

# Eegle: An open-source Julia integrative package for EEG data analysis and machine learning

Marco Congedo<sup>1\*</sup> and Fahim Doumi<sup>1,2\*</sup>

<sup>1</sup> University Grenoble Alpes, CNRS, Grenoble-INP, Grenoble, France <sup>2</sup> University Federico II, Naples, Italy. \* Corresponding author \* These authors contributed equally.

DOI: [10.xxxxxx/draft](https://doi.org/10.xxxxxx/draft)

## Software

- [Review](#)
- [Repository](#)
- [Archive](#)

Editor: [\[Link\]](#)

Submitted: 18 January 2026

Published: unpublished

## License

Authors of papers retain copyright and release the work under a Creative Commons Attribution 4.0 International License ([CC BY 4.0](#)).

## Summary

Existing since the 1920s, Electroencephalography (EEG) is the first non-invasive neuroimaging modality developed by mankind. Despite many more sophisticated modalities having been developed since, to date EEG is still by far the most widely used. This is due to a number of distinct advantages over other modalities, such as the high temporal resolution, the low price and encombrement of equipment, the silent operation and the total non-invasiveness.

The recent explosion of research on EEG-based Brain-Computer Interfaces (BCIs) has fostered the need for efficient tools for EEG analysis and machine learning. While such tools exist for older languages such as Python and Matlab, they are not available for the more recent Julia language, which has been specifically created with these needs in mind. *Eegle.jl* leverages the rich and efficient scientific Julia ecosystem and integrates it to offer a simple and unified framework for both EEG data analysis and machine learning. In order to promote interoperability of Julia and Python, we also release *pyLittleEegle*, a Python clone of the BCI-related capabilities found in *Eegle.jl*. Both packages work seamlessly with the *FII BCI Corpus*, the first large curated and annotated databases for the motor imagery and P300 BCI modalities.

## Statement of need

In 1893 Hans Berger fell off his horse during his military training in Germany and was nearly trampled. On that same day, his sister had a bad feeling about Hans and wrote him a telegram asking if everything was all right. To the 19 y.o. man, the coincidence appeared stunning. He thought that he had somehow transmitted his feelings to his sister with some form of 'telepathy' (Buzsáki, 2006). He then decided to become a psychiatrist and to apply science to study the phenomenon. Based upon previous research of Richard Caton on the electrical activity of the exposed cortex of monkeys (Caton, 1875), he obtained the first human electroencephalographic recording in the middle of the 1920s (Berger, 1929).

Berger would have never imagined that, a century later, his creature would be the cornerstone of a new form of 'telepathy', known as Brain-Computer Interface (BCI). By means of an EEG-based BCI, a human can send a command to a machine relying entirely on the EEG readings. In fact, a BCI is defined as a system that enables the information transfer without using the muscles or the peripheral nerves<sup>1</sup> at all (Wolpaw & Wolpaw, 2012). The EEG has been instrumental for the inception of this research, due to the seminal work of Jacques Vidal (Vidal, 1973). Still today, EEG is by far the preferred neuroimaging modality for non-invasive BCIs thanks to its unique characteristics:

- high temporal resolution (~1ms),

<sup>1</sup>it is a peripheral nerve, for instance, that controls the movements of the eyes, which can be used to send commands.

- instantaneous measure of brain electrical potentials (no delay in the measure),
- high consistency (e.g., same EEG power spectra on the same individuals on two successive days at the same hour),
- sensitivity (for example, it is very useful for the detection of epilepsy and minimal consciousness states),
- solid research tradition (one century-long),
- total silentness and truly non-invasiveness (e.g., allowing daily use on anybody, including newborn children and patients with any condition),
- need of small, light, and inexpensive equipment (the size of EEG electronics can be reduced to the size of a common chip),
- use of wireless recording in natural (out-of-the-lab) environments.

While BCI research is relatively new, EEG has a long-standing tradition in clinical and cognitive brain research. All-in-all, a search on PubMed for the terms (“EEG” or “electroencephalography”) yielded 217,092 results on Jan 18 2026, with a positive trend starting at the dawn of the third millennium, a phenomenon that we name the ‘rebirth of EEG’.

