization of the EEG signals?
2. How do evolutionary algorithms provide a data-driven feature selection?
3. When conducting the evolutionary feature selection optimization problem, what is the effect of using both supervised and unsupervised learning strategies and a set of stopping criteria?

Future works

- A priori knowledge → spatial relationships
- Weight silhouette score
- Hybrid application of supervised and unsupervised approaches

3.4 Classification



3.4. Classification

At a glance

Literature

- Classic ML techniques [26]
- eXtreme Gradient Boosting (XGBoost) [27]
- Deep learning [6]

3.4. Classification

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Literature

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Research questions

1. What are the advantages and disadvantages of applying classical machine learning techniques to the EEG signals?
2. What could be the impact of input formulations on deep learning models, wanting to maintain the characterization of the EEG data over time, frequency, and space?

Proposal

- Assess relevant features with XGBoost
- Novel input formulation for deep learning architectures
- Maintain time, frequency, and space information
- Exploit relevant IMFs

3.4. Classification

Interesting results [1/2]

XGBoost application

- On Z-scored MM (4924x1280) and MI (4025x1280)
- Parameter tuning
- Accuracy: MM = 65.0%, MI = 60.9%

3.4. Classification

Interesting results [1/2]

XGBoost application

- On Z-scored MM (4924x1280) and MI (4025x1280)
- Parameter tuning
- Accuracy: MM = 65.0%, MI = 60.9%
- Use relevant features as input to SVM
- Accuracy: MM = 68.6% (cubic), MI = 64.4% (quadratic)

Motor Movement

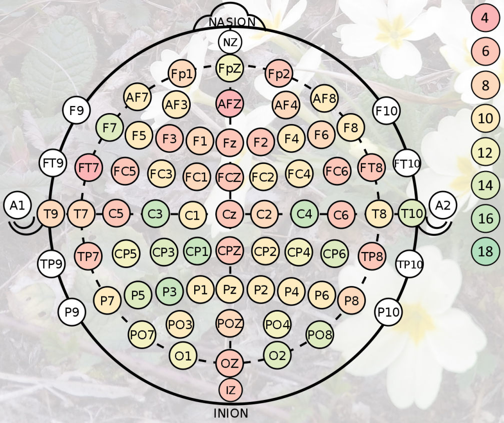
Method	SVM model	Selected features	Accuracy (%)
GA trade-off	cubic	646	67.8
PSO trade-off	quadratic	675	68.0
XGBoost	cubic	640	**68.6**

Motor Imagery

Method	SVM model	Selected features	Accuracy (%)
PSO trade-off	quadratic	714	64.0
XGBoost	quadratic	640	**64.4**

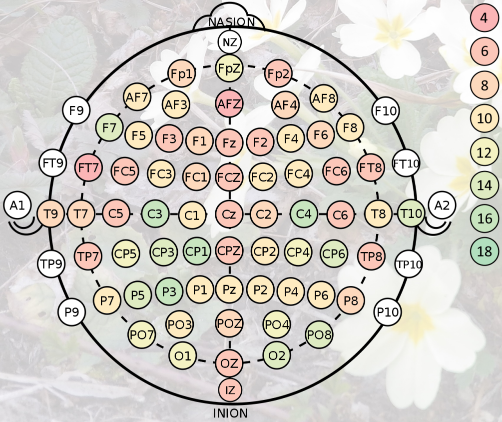
3.4. Classification

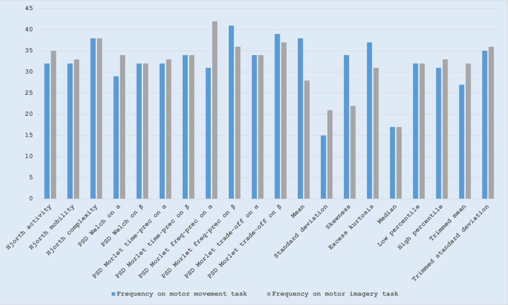
Interesting results [2/2]



3.4. Classification

Interesting results [2/2]





Research questions

1. What are the advantages and disadvantages of applying classical machine learning techniques to the EEG signals?
2. What could be the impact of input formulations on deep learning models, wanting to maintain the characterization of the EEG data over time, frequency, and space?

