

EEG as a Promising Tool for Parkinson's Disease Diagnosis and Cognitive Assessment

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Keywords

Electroencephalogram (EEG), brain-computer interface (BCI), artificial intelligence, computer vision, natural language processing, machine learning

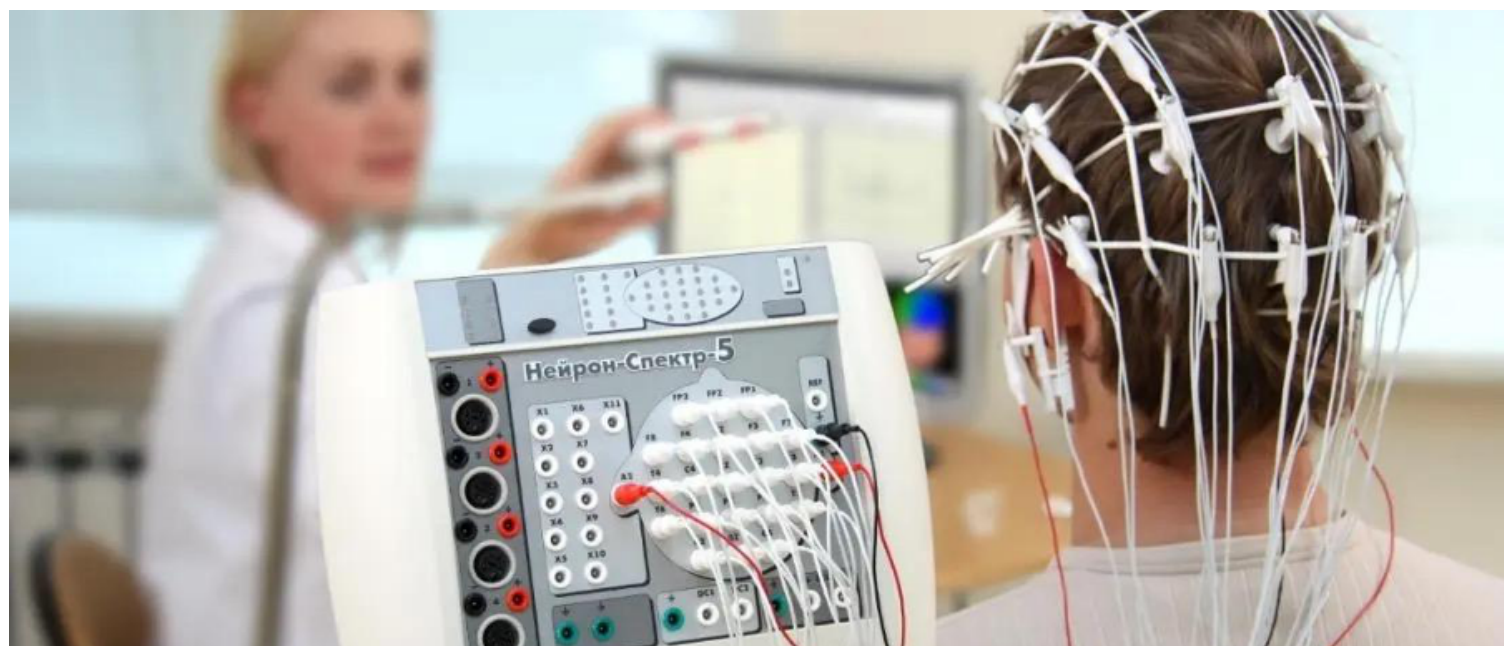


Image credit: Baburov, 2009.

Abstract

This article explores the potential of using Electroencephalography (EEG) and machine learning to improve the early diagnosis and cognitive assessment of Parkinson's disease (PD). Highlighting challenges in PD diagnosis, the article reviews recent studies that leverage EEG to detect specific brain wave alterations associated with cognitive decline in PD patients. Various EEG-based approaches are discussed, including machine learning integration for predicting cognitive impairment, identifying electrical activity alterations, and innovative techniques like Holo-Hilbert Spectral Analysis (HHSA). The article emphasizes the significance of EEG dynamics as potential early-stage PD biomarkers, particularly through methods like discrete wavelet transform (DWT). The integration of EEG and machine learning is presented as a promising framework for accurate and efficient PD diagnosis. A case study introduces an automated EEG analysis system using big data, showcasing its effectiveness in classifying patterns related to various neurological conditions. Acknowledging open questions, the article underscores the need for further research in refining EEG-based methodologies for Parkinson's diagnosis. Overall, it highlights the potential of EEG and machine learning to make Parkinson's diagnosis more accessible and humane, fostering hope for improved patient outcomes.

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Introduction

Parkinson's disease (PD) is a common brain abnormality affecting millions around the globe. It causes uncontrollable movements and difficulty with balance and coordination. Cognitive decline and dementia are significant symptoms of Parkinson's disease. Early detection is critical to prevent disease progression. Due to the disease's link to the brain, Electroencephalography (EEG) is one of the most effective diagnostic tools. EEG measures low-frequency brain waves, known as delta and theta waves. A University of Iowa research team found that cognitive dysfunction in PD is linked to reduced strength of these specific brain waves when a patient is required to think, suggesting that EEG might be useful for diagnosing cognitive impairment in PD patients. EEG offers continuous, repeatable monitoring of a patient's cognitive status, whereas traditional methods involve time-consuming, one-time tests administered by neurologists.

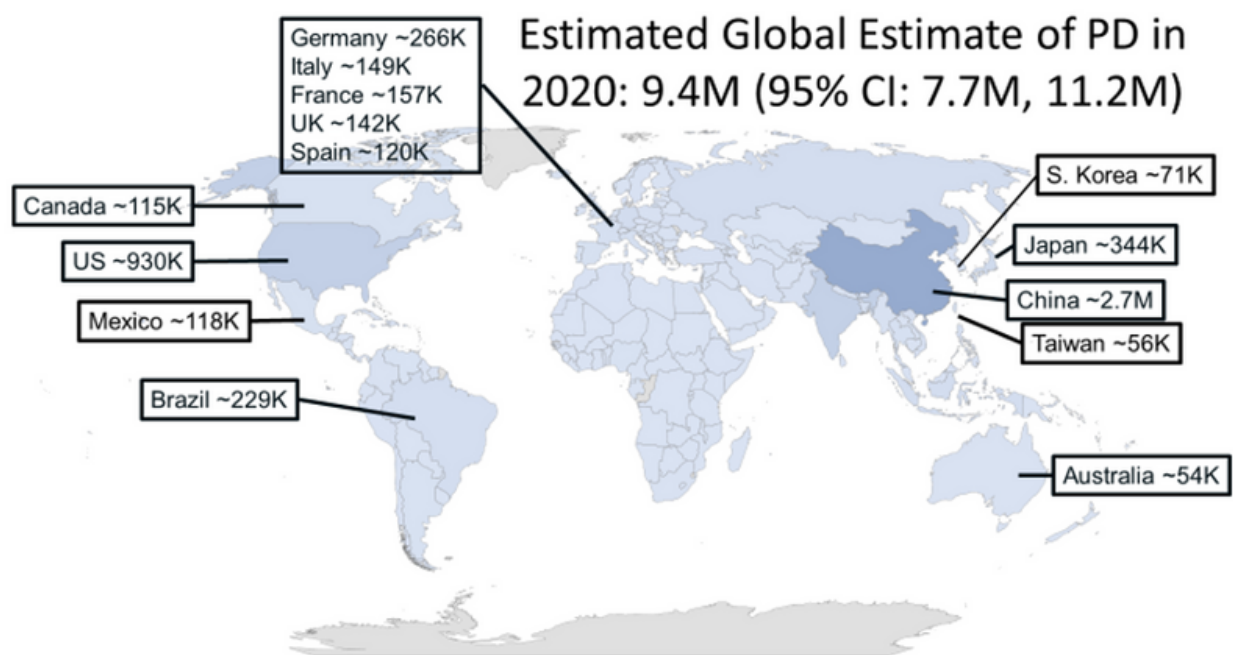


Fig. 1. Age-standardised prevalence of Parkinson's disease per 100,000 population by location for both sexes, 2016. Estimation of the 2020 Global Population of Parkinson's Disease (PD) - MDS Abstracts. (2020, September 7). MDS Abstracts.

