Classifying mental states using Brain-Computer Interfaces: A systematic review

Jaime A. Riascos-Salas[1*], M. H. Fischer[1], and Klaus, Gramann[2]

[1]*Potsdam Embodied Cognition Group (PECoG), University of Potsdam, Potsdam, Germany*

[2]*Technical University of Berlin (TUB), Berlin, Germany*

riascossal@uni-potsdam.de*

BACKGROUND

- Electroencephalography (EEG) measures brain activity, providing insights into mental states and their impact on behavior (Roy and Frey, 2016).
- EEG is crucial for Brain-Computer Interface (BCI), which translates neural signals into device commands (active, reactive, passive BCIs) (Alimardani and Hiraki, 2020; Zander & Kothe, 2011).
- EEG complexity, variability, and optimal feature/algorithm selection challenge BCI development for accurate mental state decoding (Cohen, 2017).
- This paper reviews passive BCI research focusing on features and machine learning for decoding mental states (attention, cognition, emotion, fatigue) to summarize common techniques, accuracy achieved, and main mental states studied in the literature to guide future research.

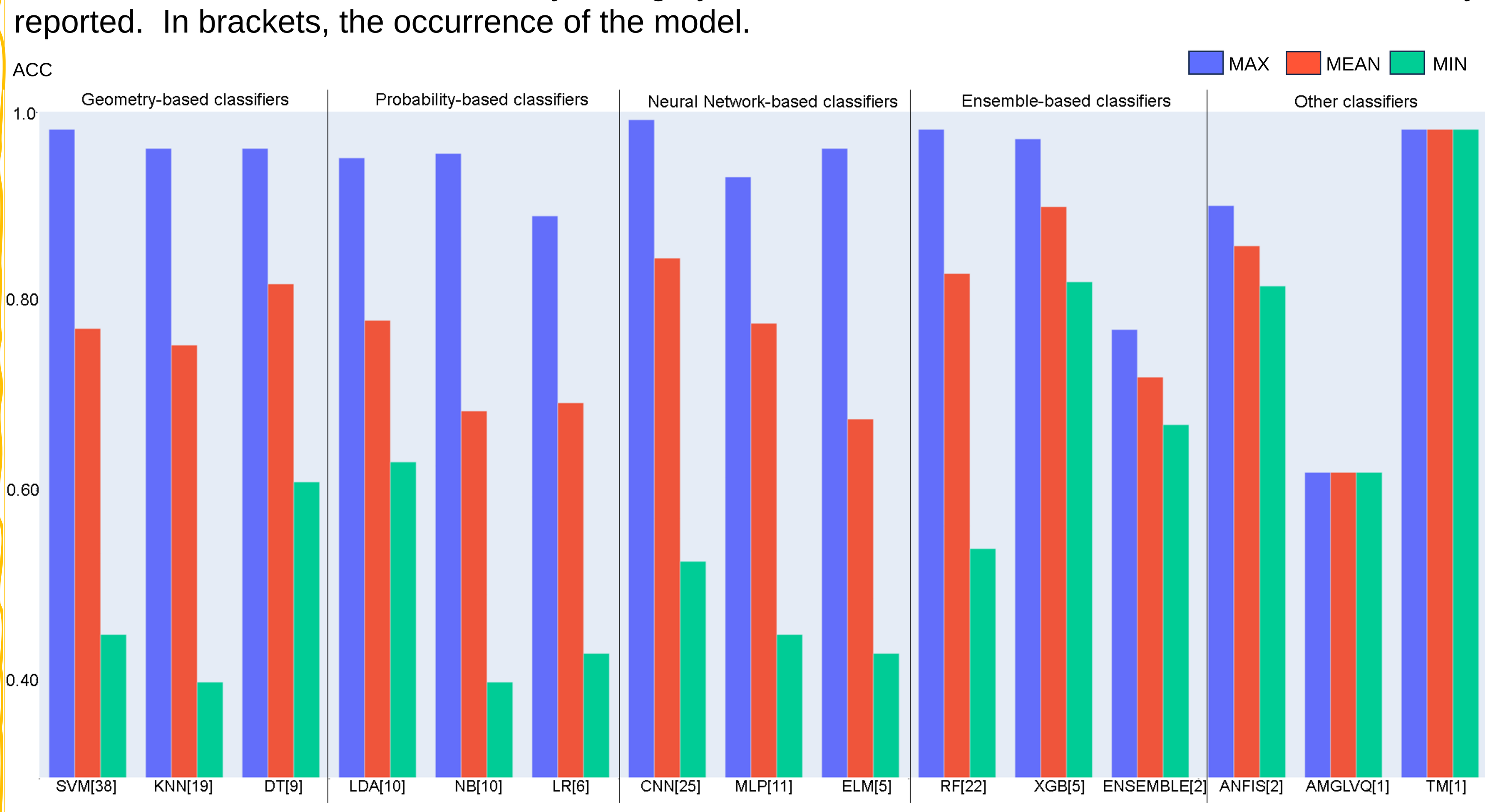
MATERIALS AND METHODS

- We conducted comprehensive literature searches across prominent repositories (PubMed, Science Direct, IEEE) from 2018 to 2023 (including July 31st, 2023)
