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BRAIN INFORMATICS SYSTEMS FOR PRECISION MANAGEMENT OF NEURODEGENERATIVE DISEASES

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Abstract:

Neurodegenerative disorders, such as Alzheimer's, Parkinson's, and ALS, pose intricate challenges due to their progressive characteristics and varied clinical symptoms. Brain informatics, an interdisciplinary domain that combines neuroscience, data science, and computational resources, has surfaced as a game-changing platform for comprehending, forecasting, and managing these conditions. This review investigates how brain informatics contributes to monitoring disease advancement, constructing individualized brain maps, facilitating immediate clinical interventions, and combining multi-modal data from genomics to imaging. It also delves into the creation of digital phenotyping, the significance of wearable technology, and the use of machine learning in precision neurology. Furthermore, it discusses the drawbacks of current systems, such as issues with data standardization, ethical dilemmas, AI biases, and barriers to accessibility. In summary, the fusion of emerging technologies with clinical neuroscience offers potential for more customized, predictive, and participatory care models in the management of neurodegenerative diseases.

Keywords: *Brain Informatics, Neurodegenerative Diseases, Artificial Intelligence, Neuroimaging, Wearable Device.*

1. Introduction

Neurodegeneration implies the gradual deterioration of neurons, affecting either their structure, their function or both, ultimately resulting in neuronal death. Neurodegeneration represents the pathological signature of various chronic and untreatable brain disorders, with Alzheimer's disease (AD), Parkinson's disease (PD), and amyotrophic lateral sclerosis (ALS) being the most notable. The characteristics of these disorders encompass the disruption of synaptic functions, the inadequate buildup of misfolded proteins like amyloid-β, tau, and α-synuclein, oxidative stress, mitochondrial dysfunction, and neuroinflammation. All these occurrences progressively result in cognitive and motor difficulties that significantly diminish the quality of life and impose a substantial societal burden.

Technically, diagnosing neurodegenerative disorders is a complex process filled with many delays in diagnosis and the potential for initial treatments to adversely affect the outcomes. While neurodegenerative disorders suffer from the lack of specificity of individual tests and markers, an accurate diagnosis is often made only after an exhaustive and expensive series of tests. Traditionally, the methods used to conduct a clinical assessment, measure damage, and examine the spine have been MRI, CT, and EEG. Brain informatics serves as a multidisciplinary new emerging field embracing neuroscience, cognitive science, data science, and computational technologies for the systematic study of brain function and dysfunction. Incorporating the huge amount of brain data with AI algorithms spearheaded advancements in pattern recognition, early diagnostics, and simulation of brain disorders, thereby positioning brain informatics as a core foundation of precision neurology.

1.1 Objectives of the study

- To analyze the role of brain informatics in understanding and predicting neurodegenerative disease progression through integration of multi-modal data such as genomics, imaging, and clinical parameters.
- To evaluate the application of machine learning and digital phenotyping in precision neurology, focusing on real-time monitoring, early diagnosis, and personalized patient care strategies.
- To explore the development of individualized brain mapping systems for improving clinical decision-making and enabling tailored therapeutic interventions in neurodegenerative disorders.
- To examine the technical, ethical, and accessibility challenges in implementing brain informatics systems, including data standardization, AI bias, and global healthcare disparities.

2. Core components of brain informatics

2.1 Neuroimaging

Neuroimaging is an essential part in studying brain functions because it enables us to understand the structure and activity of the brain non-invasively. Neuroimaging techniques can help comprehend the roles of brain regions involved in different cognitive and behavioral processes such as perception, attention, memory, language, and decision making. Standard techniques involved are fMRI, Electroencephalogram (EEG), and Magnetoencephalography (MEG) [1].

Functional Magnetic Resonance Imaging (fMRI)

Functional magnetic resonance imaging (fMRI) is a method that assesses blood flow variations to deduce neural activity, making it an essential tool for charting functional networks and brain connectivity. It offers high spatial resolution, enabling precise identification of brain activity during both active tasks and periods of rest. Recent improvements in fMRI technology feature increased spatial resolution for examining tiny brain structures and real-time fMRI for neurofeedback uses. Multimodal imaging integrates fMRI with EEG or MEG to provide better spatial-temporal understanding. Ultra-high field fMRI (7T+) delivers enhanced sensitivity and accuracy in brain mapping [1].