## State of the field

Older languages such as Python and Matlab have their established software ecosystems for EEG data analysis and machine learning. Here below are the most frequently adopted software:

### Python

Package	Description
MNE( <a href="#">Gramfort et al., 2013</a> )	Open-source Python package for exploring, visualizing, and analyzing human neurophysiological data: MEG, EEG, sEEG, ECoG, NIRS, and more
scikit-learn( <a href="#">Pedregosa et al., 2011</a> )	Machine learning in Python (generic, not specific to EEG)
MOABB[moabb:2025]	Reproducible benchmarking for EEG-based BCIs
Braindecode( <a href="#">Aristimunha et al., 2025</a> )	Braindecode: toolbox for decoding raw electrophysiological brain data with deep learning models

### Matlab

Package	Description
EEGLAB( <a href="#">Delorme &amp; Makeig, 2004</a> )	An interactive Matlab toolbox for processing continuous and event-related EEG, MEG
FieldTrip( <a href="#">Oostenveld et al., 2011</a> )	Open-source software for advanced analysis of MEG, EEG, and invasive electrophysiological data
Brainstorm( <a href="#">Tadel et al., 2011</a> )	A user-friendly application for MEG/EEG analysis

### Julia

Julia is a young open-source and cross-platform language specifically conceived for scientific computing ([Bezanson et al., 2017](#)). It is rapidly gaining momentum in the scientific community

thanks to its conceptual affinity with mathematics and compatibility with the best available computing protocols. Although it is a high-level language, like Python and Matlab, it is (just-in-time) compiled, thus efficient. Moreover, Julia's syntax is elegant and permissive, allowing the programmer to adopt his/her preferred writing style. That is to say, the same routine in Julia can be written using a syntax closely resembling C, Python, or Matlab, to name a few. This accelerates the learning curve for people knowing other programming languages.

For these reasons, the use of Julia may greatly benefit the field of EEG data analysis and machine learning. However, there are only a few active projects at the moment. The most active appear `NeuroAnalyzer.jl` (Wysokiński, 2024) and `unfold.jl` (Ehinger & Alday, 2026). The first focuses on sleep data and the second on event-related potentials. `Eegle.jl` is a generic package for EEG, thus its scope intersects only weakly with these specific packages.

Software design

In this context, we have created for the Julia language `Eegle.jl`, which stands short for *EEG General Library* (Congedo & Doumi, 2026). The package acts as foundational building block enabling the integration of diverse state-of-the-art packages specifically conceived for EEG data and leveraging the powerful Julia scientific ecosystem.

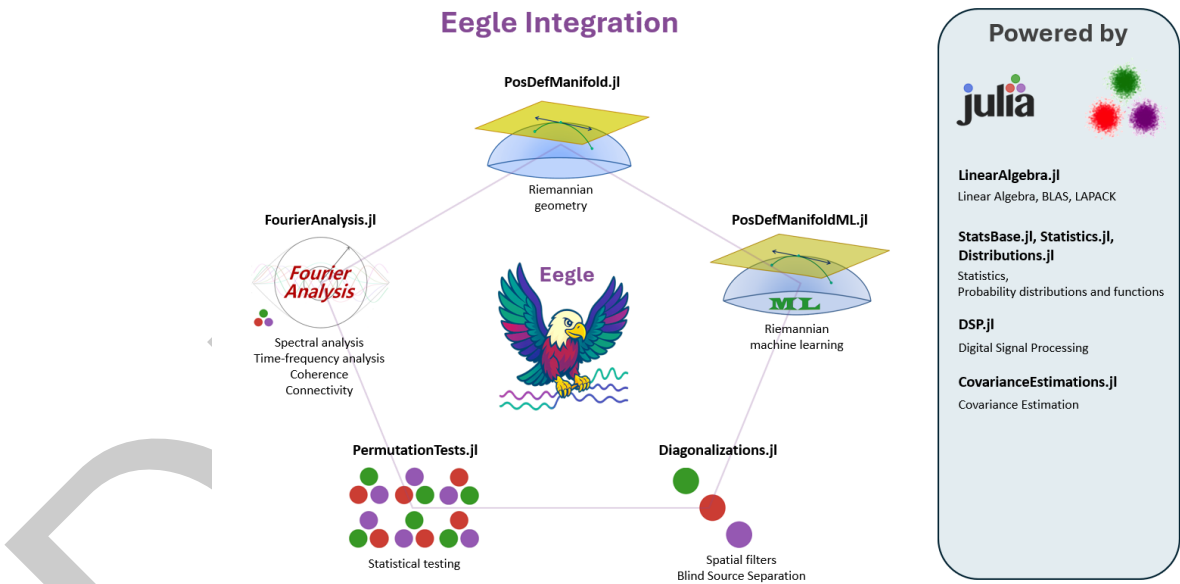


Figure 1: Julia package ecosystem currently integrated by `Eegle.jl`.