- We used the following search terms in titles, abstracts, and keywords: ("feature extraction" OR "classification algorithms" OR "machine learning algorithms") AND ("brain-computer interfaces" OR "BCI") AND ("EEG" OR "electroencephalography" OR "EEG-based" OR "electroencephalography-based").
- Initial screening excluded 415 out of 953 papers based on title and abstract (e.g., lack of EEG focus, reviews/editorial, non-BCI topics).
- We then classified the remaining papers by EEG paradigms (SSVEP, Motor Imagery, etc.), with 120 focusing on passive BCIs.
- Finally, 72 papers were selected to provide comprehensive reporting on EEG procedures, feature extraction methods, and the classification of mental states.

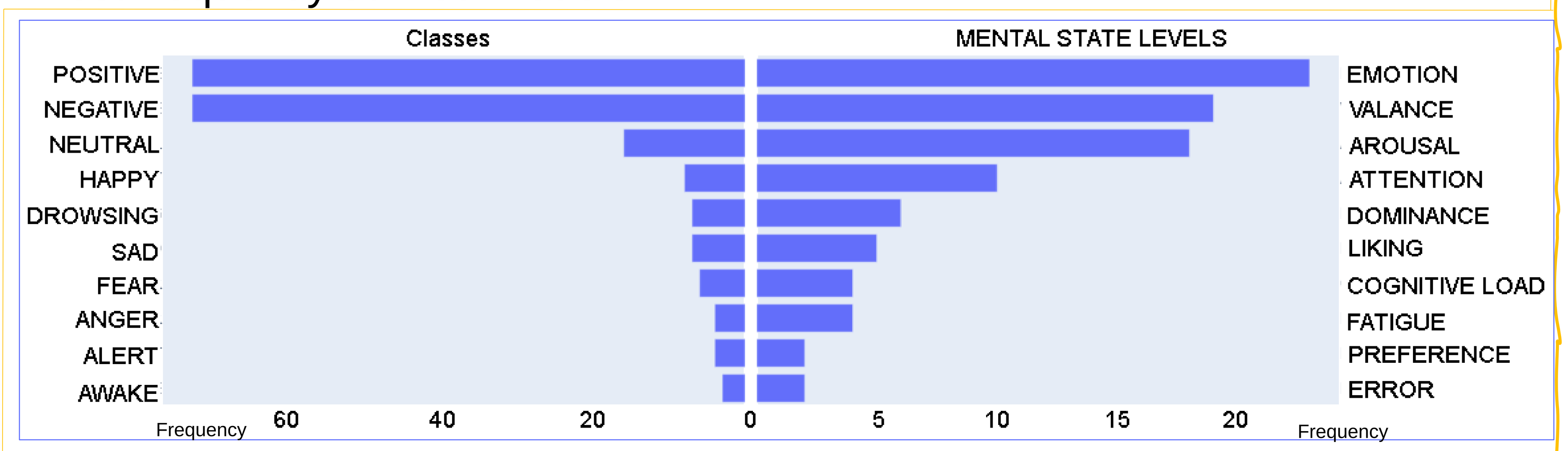
RESULTS

We systematically categorized selected papers based on machine learning algorithms and EEG feature, creating five categories for each. Then, we analyzed the frequency of use, accuracies and labels to identify trends in BCI design for mental state classification.

The three most used classifiers by category with the maximal, minimal, and mean accuracy reported. In brackets, the occurrence of the model.