Electroencephalogram (EEG)

EEG measures electrical activity from the scalp to illustrate the timing and patterns of brain function. It provides exceptional temporal resolution, allowing for the capture of swift changes in brain activity that are vital for examining dynamic cognitive processes. Innovations like high-density electrode arrays and real-time source localization boost accuracy and are valuable in areas such as neurofeedback and brain-computer interfaces. Wearable EEG devices facilitate monitoring beyond the laboratory setting. When integrated with methods like fMRI, EEG delivers comprehensive insights into both the timing and location of brain activity [1].

AI-Driven imaging analysis for early detection

AI-based imaging analysis is transforming the early identification of neurodegenerative conditions such as Alzheimer's and Parkinson's. By employing sophisticated algorithms and multimodal imaging methods, these AI tools can recognize subtle changes and biomarkers in the brain, improving diagnostic precision and allowing for timely interventions. Research has demonstrated that AI models can deliver high levels of diagnostic accuracy, with sensitivity rates between 80% and 100% and specificity soaring to 85% [2].

2.2 Data analytics and machine learning

The use of machine learning in computational intelligence is rapidly growing and demonstrates significant promise in the recognition, management, treatment, and surveillance of complex disorders, particularly neurodegenerative diseases like Alzheimer's and Parkinson's [3]. Deep learning techniques, such as neural networks, have proven capable of tracking changes in brain structure and function linked to infections, as well as monitoring patients' motor and cognitive symptoms and their responses to therapies. Investigations in transcriptomics have revealed potential diagnostic biomarkers for Alzheimer's disease and have demonstrated the effects of therapeutic treatments in animal models of Huntington's disease.

Explainable artificial intelligence (XAI) in Alzheimer's Disease (AD) provides clear insights into diagnostic procedures, helping clinicians comprehend and have confidence in AI-driven conclusions. By offering tailored treatment plans, XAI enables both clinicians and patients to make educated decisions based on personal traits and the progression of the disease [4]. XAI improves management of Parkinson's Disease (PD) by clarifying the decisions made by AI models, assisting in the interpretation of diagnoses and prognoses, and supporting personalized treatment choices [5]. By utilizing fundamental clinical characteristics and Jacobian maps derived from deformation fields, an advanced convolutional neural network (CNN) was trained to differentiate between healthy controls and those with PD [6].

2.3 Cognitive informatics and modeling

Cognitive informatics and modeling employ computational approaches to comprehend and forecast how neurodegenerative disorders influence brain functionality and cognitive abilities. This discipline emphasizes essential cognitive functions such as memory, attention, and language, regarding the brain as an information-processing entity that deteriorates over time. By merging clinical information, imaging techniques, and biomarkers, it aids in simulating disease progression, recognizing early indicators, and facilitating diagnosis and prognosis. Cognitive networks specific to diseases aid in illustrating how functions such as memory, language, and attention decline across various neurodegenerative disorders.

2.4 Brain-Computer Interfaces (BCIs)

A brain-computer interface (BCI) is a technology that creates a direct communication link between the brain and external devices by converting signals from the central nervous system into actionable commands. BCIs are being widely researched for their potential applications in neurorehabilitation, especially for those with motor or cognitive disabilities. BCIs can function in various modes [15]: Active mode (the user consciously alters brain activity), Reactive mode (the brain reacts to external stimuli), and Passive mode (monitors cognitive states like fatigue or attention without conscious control).

BCI combined with Virtual Reality (VR) merges immersive experiences with brain feedback for improved neurorehabilitation [16]. BCI alongside IoT allows neurodegenerative patients to control smart home devices via brain signals, increasing their independence [17]. Functional near-infrared spectroscopy (fNIRS) and fMRI are being integrated with BCIs to enhance the accuracy of signal analysis.