`Eegle.jl` is organized as a collection of independent modules. They are all re-exported, along with fundamental external packages.

Internal modules

Code Unit	Description
BCI.jl	Brain-Computer Interface machine learning based on Riemannian geometry
Database.jl	Utilities for handling and selecting databases
ERPs.jl	Operations on Event-Related Potentials and BCI trials

Code Unit	Description
FileSystem.jl	Manipulation of files and directories
InOut.jl	Reading and writing of data
Miscellaneous.jl	Miscellaneous functions
Preprocessing.jl	EEG preprocessing
Processing.jl	EEG processing

## 81 Re-exported external packages

Package	Scope
<a href="#">CovarianceEstimation.jl</a>	Covariance matrix estimations
<a href="#">Diagonalizations.jl</a>	Spatial filters, (approximate joint) diagonalization algorithms
<a href="#">Distributions.jl</a>	Julia standard package for statistical distributions
<a href="#">DSP.jl</a>	Julia standard package for digital signal processing
<a href="#">FourierAnalysis.jl</a>	FFT-based frequency domain and time-frequency domain analysis
<a href="#">LinearAlgebra.jl</a>	Julia standard package for matrix types and linear algebra (BLAS, LAPACK)
<a href="#">NPZ.jl</a>	Support for the <i>NPZ</i> (NumPy) binary data format
<a href="#">PermutationTests.jl</a>	Low-level statistics, very fast (multiple comparison) permutation tests
<a href="#">PosDefManifold.jl</a>	More linear algebra, operations on the manifold of positive-definite matrices
<a href="#">PosDefManifoldML.jl</a>	Machine learning on the manifold of positive-definite matrices
<a href="#">StatsBase.jl</a>	Julia standard package for basic statistics
<a href="#">Statistics.jl</a>	Julia standard package for statistics

82 This organization follows the spirit of Julia: it allows the centralization of all the above  
83 resources under a single package, yet it allows each package to be fully independent (including  
84 the documentation) to enable independent development and maintenance of each package.  
85 As a consequence of this organization, Eegle.jl is a mighty, yet small and agile package.

## 86 Research Impact Statement

87 Although still in its infancy, Eegle.jl has stimulated several developments to the benefit of  
88 the whole BCI community:

### 89 FII BCI Corpus

90 Eegle.jl has been instrumental in creating the **FII BCI Corpus** ([Doumi et al., 2025a, 2025b](#)).  
91 The corpus comprises a selection of BCI databases annotated and curated for both the motor  
92 imagery and P300 BCI paradigms. Along with EEG data and class labels, the corpus provides  
93 comprehensive metadata that allows selecting the data for the study at hand and extracting  
94 relevant information. This is the first large open-access corpus of its kind. The annotation  
95 makes it particularly easy and principled to carry out machine learning research on BCI data —  
96 see, for example, the [Tutorial ML 2](#) of Eegle.jl. The synergy between Eegle.jl and the corpus

97 has resulted in a comprehensive benchmark of accuracy on BCI data using state-of-the-art  
98 Riemannian geometry classifiers — [see here](#).

## 99 **pyLitteEegle**

100 The core capabilities of Eegle.jl have been cloned and translated into the Python language,  
101 yielding the **pyLittleEegle** package (Doumi, 2025). This package replicates all functionalities  
102 related to database selection, EEG data reading and processing, as well as data structuring for  
103 analysis. Furthermore, it handles data encoding and preparation for classification tasks using  
104 scikit-learn (Pedregosa et al., 2011), thus making the corpus easily accessible in Python as  
105 well. Taken together, Eegle.jl and pyLittleEegle promote interoperability between Julia  
106 and Python for BCI research, which is also new in the community.

## 107 **License**

108 Eegle.jl is released under the MIT license.

## 109 **AI usage disclosure**

110 Generative AI tools were used in the development of this software only for hastening the writing  
111 of non-computing routines, such as the download GUI and some routines for the automatic  
112 generation of code blocks in the tutorials.  
113 For writing the manuscript, generative AI tools have been used only for spelling and grammar  
114 error checking.