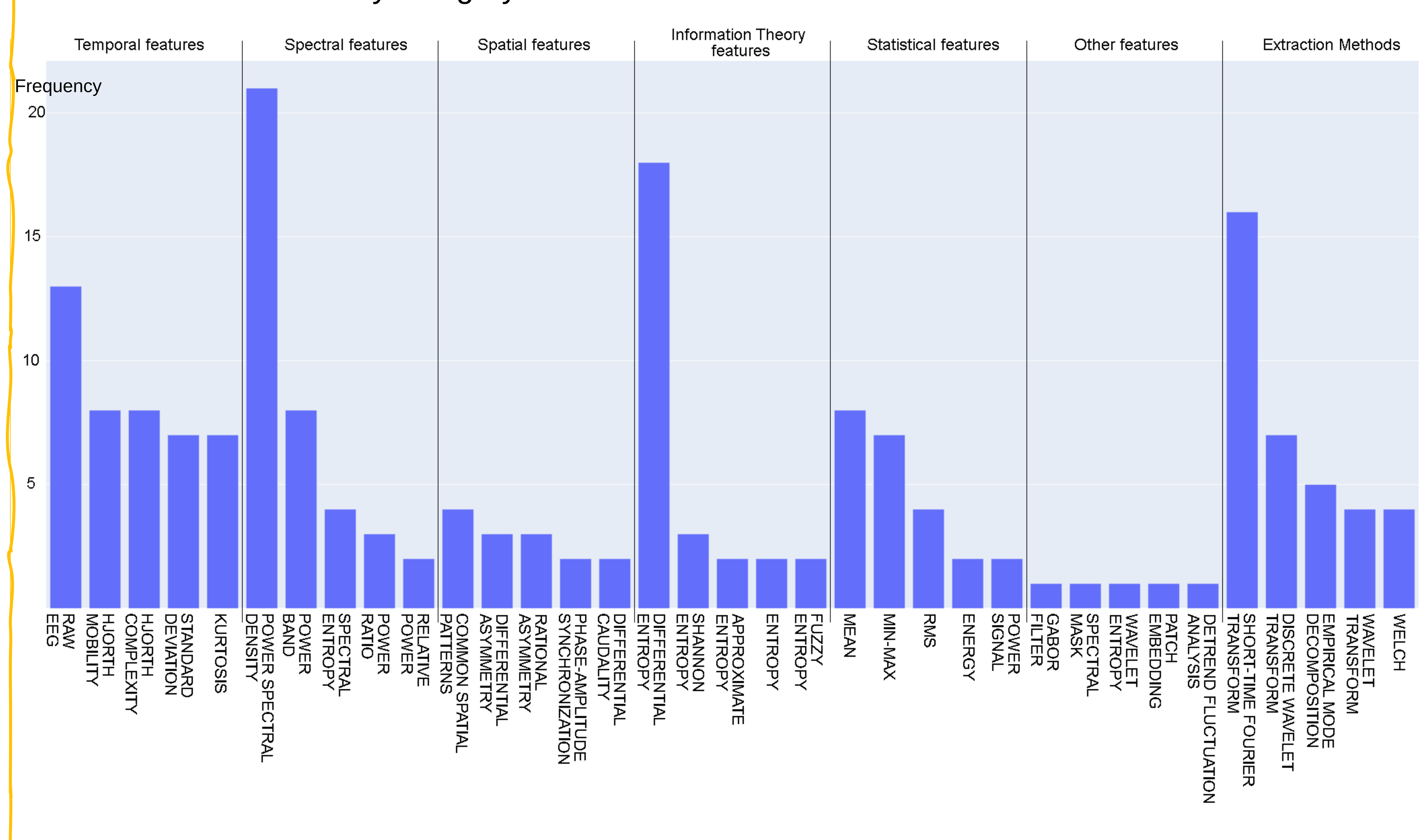


Most classifiers (excluding Ensemble and AMGLVQ) achieved over 90% accuracy in at least one study. Notably, our findings illustrated the dominance of geometric models, with a total of 66 occurrences and an average accuracy exceeding 70%. Convolutional Neural Networks (CNNs) emerged as the most proficient classifiers, boasting an average accuracy of 84% among the most frequently utilized models



We observed a balanced evaluation of various mental states levels, where inside of them, there are several classes, highlighting the binary (positive/negative) prominence of the studies analyzed.

The most used features by category.