3. Early detection through informatics

Recognizing a neurodegenerative disease in its early stages can significantly impact patient care. Conditions like Alzheimer's disease (AD), Parkinson's disease (PD), and amyotrophic lateral sclerosis (ALS) are often identified only after considerable symptoms have developed over time. Artificial Intelligence (AI) has demonstrated remarkable abilities to identify subtle neurological changes well in advance of clinical symptoms. Machine learning (ML) and deep learning (DL) algorithms can process intricate datasets, including brain imaging, genetic markers, and behavioral information, to identify individuals with greater accuracy than traditional techniques [7]. These technologies can recognize early changes in speech, motor function, and cognitive performance that may be overlooked by human evaluators. By integrating such models into routine healthcare supervision systems, it becomes feasible to apply proactive detection strategies [8].

Supervised and unsupervised learning techniques, such as Support Vector Machines (SVMs) and Convolutional Neural Networks (CNNs), are extensively employed in MRI and PET imaging to accurately assess the stages of neurodegenerative diseases. Natural Language Processing (NLP) techniques have been employed for written assessments and language-targeting methods in analyzing linguistic complexity among individuals at risk for neurodegenerative diseases. Research has indicated that NLP models can differentiate between healthy elderly individuals and those in the early stages of dementia with over 90% accuracy, making them a promising tool for non-invasive evaluations. AI-based analysis of EHRs is already being implemented in various hospital networks, enhancing the early detection of neurological issues and cognitive impairments [2].

4. Disease progression

4.1 Digital biomarkers for the early detection of neurodegenerative diseases

4.1.1 Voice

One of the most promising digital markers for the early identification of neurodegenerative diseases is related to voice and speech patterns. Conditions such as Parkinson's Disease (PD), Alzheimer's Disease (AD), Amyotrophic Lateral Sclerosis (ALS), and Frontotemporal Dementia (FTD) often impact motor function, cognitive abilities, and language skills—all of which are closely mirrored in vocal characteristics [9]. In disorders like PD and ALS, changes in vocal cord function can lead to speech that is quieter, monotone, slurred, and characterized by tremors. In conditions such as AD and FTD, speech may become slower, less fluid, and marked by pauses, repetitions, and difficulty finding words. By utilizing smartphones, microphones, or wearable devices, machine learning (ML) algorithms can analyze features like pitch, jitter and shimmer, speaking rate and articulation, frequency and duration of pauses, and acoustic properties and vocabulary richness [10].

4.1.2 Handwriting

Neurodegenerative diseases such as AD, PD, and Huntington's Disease (HD) frequently demonstrate subtle motor, cognitive, and visuospatial challenges well before a clinical diagnosis is made, and handwriting captures all three of these aspects simultaneously. Changes in writing pressure, tremor, and speed may indicate motor dysfunction, making handwriting a crucial digital biomarker for early detection, particularly in PD [11]. Modern technologies utilize smart pens, tablets, and machine learning algorithms to analyze handwriting in real-time. Metrics such as stroke speed, pen pressure, writing duration, and the size and spacing of letters can be measured to uncover disease-specific patterns, even in the preclinical stage.

4.1.3 Speech and gait analysis

Machine learning (ML) models leverage data from cognitive evaluations, behavioral patterns, and brain imaging to pinpoint individuals at risk for conditions such as AD, PD, and mild cognitive impairment (MCI). AI has demonstrated considerable potential in observing and anticipating cognitive decline linked to neurodegenerative disorders [2].

4.2 Longitudinal brain mapping in specific diseases

4.2.1 Alzheimer's Disease (AD)

As the illness advances, atrophy affects the neocortex, influencing higher-level cognitive functions such as language and executive skills. The functional decline seen in AD follows a recognizable pattern, with memory loss being the initial and most significant sign. As the illness progresses, individuals frequently encounter challenges with language, including difficulties in finding words and diminished verbal fluency, eventually leading to deficits in executive functioning [12]. Informatics tools that integrate diverse biomarkers and clinical evaluations merge cerebrospinal fluid (CSF) analysis, positron emission tomography (PET) imaging, and Mini-Mental State Examination (MMSE) scores collected over extended periods, providing a thorough understanding of the disease's development [8].