Challenges in Parkinson's Disease Diagnosis

Diagnosing Parkinson's disease is a complex process that involves several challenges. With no specific tests available, the diagnosis depends on a neurologist's evaluation of a patient's medical history and neurological symptoms. For an early diagnosis, it is crucial to consult general practitioners and seek expert opinions from movement disorder specialists. The latest diagnostic criteria from the Movement Disorder Society align with current knowledge. However, misdiagnoses are common, which reflects the issue of diagnostic accuracy. Usually, Parkinson's disease is identified after the onset of motor symptoms, which can take years to develop. Although a technique is available for detecting abnormal protein deposits linked to Parkinson's, it is not widely accessible.

Non-specific symptoms such as reduced sense of smell, sleep disturbances, depression, and anxiety further complicate the diagnostic process. In conclusion, the process of diagnosing Parkinson's disease is challenging due to the lack of specific tests, misdiagnoses, delayed identification, and the presence of non-specific symptoms. Therefore, there is a great need for improved diagnostic methods.

Recent EEG Advancements

Parkinson's Cognitive Impairment Prediction:

Researchers from the University of Iowa Carver College of Medicine conducted an experiment utilizing electroencephalography (EEG) to predict cognitive impairments in Parkinson's disease (PD) patients. By measuring participants' brain waves during specific tasks, the study revealed a task-independent correlation between reduced cognitive function and low-frequency brain waves. The researchers highlighted EEG's wide availability and cost-effectiveness for this investigation.

Alterations in Electrical Activity in PD - Machine Learning Integration:

A study published in Frontiers in Aging Neuroscience explored the potential of EEG for identifying alterations in the electrical activity of individuals with Parkinson's. Analyzing EEG signals, the research noted increased powers in theta and delta bands and reduced powers in alpha and beta bands. This study exemplified the integration of machine learning, using common spatial patterns, entropy, and other techniques to detect Parkinson's from resting-state EEG signals. The findings suggested a promising avenue for accurate and efficient Parkinson's diagnosis.

Holo-Hilbert Spectral Analysis (HHSA) in Dopaminergic Circuit Abnormalities:

Examining dopaminergic subcortical-cortical circuit abnormalities in PD patients, this study introduced Holo-Hilbert Spectral Analysis (HHSA) due to traditional EEG analysis limitations. Findings revealed reduced β bands in frontal and central regions, decreased γ bands, and additional alterations in late-stage PD patients. Positive correlations were observed between θ and β bands across brain regions and depression scores. Machine learning algorithms, prioritizing HHSA features, achieved high accuracy, emphasizing HHSA's efficacy in assessing depression severity and diagnosing PD.

Early-Stage PD Biomarkers using EEG Dynamics:

Investigating early-stage Parkinson's, this study utilized eyes-closed resting-state EEG. Employing the AR Burg method and wavelet packet entropy (WPE) method, the research identified significant alterations in EEG dynamics. Increased powers in δ - and θ -bands, decreased powers in α - and β -bands, and elevated entropy in the γ -band were observed in PD patients compared to controls. These observed changes suggested potential early signs of cortical dysfunction, proposing EEG dynamics as potential biomarkers for early-stage PD diagnosis and intervention.

Efficient Methods for PD Detection with DWT and Machine Learning:

For efficient Parkinson's detection, a study introduced discrete wavelet transform (DWT) in EEG preprocessing, emphasizing the significance of DWT coefficients and strategic EEG channel selection. Features extracted using various entropy measures enabled machine learning techniques to classify PD/HC cases. Results on SanDiego and UNM datasets demonstrated high accuracy, particularly with DWT+TShEn achieving around 99.5%, underscoring the method's effectiveness and the importance of DWT coefficients and EEG channel selection.