CLASSIFIER	FEATURE	MAX	MIN	MEAN
SVM	POWER SPECTRAL DENSITY [12]	0,94	0,45	0,73
	DIFFERENTIAL ENTROPY [8]	0,94	0,49	0,74
	SHORT-TIME FOURIER TRANSFORM [7]	0,94	0,52	0,78
CNN	DIFFERENTIAL ENTROPY [10]	**0,98**	0,64	**0,86**
	RAW EEG [10]	**0,98**	0,53	0,83
	SHORT-TIME FOURIER TRANSFORM [7]	**0,98**	0,64	0,85
RF	POWER SPECTRAL DENSITY [8]	0,94	0,65	0,85
	SHORT-TIME FOURIER TRANSFORM [5]	0,94	0,66	0,82
	MEAN [5]	0,96	**0,75**	**0,86**
KNN	POWER SPECTRAL DENSITY [10]	0,95	0,40	0,75
	KURTOSIS [5]	0,92	0,40	0,67
	SHORT-TIME FOURIER TRANSFORM [4]	0,95	0,65	0,77
LDA	EMPIRICAL MODE DECOMPOSITION [3]	0,95	0,70	0,81
	DISCRETE WAVELET TRANSFORM [2]	0,88	0,70	0,79
	POWER BAND [2]	0,77	0,69	0,73

Finally, we grouped the most five used classifier with the most used feature, presenting the max, min and mean accuracy achieved for such combination. Where CNN achieves high and mean accuracies and RF min and mean. In brackets the number of occurrences.

Our investigation revealed the prominence of temporal and spectral features, with 43 and 38 occurrences, respectively. Power Spectral Density (PSD) was the most frequently reported feature (21 occurrences), followed closely by Differential Entropy (18 occurrences). In terms of feature extraction methods, Fourier Transform (16), Wavelet Transform (11), and Empirical Mode Decomposition (5) were the most common techniques.

CONCLUSIONS

- Intriguingly, only 2.8% of the works (two papers) performed an online classification (Beltrán, E. T. M, et al. 2022 and Edla, Damodar Reddy, et al. 2018).
- CNN offer automatic feature extraction and classification, potentially simplifying the process. However, their complexity and real-time implementation constraints must be considered (Craik and Contreras-Vidal, 2019).
- Spectral features, particularly PSD, are widely used in cognitive assessment, from emotion recognition to fatigue (Gao et al, 2020). As mental state identification often involves contrasting classes (e.g., positive/negative valence), information theory measures like differential entropy can quantify differences between EEG signals associated with each state.
- Trade-offs between complex machine-learning approaches and simple informative features are desirable (Lotte et al., 2018).

References

Roy, R.N. and Frey, J. (2016). Neurophysiological Markers for Passive Brain–Computer Interfaces. In Brain–Computer Interfaces 1 (eds M. Clerc, L. Bougrain and F. Lotte). https://doi.org/10.1002/9781119144977.ch5

Mridha MF, Das SC, Kabir MM, Lima AA, Islam MR, Watanobe Y. Brain-Computer Interface: Advancement and Challenges. Sensors (Basel). 2021 Aug 26;21(17):5746. doi: 10.3390/s21175746. PMID: 34502636; PMCID: PMC8433803.

Alimardani, M., & Hiraki, K. (2020). Passive Brain-Computer Interfaces for Enhanced Human-Robot Interaction. Frontiers in Robotics and AI, 7.

Cohen, M. X. (2017). Analyzing neural time series data: theory and practice. MIT press.

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.

Gao, Z., Wang, X., Yang, Y., Mu, C., Cai, Q., Dang, W., & Zuo, S. (2020). EEG-based spatio–temporal convolutional neural network for driver fatigue evaluation. IEEE transactions on neural networks and learning systems, vol. 30, no. 9, pp. 2755-2763, Sept. 2019, doi: 10.1109/TNNLS.2018.2886414.

Lotte, F., Bougrain, L., Cichocki, A., Clerc, M., Congedo, M., Rakotomamonjy, A., & Yger, F. (2018). A review of classification algorithms for EEG-based brain–computer interfaces: a 10 year update. Journal of neural engineering, 15(3), 031005.

Zander, T. O., & Kothe, C. (2011). Towards passive brain–computer interfaces: applying brain–computer interface technology to human–machine systems in general. Journal of neural engineering, 8(2), 025005.

SVM (Support Vector Machine), **KNN** (K-Nearest Neighbors), **DT** (Decision Trees), **LDA** (Linear Discriminant Analysis), **NB** (Naïve Bayes), **LR** (Logistic Regression), **CNN** (Convolutional Neural Network), **MLP** (Multilayer Perceptron), **ELM** (Extreme Learning Machine), **RF** (Random Forest), **XGB** (XGBoost), **ANFIS** (Adaptive Network-based Fuzzy Inference System), **AMGLVQ** (Adaptive Multilayer Generalized Learning Vector Quantization), **TM** (Template Matching)

PECoG
Potsdam Embodied Cognition Group

Link to the GitHub repository: