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RESEARCH ARTICLE

AI Perspectives Within Computational Neuroscience: EEG Integrations and the Human Brain

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Abstract: Current advancements within the realm of computational neuroscience, combined with the transformative capabilities of artificial intelligence (AI), have opened new paths for understanding the human brain's interconnected complexity. This research exploration integrates electroencephalography (EEG), computational neuroscience, along with AI toward the investigation of complex cognitive mechanisms and neural activations associated with the various types of mental states. As a non-invasive tool, EEG mainly captures the internal electrical activity that reveals the interconnected cognitive processes in real time. By leveraging AI techniques—such as deep learning (DL), machine learning (ML), transfer learning, and convolutional neural networks (CNN)—this investigation deciphers EEG data to identify various specific neural patterns accompanying various types of cognitive states, memory formation, and especially toward emotional responses. To further refine these results and findings, this study organizes applications chronologically, presenting a developmental perspective on the AI-driven EEG advancements and their significance in detecting nuanced brain activity. This research not only addresses how experimental methods impact cognitive state reliability but also examines the amygdala's role in EEG during emotional stimuli, thus expanding our multimodal level for understanding of emotional and memory-related neural signatures. By merging EEG data with AI-calibrated models, this investigation proposes new perspectives on the neural basis of attention, perception, and cognitive function, potentially informing early diagnosis of neurological disorders and enhancing brain-computer interfaces. Through this multidisciplinary lens, the exploration advances clinical applications and cognitive interventions, highlighting the interplay between EEG, computational neuroscience, and AI as an essential frontier in terms of both science and neurotechnology.

Keywords: artificial intelligence, biomedical engineering, computational neuroscience, cognitive computing, deep learning, electroencephalography, machine learning

1. Introduction

The homo sapiens epicenter of cognition retrospect the human mind, a repository of extraordinary complexity and with a wide range of leveling depth, has captivated scholars, scientists, and curious thinkers for many centuries. This complex organ, which is responsible for generating thoughts, emotions, memories, and most importantly human behaviors, shapes human experience and the uniqueness toward individual identity. However, these levels of complexities in terms of cognition and the underlying interconnected neural mechanisms still remain an enigma, sparking continuous inquiry across the diverse disciplines and domains alike. Today, as rapid technological advancements rush, the potential toward the decipher of these anonymities has reached unprecedented levels of apex expandability. At the forefront of this investigative exploration is the conjunction of electroencephalography (EEG), computational neuroscience, and artificial intelligence (AI)—a very powerful troika promising new and innovative insights into the neural basis of cognitive computing and its associated emotional processes [1–3].

EEG, a non-invasive technique for recording the brain's electrical activity, provides a dynamic view of neural oscillations linked to various cognitive states and functions. By capturing real-time neural signals, EEG enables the examination of cognitive processes with a temporal resolution unattainable by other neuroimaging techniques. In the recent years, advancements in EEG technology have allowed for higher precision and spatial resolution, paving the way for more nuanced explorations of brain function [4–6]. This research leverages high-resolution EEG data to investigate key cognitive domains, including attention, memory formation, and emotion processing, exploring neural signatures associated with each state.

AI has transfigured neuroscience by empowering the analysis of many large, complex datasets. Machine learning (ML) algorithms, including transfer learning and especially deep learning (DL)

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neural networks, can excerpt very dense intricate insights from EEG signals that were once truly beyond reach. These AI models identify delicate neural patterns and provide a very sophisticated analysis of brain dynamics perspectives, at the same time, detecting diverse neural signatures across various types of cognitive states [7–9]. Moreover, the usage of transfer learning techniques extends the AI's adaptableness by reprocessing learned available knowledge from many related tasks, increasing the accuracy toward identifying EEG patterns associated with the specific types of mental states [10, 11]. This AI-driven approach augments the analysis of types of EEG data, providing a very powerful instrument to decode the complex patterns associated within the EEG signals that associate with individual human cognition, emotion, and memory.

Simultaneously, the field of computational neuroscience has made significant progress in mapping the structural and functional architecture of the brain, revealing its remarkable complexity and interconnectivity. Foundational research on neural circuits and brain networks has established a framework for understanding how thoughts are generated and actions orchestrated [12–14]. The integration of EEG with AI and neuroscience principles provides a more comprehensive approach to bridging neural activity patterns and the underlying neural networks. This interdisciplinary synergy holds promise for translating complex EEG patterns into actionable insights that inform both the science of cognition and its practical applications.

This investigative exploration aims to discourse the primary fundamental questions that lie at the juncture of EEG, AI, and computational neuroscience. How do the neural circuits compose attention and human emotional processing? What type of patterns govern the memory formations as they are captured by EEG data signals? How do diverse experimental paradigms actually impact the reliability of new results and findings within the cognitive states? Through these examinations, this study advances current available knowledge by the contribution of new perspectives on neural activity interconnected with the cognitive and emotional functions of the human brain. Beyond all the aspects of theoretical contributions, this exploration has consequences for clinical neurology, brain-computer interfaces (BCIs), and toward personalized cognitive interventions, enhancing both the diagnostic capabilities and also the therapeutic strategies.

The following layers of this investigation feature the methodologies and experimental analysis employed, results with the findings obtained, and the associated wider implications of integrating EEG, AI, and computational neuroscience. This research represents a groundbreaking step toward extrication of the interconnected intricacies of the human mind, transcending outmoded boundaries to further attach the combined power of EEG data technology, AI methodologies, and the neuroscientific insights. This attempt invites us to embrace a completely new era of exploration, one that influences interdisciplinary collaboration to illuminate the enigmatic processes of the complex human cognition and consciousness.

2. Methods and Experimental Analysis

Concerning the methodological and experimental framework for this investigative exploration which mainly employs a comprehensive and a very multidimensional approach that participates with EEG, computational neuroscience, and AI to explore the interconnected complexities of the human cognition. A diverse regiment of various types of participants was engaged to ensure the representativeness, with the association for the recruitment strategies emphasizing for a wider diversity in terms of age, gender, and cognitive profiles. Ethical guidelines were strictly followed to, with an informed consent obtained from all the various types of participants to safeguard their individual rights and also ensuring for a high standard of well-being. The EEG data were collected using high-density electrode array system within a controlled laboratory environments with its associated device peripherals to maintain the model accuracy, consistency, and reliability. Following the international 10–20 system concerning the electrode placements, the study also ensured high-resolution spatial and the temporal recordings of the neural activity, capturing a very detailed information on brain dynamics across various cognitive states. For further EEG data information and visualization for the waveforms which were also resourced for the investigative exploration is provided and mentioned within the acknowledgments section.

The study employed a well-established experimental paradigm to prompt the specific types of the cognitive states, such as attention, memory, and emotion, which allowed for the embattled neural region investigations. To maximize data quality, EEG data preprocessing involved many advanced techniques for the noise reduction, artifact correction, and signal enhancement. Afterward steps included the filtering process, independent component analysis, and spatial filtering for the minimized ocular, muscle, and the line-noise artifacts. These preprocessing steps ensured that the EEG data recollect only the required relevant signals, thus improving the reliability and the interpretability of the associated subsequent analyses.

Next, the features and functionalities which were extracted from the EEG data encompassed of multiple dimensions, including temporal, frequency, and spatial domains, providing a very rich dataset for the experimental analysis. These extracted features served as the many inputs for various AI algorithms, with ML models and DL architectures, such as the convolutional neural networks (CNNs), specifically personalized for the time series and spatial data.

Each of the AI model underwent demanding cross-validation to prevent the overfitting, and parameters were fine-tuned to optimize model accuracy and generalizability. The integration of these AI models with principles from computational neuroscience along with the usage of KNIME Data Analytics enabled the identification of neural signatures associated with various types of distinct cognitive processes, facilitating toward a deeper understanding of EEG feature-cognition relationships. Statistical analyses were also applied to further evaluate the relationships between EEG features and cognitive states, employing techniques such as correlation analysis, multivariate analysis of variance, and linear discriminant analysis to mainly assess the significance and reliability of the results and findings. To further validate the results, permutation testing and bootstrapping were also utilized, for ensuring a very robust type of inferences across the types of cognitive domains. This type of analysis framework provided the critical insights into the specific neural patterns associated with the interconnected cognitive states, contributing to a more nuanced understanding of the regions for neural activity.

The results and findings from these investigations were interpreted for various potential applications across various fields and systems. In clinical neuroscience, these insights may contribute to the early detection of neurological disorders by identifying early biomarkers in terms of the neural activity patterns. The integration of these perceptions into BCIs could facilitate novel types of communication methods between the brain and device peripheral technology, opening new possibilities for assisting individuals with communication impairments or developing neuroadaptive devices. Throughout the exploration, rigorous ethical protocols were followed to maintain participant confidentiality, data security, and integrity in terms of the reporting. This methodology offered a very cohesive framework for exploring the complex cognitive processes, with significant implications for both the theoretical understanding and the practical applications toward computational neuroscience and neurotechnology.