Common Spatial Pattern-Based Techniques for PD Detection:

This study proposed innovative common spatial pattern-based techniques for detecting Parkinson's in both off-and-on-medication states. Initial preprocessing eliminated major artefacts, and various metrics, including variance, band power, and multiple entropy types, were utilized to extract features from spatially filtered EEG signals. Machine learning algorithms achieved competitive results, showcasing the effectiveness of common spatial patterns and log energy entropy. Features extracted from alpha and beta bands played a crucial role in achieving high classification accuracy.

Machine Learning and EEG Integration

Integrating EEG and machine learning has provided a framework for developing accurate EEG-based predictive systems. Machine learning algorithms enable the automation, extension, and improvement of EEG data analysis. People increasingly apply them to EEG data for pattern analysis, group membership classification, and brain-computer interface purposes. Researchers have employed machine learning algorithms to classify EEG signals, and several studies have assessed the performance of various machine learning algorithms in classifying EEG signals. They can also categorize EEG signals from the brain into words. Deep learning techniques are now present in all EEG decoding applications and represent the current state of the art.

A recent study published in MDPI proposed an innovative and improved machine learning-based BCI system that analyzes EEG signals obtained from motor imagery to distinguish among diverse limb motor tasks. The study used a novel feature extraction method based on the wavelet transform and a hybrid machine learning model based on the convolutional neural network (CNN) and the support vector machine (SVM) to classify the EEG signals. The proposed system achieved high classification accuracy and outperformed other state-of-the-art methods.

However, many open questions still exist, such as determining the most effective models and assessing the potential use of EEG data for diagnosing psychological disorders.