4.2.2 Parkinson's Disease (PD)

The monitoring of motor symptoms in PD has greatly advanced due to the use of wearable technologies. Gadgets like smartwatches and accelerometers can continuously monitor gait patterns, tremor frequency, and bradykinesia, offering real-time data that can be extremely useful for clinicians in evaluating disease advancement and treatment efficacy. Moreover, the combination of dopamine transporter imaging with speech analysis provides a holistic perspective on both motor and non-motor symptoms. Speech analysis can detect subtle shifts in vocal patterns and enunciation, which often serve as early indicators of cognitive deterioration in PD [12].

4.2.3 Amyotrophic Lateral Sclerosis (ALS)

To evaluate disease progression and estimate outcomes, electromyography (EMG) is frequently used to assess muscle electrical activity and identify patterns of denervation. Functional evaluations, such as the ALS Functional Rating Scale-Revised (ALSFRS-R), offer a standardized assessment of a patient's capabilities across various areas, including speech, swallowing, and mobility. Recent developments in machine learning and predictive analytics have resulted in the creation of predictive neural networks that can more accurately predict disease advancement and patient outcomes [10].

5. Personalized brain mapping and precision tools

5.1.1 Integration of omics and imaging data

Merging omics data (genomics, proteomics, metabolomics, and transcriptomics) with cutting-edge imaging methods (MRI, PET, and fMRI) is crucial for forming detailed profiles of individual brains. This multi-faceted strategy enables researchers to uncover complex biological interactions that play a role in brain function and disease, improve understanding of processes involved in neurodegenerative disorders, and promote precision medicine by crafting personalized treatment strategies [13].

5.1.2 Creation of neuroinformatics databases

The development of neuroinformatics databases that aggregate brain patterns specific to populations is vital for propelling neuroscience research forward. These databases fulfill several essential roles: data standardization, normative data identification, encouragement of collaborative research, and applications of machine learning and AI. The large volumes of data housed in these databases can be utilized for machine learning and artificial intelligence applications to uncover patterns and anticipate outcomes, further improving personalized medicine strategies.

6. Clinical application and real-time support

6.1 Continuous brain signal monitoring during therapy/rehabilitation

Brain informatics facilitates ongoing observation of neural activity through sophisticated neurophysiological techniques such as electroencephalography (EEG), magnetoencephalography (MEG), and functional near-infrared spectroscopy (fNIRS). For example, in Parkinson's disease treatment, closed-loop deep brain stimulation (DBS) systems utilize real-time brain data to adjust stimulation strength, enhancing treatment effectiveness while reducing adverse effects. In the context of Alzheimer's and stroke recovery, EEG-based neurofeedback therapy allows individuals to retrain cognitive functions by actively influencing brain rhythms [14].

6.2 Integration of wearable devices and mobile health technologies

Wearable technology like smartwatches, headbands, biosensors, and portable EEG caps have become essential components of brain informatics systems. These devices passively gather physiological information such as movement patterns, sleep disruptions, heart rate variability, and brain activity. In dementia management, motion detectors and wristbands can identify restlessness or nighttime wandering—early indicators of cognitive decline. In Parkinson's disease, inertial measurement units (IMUs) monitor tremors, gait freezing, and bradykinesia in everyday environments, supplying continuous symptom tracking beyond the clinical setting [2].

6.3 Brain–Computer Interface (BCI) systems for motor and cognitive rehabilitation

BCI systems represent an innovative clinical application of brain informatics by converting neuronal activity into actionable instructions for devices or software, independent of muscular movement. For individuals with ALS, non-invasive BCIs enable communication via eye movements or EEG signals. In the cases of Parkinson's and stroke, BCI-based neurorehabilitation allows patients to engage in cognitive and motor training within virtual environments by modulating their brain signals. These systems are progressively being enhanced with AI to improve signal classification accuracy, minimize noise, and personalize therapy in real-time [16].