## 115 **Acknowledgements**

116 We acknowledge the contributions to Eegle.jl of Dr. Alexandre Bleuzé and of Abdeljalil  
117 Anajjar.

## 118 **References**

- 119 Aristimunha, B., Guetshel, P., Wimpff, M., Gemein, L., Rommel, C., Banville, H., Sliwowski,  
120 M., Wilson, D., Brandt, S., Gnassounou, T., Paillard, J., Junqueira Lopes, B., Sedlar, S.,  
121 Moreau, T., Chevallier, S., Gramfort, A., & Schirrmester, R. T. (2025). Braindecode:  
122 Toolbox for decoding raw electrophysiological brain data with deep learning models. In  
123 *Zenodo repository*. Zenodo. <https://zenodo.org/records/17699192>
- 124 Berger, H. (1929). Über das elektroenkephalogram des menschen. *Archives of Psychiatry*, 87.
- 125 Bezanson, J., Edelman, A., Karpinski, S., & Shah, V. B. (2017). A fresh approach to numerical  
126 computing. *SIAM Review*, 59(1), 65–98.
- 127 Buzsáki, G. (2006). *Rhythms of the brain*. Oxford University Press. <https://academic.oup.com/book/11166>
- 128
- 129 Caton, R. (1875). The electrical currents of the brain. *British Medical Journal*, 278.
- 130 Congedo, M., & Doumi, F. (2026). *Eegle.jl: A julia integrative package for EEG data analysis*  
131 *and machine learning*. GitHub repository. <https://github.com/Marco-Congedo/Eegle.jl>
- 132 Delorme, A., & Makeig, S. (2004). EEGLAB: An open source toolbox for analysis of single-  
133 trial EEG dynamics including independent component analysis. *Journal of Neuroscience*  
134 *Methods*, 134(1), 9–21. <https://doi.org/10.1016/j.jneumeth.2003.10.009>

- 135 Doumi, F. (2025). *pyLittleEagle: Python tools for working with the FII BCI corpus*. GitHub  
136 repository. <https://github.com/FhmDmi/pyLittleEagle>
- 137 Doumi, F., Esposito, A., Arpaia, P., & Congedo, M. (2025a). *FII BCI corpus MI*. Zenodo.  
138 <https://doi.org/10.5281/zenodo.17801878>
- 139 Doumi, F., Esposito, A., Arpaia, P., & Congedo, M. (2025b). *FII BCI corpus P300*. Zenodo.  
140 <https://doi.org/10.5281/zenodo.17793672>
- 141 Ehinger, B., & Alday, P. (2026). *Unfold.jl: Event-related regression toolbox* (Version v0.8.9).  
142 Zenodo. <https://doi.org/10.5281/zenodo.18255786>
- 143 Gramfort, A., Luessi, M., Larson, E., Engemann, D. A., Strohmeier, D., Brodbeck, C.,  
144 Goj, R., Jas, M., Brooks, T., Parkkonen, L., & Hämäläinen, M. S. (2013). MEG and  
145 EEG data analysis with MNE-python. *Frontiers in Neuroscience*, 7(267), 1–13. <https://doi.org/10.3389/fnins.2013.00267>  
146
- 147 Oostenveld, R., Fries, P., Maris, E., & Schoffelen, J.-M. (2011). FieldTrip: Open source software  
148 for advanced analysis of MEG, EEG, and invasive electrophysiological data. *Computational*  
149 *Intelligence and Neuroscience*, 2011, 156869.
- 150 Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., Blondel, M.,  
151 Prettenhofer, P., Weiss, R., Dubourg, V., Vanderplas, J., Passos, A., Cournapeau, D.,  
152 Brucher, M., Perrot, M., & Duchesnay, E. (2011). Scikit-learn: Machine learning in Python.  
153 *Journal of Machine Learning Research*, 12, 2825–2830.
- 154 Tadel, F., Baillet, S., Mosher, J. C., Pantazis, D., & Leahy, R. M. (2011). Brainstorm: A user-  
155 friendly application for MEG/EEG analysis. *Computational Intelligence and Neuroscience*,  
156 2011, 879716.
- 157 Vidal, J. J. (1973). Toward direct brain–computer communication. *Annual Review of Biophysics*  
158 *and Bioengineering*, 2, 157–180.
- 159 Wolpaw, J., & Wolpaw, E. W. (2012). *Brain-computer interfaces: Principles and practice*.  
160 Oxford University Press.
- 161 Wysockiński, A. (2024). *NeuroAnalyzer* (Version 0.24.11). [https://doi.org/10.5281/zenodo.](https://doi.org/10.5281/zenodo.14010334)  
162 [14010334](https://doi.org/10.5281/zenodo.14010334)