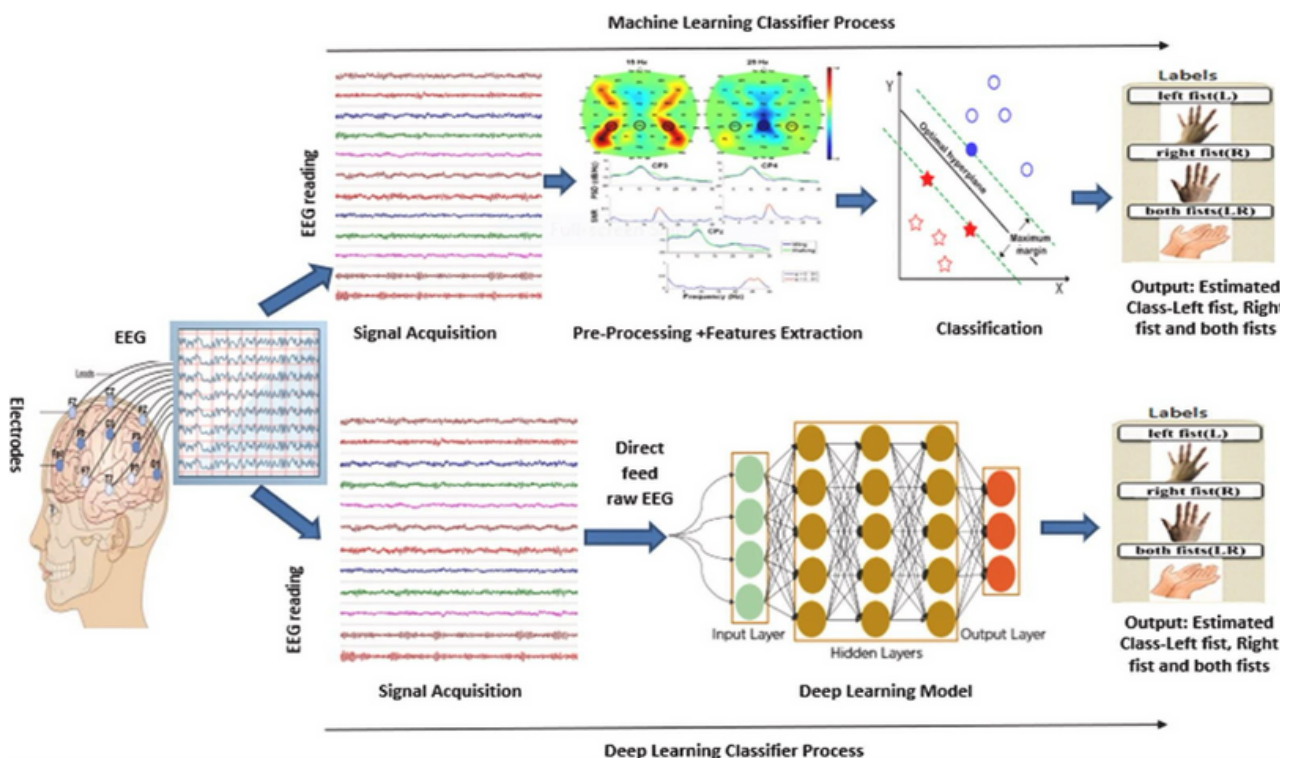


Fig. 2. EEG-Brain computer interface system. Taken from Pawan, & Dhiman, R. (2023). Machine learning techniques for electroencephalogram based brain-computer interface: A systematic literature review. Measurement: Sensors, 28, 100823.

Figure 2 illustrates the four components of the brain-computer interface system: signal acquisition, pre-processing, feature extraction, and classification and their respective applications. The BCI system collects brain signals, cleans them up, finds patterns, and then labels them.

Advancements in Automated EEG Analysis Systems

1. Introduction

Electroencephalograms (EEGs) play a pivotal role in the monitoring and diagnosis of various neurological conditions. However, the manual interpretation of EEGs demands considerable time and specialized expertise. This case study introduces an automated EEG analysis system that harnesses the power of machine learning and principles rooted in big data.

2. Significance of Automated EEG Analysis

EEGs are fundamental in healthcare for tracking brain activity. The automated system seeks to classify patterns, improving diagnostic capabilities for conditions such as epilepsy, depth of anesthesia, coma, encephalopathy, and brain death. By automating the process, diagnosis times and costs are significantly reduced, providing real-time insights.

3. TUH EEG Corpus and the Big Data Opportunity

The TUH EEG Corpus serves as a substantial big data resource for evaluating high-performance deep learning models. Comprehensive physician reports and detailed patient histories enrich the development of effective deep-learning algorithms. The study advocates for a hybrid structure, combining hidden Markov models (HMMs) and deep learning, achieving clinically acceptable performance levels.

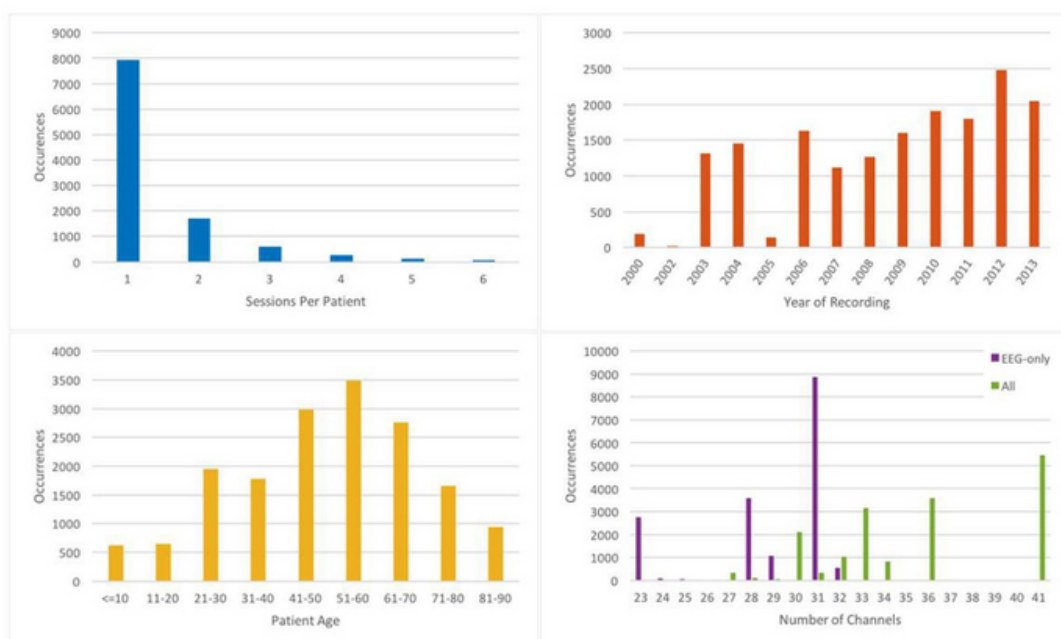


Figure 3| Some relevant statistics demonstrating the variety of data in TUH-EEG

4. Patterns of Clinical Interest

The study outlines six clinical interest patterns, strategically categorized for diagnosing brain disorders and modeling background EEG activity.