6.4 Immediate feedback systems for caregivers and clinicians

Platforms for real-time feedback driven by brain informatics ensure that clinicians and caregivers receive prompt, actionable insights regarding a patient's condition. These systems integrate data from multiple sources—vital signs, cognitive test results, and behavioral changes—into visual dashboards and alerts. In clinical environments, this feedback helps in modifying medications, adjusting cognitive-behavioral therapy (CBT), and pacing physical rehabilitation. Some systems incorporate voice and facial recognition technologies that detect mood fluctuations or confusion, facilitating early behavioral interventions.

6.5 Remote patient monitoring and tele-neuroinformatics

Tele-neuroinformatics platforms have become increasingly significant, particularly following COVID-19, as they enable remote management of neurodegenerative diseases. These systems utilize cloud-connected devices to gather and transmit patient data to healthcare providers. Neurologists can monitor disease progression, medication effects, or the efficiency of interventions from a distance. Remote oversight also contributes to decentralized clinical trials, enabling a diverse range of patient participants while lowering trial costs and durations.

6.6 Alert and early warning systems for episodic symptoms

Sophisticated brain informatics systems can detect early physiological or behavioral indicators of acute neurological episodes, such as seizures, freezing of gait (FoG), or abrupt cognitive lapses. AI-driven platforms analyze biosensor and EEG data in real-time to identify precursors to these incidents and issue alerts to caregivers or emergency contacts. Predictive models that utilize gait data from wearables can notify a Parkinson's patient mere seconds before a freezing episode occurs, allowing for preemptive measures.

7. Challenges and limitations

7.1 Data heterogeneity and standardization issues

A significant challenge of brain informatics systems stems from the diversity of the data involved. Research on neurodegenerative diseases draws on various sources of data—including neuroimaging, electrophysiological signals, genomic data, wearable technology, and electronic health records—which are produced under differing spatial, temporal, and technical circumstances. The absence of standardized data acquisition methods and inconsistent data labeling across different institutions hampers comparisons between studies, large-scale analyses, and meta-learning. Establishing universally accepted data curation processes and unified protocols is vital for making integrative brain informatics both scalable and trustworthy [18].

7.2 Privacy and ethical concerns in handling brain data

Data related to the brain is among the most sensitive forms of biomedical information, often disclosing not just health conditions but also behavioral traits, cognitive abilities, and emotional tendencies. The ethical considerations surrounding the collection, storage, and analysis of such data bring forth significant issues related to patient privacy, informed consent, and data ownership. An emerging discourse on "neuro-rights" advocates for legal protections related to cognitive liberty, mental privacy, and psychological integrity. Until robust ethical frameworks are established globally, these issues will hinder the widespread use of brain informatics in clinical settings [19].

7.3 Interoperability among devices, platforms, and datasets

The existing landscape of brain informatics technology comprises a diverse range of hardware and software solutions—each developed independently by various academic, clinical, and commercial entities. A primary limitation arises from the lack of interoperability among these tools. Initiatives like FHIR (Fast Healthcare Interoperability Resources) and the Brain Imaging Data Structure (BIDS) aim to establish standardized formats, but widespread adoption remains a work in progress. Addressing interoperability issues is essential for achieving smooth, personalized informatics-driven healthcare.

7.4 Bias in AI algorithms due to limited or skewed datasets

AI-driven decision-support tools play a pivotal role in brain informatics platforms; however, their precision and applicability rely heavily on the quality and variety of the training data. Many existing datasets in neurodegenerative research are limited in size, homogeneous, or lack representation from underrepresented groups such as ethnic minorities, rural inhabitants, and women. This introduces biases into machine learning models, which can lead to lower diagnostic accuracy or treatment predictions for specific subgroups. To tackle these biases, it is crucial to focus on inclusive data collection as well as the development of fairness-aware machine learning models, ongoing validation, and transparency in algorithms [20].