3. Related Works

3.1. Background research and investigative explorations for available knowledge

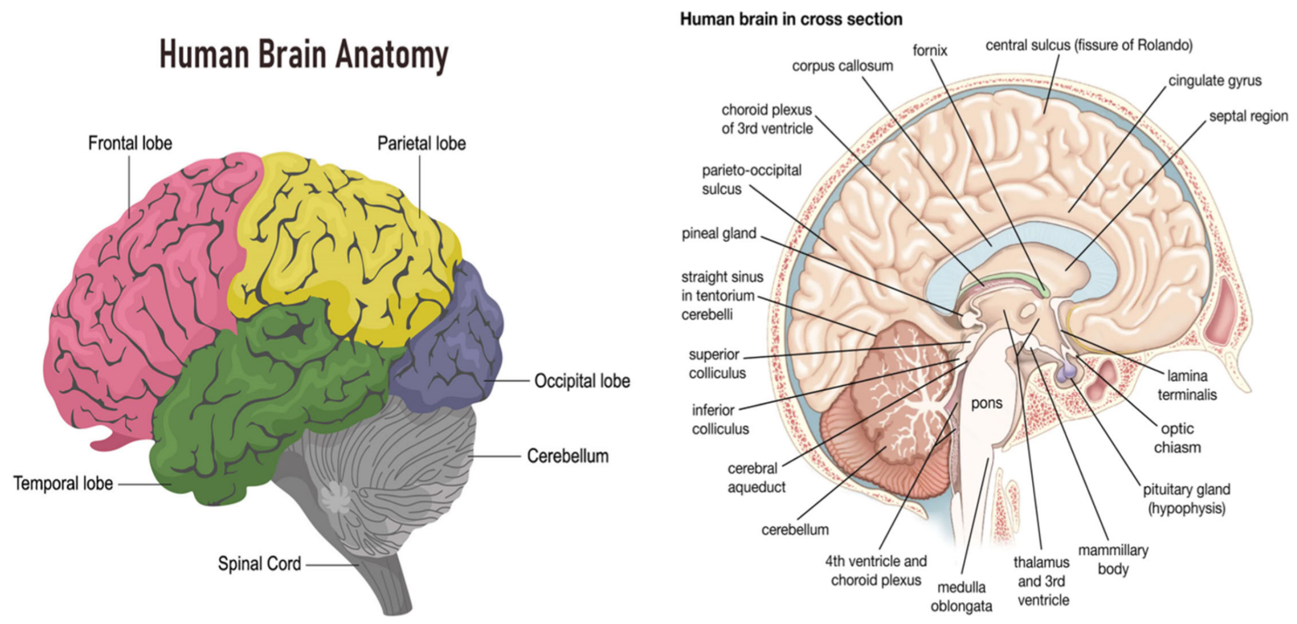
The human brain is a wondrous mystery of curiosity, a complex and truly astonishing organ, that orchestrates the bodily functions while at the same time simultaneously processing and integrating a wide range of sensory information. Structurally in terms of human biology, the brain consists of the cerebrum, brainstem, and cerebellum, all protected within the skull. The cerebrum, also termed as the brain's largest region, is mainly divided into two hemispheres, each containing an outer layer of gray matter which is known as the cerebral cortex and an internal core of white matter. The cerebral cortex, comprising of the neocortex and allocortex, is also responsible for the higher interconnected cognitive functions such as reasoning, language, and decision-making. The cerebrum is also further divided into the four primary lobes: the frontal, temporal, parietal, and occipital lobes, each specializing within the distinct cognitive and sensory tasks. The frontal lobe is fundamental for executive functions, while the occipital lobe is dedicated primarily toward visual processing. Within these lobes, specific cortical regions are specialized for the sensory, motor, and associative tasks, contributing to a rounded integration of brain functions across regions [1]. While the hemispheres have functional similarities, certain abilities, such as language processing and visual-spatial skills, are lateralized, meaning they are predominantly managed by one hemisphere over the other [2, 3]. The brainstem connects the cerebrum to the spinal cord, supporting essential life functions such as breathing and heart rate, while the cerebellum plays a crucial role in motor coordination, ensuring the smooth and balanced movements. Embedded within the human brain is the ventricular system, which includes interconnected ventricles that produce and circulate cerebrospinal fluid, essential for cushioning the brain and maintaining homeostasis. Beneath the cortex lie the most vital structures, including the thalamus, hypothalamus, and limbic system, each integral consists toward maintaining the brain's comprehensive functionality. Collectively, the brain comprises over 86 billion neurons and numerous glial cells, forming intricate neural circuits that mainly underpin cognition, emotion, and behavior [4, 5]. The brain is safeguarded by the skull, cerebrospinal fluid, and the blood-brain barrier, all of which protect it from physical injuries and infections. Despite these protections, the brain remains vulnerable to various diseases, traumatic injuries, strokes, and neurodegenerative conditions, such as Alzheimer's and Parkinson's disease. The anatomical structure of the brain is studied in neuroanatomy, while its functions are explored through neuroscience. Researchers in these fields utilize methods like animal models, neuroimaging techniques, and detailed analyses of clinical history to uncover brain function. Concepts like consciousness and cognition have long been subjects of philosophical inquiry, with contributions from historical practices, such as phrenology, to modern debates in the philosophy of mind. The mind, while often considered distinct from the body, is intimately connected with consciousness, perception, and emotion. Although the nature of the mind remains debated, neuroscientific research continues to bridge the gap between physical brain structures and the phenomenon of consciousness, aiming to illuminate the complexities of the human mind from both scientific and philosophical perspectives [6]. The frontal lobe is exceptionally versatile, performing a wide range of functions, including reasoning, motor control, emotion regulation, and language production. Within the frontal lobe, specific regions play many essential roles: the motor cortex coordinates movement, the prefrontal cortex manages higher-level reasoning, and Broca's area is critical for language production. The motor system orchestrates movement by transmitting commands from the brain to muscles via motor neurons. These commands travel through the corticospinal tract, which directs signals through the spinal cord, while cranial nerves control facial movements and other specialized functions. Gross movements, such as walking, are generated by the motor cortex, which includes the primary motor cortex, premotor areas, and supplementary motor areas. Fine motor control, such as hand and mouth movements, is represented by the motor homunculus, where neural impulses cross in the medulla before reaching muscles through lower motor neurons within the spinal cord. The cerebellum and basal ganglia refine these complex, coordinated movements, enhancing the precision of motor activities [10–13].

The sensory system is responsible for receiving and processing sensory information from the environment. This system relies on the spinal cord, cranial nerves, and specific brain regions that respond to sensory data. The brain interprets signals from special senses like vision, smell, hearing, and taste, with the sensory cortex—adjacent to the motor cortex—converting these signals into nerve impulses. Pathways like the dorsal column–medial lemniscus carry fine touch and vibration information, while the spinothalamic tract transmits pain and temperature signals.

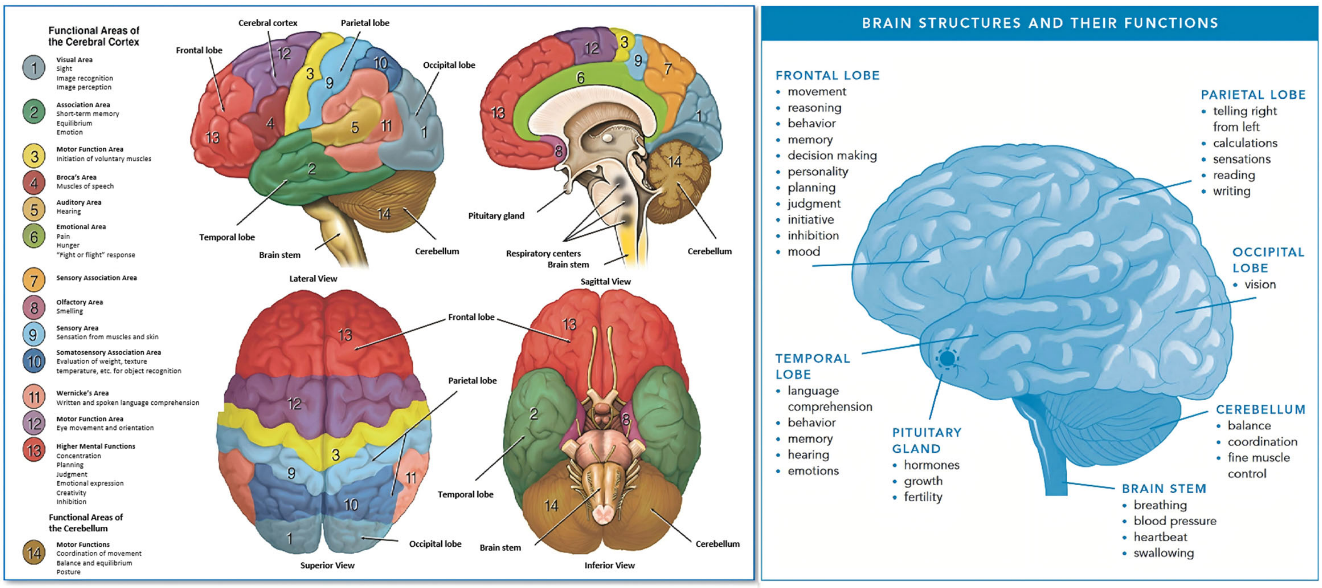
Vision processing begins when light hits the retina, activating photoreceptors that convert visual stimuli into electrical signals that travel through the optic nerves to the visual cortex. Similarly, sound and balance information from the inner ear is processed in the auditory cortex and transmitted through the vestibulocochlear nerve. Smell is mediated by the olfactory nerve, while taste receptors convey signals to the gustatory cortex, contributing to a complete sensory experience [14–16]. In maintaining homeostasis, the brain autonomously regulates bodily functions. The vasomotor center in the medulla manages blood pressure and heart rate through sympathetic and parasympathetic pathways, while the respiratory centers in the medulla and pons control breathing rates in response to sensory inputs. The hypothalamus, a critical neuroendocrine regulator, influences circadian rhythms, autonomic functions, fluid and food intake, and body temperature regulation. It responds to environmental changes by inducing fever or adjusting metabolic processes. Various regions within the hypothalamus oversee functions like appetite and arousal, while the anterior hypothalamus synchronizes circadian rhythms, ensuring that bodily functions adapt seamlessly to environmental conditions. Figure 1 (a) and (b) provide conceptual overviews of these complex processes, highlighting the intricate interactions that underlie brain function and adaptability.

Figure 1
An overview of the human brain. (a) Visualization for anatomy perspectives and the cross-sectional illustration. (b) Visualization for structure orientations and their associated functional areas of activations

(a)



(b)



Emotions are complex experiences involving both physiological and psychological components, such as appraisal, expression, autonomic responses, and action tendencies, activating a network of brain regions. While the exact localization of emotions remains debated, the amygdala, orbitofrontal cortex, anterior insula, and lateral prefrontal cortex are consistently implicated in emotional processing. These structures contribute to generating and regulating emotional responses, with other regions, such as the ventral tegmental area and nucleus accumbens, involved in incentive salience. Happiness, sadness, and fear are linked to distinct areas, such as the basal ganglia, subcallosal cingulate cortex, and amygdala, respectively, providing insight into the neural basis of emotional experiences. Cognition, a fundamental aspect of brain function, encompasses various executive functions, including attentional control, cognitive inhibition, working memory, and cognitive flexibility. Higher-order executive functions, such as planning, foresight, and abstract reasoning, require coordination across multiple brain areas.

The prefrontal cortex serves as the central hub for mediating these executive processes. Planning, for example, engages the dorsolateral prefrontal cortex (DLPFC), anterior cingulate cortex, and right prefrontal cortex, while working memory operations involve the DLPFC, inferior frontal gyrus, and parietal regions. Inhibitory control relies on interactions between the prefrontal cortex, caudate nucleus, and subthalamic nucleus. This intricate network enables individuals to perform complex cognitive tasks, make decisions, and adapt to changing environments, showcasing the brain's remarkable capacity for thought and adaptation [16–18]. This exploration aims to bridge the gap between the brain's physical structure and the spectacle of consciousness, providing insights toward the profound complexities which define human cognition, emotion, and consciousness.

