Proceedings of CONF-MLA 2025 Symposium: Intelligent Systems and Automation: AI Models, IoT, and Robotic Algorithms
DOI: 10.54254/2755-2721/2025.LD26330

The Application of Artificial Intelligence in Neuroscience and Exploration of Deep Learning Methods

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Abstract. The rapid progress in artificial intelligence (AI), especially in deep learning and reinforcement learning, is driving new opportunities in neuroscience, enabling innovative solutions to a range of brain-related problems. This paper explores how AI technologies can be applied to specific issues in brain science, particularly in the practical applications of brain-machine interfaces, neuroimaging analysis, and neural network modeling. Through a review of relevant literature and analysis of case studies, it highlights how AI, particularly deep and reinforcement learning, draws inspiration from neural mechanisms to effectively simulate and interpret brainwaves, imaging data, and other complex neurological signals. In particular, brain data like functional magnetic resonance imaging, electroencephalography, and electrical signals are analyzed using deep neural networks (DNN), convolutional neural networks (CNN), and reinforcement learning models. The performance of brain-machine interfaces is shown to be significantly enhanced, and notable improvements are observed in the early detection of neurodegenerative diseases. However, major challenges remain in AI applications, including the complexity of signal decoding, interference from data noise, and the high computational demands of real-time processing. The results show that integrating AI with brain science offers clear benefits but also presents challenges, highlighting the need for improved algorithms and stronger interdisciplinary collaboration in future research.

Keywords: Artificial Intelligence, Deep Learning, Brain-Computer Interface, Neuroimaging Analysis, Neurodegenerative Disease Prediction

1. Introduction

With the rapid progression of artificial intelligence (AI) technologies, particularly in the domains of deep learning and reinforcement learning, the integration of AI into neuroscience has become a critical area of scholarly inquiry. AI has exhibited considerable potential in boosting various aspects of neuroscience research, including electroencephalogram (EEG) signal processing, brain-computer interface (BCI) development, neuroimaging analysis, and neural network modeling, improving both the accuracy and efficiency of data interpretation and system performance. Notably, AI has made initial progress in decoding brain-computer interface signals and early prediction of neurological diseases. However, despite theoretical and practical progress, the application of AI in neuroscience continues to encounter significant challenges, such as the complexity of decoding high-noise data, computational constraints in real-time processing, and persistent ethical and privacy issues. Thus,

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this paper aims to explore how AI technologies are applied in neuroscience, with a particular focus on the practical implementation of deep learning and reinforcement learning in brain-computer interfaces, neuroimaging data analysis, and neural network modeling. Besides, it evaluates existing achievements and limitations while also proposing targeted solutions. Through a review of existing literature and case studies, this paper identifies current technological bottlenecks and research gaps, anticipates future trends in the integration of AI and neuroscience, and offers new perspectives and theoretical foundations to support further investigation in this interdisciplinary field.

2. Fundamentals of artificial intelligence and its implications for brain science

2.1. Deep learning and neural network architectures

The rapid advancement of AI is largely driven by breakthroughs in deep learning, particularly in the optimization of neural network architectures and computational power. The success of AlexNet in 2012 on large-scale image classification made deep neural networks (DNNs) and convolutional neural networks (CNNs) key pillars of AI research. Inspired by biological neural systems, these models employ hierarchical feature extraction mechanisms to automatically learn complex data patterns, providing powerful computational tools for brain science research. In recent years, deep learning has seen widespread use in neuroimaging data analysis, like the automated interpretation of functional magnetic resonance imaging (fMRI) and EEG data. These advancements have enabled precise characterization of the spatiotemporal dynamics of neural activity, thus facilitating early detection of neurological disorders and boosting the understanding of cognitive functions. However, despite the progress in simulating biological neural systems, significant differences remain between artificial and biological networks. Current models typically rely on large-scale labeled datasets for training, whereas the human brain can efficiently learn from minimal examples. Besides, artificial neural networks still face limitations in generalization and interpretability, making it challenging to replicate the flexibility of human cognition and decision-making. Future studies should incorporate neuroscience insights, such as synaptic plasticity, sparse coding, and spatiotemporal dynamics, to create biologically plausible AI systems and promote a closer integration between AI and brain science.

2.2. Reinforcement learning and its role in decision-making mechanisms

Reinforcement learning (RL), a core field within artificial intelligence, explores how an agent learns to make optimal decisions by interacting with its environment and learning from trial and error. Its theoretical framework is deeply influenced by cognitive neuroscience, particularly in areas such as reward-driven learning, exploration-exploitation trade-offs, and multi-step decision reasoning, which exhibit similarities to biological brain functions. In recent years, reinforcement learning has been increasingly utilized in brain science to investigate decision-making under uncertainty and how reward mechanisms drive adaptive changes in neural circuits. Also, reinforcement learning plays a key role in brain-machine interfaces (BMIs), particularly in neural signal decoding, adaptive neuromodulation, and neurorehabilitation training. However, despite its promising applications in cognitive and neuroscience research, reinforcement learning still faces significant challenges. For example, current RL models require extensive data to learn, unlike the human brain, which learns efficiently from few trials. In addition, developing reinforcement learning algorithms that align with neural physiological principles remains a key challenge in accurately modeling brain cognitive functions. Therefore, future research should incorporate neuroscience data to improve RL models,

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enabling more accurate representations of brain learning and decision-making, and advancing AI applications in cognitive science and neurological treatment.

3. Key applications of artificial intelligence in neuroscience

3.1. Enhancing brain-computer interfaces through AI

BCIs establish direct communication pathways between the brain and external devices, playing a crucial role in both neuroscience research and clinical practice. By converting neural signals into actionable commands, BCIs offer transformative potential for individuals with motor disabilities, including those affected by quadriplegia or amyotrophic lateral sclerosis (ALS) [1,2]. AI has been pivotal in improving BCI performance by enhancing neural signal decoding, system adaptability, and overall user experience. The main AI techniques used in BCIs are deep learning, reinforcement learning, and canonical correlation analysis (CCA). Deep learning models like CNNs and recurrent neural networks (RNNs) are highly effective in processing complex, high-dimensional neural data, improving decoding accuracy. RL optimizes adaptive feedback mechanisms, thereby enabling personalized system adjustments in real time [3]. CCA has enhanced visual BCI usability, achieving decoding accuracies over 90% in steady-state visual evoked potential (SSVEP) tasks [4]. And these advancements have enabled various practical applications. In motor control and neurorehabilitation, AI-powered BCIs help paralyzed patients operate robotic arms and support motor recovery [2]. For communication support, invasive BCIs using CNNs and GANs assist locked-in patients in regaining speech functions. In mobility control, non-invasive deep learning-based BCIs have been developed for wheelchair navigation, achieving accuracy rates up to 92%, greatly enhancing independence for users with severe motor disabilities.

3.2. Ai-powered neuroimaging and early diagnosis

Neuroimaging techniques such as functional magnetic resonance imaging (fMRI) and EEG provide critical insights into brain structure and function. However, their clinical utility is often limited by the complexity and noise inherent in the data. AI has emerged as a powerful tool to address these challenges, thus enabling automated feature extraction and pattern recognition that facilitate early diagnosis of neurological disorders and support personalized treatment planning.

Deep learning models, particularly CNNs, have been widely applied to fMRI and EEG data analysis. For instance, CNNs have demonstrated the ability to identify subtle hippocampal structural alterations in patients with Alzheimer’s disease, achieving an accuracy rate of up to 85% [5]. Autoencoders, another type of deep learning architecture, effectively reduce the dimensionality of high-resolution fMRI data while preserving diagnostically relevant features, thereby enhancing the early detection of Parkinson’s disease [6]. In addition, support vector machines (SVMs) have demonstrated strong performance in classifying EEG patterns related to depression, achieving an 82% accuracy rate in distinguishing affected individuals from healthy controls.

AI-driven neuroimaging is transforming clinical practice across three key domains. In particular, AI-driven neuroimaging is reshaping clinical practice by enabling earlier, more precise, and more personalized interventions. It facilitates early diagnosis by detecting biomarkers for conditions like Alzheimer’s disease up to ten years before symptoms appear. Moreover, it also enhances treatment personalization, as AI models can analyze brain connectivity to predict individual responses to antidepressants. Furthermore, AI contributes to biomarker discovery, uncovering patterns such as

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altered functional connectivity in the default mode network associated with schizophrenia, which improves diagnostic accuracy [5].

3.3. Modeling brain function through deep learning and neural simulation

Understanding how the brain functions and simulating its cognitive processes are central goals in both neuroscience and artificial intelligence. Deep learning, in particular, has emerged as a key tool in this endeavor, offering models that not only emulate neural mechanisms but also help uncover the computational principles underlying cognition. These brain-inspired models provide a two-way bridge: they draw from neuroscience to design more biologically plausible AI systems and, in turn, offer insights that inform our understanding of the brain.

To simulate specific cognitive functions, researchers have developed a range of neural networks. RNNs, particularly long short-term memory (LSTM) modes, are widely employed to capture the dynamics of working memory. These models, when trained on sequential memory tasks, display activity patterns akin to neurons in the prefrontal cortex and replicate human-like memory retention and recall. Similarly, CNNs, inspired by the hierarchical structure of the visual cortex, emulate the organization of the brain's ventral stream and have demonstrated high efficacy in object recognition tasks [7]. Recent advancements further strengthen the link between AI models and brain function. For example, Meta AI's Wav2Vec 2.0, a self-supervised learning model for speech, demonstrates processing patterns that align with those of the human auditory cortex. Its transformer architecture maps closely to cortical areas involved in phonetic and semantic interpretation, highlighting the model's potential to not only replicate but also elucidate neural mechanisms.

Beyond simulation, neuroscience has also inspired key innovations in AI design. Neuroplasticity, defined as the brain's capacity to reorganize its structure and function in response to experience, has greatly influenced the development of meta-learning frameworks. By incorporating computational analogues of synaptic plasticity, these algorithms enable efficient adaptation to novel tasks from limited data, thereby emulating the brain's inherent flexibility in learning and generalization [8]. Conversely, AI is increasingly contributing to neuroscience by uncovering previously unidentified functional roles of brain regions. For instance, reinforcement learning-based AI agents have pointed to the basal ganglia's role in reward prediction, a finding later confirmed by neuroscientific studies [7].

4. Existing challenges and future prospects of artificial intelligence in brain science

4.1. Key technical bottlenecks

The application of AI in neuroscience is hindered by the scarcity and variability of neural data. EEG and fMRI datasets are often high-dimensional, noisy, and expensive to acquire at high resolution. In addition, inter-individual, cultural, and cross-species differences limit model generalizability, especially when training on narrow or non-standardized datasets. The lack of annotated, diverse, and reproducible data remains a major obstacle to developing robust and transferable AI models in brain research [9].

The growing complexity of deep learning models in brain signal decoding and neuroimaging has led to substantial computational and energy demands. This is especially problematic for real-time applications such as BCIs, where efficiency must be maintained without compromising accuracy. Although cloud-based platforms offer scalable resources, they introduce latency and raise data privacy concerns. An emerging alternative lies in neuromorphic and low-power AI hardware, yet

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their adoption within neuroscience pipelines remains nascent. To support real-time decoding and long-term wearable systems, energy-efficient, high-performance AI systems are critical [10].

Interpretability and safety are critical requirements for AI systems in neuroscience, particularly in clinical and assistive applications. Yet, most advanced models, especially deep neural networks, operate as opaque “black boxes,” limiting users’ ability to understand or trust their outputs. This opacity is especially problematic in diagnostic and therapeutic contexts, where decisions must be accountable and transparent. The absence of explainability also hinders the detection of failure modes and biases, increasing the risk of harmful or misleading outcomes. Ensuring both accuracy and interpretability in AI models remains a major challenge in the field [11].

4.2. Future research directions

Future efforts to model brain function more effectively should prioritize unified AI frameworks capable of integrating heterogeneous neural data, such as EEG, fMRI, MEG, and single-neuron recordings. By combining modalities with complementary temporal and spatial characteristics, multimodal approaches can substantially improve both the robustness and accuracy of brain signal decoding. For example, integrating EEG’s high temporal resolution with fMRI’s spatial precision enables more comprehensive characterization of dynamic brain states. Emerging techniques such as self-supervised learning and attention-based architectures offer promising solutions for aligning and interpreting these heterogeneous data sources [6].

The human brain is not static; it continuously adapts through neuroplasticity. Future AI systems should incorporate this feature by enabling adaptive learning mechanisms that evolve alongside changes in the brain. For example, personalized neurotechnologies like neuroprosthetics, cognitive training platforms, and disease modeling systems require continuous adaptation to users’ evolving brain states. In this context, AI-driven BCIs can leverage meta-learning and reinforcement learning to support real-time responsiveness and long-term adaptability. Such capabilities are crucial for accommodating individual variability and rehabilitation progress over time [8].

The increasing integration of AI into neuroscience necessitates careful attention to emerging ethical challenges. Unlike conventional data, neural signals can expose intimate cognitive and emotional information, underscoring the need for rigorous consent procedures and data protection standards. At the same time, algorithmic bias, driven by imbalanced or non-representative datasets, may reinforce existing health inequities. And the development of brain-machine interfaces further complicates the ethical landscape, prompting new legal and philosophical debates around individual autonomy, identity, and cognitive sovereignty. Guiding these technologies responsibly will require interdisciplinary collaboration across neuroscience, engineering, and ethics.

5. Conclusion

The integration of AI into neuroscience has markedly advanced our understanding of brain function and driven the development of transformative technologies, including BCIs, neuroimaging analysis, and biologically inspired neural modeling. By enabling the efficient processing of high-dimensional and noisy neural data, AI has improved the decoding of brain signals, supported early diagnosis of neurological disorders, and enabled the creation of adaptive neurotechnologies. Nonetheless, critical challenges remain. The limited availability and heterogeneity of high-quality neural data constrain the generalizability of AI models, particularly across diverse populations and species. Moreover, the opaque nature of many AI systems, particularly deep learning models, raises serious concerns about interpretability and trust, especially in clinical and diagnostic contexts where decision transparency is critical. These concerns are compounded by ethical challenges, such as data privacy, algorithmic bias, and the need for transparent consent, which complicate the responsible deployment of AI in neuroscience. Addressing them requires not only technical innovation but also a realignment of research priorities. Integrating diverse neural modalities is vital for improving model robustness and accuracy, while incorporating neuroplasticity-inspired principles can enhance adaptability and personalization. Achieving these aims calls for sustained interdisciplinary collaboration across neuroscience, AI, ethics, and policy, ensuring that progress remains both scientifically sound and ethically grounded. By confronting both technical limitations and ethical complexities, the field will be better positioned to drive meaningful advances in brain science and improve outcomes in neurological healthcare.

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