Conclusion

Brain informatics systems are revolutionizing the way we manage neurodegenerative diseases by fusing neuroscience, data science, artificial intelligence, and clinical neurology into a cohesive and intelligent framework. The progression of conditions such as Alzheimer's, Parkinson's, ALS, and Huntington's disease is now being understood through real-time brain activity, longitudinal imaging data, behavioral trends, and multi-omics data combined to provide dynamic and individualized insights. This advancement facilitates earlier diagnoses, improved risk assessment, and the creation of tailored treatment strategies that were once out of reach. With integrative platforms that merge neuroinformatics databases, machine learning techniques, and wearable technology, brain informatics extends its reach beyond medical facilities—into residential settings, everyday activities, and long-term care systems. Nonetheless, challenges such as standardization of data, ethical dilemmas, and limited access in under-resourced areas remain and need to be tackled through interdisciplinary collaboration and policy reforms. In summary, brain informatics has the transformative potential to shift neurodegenerative disease management towards a more proactive, personalized, and participatory approach—ultimately transforming the focus from merely controlling symptoms to a system-based understanding and intervention.

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References

1. Yen, C., Lin, C.-L., & Chiang, M.-C. (2023). Exploring the frontiers of neuroimaging: A review of recent advances in understanding brain functioning and disorders. Life, 13(7), 1472. https://doi.org/10.3390/life13071472
2. Hassan Ali. (2022). AI in neurodegenerative disease research: Early detection, cognitive decline prediction, and brain imaging biomarker identification. https://doi.org/10.5281/ZENODO.14890442
3. Aborode, A. T., Emmanuel, O. A., Onifade, I. A., Olotu, E., Otorkpa, O. J., Mehmood, Q., Abdulai, S. I., Jamiu, A., Osinuga, A., Oko, C. I., Fakorede, S., Mangdow, M., Babatunde, O., Olapade, Z., Victoria, A. G., Salami, A., Usman, I. A., Agboli, V. I., & Adesola, R. O. (2025). The role of machine learning in discovering biomarkers and predicting treatment strategies for neurodegenerative diseases: A narrative review. NeuroMarkers, 2(1), 100034. https://doi.org/10.1016/j.neumar.2024.100034
4. Fania, L., et al. (2024). Explainable artificial intelligence in Alzheimer's disease: Diagnostic and therapeutic applications.

5. Salimi-Badr, A., et al. (2023). Explainable AI for management of Parkinson's disease. Engineering Applications of Artificial Intelligence.
6. Wang, H., Toumaj, S., Heidari, A., Souri, A., Jafari, N., & Jiang, Y. (2025). Neurodegenerative disorders: A holistic study of the explainable artificial intelligence applications. Engineering Applications of Artificial Intelligence, 153, 110752. https://doi.org/10.1016/j.engappai.2025.110752
7. Arya, A. D., Verma, S. S., Chakarabarti, P., Chakrabarti, T., Elngar, A. A., Kamali, A.-M., & Nami, M. (2023). A systematic review on machine learning and deep learning techniques in the effective diagnosis of Alzheimer's disease. Brain Informatics, 10(1). https://doi.org/10.1186/s40708-023-00195-7
8. Mukherji, D., Mukherji, M., Mukherji, N., & Alzheimer's Disease Neuroimaging Initiative. (2022). Early detection of Alzheimer's disease using neuropsychological tests: A predict–diagnose approach using neural networks. Brain Informatics, 9(1). https://doi.org/10.1186/s40708-022-00169-1
9. Sajal, Md. S. R., Ehsan, Md. T., Vaidyanathan, R., Wang, S., Aziz, T., & Mamun, K. A. A. (2020). Telemonitoring Parkinson's disease using machine learning by combining tremor and voice analysis. Brain Informatics, 7(1), 12. https://doi.org/10.1186/s40708-020-00113-1
10. Farrokhi, Z., Zakavi, S. A., Sarafraz, A., Valifard, M., Yousefzadeh, S., Mashhadi Tafreshi, Z., Anbiyaee, O., Rostami, N., Asadi Anar, M., & Deravi, N. (2025). Acoustic signatures of bulbar ALS: Predictive modeling with sustained vowels and LightGBM. eNeurologicalSci, 40, 100579. https://doi.org/10.1016/j.ensci.2025.100579
11. Saint-Jalmes, M., Fedyashov, V., Beck, D., Baldwin, T., Faux, N. G., Bourgeat, P., Fripp, J., Masters, C. L., & Goudey, B. (2023). Disease progression modelling of Alzheimer's disease using probabilistic principal components analysis. NeuroImage, 278, 120279. https://doi.org/10.1016/j.neuroimage.2023.120279
12. Sorino, P., Lombardi, A., Lofù, D., Colafiglio, T., Ferrara, A., Narducci, F., Sciascio, E. D., & Di Noia, T. (2025). Detecting label noise in longitudinal Alzheimer's data with explainable artificial intelligence. Brain Informatics, 12(1), 15. https://doi.org/10.1186/s40708-025-00261-2
13. Iturria-Medina, Y., Adewale, Q., Khan, A. F., Ducharme, S., Rosa-Neto, P., O'Donnell, K., Petyuk, V. A., Gauthier, S., De Jager, P. L., Breitner, J., & Bennett, D. A. (2022). Unified epigenomic, transcriptomic, proteomic, and metabolomic taxonomy of Alzheimer's disease progressio n and heterogeneity. Science Advances, 8(46), eabo6764. https://doi.org/10.1126/sciadv.abo6764
14. Bosch-Bayard, J., Aubert-Vazquez, E., Brown, S. T., Rogers, C., Kiar, G., Glatard, T., Scaria, L., Galan-Garcia, L., Bringas-Vega, M. L., Virues-Alba, T., Taheri, A., Das, S., Madjar, C., Mohaddes, Z., MacIntyre, L., CHBMP, Evans, A. C., & Valdes-Sosa, P. A. (2020). A quantitative EEG toolbox for the MNI neuroinformatics ecosystem: Normative SPM of EEG source spectra. Frontiers in Neuroinformatics, 14, 33. https://doi.org/10.3389/fninf.2020.00033
15. Rouzitalab, A., Boulay, C. B., Park, J., & Sachs, A. J. (2023). Intracortical brain-computer interfaces in primates: A review and outlook. Biomedical Engineering Letters, 13(3), 375–390. https://doi.org/10.1007/s13534-023-00286-8
16. Drigas, A., & Sideraki, A. (2024). Brain neuroplasticity leveraging virtual reality and brain–computer interface technologies. Sensors, 24(17), 5725. https://doi.org/10.3390/s24175725
17. Malibari, A. A. (2023). An efficient IoT-artificial intelligence-based disease prediction using lightweight CNN

in healthcare system. Measurement: Sensors, 26, 100695. https://doi.org/10.1016/j.measen.2023.100695

18. Eteleeb, A. M., Novotny, B. C., Tarraga, C. S., Sohn, C., Dhungel, E., Brase, L., Nallapu, A., Buss, J., Farias, F., Bergmann, K., Bradley, J., Norton, J., Gentsch, J., Wang, F., Davis, A. A., Morris, J. C., Karch, C. M., Perrin, R. J., Benitez, B. A., & Harari, O. (2024). Brain high-throughput multi-omics data reveal molecular heterogeneity in Alzheimer's disease. PLOS Biology, 22(4), e3002607. https://doi.org/10.1371/journal.pbio.3002607
19. Bradshaw, A., Hughes, N., Vallez-Garcia, D., Chokoshvili, D., Owens, A., Hansen, C., Emmert, K., Maetzler, W., Killin, L., Barnes, R., Brookes, A. J., Visser, P. J., Hofmann-Apitius, M., Diaz, C., & Steukers, L. (2023). Data sharing in neurodegenerative disease research: Challenges and learnings from the innovative medicines initiative public-private partnership model. Frontiers in Neurology, 14, 1187095. https://doi.org/10.3389/fneur.2023.1187095
20. Bracher-Smith, M., Melograna, F., Ulm, B., Bellenguez, C., Grenier-Boley, B., Duroux, D., Nevado, A. J., Holmans, P., Tijms, B. M., Hulsman, M., De Rojas, I., Campos-Martin, R., Der Lee, S. V., Castillo, A., Küçükali, F., Peters, O., Schneider, A., Dichgans, M., Rujescu, D., … Escott-Price, V. (2025). Machine learning in Alzheimer's disease genetics. Nature Communications, 16(1), 6726. https://doi.org/10.1038/s41467-025-61650-z