The concept of the mind encompasses a broad spectrum of psychological phenomena, including sensation, perception, thought, reasoning, memory, belief, desire, emotion, and motivation. Traditionally, the mind has been contrasted with the physical body and the material world, especially within the natural sciences. This distinction is rooted in the intuition that the mind possesses qualities fundamentally distinct from the physical world. René Descartes' classical perspective famously positioned the mind as an independent, thinking substance, distinct from the physical. However, contemporary perspectives often regard the mind as a set of properties or capacities inherent to humans and certain other animals, viewing it as a complex system with both conscious and unconscious processes [19, 20]. In philosophy, debates around the nature of the mind have led to diverse, sometimes competing perspectives. Philosophers strive to define a "mark of the mental"—a core feature shared exclusively by mental states. Epistemic theories emphasize a subject's unique access to their own mental states, hypothesizing that this knowledge is non-inferential and distinct from external evidence. Such perspectives view mental states as private and separate from public facts. While the notion of infallible knowledge of one's mental state has been debated, epistemic approaches largely focus on conscious states, which may overlook the influence of unconscious processes [21, 22].

Consciousness-based approaches assert that conscious mental states are fundamental to the mind, arguing that unconscious states derive their significance from conscious counterparts. These theories encounter challenges in defining perception itself, as the range of conscious experiences is extensive and not easily categorized [23–25]. Another approach, intentionality-based theories, defines the mind by its ability to refer to or be about objects—a property known as intentionality. This perspective distinguishes mental states, which represent the world, from external objects that do not possess representational qualities. Intentionality-based approaches face challenges, especially when addressing non-mental entities that also exhibit intentionality, such as maps [26, 27]. Some theorists argue that the term "mind" might better represent a loosely connected set of concepts rather than a unified structure. Accordingly, interpretations of the mind vary, with some focusing on higher faculties like reasoning and others adopting broader definitions that include faculties like sensation and emotion. In everyday language, "mind" often refers to thought or internal dialogue, emphasizing the difficulty of accessing another person's mental state and highlighting its private nature. Epistemic theories underscore this concept of privileged knowledge of one's mental states, viewing them as fundamentally distinct from external, observable facts [28–30]. Consciousness-based perspectives suggest that conscious mental states are essential to understanding the mind, with unconscious states being conceptually dependent on conscious ones. This dual emphasis complicates definitions, as it suggests that conscious awareness and unconscious processes are interdependent rather than entirely distinct categories. Intentionality theories focus on the mind's representational quality, setting mental states apart from physical entities. Issues arise when considering non-mental entities with representational capabilities, like diagrams or symbols, which blur the lines between mental and non-mental representations [31–33]. In contrast, the behaviorist definitions avoid speculation about the internal mental states by focusing solely on the observable behavior and responses to the external stimuli. Functionalism extends this approach by defining mental states in terms of their roles in terms of causal interactions, emphasizing the idea of multiple realizability—the notion that different physical structures can produce identical mental states.

Despite the breadth of theoretical approaches, subjective aspects of conscious experience, often termed phenomenal consciousness, remain challenging to explain, particularly within behaviorist and functionalist frameworks, which can sometimes overlook the deeply personal, qualitative dimensions of consciousness [34–36]. The mental faculties of thought, memory, and imagination represent essential functions of the mind. Thought enables individuals to interpret the world, facilitating problem-solving, reasoning, and decision-making processes. Memory, the capacity to store and retrieve information, plays a prominent role in both philosophy and cognitive neuroscience, while imagination allows for the creative generation of new ideas within the mind. Consciousness, evident in humans and other mammals, encompasses subjectivity, awareness, and a relational understanding of oneself within the environment. It remains a central focus across disciplines, including philosophy, psychology, neuroscience, and cognitive science, often being divided into phenomenal consciousness (subjective experience) and access consciousness (cognitive processing availability) [37–39].

In categorizing mental phenomena, distinctions like sensory versus non-sensory, qualitative versus propositional, and conscious versus unconscious are often used. Sensory states, which depend on sensory inputs, are essential for understanding the external world, while non-sensory phenomena like beliefs and thoughts lack sensory input. Qualitative states are those with subjective qualities, known as qualia, and offer a sense of personal experience. Propositional attitudes, like beliefs or desires, are directed toward specific propositions and contribute to complex mental structures [40, 41]. Beyond these psychological frameworks, memetics offers a unique analogy to Darwinian evolution, suggesting that cultural information (memes) propagates through minds much like genes replicate in biological organisms. This theory posits that the spread of ideas, beliefs, and behaviors constitutes a form of cultural evolution, where ideas undergo selection and adaptation within human societies.

Neuroscience provides a biological basis for the mind by studying the nervous system's structure and function and exploring how neural networks interact to generate reflexes, sensory integration, emotional responses, learning, and memory. Epigenetic mechanisms, such as chemical modifications to DNA, play crucial roles in gene expression, influencing learning and memory processes. Computational neuroscience attempts to model brain functions through simulations of structures like the thalamus and cortex, with ongoing efforts to replicate higher-order brain functions [42–44]. Cognitive science, a multidisciplinary field, examines how mental functions such as perception, memory, language, and decision-making enable individuals to process information. Initially dominated by computational theories, cognitive science has since integrated neurobiological and intentional models of cognition, emphasizing the interaction between mind and environment. The theory of embodied cognition has recently gained prominence, proposing that cognition is deeply intertwined with physical interactions within one's environment. Psychology, which systematically studies human performance and mental processes, investigates how factors like perception, emotion, personality, and social influences shape human behavior. Professionals such as psychiatrists and neurologists address mental health conditions, integrating both cognitive and biological understandings of the mind [45, 46]. Mental health, parallel to physical health, represents a state of the emotional and psychological well-being. It also encompasses the ability to manage stress, maintain relationships, and exhibit resilience. While the World Health Organization acknowledges that the definitions of mental health vary across different cultures, it generally refers to the positive indicators such as competence, capability, and the ability to flourish. In addition to human cognition, the study of animal cognition examines mental capabilities across various species, drawing from fields like comparative psychology, ethology, and evolutionary psychology to explore intelligence, language acquisition, and cognitive processes. AI, a field very closely related to these wide range of disciplines, seeks to develop machines which are capable of human-like tasks. Foundational contributions by figures like Alan Turing and John McCarthy have propelled AI into application systems such as natural language processing and facial recognition. The recurring ongoing debate around the mind's nature—whether as a distinct entity or a product of the brain functions—bears significant implications for AI development, especially within the quest to replicate or simulate features of human cognition [47–49]. EEG is an essential neuroimaging technique for measuring electrical brain activity, offering significant insights into brain function. EEG signals are generated by postsynaptic potentials in the pyramidal neurons across various brain regions, providing a view of neuronal activity that is non-invasive and relatively accessible [42–52]. By positioning electrodes along the scalp—most commonly using the International 10–20 system or similar standardized arrangements—EEG captures voltage fluctuations produced by brain activity. These fluctuations reflect complex electrical activities that are subject to the orientation and positioning of the electrodes relative to the brain's activity sources. Because of the limitations imposed by intervening tissues and bones, deeper brain regions contribute minimally to EEG signals. Nonetheless, EEG's high temporal resolution allows it to capture millisecond-level fluctuations critical for understanding brain function in real time.

Electrocorticography, a more invasive technique, involves the direct surgical placement of electrodes onto the brain's surface, providing higher spatial resolution data than EEG but requiring surgical intervention. In clinical settings, EEG plays a pivotal role, especially in diagnosing and monitoring various brain disorders. For example, it can detect abnormal electrical discharges like spikes and sharp waves, often associated with epilepsy. EEG helps pinpoint the onset and evolution of seizures, making it invaluable in clinical diagnosis and treatment planning. It is also widely used in assessing sleep disorders, determining anesthesia depth, and evaluating brain function in cases of brain damage or dysfunction, including detecting tumors and other abnormalities [40–60].

Although high-resolution imaging techniques like MRI and CT have assumed some diagnostic functions that EEG once held, EEG remains crucial, especially within epilepsy monitoring units, where it captures seizure events that guide localization and treatment strategies. The use of ambulatory video EEG, combining EEG recordings with synchronized video and audio, is beneficial in cases where routine EEG findings are inconclusive, providing a comprehensive view of brain activity and seizure events over extended periods.

EEG plays a very critical role in terms of intensive care units, helping clinicians to detect non-convulsive seizures and also monitor the impact of the sedatives and anesthesia on brain function visualized in Figure 2[1]. This application system is particularly valuable in predicting outcomes for mainly comatose patients and making informing decisions during the epilepsy surgery. Implanting electrodes directly into the brain enhances spatial resolution, allowing for a very detailed analysis of the regions which are really crucial for the seizure initiation and its spread, despite EEG's limited spatial resolution and due to the diffusing nature of the signals. EEG derivatives like evoked potentials and event-related potentials (ERP) are also very instrumental within cognitive psychology and psychophysiological research, shedding further light toward the complex cognitive processes.