Patterns for Diagnosing Brain Disorders:

1. Spike and Sharp Waves (SPSW): Indicative of epileptic seizures.
2. Periodic Lateralized Epileptiform Discharges (PLED): Associated with destructive structural lesions.
3. Generalized Periodic Epileptiform Discharges (GPED): Manifests as periodic short-interval diffuse discharges.

Patterns Modeling Background EEG Activity:

4. Eye Movement (EYEM): Spike-like signals during patient eye movement.
5. Artifacts (ARTF): Recorded electrical activity not of cerebral origin.
6. Background (BCKG): Denotes data not falling into the above classes, crucial for machine learning systems.

Event	Train	Train % (CDF)	Eval	Eval % (CDF)
SPSW	645	0.8% (1%)	567	1.9% (2%)
GPED	6,184	7.4% (8%)	1,998	6.8% (9%)
PLED	11,254	13.4% (22%)	4,677	15.9% (25%)
EYEM	1,170	1.4% (23%)	329	1.1% (26%)
ARTF	11,053	13.2% (36%)	2,204	7.5% (33%)
BCKG	53,726	63.9% (100%)	19,646	66.8% (100%)
Total:	84,032	100.0% (100%)	29,421	100.0% (100%)

Figure 4 | An overview of the distribution of events in the subset of the TUH EEG Corpus used in our experiments.

5. Three-Pass System for High Performance

The proposed three-pass system seamlessly integrates HMMs for accurate temporal segmentation and deep learning for classification.

First Pass:

The signal is transformed into EEG events using an HMM-based system, modelling temporal evolution.

Second Pass:

Three stacked denoising autoencoders (SDAs) map event labels onto a composite epoch label vector.

Temporal and spatial context analysis enhances sequential decoding using HMMs.

Third Pass:

Probabilistic grammar applies left and right context with the current label vector.

Produces a final decision for an epoch.

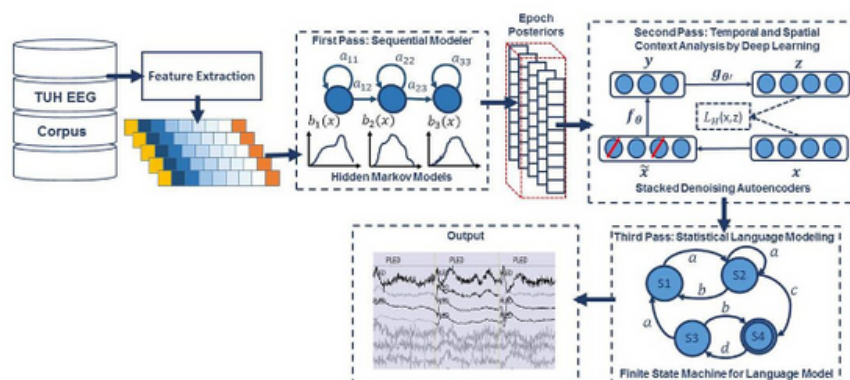


Figure 5| A three-pass architecture for automatic interpretation of EEGs that integrates hidden Markov models for sequential decoding of EEG events with deep learning for decision-making based on temporal and spatial context.

6. Performance Evaluation

The hybrid HMM/deep learning system demonstrates a sensitivity exceeding 90% and specificity below 5%, rendering automated analysis viable for clinicians. The system's low false alarm rate proves critical for spike detection applications.

Pass	Sensitivity	Specificity
1 (HMM)	86.78	17.70
2 (SdA)	78.93	4.40
3 (SLM)	90.10	4.88

Figure 6| A table showing specificity and sensitivity for each pass of processing.

The proposed automated EEG analysis system, employing a three-pass approach, exhibits promising results in classifying clinical interest patterns. This advancement contributes to reducing diagnosis time, cutting costs, and enhancing the efficiency of EEG-based diagnostic processes.