Conclusions

- Classical ML efficient → flexibility
- eXtreme Gradient Boosting has matching features to EFS proposal
- Novel input lacks testing

4. Discussion & Conclusions

Brief discussion

- Many other experiments
- Capture EEG characteristics
- Flexible pipeline → four modules

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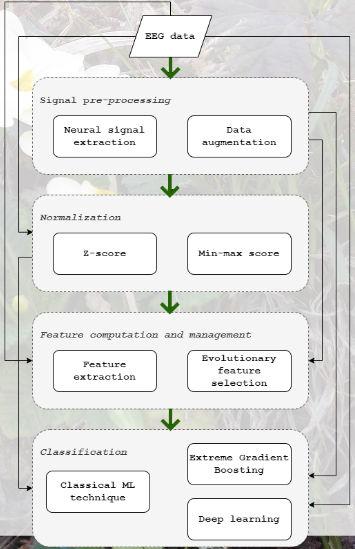


4. Discussion & Conclusions

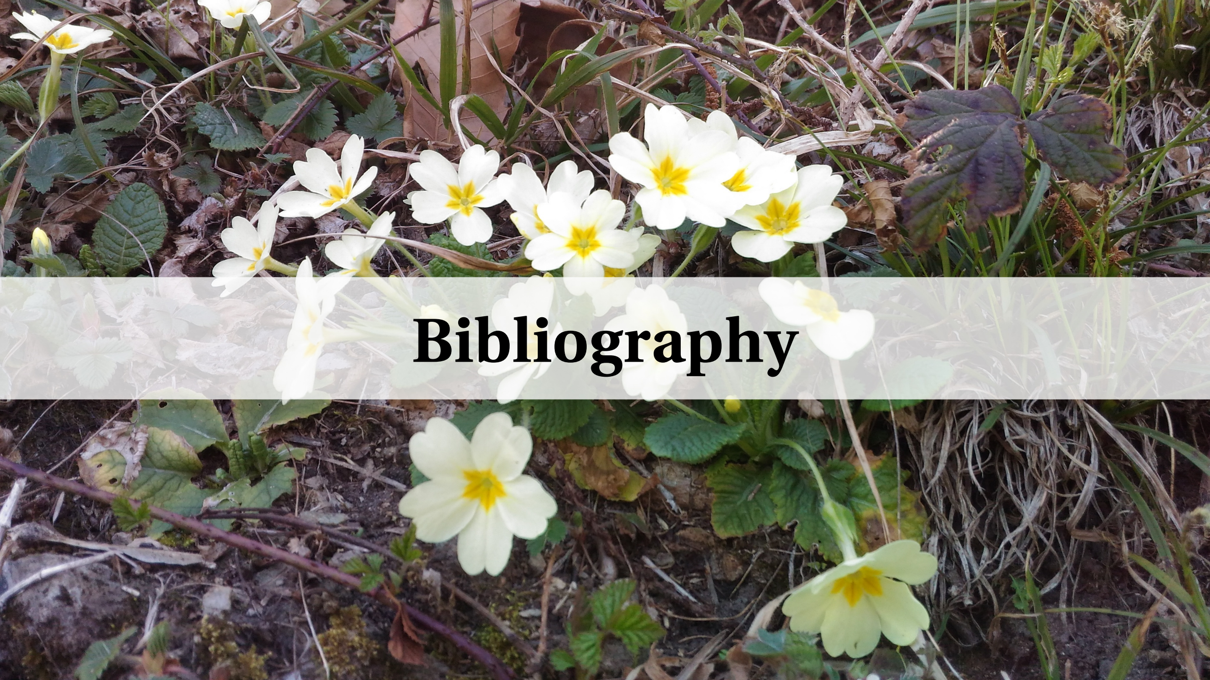
Brief discussion

- Many other experiments
- Capture EEG characteristics
- Flexible pipeline → four modules

Conclusions

- Further testing
- Generalizability
- Add new modules and techniques


Thank you!



Bibliography

Bibliography I

[1] Padfield, N., Zabalza, J., Zhao, H., Masero, V., & Ren, J. (2019). EEG-based brain-computer interfaces using motor-imagery: Techniques and challenges. *Sensors, 19(6)*, 1423.

[2] Vaid, S., Singh, P., & Kaur, C. (2015, February). EEG signal analysis for BCI interface: A review. *In 2015 fifth international conference on advanced computing & communication technologies* (pp. 143-147). IEEE.

[3] Gomez-Pilar, J., Corralejo, R., Nicolas-Alonso, L. F., Álvarez, D., & Hornero, R. (2016). Neurofeedback training with a motor imagery-based BCI: neurocognitive improvements and EEG changes in the elderly. Medical & biological engineering & computing, 54(11), 1655-1666.

[4] Liu, Y., Li, M., Zhang, H., Wang, H., Li, J., Jia, J., ... & Zhang, L. (2014). A tensor-based scheme for stroke patients' motor imagery EEG analysis in BCI-FES rehabilitation training. Journal of neuroscience methods, 222, 238-249.

[5] Mane, R., Chouhan, T., & Guan, C. (2020). BCI for stroke rehabilitation: motor and beyond. Journal of Neural Engineering, 17(4), 041001.

[6] Roy, Y., Banville, H., Albuquerque, I., Gramfort, A., Falk, T. H., & Faubert, J. (2019). Deep learning-based electroencephalography analysis: a systematic review. Journal of neural engineering, 16(5), 051001.

[7] Zhang, K., Xu, G., Han, Z., Ma, K., Zheng, X., Chen, L., ... & Zhang, S. (2020). Data augmentation for motor imagery signal classification based on a hybrid neural network. Sensors, 20(16), 4485.

[8] Kaiser, V., Bauernfeind, G., Kreilinger, A., Kaufmann, T., Kübler, A., Neuper, C., & Müller-Putz, G. R. (2014). Cortical effects of user training in a motor imagery based brain–computer interface measured by fNIRS and EEG. Neuroimage, 85, 432-444.

[9] Biasiucci, A., Franceschiello, B., & Murray, M. M. (2019). Electroencephalography. Current Biology, 29(3), R80-R85.

[10] Urigüen, J. A., & Garcia-Zapirain, B. (2015). EEG artifact removal—state-of-the-art and guidelines. Journal of neural engineering, 12(3), 031001.

[11] Calcagno, S., La Foresta, F., & Versaci, M. (2014). Independent component analysis and discrete wavelet transform for artifact removal in biomedical signal processing. American Journal of Applied Sciences, 11(1), 57.

[12] Dinarès-Ferran, J., Ortner, R., Guger, C., & Solé-Casals, J. (2018). A new method to generate artificial frames using the empirical mode decomposition for an EEG-based motor imagery BCI. Frontiers in neuroscience, 12, 308.

Bibliography II

[13] Huang, N. E., Shen, Z., Long, S. R., Wu, M. C., Shih, H. H., Zheng, Q., ... & Liu, H. H. (1998). The empirical mode decomposition and the Hilbert spectrum for nonlinear and non-stationary time series analysis. Proceedings of the Royal Society of London. Series A: mathematical, physical and engineering sciences, 454(1971), 903-995.

[14] Rehman, N., & Mandic, D. P. (2010). Multivariate empirical mode decomposition. Proceedings of the Royal Society A: Mathematical, Physical and Engineering Sciences, 466(2117), 1291-1302.

[15] Gallego-Jutglà, E., Solé-Casals, J., Rutkowski, T. M., & Cichocki, A. (2011, October). Application of Multivariate Empirical Mode Decomposition for Cleaning Eye Blinks Artifacts from EEG Signals. In IJCCI (NCTA) (pp. 455-460).

[16] Wang, Q., & Sourina, O. (2013). Real-time mental arithmetic task recognition from EEG signals. IEEE Transactions on Neural Systems and Rehabilitation Engineering, 21(2), 225-232.

[17] Tiwari, A., & Chaturvedi, A. (2019, November). A multiclass EEG signal classification model using spatial feature extraction and XGBoost algorithm. In 2019 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS) (pp. 4169-4175). IEEE.

[18] Zhang, X., Yao, L., Zhang, D., Wang, X., Sheng, Q. Z., & Gu, T. (2017, November). Multi-person brain activity recognition via comprehensive EEG signal analysis. In Proceedings of the 14th EAI international conference on mobile and ubiquitous systems: computing, networking and services (pp. 28-37).

[19] Jolliffe, I. T., & Cadima, J. (2016). Principal component analysis: a review and recent developments. Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences, 374(2065), 20150202.

[20] McFarland, D. J., Anderson, C. W., Muller, K. R., Schlogl, A., & Krusienski, D. J. (2006). BCI meeting 2005-workshop on BCI signal processing: feature extraction and translation. IEEE transactions on neural systems and rehabilitation engineering, 14(2), 135-138.

[21] Saibene, A. & Gasparini, F. (2020). Human-Machine Interaction: EEG Electrode and Feature Selection Exploiting Evolutionary Algorithms in Motor Imagery Tasks. *ThinkMind Library*, CENTRIC 2020, 8–14.

[22] Saibene, A., & Gasparini, F. (2021). GA for feature selection of EEG heterogeneous data. *arXiv preprint arXiv:2103.07117*.

[23] Zyma, I., Tukaev, S., Seleznov, I., Kiyono, K., Popov, A., Chernykh, M., & Shpenkov, O. (2019). Electroencephalograms during mental arithmetic task performance. *Data*, 4(1), 14.

Bibliography III

[24] Schalk, G., McFarland, D. J., Hinterberger, T., Birbaumer, N.,1 & Wolpaw, J. R. (2004). BCI2000: a general-purpose brain-computer interface (BCI) system. *IEEE Transactions on biomedical engineering, 51(6)*, 1034-1043.

[25] Goldberger, A. L., Amaral, L. A., Glass, L., Hausdorff, J. M., Ivanov, P. C., Mark, R. G., ... & Stanley, H. E. (2000). PhysioBank, PhysioToolkit, and PhysioNet: components of a new research resource for complex physiologic signals. *circulation, 101(23)*, e215-e220.

[26] Craik, A., He, Y., & Contreras-Vidal, J. L. (2019). Deep learning for electroencephalogram (EEG) classification tasks: a review. Journal of neural engineering, 16(3), 031001.

[27] Chen, T., & Guestrin, C. (2016, August). Xgboost: A scalable tree boosting system. In Proceedings of the 22nd acm sigkdd international conference on knowledge discovery and data mining (pp. 785-794).