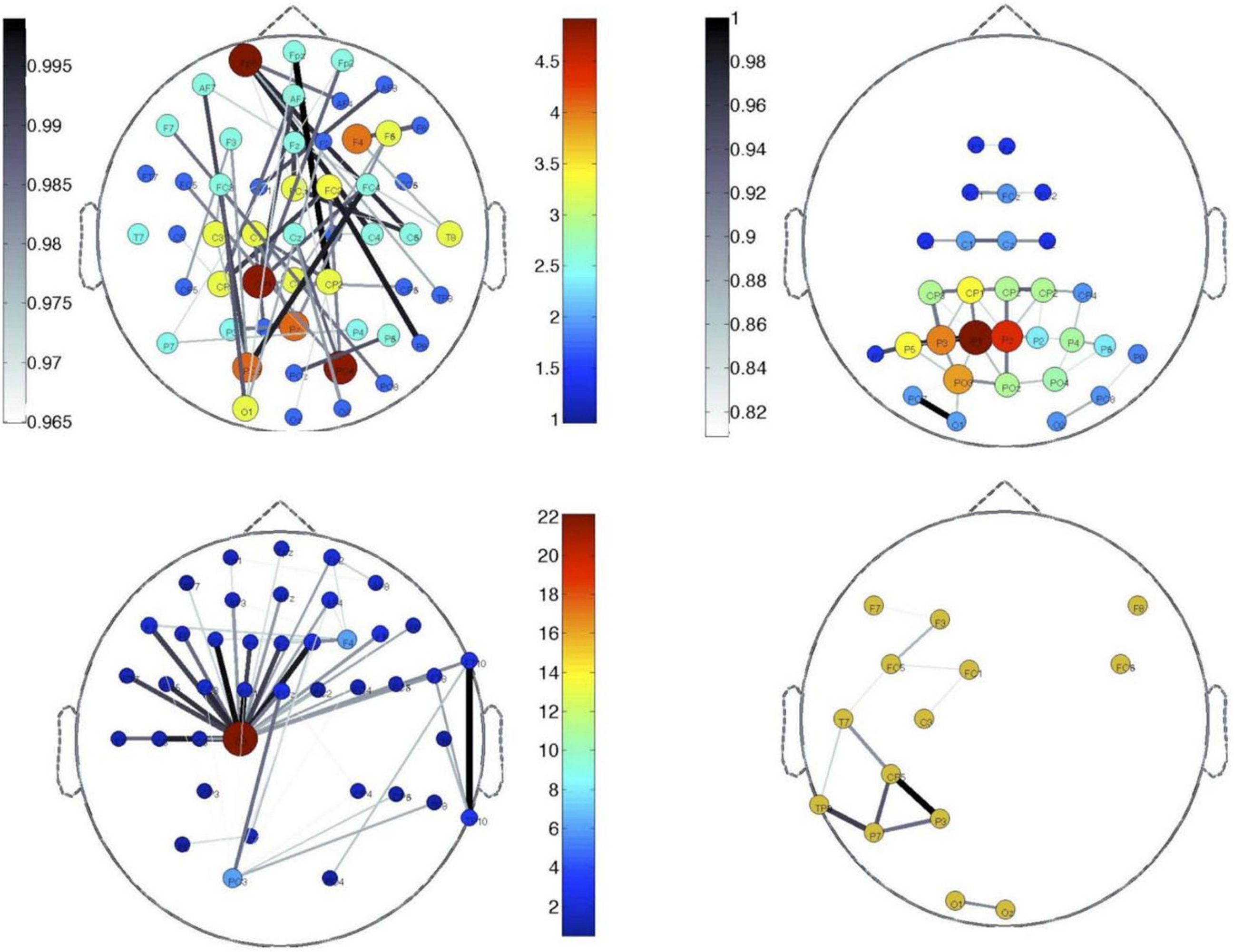
EEG offers several advantages over alternative neuroimaging methods, such as functional magnetic resonance imaging (fMRI), positron emission tomography, and magnetoencephalography (MEG). Its cost-effectiveness and portability make it accessible for both research and clinical applications, particularly in studies requiring high temporal resolution. Unlike fMRI and MEG, EEG requires minimal equipment, making it relatively mobile and tolerant of minor subject movement, enabling the study of auditory responses and other dynamic environments. Its non-invasive nature and lack of exposure to magnetic fields or radioligands reduce potential risks for subjects, allowing EEG to be used safely across a range of populations and life stages, including studies of adolescent brain maturation. EEG is particularly suited to ERP studies due to the simplicity of its experimental paradigms compared to fMRI, which often requires more complex designs. While EEG's spatial resolution is limited and cannot match the precision of fMRI in localizing brain activity, it is frequently combined with other neuroimaging techniques like fMRI and MEG to obtain a more holistic understanding of brain function [51–60].

Despite its strengths, EEG has limitations. The spatial resolution is comparatively low, complicating the precise localization of brain activity. EEG's sensitivity is limited to activity near the scalp, making it difficult to detect signals from deeper brain structures.

The "inverse problem"—determining the specific source of EEG signals—can lead to inaccuracies in source localization. EEG recording is a time-intensive process, often requiring precise electrode placement and the use of conductive gels or pastes to ensure adequate contact with the scalp. The signal-to-noise ratio is typically low, necessitating sophisticated data analysis techniques and large sample sizes for meaningful results. Nonetheless, EEG remains a valuable tool in neuroscience, and combining it with other neuroimaging methods can help mitigate its spatial resolution limitations. EEG can capture a broad range of brainwave frequencies associated with different mental states and physiological processes. Delta waves (up to 4 Hz), for example,

[1]https://nl.mathworks.com/matlabcentral/fileexchange/57372-easy-plot-eeg-brain-network-matlab

Figure 2
A visual representation of computational neuroscience



are the slowest but have high amplitude, appearing primarily during deep sleep-in adults and in infants. Theta waves (4–7 Hz) often occur in young children, during drowsiness, or in meditative states, while alpha waves (8–12 Hz) dominate relaxed wakefulness and are frequently used to classify sleep stages in polysomnography. Beta waves (13–30 Hz) are associated with mental activity, cognition, and alertness, while gamma waves (30–100 Hz) are thought to facilitate communication between brain regions during cognitive and motor tasks.

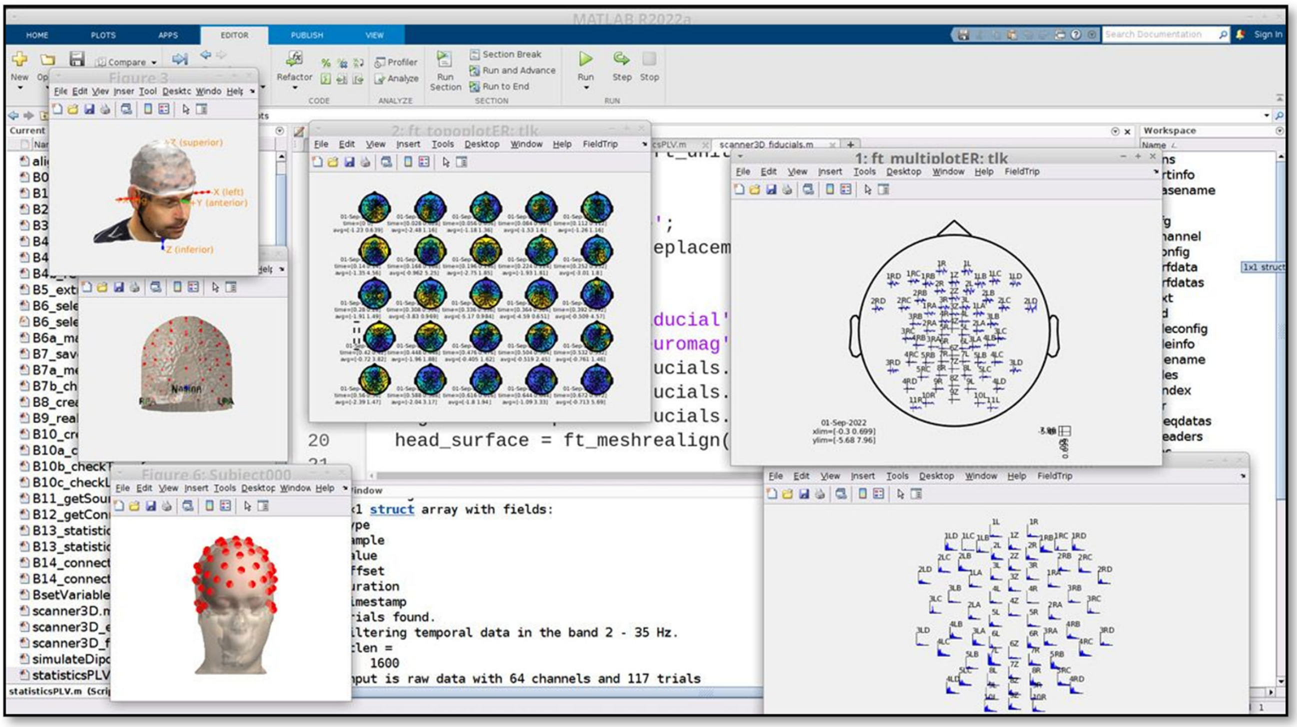
Artifacts within EEG recordings—such as ocular, muscular, cardiac, and environmental artifacts—are managed through various types of advanced algorithms like regression and blind source separation, ensuring that of the accuracy of EEG interpretations. Abnormal EEG activity can also signify various conditions, with epileptiform discharges indicating cortical irritability and non-epileptiform patterns suggesting a focal damage or generalized brain disturbances. EEG has harvested attention for its diagnostic value in traumatic brain injuries and conditions like ADHD, PTSD. Quantitative EEG analysis, using algorithms to translate EEG data into identifiable patterns, supports diagnosing and treating diverse neurological conditions. Despite its technical challenges, EEG remains an essential tool in terms of brain activity studies, offering clinicians critical insights into the brain health and aiding in managing neurological disorders. Figure 3[2] provides further technical insights into EEG data processing and visualization, which plays a very crucial role toward interpreting complex EEG data.

Advancements within AI, and DL, and ML are significantly transforming computational neuroscience, especially by enhancing our perspective understanding of the human cognitive processes through EEG technology. These innovations are widely applicable, from improving marketing insights and individual user experiences toward increasing cognitive efficiency within individuals.

A leading example of this would be EMOTIV, a pioneering company specializing within EEG-based brain research. Leveraging AI, ML, and DL models, EMOTIV has made brain research more accessible and cost-effective, automating the entire processes of data collection and its associated analysis. This approach further expands EEG's usability across a wide diversity for various fields, including consumer research and education, by

[2]https://physionet.org/content/?csrfmiddlewaretoken=MBaya0jY6eCFvMIZSnlms25Whmhk584W8nDrYu6nYh0kxazc6hYUYe6ilTlxUFMe&topic=EEG&csrfmiddlewaretoken=MBaya0jY6eCFvMIZSnlms25Whmhk584W8nDrYu6nYh0kxazc6hYUYe6ilTlxUFMe&orderby=relevance-desc&csrfmiddlewaretoken=MBaya0jY6eCFvMIZSnlms25Whmhk584W8nDrYu6nYh0kxazc6hYUYe6ilTlxUFMe&types=0

Figure 3
A visual representation of EEG and the human mind



providing valuable insights for individuals and many types of organizations. The integration of ML and DL into computational neuroscience, particularly EEG, holds tremendous potential for applications within the BCIs and human emotional recognition, pushing the field into new accelerated and innovative directions.

Understanding the complex roles of AI, ML, and DL within EEG data analysis requires clarifying these key terminologies. Although often used very interchangeably, AI is a broad field that encompasses various features, techniques, including ML and DL. ML involves training algorithms to recognize patterns and make probabilistic predictions, while DL, a subset of ML, automates complex learning tasks, minimizing human intervention.

Analyzing the EEG data has historically presented many challenges due to the brain's intricate neural networks. Although EEG technology is very much affordable and non-invasive, extracting actual meaningful information from its noisy data requires a rundown of complex preprocessing steps, limiting its efficiency in terms of applications like emotion recognition. To address these challenges, EEG classification frameworks have been developed and are still being further updated, consisting of data preprocessing, classification, prediction, and evaluation phases. While EEG still remains cost-effective, its application was previously constrained by issues such as data reliability and mainly the processing speed. Today, ML and DL methods are redefining all these limitations, making EEG data more interpretable and valuable for various real-world applications.