Conclusion

EEG shows promise in diagnosing Parkinson's disease and assessing cognitive impairment by detecting specific brain wave alterations. Recent advancements, particularly integrating EEG with machine learning, offer a potential pathway for accurate and efficient diagnoses. However, further research is needed to determine optimal models and fully utilise the potential of EEG in diagnosing psychological disorders associated with Parkinson's disease.

References

Brain waves may predict cognitive impairment in Parkinson's disease | Carver College of Medicine. (n.d.).

<https://medicine.uiowa.edu/content/brain-waves-may-predict-cognitive-impairment-parkinsons-disease>

Pawan, & Dhiman, R. (2023). Machine learning techniques for electroencephalogram based brain-computer interface: A systematic literature review. *Measurement: Sensors*, 28, 100823.

<https://doi.org/10.1016/j.measen.2023.100823>

Gemein, L., Schirrmester, R. T., Chrabąszcz, P., Wilson, D., Boedecker, J., Schulze-Bonhage, A., Hutter, F., & Ball, T. (2020). Machine-learning-based diagnostics of EEG pathology. *NeuroImage*, 220, 117021.

<https://doi.org/10.1016/j.neuroimage.2020.117021>

Saeidi, M., Karwowski, W., Farahani, F. V., Fiok, K., TaïAr, R., Hancock, P. A., & Aljuaid, A. M. (2021). Neural Decoding of EEG Signals with Machine Learning: A Systematic Review. *Brain Sciences*, 11(11), 1525.

<https://doi.org/10.3390/brainsci11111525>

Ramírez-Arias, F. J., García-Guerrero, E. E., Tlelo-Cuautle, E., Colores-Vargas, J. M., García-Canseco, E., López-Bonilla, O. R., Galindo-Aldana, G., & Inzunza-González, E. (2022). Evaluation of machine learning algorithms for classification of EEG signals. *Technologies (Basel)*, 10(4), 79.

<https://doi.org/10.3390/technologies10040079>

Applying EEG Data to Machine Learning, Part 1 - Expert Projects. (n.d.).

<https://docs.edgeimpulse.com/experts/novel-sensor-projects/eeg-data-machine-learning-part-1>

Estimation of the 2020 Global Population of Parkinson's Disease (PD) - MDS Abstracts. (2020, September 7). MDS Abstracts.

<https://www.mdsabstracts.org/abstract/estimation-of-the-2020-global-population-of-parkinsons-disease-pd/>

Meysam Golmohammadi, Amir Hossein Harati Nejad Torbati, Silvia Lopez de Diego, Iyad Obeid and Joseph Picone. Automatic Analysis of EEGs Using Big Data and Hybrid Deep Learning Architectures.

<https://www.frontiersin.org/articles/10.3389/fnhum.2019.00076/full>

Kuo-Hsuan Chang, Isobel Timothea French, Wei-Kuang Liang, Yen-Shi Lo, Yi-Ru Wang¹, Mei-Ling Cheng, Norden E. Huang, Hsiu-Chuan Wu, Siew-Na Lim, Chiung-Mei Chen, Chi-Hung Juan.

<https://www.frontiersin.org/articles/10.3389/fnagi.2022.832637/full>

Han CX, Wang J, Yi GS, Che YQ. Investigation of EEG abnormalities in the early stage of Parkinson's disease. Cogn Neurodyn.

<https://www.ncbi.nlm.nih.gov/pmc/articles/PMC3713203/>

Aljalal, M., Aldosari, S.A., Molinas, M. et al. Detection of Parkinson's disease from EEG signals using discrete wavelet transform, different entropy measures, and machine learning techniques.

<https://www.nature.com/articles/s41598-022-26644-7>

Aljalal M, Aldosari SA, AlSharabi K, Abdurraqueeb AM, Alturki FA. Parkinson's Disease Detection from Resting-State EEG Signals Using Common Spatial Pattern, Entropy, and Machine Learning Techniques.

<https://www.ncbi.nlm.nih.gov/pmc/articles/PMC9139946/>