Role of Machine Learning in Advancing Electroencephalographic Signal Processing in Individuals Utilizing Neuroprosthetics

B. Pham[1], P. Uchila[2], V. Sriram[3] T. Johnson[4] S.H Chandran[5] S. Seredina[6] A. Herrera[7] S. Suresh[8] P. Jain[9] G. Osman[10] K. Durodola[11] S. Sutar[12]

1 - University of California, Los Angeles 2 - Harmony School of Innovation - Sugar Land 3 - Lebanon Trail High School, 4 - Northwestern University, 5 - Edison High School, 6 - Baruch College, 7 -, 8 Ardrey Kell High School, 9 - Rutgers University, 10 - Justice High School, 11 -, 12 - California Academy of Mathematics and Science

Introduction

A brain-computer interface is a system that detects brain activity and translates neural signals instructions for a computer or external device. BCIs are a type of neuroprosthetic used to facilitate people with disabilities in performing actions. Although much advancements have been made in the field of BCIs, a pressing issue in its effectiveness and viability in the real world is its ability to decode neural signals, most often electroencephalographic data, and translate this to digital commands. Machine learning is a specific emerging technique in many EEG signal classification algorithms, and can be used to improve pattern analysis and decode instructions, such as motor intention. In our research, we analyze different machine learning systems, and compare them to one another, while referencing research trends on this field.

Objectives

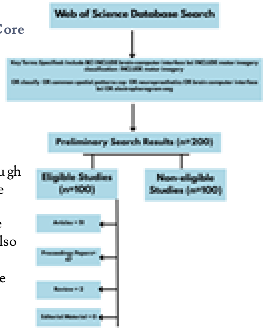
- ➢ Evaluate methods for the processing of EEG signals for neuroprosthetic applications that involve the usage of machine learning techniques
- ➢ Analyze existing technologies, highlight trends in technological development, and identify the most effective approaches

Methods

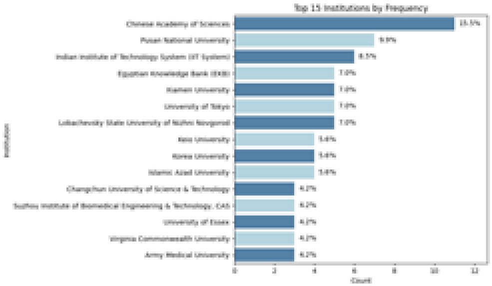
Articles were taken from the **Web of Science Core Collection**.

Keywords were:

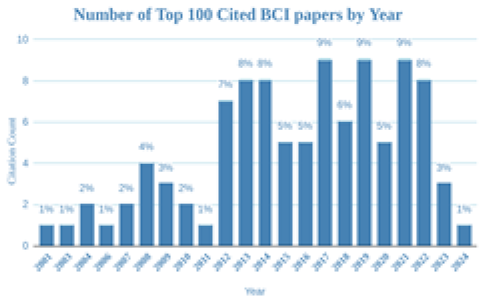
- **Brain Computer Interface**
- **EEG Signal Processing**
- **Motor Imagery**
- **Neuroprosthetics**



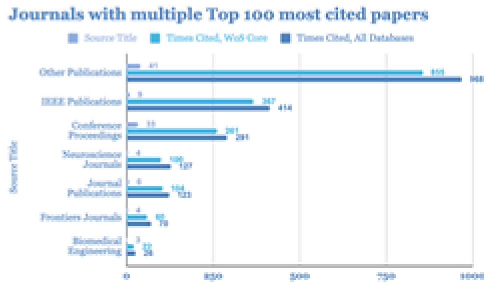
Afterwards, top 100 articles were retained through manual screening on their relevance to machine learning techniques (e.g. Convolutional Neural Networks, Support Vector Machines) and were ranked in order of their relevance. Screenings also evaluated each study's approach to EEG classification, determined what type of machine learning technology was used, and measured classifier accuracy.



- Chinese Academy of Science most frequent at 15.5%
- Pusan National University second at 9.9%
- Indian Institute of Technology follows at 8.5%
- Contributions are global, but has limited research centers
- Strong representation from East Asia



- High impact BCI rose in 2010s
- Highest concentration of papers in 2013 & 2021
- Reflects rapid progress in EEG based BCI methods
- Reflects integration of machine learning techniques over time



- Institute of Electrical and Electronics Engineers (IEEE) made up largest majority of citations
- Conference Proceedings made up second largest majority
- Around half of publications are still from less cited journals

Results

Emerging deep learning and hybrid architectures show increasing promise, including attention-based spatiotemporal models for fine limb decoding (MA et al, 2022) and mixed-reality motor imagery training for robotic-ar, control (Sun et al, 2024). However, these methods typically require more computational resources and extensive training data, contributing to the ongoing dominance of classical pipelines in practical research and clinical prototyping.

Across the 100 publications reviewed, classical machine learning pipelines remain the predominant approach for motor-imagery EEG classification, despite rapid progress in deep learning. High-performing CSP-based pipelines, such as OVR-CSP with LDA (Wang et al., 2018), still can match or exceed deep learning accuracy in small-sample, low-SNR EEG settings. Many studies also highlight the continued strength of subject-adaptive feature extraction and lightweight boosting-style classifiers, which generalize well across individuals without requiring large datasets.

China remains the largest contributor to these high performing studies, followed by India and other East Asian countries. Publication volume has grown steadily since the early 2010s. Persistent challenges across literature include low signal-to-noise ratio, stronger inter-subject variability, and ensuring real-time decoding performance suitable for rehabilitation and neuroprosthetic applications.

Discussion

Studies that utilize modern deep learning techniques that became widespread in the mid 2010s such as Convolutional Neural Networks (CNNs) consistently demonstrate more accurate classification as opposed to traditional methods. For example, Zhang et. al (2025) compared various CNNs and traditional approaches utilizing Common Spatial Patterns (CSPs). Results showed that CNNs outperformed CSPs in both offline and online settings. Other studies such as Wang et. al (2018) showed that CNNs outperformed Recurrent Neural Networks (RNNs). It is important to note that these gains are marginal when testing on real-world signals. This is corroborated by the articles above: CNN based techniques achieve around only 15-20% improved accuracy over CSP or SVM techniques on training data, but only 5-10% more on non-training data. This may be because most studies only test on 10-20 subjects, raising concerns about overfitting and highlighting the challenges of addressing inter-subject variability.

However, bibliometric data shows an increasing trend in the publication of relevant articles since the mid 2010s, and future research will benefit from continued advances in deep learning and access to vast collections of training data. New approaches are being explored: recent work, such as Zare et. al (2023) combines spatial CNNs with temporal transformer-based architectures. This approach currently does not outperform normal CNNs, demonstrating the incremental nature of current progress.

Conclusion

Among the machine-learning techniques reviewed, deep learning methods specifically those using CNNs or spatiotemporal architectures were the most effective for decoding motor-intention signals. As these models evolve into transformer-based and application-oriented architectures, they improve modern neuroprosthetic systems that require flexible decoding. However, intention signals vary widely across individuals, and accuracy depends significantly on the motor task. Furthermore, research has fully not transitioned into CNNs or other deep learning-based systems, as these require vast amounts of input data for marginal improvements over traditional models. As more data does become widely available and deep learning methods more reliable, only then should research focus on improving hybrid or transformer-based models for complex motor decoding. Progress is incremental, but will eventually develop neuroprosthetics that are more reliable and capable of imitating natural movement.

References

Zhang, Y., Wang, W., Liu, G., Qiao, Y., Shi, R., Duan, Y., Du, Y., Li, S., Guo, F., McHugh, T. J., & Duan, F. (2024). Research on EEG signal classification method based on brain-computer interface control of Rehabilitation Robot. 2024 17th International Convention on Rehabilitation Engineering and Assistive Technology (i-CREATe), 1–6. https://doi.org/10.1109/i-create62067.2024.10776552

Wang, Z., Cao, L., Zhang, Z., Gong, X., Sun, Y., & Wang, H. (2018). Short time fourier transformation and deep neural networks for motor imagery brain computer interface recognition. Concurrency and Computation: Practice and Experience, 30(23). https://doi.org/10.1002/cpe.4413

Zare, S., & Sun, Y. (2024). EEG motor imagery classification using integrated transformer-CNN for Assistive Technology Control. 2024 IEEE/ACM Conference on Connected Health: Applications, Systems and Engineering Technologies (CHASE), 189–190. https://doi.org/10.1109/chase60773.2024.00033

Ma, X., Qiu, S., & He, H. (2018). Time-distributed attention network for EEG-based motor imagery decoding from the same limb. IEEE Transactions on Neural Systems and Rehabilitation Engineering, 30, Article TBD (no issue/page numbers provided). https://doi.org/10.1109/TNSRE.2022.3141231

Sun, H., Yan, X., Yang, J., & Li, Q. (2024). Development of a brain-controlled robotic arm system for motor imagery based on MR visual guidance. In Proceedings of the 2024 4th International Conference on Bioinformatics and Intelligent Computing (pp. 159–164). ACM. https://doi.org/10.1145/3665689.3665716

Wang, Z., Du, X., Wu, Q., & Dong, Y. (2018). Research on the multi-classifier features of the motor imagery EEG signals in the brain-computer interface. In Tenth International Conference on Digital Image Processing (ICDIP 2018) (Vol. 10806, Paper 1080662). SPIE. https://doi.org/10.1117/12.2503307