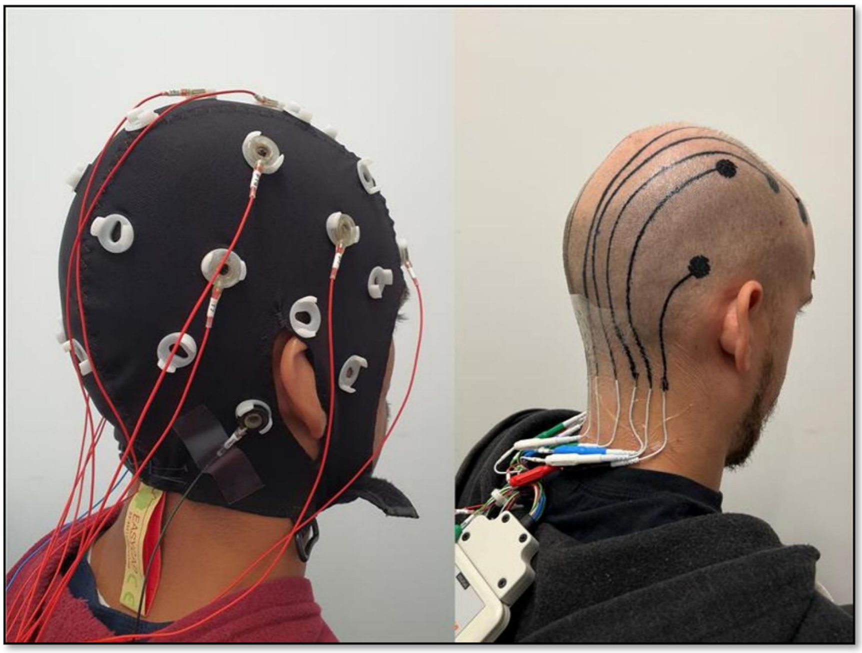
Concerning the domain of BCIs, the use of ML and DL methods have driven much significant advancements, particularly within EEG-based systems and device peripheral applications. ML in BCIs primarily involves classification tasks and individual-adaptive algorithms. Preprocessing and feature extraction are very crucial initial steps, involving data acquisition, cleaning, and pattern extraction for an optimum analysis visualized in Figure 4 [61].

Within various types of classification tasks, supervised and unsupervised learning are commonly applied; supervised learning relies mainly on labeled datasets, while unsupervised learning operates without the labels. Transfer learning, a technique enabling classifiers to adapt across various types of different users and tasks, is especially useful in terms of EEG applications where consistent feature spaces and distributions may not be guaranteed. Reinforcement learning (RL) is a highly relevant toward BCIs, as it allows the associated and interconnected devices to adapt in response to the user actions through a reward-based learning. RL also supports interactive applications where the brain regions' activity can control computers or other devices, providing adaptable solutions for users and individuals in real time.

The incorporation of AI into neuroscience has presented powerful tools for analyzing complex neural data patterns, opening new avenues toward the understanding of cognitive functions. AI's capacity to recognize underlying patterns within intricate neural signals makes it invaluable for brain function analysis. For instance, IBM has applied AI to simulate large-scale neural networks, allowing neuroscientists to develop hypotheses and evaluate them before engaging in an extensive animal study. AI is also crucial in the BCI domain as well, where it enables direct communication between the human brain and its associated and interconnected external devices, empowering individuals with neuromuscular impairments to control digital interfaces using the brain signals alone.

AI-powered classifiers in BCIs also facilitate communication with computers, and technologies like BrainGate have employed AI to interpret brain signals for cursor control, thereby assisting within motor functions. AI plays an essential role in controlling

Figure 4
The concept of the brain-AI closed-loop system (BACLoS) and images of wearable electroencephalography (EEG) devices composed of tattoo-like electronics and a wireless EEG earbud device (e-EEGd)



prosthetics, enhancing the quality of life for certain individuals who are unfortunate with disabilities by enabling them to regain mobility through brain-controlled devices.

AI's contributions extend further to genetic-level research, where it hugely helps analyze gene expression in neurons and build simulation models of impulse propagation, advancing our current understanding of cellular mechanisms in neurodegenerative diseases visualized in Figure 5[3]. AI is also very instrumental in the study of connectomes—complex neural connections within the human brain—using advanced algorithms to process network-structured data.

This application system mainly aids in the early diagnosis of neurodevelopmental and neurodegenerative disorders, including autism and motor delays, by detecting the abnormalities within neural connectivity. In neuroimaging, AI has significantly improved data interpretation, including image reconstruction, registration, noise reduction, and enhancement tasks. AI-enhanced imaging technologies can also optimize MRI data, increasing signal clarity and reducing radiation exposure during scans. AI enables the synthesis of CT images from MRI data, improving the patient positioning and dose of calculations in medical imaging.

AI's role in aging research is highly demonstrated through its capacity to estimate the biological age from structural MRI data using CNN. By sidentifying the key features associated with brain aging, AI aids in early detection of neurodegenerative risks.

The integration of AI into computational neuroscience has revolutionized the field, enabling more sophisticated analysis of neural data, enhancing BCIs, advancing genetic studies, improving neuroimaging, and providing new insights into aging. As AI continues to accelerate and evolve, its computational and pattern-recognition strengths are expected to drive further breakthroughs, helping researchers and scientists unravel the brain's complexities and advancing our understanding of human cognition.

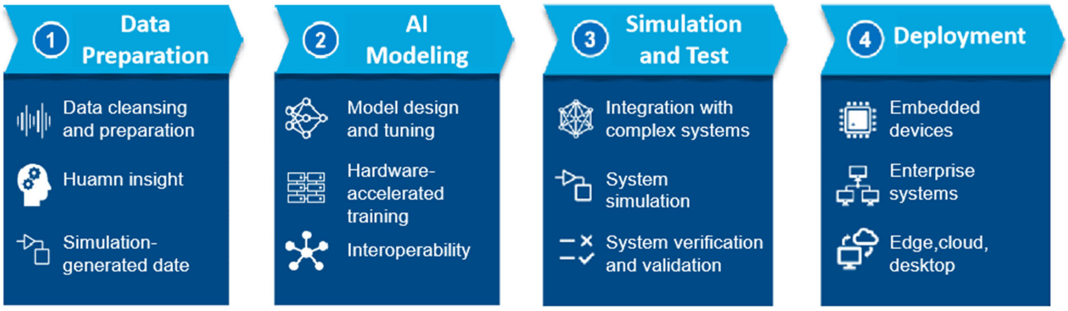
3.2. AI within EEG integrations: A case study analysis

A recent study has highlighted the remarkable potential of deep neural networks in accurately predicting the brain age of different types of healthy individuals, utilizing electroencephalogram (EEG) data collected during overnight sleep studies. By analyzing these EEG recordings, the model demonstrated a groundbreaking ability to calculate an individual's brain age with an impressive mean absolute error of only 4.6 years. This innovative approach has much broader implications as it established that EEG-predicted brain age indices vary notably among populations affected by various types of health conditions. These findings offer a promising avenue for exploring how specific physiological and neurological conditions might influence an individual's brain age relative to their chronological age, which may serve as a crucial marker for brain health in the near future. One of the study's most significant discoveries was the identification of a strong, statistically significant association between the Absolute Brain Age Index and several health conditions, particularly those affecting the neurological and sleep-related functions. Key health conditions that linked to deviations in brain age included epilepsy, seizure disorders, and stroke.

The study also found notable connections between brain age indices and markers of sleep-disordered breathing, such as apnea-hypopnea index, arousal index, and lower sleep efficiency. Certain conditions, including diabetes, depression, severe excessive daytime sleepiness, hypertension, and issues with memory or concentration, were associated with elevated Brain Age Indices compared to a control group of different types of healthy individuals. This deviation suggests a potential link between these

[3]https://ww2.mathworks.cn/solutions/automotive/electric-vehicle.html

Figure 5
The AI processing pipeline and system applications toward computational neuroscience



health factors and accelerated brain aging or an increased brain age relative to an individual's chronological age. The study's results are also particularly valuable as they suggest the possibility of using an individual's Brain Age Index as a diagnostic indicator, helping clinicians identify and monitor the progression of various health conditions.

The precision of the AI model, according to Yoav Nygate, the lead author and senior AI engineer at EnsoData, is crucial in uncovering clinical phenotypes detectable through physiological signals. These AI model deviations may reveal early indicators of disease or health deterioration, providing a powerful non-invasive assessment tool. The model's accuracy not only demonstrates the potential for advanced neural networks to interpret complex EEG data but also underscores the feasibility of identifying specific health conditions and related comorbidities through EEG analysis.

The model was mainly developed by training a deep neural network on an extensive dataset of raw EEG signals recorded during clinical sleep studies. The training dataset included 126,241 individual sleep studies, with validation performed on 6,638 studies, and a final test conducted on a holdout set of 1,172 studies. To calculate brain age, researchers utilized an Absolute Brain Age Index, defined by subtracting an individual's chronological age from their EEG-predicted brain age.

This index provides a quantitative measure that could eventually be further standardized to assess brain health. The researchers carefully controlled for variables such as sex and body mass index to refine the model's predictive accuracy and address potential confounding factors. This rigorous approach ensures that the findings are robust and reliable across diverse population groups, strengthening the case for using AI in clinical settings.

Nygate emphasized the study's importance in offering preliminary evidence for the role of AI's potential as a diagnostic tool in brain health assessment. The Brain Age Index, with further research and clinical validation, may one day serve as a widely recognized biomarker for neurological health—similar to how blood pressure is used to predict cardiovascular risk. This AI-driven approach could provide a very proactive way to assess and manage brain health, especially for individuals at risk for neurological and psychological conditions.

The study's abstract has been published in the journal Sleep's online supplement and was presented as a poster at the Virtual SLEEP 2021 event, hosted by the Associated Professional Sleep Societies, a joint effort between the American Academy of Sleep Medicine and the Sleep Research Society. This research marks an important step toward integrating AI and DL into clinical neuroscience, offering the potential for significant advances in personalized brain health monitoring and management.

4. Results and Findings

This research exploration investigation presents a systematic and rigorous approach for selecting and analyzing EEG seizure detection and prediction datasets. By following the Preferred Reporting Items for the Systematic Examination and Meta-Analysis guidelines, the exploration aimed to ensure a thorough, unbiased dataset selection process. This process involved exploring both available knowledge and modern data repositories to create a dataset pool that is diverse, relevant, and is of high quality. The final selection balances toward a well-cited coverage of studies with publicly accessible EEG seizure datasets, providing a robust foundation for further investigation and analysis within seizure prediction and detection. The dataset selection methodology and the experimental analysis was processed and implemented within several key stages.

4.1. Background investigation and dataset selection

The initial phase involved an extensive search through academic databases like Scopus and Web of Science. The authors used targeted keywords such as "seizure prediction" and "seizure detection" and applied filters to focus on various studies with high citation counts. This initial search identified a broad range of studies, which were then refined by eliminating duplicates and applying exclusion criteria to include only studies that directly investigated EEG signals, multimodal signals, or spike detection. In addition to academic databases, the authors utilized modern data search platforms, including Google Dataset Search, Kaggle, and PhysioNet, to identify publicly accessible datasets. This dual approach ensured a comprehensive selection that included recent, high-quality datasets suitable for seizure prediction and detection research.

4.2. Dataset categorization and preprocessing

Once selected, the datasets were organized based on primary characteristics and structural properties to inform the ML techniques best suited to each dataset. This categorization highlighted distinctions, such as whether a dataset contained continuous or segmented data, which informed the preprocessing steps. The University of Bonn dataset underwent visual inspection to remove artifacts, while the Hauz Khas dataset applied band filtering between 0.5 and 70 Hz. Tailoring preprocessing strategies to each dataset helped optimize data quality and relevance for ML applications.

4.3. Selection for seizure detection and prediction

The authors also evaluated the suitability of each dataset for either seizure detection or prediction. This was determined by analyzing whether datasets contained ictal, preictal, or interictal segments. For instance, datasets like those from the University of Bonn and certain Kaggle sources were deemed more appropriate for detection tasks, as they predominantly contained ictal data without preictal segments. Conversely, datasets like Hauz Khas, which include interictal, preictal, and ictal segments, were considered versatile, making them suitable for both detection and prediction tasks. This systematic differentiation enables a focused application of datasets according to their inherent strengths in addressing specific research objectives.

4.4. Analysis of intracranial EEG (iEEG) datasets

The investigative exploration extended to analyzing iEEG datasets, such as those from St. Anne's University Hospital and the Mayo Clinic, which are critical for understanding epilepsy and supporting robust algorithm development for iEEG data analysis. These iEEG datasets offer high-quality, clinically relevant data that enhance the potential for effective seizure prediction models. This aspect of the study emphasizes the value of iEEG data in developing reliable, high-performance algorithms.

4.5. Performance evaluation of DL architectures

The authors also tested several DL architectures on prominent datasets, such as the Temple University Hospital (TUH) and the Neurology and Movement Therapy (NMT) datasets, assessing each model's generalization capabilities. They identified many influential factors affecting toward the model performance, such as differences in data distributions and demographic characteristics between datasets. While the CNN-based architectures, including a hybrid model, showed strong performance on the context of the TUH dataset, a slight performance decline was observed on for the NMT dataset. This discrepancy suggests that the data composition and demographics can impact the overall effectiveness of DL models and further highlights that the need for models to be robust across varied datasets is a very crucial factor.

4.6. Generalization and transfer learning

The exploration underscored the complex position of training and testing DL models across various types of diverse datasets to enhance their generalization. This approach was particularly notable toward introducing the NMT dataset, sourced from the Pak-Emirates Military Hospital, which serves as a valuable resource for advancing EEG-based diagnostic tools, particularly investigated for the underrepresented populations.

The incorporation of a wide variety of diverse datasets within training processes promotes the adaptability of models, supporting many broader applications of EEG-based seizure detection and prediction models within the global healthcare settings.

This exploration also provides critical insights into how the structural and compositional aspects of datasets can further shape the selection of ML strategies, aiding researchers and clinicians in optimizing their model selection and improving the overall accuracy in seizure detection and prediction. Figures 6, 7, 8, and 9 toward the investigations offer visual overviews of these exploration findings and document the archived implementations, further supporting the study's systematic and methodological experimental analysis approach. This comprehensive analysis positions the study as a valuable contribution toward the field, paving the way for more accurate and further effective seizure prediction tools grounded within EEG data science.

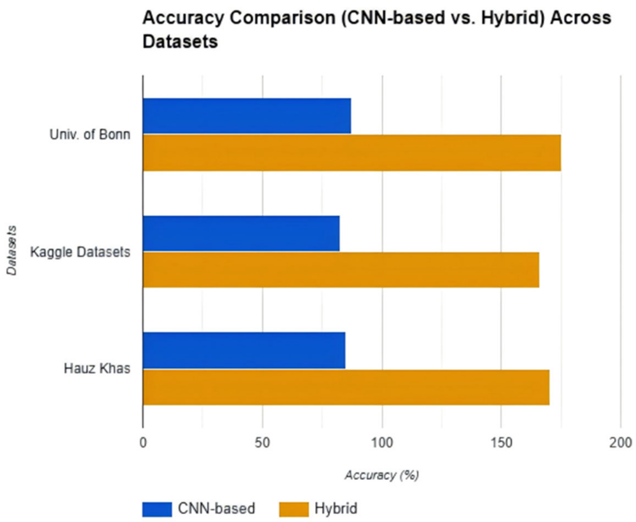
5. Discussions and Conclusions

This chronicle investigation provides a very comprehensive analysis of the types of publicly available EEG seizure datasets, emphasizing their distinctive features and the insights they can truly offer. By focusing on the main unique issues which are relevant toward seizure prediction and detection, this investigation offers clinicians, researchers, and engineers an essential framework for making proper informed choices when selecting DL, ML algorithms tailored to their individual research methods and associated objectives. Unlike many other types of studies that primarily emphasize the novelty of ML advancements, this exploration places a critical spotlight on leveraging the dataset attributes to drive a more meaningful advancements within seizure detection and especially prediction within epilepsy research.

Through this innovative approach, the investigation also underscores the overall collected importance of understanding types of dataset characteristics to optimize the overall effectiveness of DL and ML algorithms and highlights the desired need for a much more in-depth analysis of how various studies and experiments will mainly use these types of resourceful datasets. This analysis includes examining many of the assumptions and methodologies adopted to address the most common dataset challenges, such as noise reduction, class imbalance, and segment variability. This examination also suggests toward that future research could greatly contribute and also benefit from the development of a formalized characterization model. Such a model would be able to incorporate various dimensions of both dataset properties and both DL and ML techniques, providing a better-structured approach in terms of dataset evaluation. By enhancing dataset assessment through this model, researchers could better determine the suitability of a dataset for specific DL and ML applications, helping them to select datasets and algorithms that align more closely within their research goals and scopes. In addition to its main focus on seizure datasets, the investigation introduces a novel deep network designed for EEG-based emotion recognition. The proposed model, also a type of hybrid architecture combining CNN with Stacked Autoencoders (SAE), was also evaluated on widely recognized datasets such as DEAP and SEED.

While the primary emphasis was mainly on the performance of this network, the authors still acknowledged that other approaches, such as end-to-end training, could also harvest much better strong performance. Future directions for this work include the incorporation of label information during feature extraction and the exploration of different types of autoencoder-based architectures specifically for emotion recognition tasks. The results of the proposed network demonstrated a well-rounded superior performance compared to the traditional CNN models, achieving a very high recognition accuracies: 89.49% for valence

Figure 6
An overview visualization of the research findings 1 (accuracy comparison for CNN-based vs Hybrid)



and 92.86% for arousal in the DEAP dataset, and also an impressive 96.77% accuracy on the SEED dataset using Pearson's correlation coefficient-based features. These results and findings underscore the network's potential for advancing EEG-based emotion classification, suggesting that future studies could explore further while integrating SAE with other classifiers to further enhance the overall classification performance. This research introduced the NMT dataset, a significant addition to the booming field that provides an extensive collection of EEG recordings categorized as normal and abnormal. This dataset serves as a valuable foundation for training DL and ML models geared toward pre-diagnostic of the datasets for EEG screening, offering researchers access to a resource that supports the refinement of algorithms for clinical applications. In evaluating DL architectures on the NMT dataset, the analysis generated critical insights into the adaptability and robustness of all these types of models. The research findings highlighted that many current DL models can truly exhibit a very strong performance when trained and tested within the same dataset. However, this performance often hugely declines considerably when the models are exposed to new and unfamiliar datasets, accentuating the need for other types of models that can generalize well across various types of data sources and can adapt to differences in terms of both acquisition settings and equipment.

The initial exploration into fine-tuning strategies has revealed promising results for improving cross-dataset performance, pointing to a critical key area for future investigation. This research emphasizes the need for further examination of fine-tuning methods and generalization techniques to strengthen DL models applied toward EEG data. Such types of explorations are greatly expected to significantly impact the technological field, particularly as the focus not only shifts toward enhancing the adaptability and robustness but toward ML algorithms in varied and real-world clinical environments. This investigation sets a well-rounded strong foundation for advancing further EEG research through well-informed dataset selection and targeted DL and ML development, aiming to bridge down the gap in between many types of laboratory research and also practical clinical applications.

Figure 7
An overview visualization of the research findings 2 (comparison of TUH and NMT datasets)

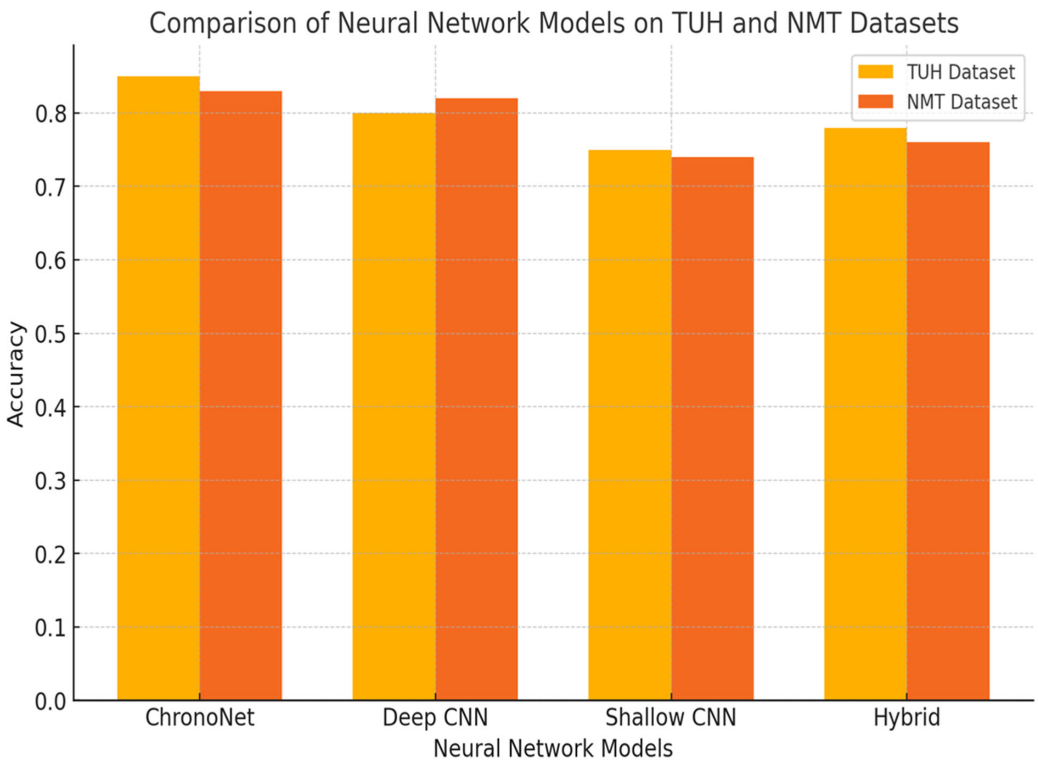


Figure 8
An overview visualization of the research findings 3 (recognition accuracy on DEAP and SEED datasets)

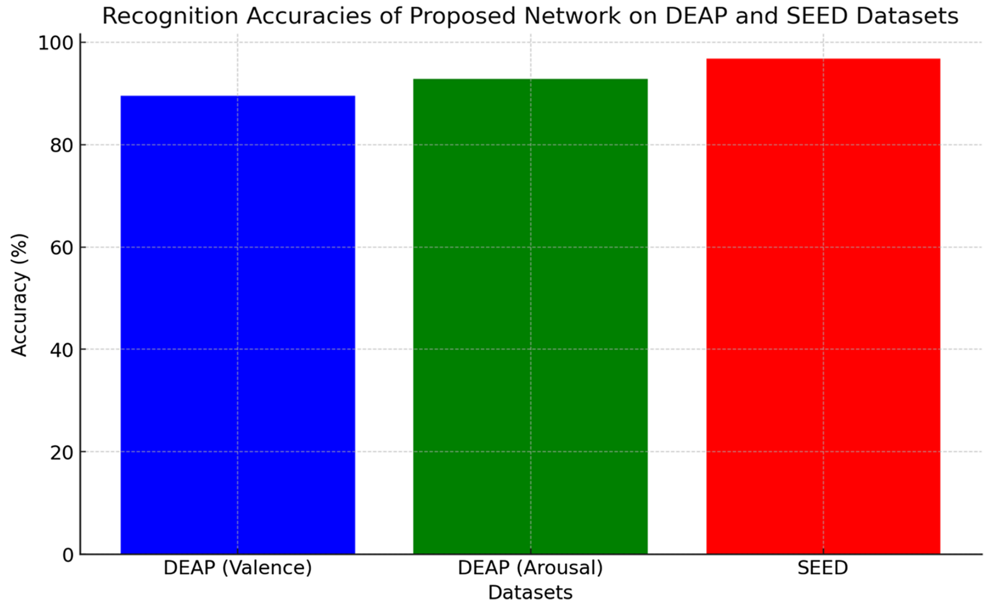


Figure 9
An overview visualization of the research findings 4

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This research exploration investigations were also deployed and utilized under the platform provided by PhysioNet which is under the support of the National Institute of General Medical Sciences and the National Institute of Biomedical Imaging and Bioengineering under NIH grant number 2R01GM104987-09. Using their provided platform of datasets and database files with digital software layouts consisting of free web access to a large collection of recorded physiologic signals that are found in (PhysioBank) and its related open-source software (PhysioToolkit) which is the implementation and simulation of analytics for the proposed research which was undergone and set in motion. There are many data sources, datasets, data models some of which are not all publicly available, because they contain various types of private information along with many others which were also retrieved from a wide variety of domains. All the data sources and various domains from which data has been included and retrieved for this research are identified, mentioned, and referenced where appropriate.

Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

Data Availability Statement

The data that support the findings of this study are openly available in PhysioNet at https://www.nigms.nih.gov/; National Institute of Biomedical Imaging and Bioengineering at https://www.nibib.nih.gov/; NIH at https://archive.physionet.org/about.shtml; PhysioBank at https://archive.physionet.org/physiobank/; PhysioToolkit at https://archive.physionet.org/physiotools/.

Author Contribution Statement

Zarif Bin Akhtar: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Writing – original draft, Writing – review & editing, Visualization. **Victor Stany Rozario:** Supervision, Project administration.

References

[1] Akhtar, Z. B., & Rozario, V. S. (2020). The design approach of an artificial human brain in digitized formulation based on machine learning and neural mapping. In *2020 International Conference for Emerging Technology*, 1–7. https://doi.org/10.1109/INCET49848.2020.9154000

[2] Akhtar, Z. B. (2025). Artificial intelligence within medical diagnostics: A multi-disease perspective. *Artificial Intelligence in Health*, 1–19. https://doi.org/10.36922/aih.5173

[3] Akhtar, Z. B. (2024). The design approach of an artificialintelligent (AI) medical system based on electronical health records (EHR) and priority segmentations. *The Journal of Engineering*, *2024*(4), e12381. https://doi.org/10.1049/tje2.12381

[4] Verzelli, P., Tchumatchenko, T., & Kotaleski, J. H. (2024). Editorial overview: Computational neuroscience as a bridge between artificial intelligence, modeling and data. *Current Opinion in Neurobiology*, *84*, 102835. https://doi.org/10.1016/j.conb.2023.102835

[5] Asif, M., Choudhary, P., & Dandawate, A. A. (2025). Computational neuroscience: Recent advancement. In S. Singh, S. N. Rai, & S. K. Singh (Eds.), *Synaptic Plasticity in Neurodegenerative Disorders* (pp. 159–190). CRC Press. https://doi.org/10.1201/9781003464648

[6] Werne, L. (2025). Computational cognitive neuroscience coursework reinforcement learning for computational psychiatry. Retrieved from: https://opencourse.inf.ed.ac.uk/sites/default/files/https/opencourse.inf.ed.ac.uk/ccn/2025/ccncourseworkdatecorrected.pdf

[7] Kringelbach, M. L., & Deco, G. (2020). Brain states and transitions: Insights from computational neuroscience. *Cell Reports*, *32*(10), 108128.

[8] Baker, K. (2025). Brain and neuroscience advances–2024 in review. *Brain and Neuroscience Advances*, *9*, 23982128251317305. https://doi.org/10.1177/23982128251317305

[9] Peng, F., Zhang, Y., Zheng, K., Bai, J., & Yang, C. (2025). Stereoscopic visual attention model based on bioinspiration. *IEEE MultiMedia*. Advance online publication. https://doi.org/10.1109/MMUL.2024.3524617

[10] Kuzawa, C. W., Chugani, H. T., Grossman, L. I., Lipovich, L., Muzik, O., Hof, P. R., . . . , & Lange, N. (2014). Metabolic costs and evolutionary implications of human brain development. *Proceedings of the National Academy of Sciences*, *111*(36), 13010–13015. https://doi.org/10.1073/pnas.1323099111

[11] Xie, L., Kang, H., Xu, Q., Chen, M. J., Liao, Y., Thiyagarajan, M., . . . , & Nedergaard, M. (2013). Sleep drives metabolite clearance from the adult brain. *Science*, *342*(6156), 373–377. https://doi.org/10.1126/science.1241224

[12] Colelough, B. C., & Regli, W. (2024). Neuro-symbolic AI in 2024: A systematic review. In *The First International Workshop on Logical Foundations of Neuro-Symbolic AI*, 1–12.

[13] Frigeri, T., Paglioli, E., de Oliveira, E., & Rhoton, A. L. (2015). Microsurgical anatomy of the central lobe. *Journal of Neurosurgery*, *122*(3), 483–498. https://doi.org/10.3171/2014.11.JNS14315

[14] Swan, M., dos Santos, R. P., & Witte, F. (2022). Quantum neurobiology. *Quantum Reports*, *4*(1), 107–126. https://doi.org/10.3390/quantum4010008

[15] Underwood, E. (2014). *A $4.5 billion price tag for the BRAIN initiative?* Retrieved from: https://www.science.org/content/article/45-billion-price-tag-brain-initiative

[16] Arsava, E. Y., Arsava, E. M., Oguz, K. K., & Topcuoglu, M. A. (2019). Occipital petalia as a predictive imaging sign for transverse sinus dominance. *Neurological Research*, *41*(4), 306–311. https://doi.org/10.1080/01616412.2018.1560643

[17] Luo, J., Agboola, F., Grant, E., Masters, C. L., Albert, M. S., Johnson, S. C., . . . , & Xiong, C. (2020). Sequence of Alzheimer disease biomarker changes in cognitively normal adults: A cross-sectional study. *Neurology*, *95*(23), e3104–e3116. https://doi.org/10.1212/WNL.0000000000010747

[18] Lancaster, M. A., Renner, M., Martin, C. A., Wenzel, D., Bicknell, L. S., Hurles, M. E., . . . , & Knoblich, J. A. (2013). Cerebral organoids model human brain development and microcephaly. *Nature*, *501*(7467), 373–379. https://doi.org/10.1038/nature12517

[19] Nowinski, W. L. (2023). High performance computing requirements for the calculation of a morphology model of the human whole brain at the nanoscale. In *2023 IEEE International Conference on Bioinformatics and Biomedicine*, 3321–3327. https://doi.org/10.1109/BIBM58861.2023.10385605

[20] Thompson-Lake, D. G., Liegeois, F. J., Braden, R. O., Jackson, G. D., Turner, S. J., Morison, L., . . . , & Morgan, A. T. (2024).

Perisylvian and hippocampal anomalies in individuals with pathogenic GRIN2A variants. *Neurology: Genetics*, *10*(2), e200129. https://doi.org/10.1212/NXG.0000000000200129
[21] Papadopoulos, S., Szul, M. J., Congedo, M., Bonaiuto, J. J., & Mattout, J. (2024). Beta bursts question the ruling power for brain–computer interfaces. *Journal of Neural Engineering*, *21*(1), 016010. http://doi.org/10.1088/1741-2552/ad19ea
[22] Frise, M. (2018). Eliminating the problem of stored beliefs. *American Philosophical Quarterly*, *55*(1), 63–79. https://doi.org/10.2307/45128599
[23] Nolfi, K. (2015). Which mental states are rationally evaluable, and why? *Philosophical Issues*, *25*(1), 41–63. https://doi.org/10.1111/phis.12051
[24] Mohd Murshid, N., Mohd Sahardi, N. F. N., & Makpol, S. (2025). Advancing Alzheimer's disease modelling by developing a refined biomimetic brain microenvironment for facilitating high-throughput screening of pharmacological treatment strategies. *International Journal of Molecular Sciences, 26*(1), 241. https://doi.org/10.3390/ijms26010241
[25] Demirkilic, U., & Tosun, B. (2024). The rise of artificial intelligence in vascular surgery: A bibliometric analysis (2020–2024). *Turkish Journal of Vascular Surgery*, *33*(2), 103–111. http://doi.org/10.9739/tjvs.2024.07.027
[26] Pernu, T. K. (2017). The five marks of the mental. *Frontiers in Psychology*, *8*, 1084. https://doi.org/10.3389/fpsyg.2017.01084
[27] Bagayatkar, A., & Ivin, B. (2024). Survey paper on machine learning and deep learning driven applications using Bayesian techniques. In *2024 IEEE 9th International Conference for Convergence in Technology,* 1–7. https://doi.org/10.1109/I2CT61223.2024.10543602
[28] Coventry, B. S., & Bartlett, E. L. (2024). Practical Bayesian inference in neuroscience: Or how I learned to stop worrying and embrace the distribution. *eNeuro*, *11*(7), 1–28. https://doi.org/10.1523/ENEURO.0484-23.2024
[29] Brunklaus, A., Pérez-Palma, E., Ghanty, I., Xinge, J., Brilstra, E., Ceulemans, B., . . . , & Lal, D. (2022). Development and validation of a prediction model for early diagnosis of SCN1A-related epilepsies. *Neurology*, *98*(11), e1163–e1174. https://doi.org/10.1212/WNL.0000000000200028
[30] Naccache, L. (2018). Why and how access consciousness can account for phenomenal consciousness. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *373*(1755), 20170357. https://doi.org/10.1098/rstb.2017.0357
[31] Gozzano, S. (2019). Locating and representing pain. *Philosophical Investigations*, *42*(4), 313–332. https://doi.org/10.1111/phin.12238
[32] Amzica, F., & da Silva, F. H. L. (2017). C2Cellular substrates of brain rhythms. In D. L. Schomer, & F. H. L. da Silva (Eds.), *Niedermeyer's electroencephalography: Basic principles, clinical applications, and related fields (7 edn)* (pp. 20–62). Oxford University Press. https://doi.org/10.1093/med/9780190228484.003.0002
[33] Kandel, E. R., Schwartz, J. H., Jessell, T. M., Siegelbaum, S., Hudspeth, A. J., & Mack, S. (2000). *Principles of neural science*. USA: McGraw-Hill.
[34] Ku, L. W., Martins, A. F., & Srikumar, V. (2024). Proceedings of the 62nd annual meeting of the association for computational linguistics. In *Proceedings of the 62nd Annual Meeting of the Association for Computational Linguistics*. https://doi.org/10.18653/v1/2024.acl-long
[35] Traut, J., Mengual, J. P., Meijer, E. J., McKillop, L. E., Alfonsa, H., Hoerder-Suabedissen, A., . . . , & Krone, L. B. (2023). Effects of clozapine-N-oxide and compound 21 on sleep in laboratory mice. *eLife*, *12,* e84740. https://doi.org/10.7554/eLife.84740.sa0
[36] Clayson, P. E., Carbine, K. A., Baldwin, S. A., & Larson, M. J. (2019). Methodological reporting behavior, sample sizes, and statistical power in studies of event-related potentials: Barriers to reproducibility and replicability. *Psychophysiology*, *56*(11), e13437. https://doi.org/10.1111/psyp.13437
[37] Alsuradi, H., Park, W., & Eid, M. (2020). EEG-based neurohaptics research: A literature review. *IEEE Access*, *8*, 49313–49328. https://doi.org/10.1109/ACCESS.2020.2979855
[38] Dora, M., & Holcman, D. (2022). Adaptive single-channel EEG artifact removal with applications to clinical monitoring. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, *30*, 286–295. https://doi.org/10.1109/TNSRE.2022.3147072
[39] Dora, M., Jaffard, S., & Holcman, D. (2022). The WQN algorithm to adaptively correct artifacts in the EEG signal. *Applied and Computational Harmonic Analysis*, *61*, 347–356. https://doi.org/10.1016/j.acha.2022.07.007
[40] Kaya, I. (2021). A brief summary of EEG artifact handling. In V. Asadpour (Ed.), *Brain-computer interface* (pp. 23–38). IntechOpen.
[41] Goldberger, A. L., Amaral, L. A., Glass, L., Hausdorff, J. M., Ivanov, P. C., Mark, R. G., . . . , & Stanley, H. E. (2000). PhysioBank, PhysioToolkit, and PhysioNet: Components of a new research resource for complex physiologic signals. *Circulation*, *101*(23), e215–e220. https://doi.org/10.1161/01.CIR.101.23.e215
[42] Kent, D. M., Leung, L. Y., Zhou, Y., Luetmer, P. H., Kallmes, D. F., Nelson, J., . . . , & Chen, W. (2021). Association of silent cerebrovascular disease identified using natural language processing and future ischemic stroke. *Neurology*, *97*(13), e1313–e1321. https://doi.org/10.1212/WNL.0000000000012602
[43] Malarkhodi, S., Mahalakshmi, N., & Deepa, M. A. (2024). Advancements in neurological health: Predicting brain age with machine learning. In *2024 3rd International Conference on Artificial Intelligence for Internet of Things*, 1–5. https://doi.org/10.1109/AIIoT58432.2024.10574543
[44] Abo-Zahhad, M., Ahmed, S. M., & Abbas, S. N. (2015). State-of-the-art methods and future perspectives for personal recognition based on electroencephalogram signals. *IET Biometrics*, *4*(3), 179–190. https://doi.org/10.1049/iet-bmt.2014.0040
[45] Chang, C., & Chen, J. E. (2021). Multimodal EEG-fMRI: Advancing insight into large-scale human brain dynamics. *Current Opinion in Biomedical Engineering*, *18*, 100279. https://doi.org/10.1016/j.cobme.2021.100279
[46] Trevizan-Baú, P., Stanić, D., Furuya, W. I., Dhingra, R. R., & Dutschmann, M. (2024). Neuroanatomical frameworks for volitional control of breathing and orofacial behaviors. *Respiratory Physiology & Neurobiology*, *323*, 104227. https://doi.org/10.1016/j.resp.2024.104227
[47] Hao, Z., Bu, T., Shi, X., Huang, Z., Yu, Z., & Huang, T. (2024). Threaten spiking neural networks through combining rate and temporal information. In *The Twelfth International Conference on Learning Representations.*
[48] Borich, M. R., Brown, K. E., Lakhani, B., & Boyd, L. A. (2015). Applications of electroencephalography to characterize brain activity: Perspectives in stroke. *Journal of Neurologic Physical Therapy*, *39*(1), 43–51. http://doi.org/10.1097/NPT.0000000000000072
[49] Dessirya, E., & Widhiastuti, E. (2024). The role of nurses in improving the quality of life of neonates through pain management: A literature review. *Indonesian Journal of Global Health Research*, *6*(S4), 59–68.
[50] Smith, J. (2024). Advanced algorithmic design for concurrent and parallel computing architectures. *International Journal of*

Advanced Engineering Technologies and Innovations, *10*(2), 430–450.
[51] Hervé, E., Mento, G., Desnous, B., & François, C. (2022). Challenges and new perspectives of developmental cognitive EEG studies. *NeuroImage*, *260*, 119508. https://doi.org/10.1016/j.neuroimage.2022.119508
[52] Valošek, J., Mathieu, T., Schlienger, R., Kowalczyk, O. S., & Cohen-Adad, J. (2024). Automatic segmentation of the spinal cord nerve rootlets. *Imaging Neuroscience*, *2*, 1–14. https://doi.org/10.1162/imag_a_00218
[53] Abiri, R., Borhani, S., Sellers, E. W., Jiang, Y., & Zhao, X. (2019). A comprehensive review of EEG-based brain–computer interface paradigms. *Journal of Neural Engineering*, *16*(1), 011001. http://doi.org/10.1088/1741-2552/aaf12e
[54] Shatalina, E., Onwordi, E. C., Whitehurst, T., Whittington, A., Mansur, A., Arumuham, A., . . . , & Howes, O. D. (2024). The relationship between SV2A levels, neural activity, and cognitive function in healthy humans: A [11C] UCB-J PET and fMRI study. *Imaging Neuroscience*, *2*, 1–16. https://doi.org/10.1162/imag_a_00190
[55] Niso, G., Krol, L. R., Combrisson, E., Dubarry, A. S., Elliott, M. A., François, C., . . . , & Chaumon, M. (2022). Good scientific practice in EEG and MEG research: Progress and perspectives. *NeuroImage*, *257*, 119056. https://doi.org/10.1016/j.neuroimage.2022.119056
[56] Chan, H. L., Kuo, P. C., Cheng, C. Y., & Chen, Y. S. (2018). Challenges and future perspectives on electroencephalogram-based biometrics in person recognition. *Frontiers in Neuroinformatics*, *12*, 66. https://doi.org/10.3389/fninf.2018.00066
[57] Alam, M. S., Jalil, S. Z. A., & Upreti, K. (2022). Analyzing recognition of EEG based human attention and emotion using machine learning. *Materials Today: Proceedings*, *56*, 3349–3354. https://doi.org/10.1016/j.matpr.2021.10.190
[58] Lotte, F., Bougrain, L., & Clerc, M. (2015). Electroencephalography (EEG)-based brain-computer interfaces. In J. G. Webster (Ed.), *Wiley encyclopedia of electrical and electronics engineering* (pp. 1–20). Wiley. http://doi.org/10.1002/047134608X.W8278
[59] Lim, R. Y., Lew, W. C. L., & Ang, K. K. (2024). Review of EEG affective recognition with a neuroscience perspective. *Brain Sciences*, *14*(4), 364. https://www.mdpi.com/2076-3425/14/4/364#
[60] Trigka, M., Dritsas, E., & Mylonas, P. (2024). New perspectives in e-learning: EEG-based modelling of human cognition individual differences. In *IFIP International Conference on Artificial Intelligence Applications and Innovations,* 290–299. https://doi.org/10.1007/978-3-031-63227-3_20
[61] de Vasconcelos, L. S., Yan, Y., Maharjan, P., Kumar, S., Zhang, M., Yao, B., . . . , & Lu, N. (2025). On-scalp printing of personalized electroencephalography e-tattoos. *Cell Biomaterials*, *1*(1), 100004.

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