Article type: Perspective

Home Page URL: https://www.alliedacademies.org/neuroinformatics-and-neuroimaging/

Artificial intelligence in PET neuroimaging: Applications in neurological and psychiatric disorders.

Emily Grant*

Department of Experimental Psychology, University of Oxford, United Kingdom.

***Correspondence to:** Emily Grant, Department of Experimental Psychology, University of Oxford, United Kingdom, E-mail: e.grant@oxbrain.ac.uk

Received: 03-Jan-2025, Manuscript No. AANN-25-169291; **Editor assigned:** 04-Jan-2025, PreQC No. AANN-25-1692915(PQ); **Reviewed:** 18-Jan-2025, QC No AANN-25-1692915; **Revised:** 21-Jan-2025, Manuscript No. AANN-25-1692915(R); **Published:** 28-Jan-2025, DOI:10.35841/aann -10.1.185

Introduction

Positron emission tomography (PET) has long been a cornerstone in neuroimaging for its ability to visualize and quantify physiological processes at the molecular level. Its applications span the diagnosis, monitoring, and research of a wide range of neurological and psychiatric disorders, from Alzheimer's disease to schizophrenia. Recent advancements in artificial intelligence (AI), particularly in machine learning and deep learning, have revolutionized the way PET neuroimaging data are processed, analyzed, and interpreted. AI techniques are capable of extracting subtle, high-dimensional patterns from PET scans that may be imperceptible to human experts, thus enabling earlier diagnosis, more precise disease characterization, and personalized treatment planning. These developments are fostering a paradigm shift in neuroimaging, where computational intelligence complements human expertise to improve both research and clinical outcomes [1].

One of the most significant contributions of AI to PET neuroimaging lies in automated image reconstruction and noise reduction. PET inherently suffers from low spatial resolution and high noise levels compared to other neuroimaging modalities. Traditional image reconstruction methods, such as filtered back projection and iterative algorithms, can be computationally intensive and limited in their ability to recover fine details. Deep learning-based reconstruction methods, including convolutional neural networks (CNNs) and generative adversarial networks (GANs), have shown remarkable improvements in image quality. These models can learn complex mappings from raw PET data to high-quality images, reducing acquisition time and radiation dose while maintaining diagnostic accuracy. AI-based denoising techniques also enable clearer visualization of small brain structures, enhancing the detection of early pathological changes [2].

AI has also advanced the quantitative analysis of PET neuroimaging, which is crucial for measuring biomarkers such as glucose metabolism, amyloid-beta deposition, tau pathology, and neurotransmitter receptor binding. Automated segmentation algorithms powered by deep learning can accurately delineate brain regions of interest, replacing or augmenting traditional atlas-based approaches. These models can adapt to individual anatomical variations and pathological changes, allowing for more reliable biomarker quantification. Furthermore, AI enables the integration of PET data with complementary modalities such as structural MRI or diffusion imaging, improving localization and interpretation of metabolic and molecular alterations. Multimodal fusion techniques powered by AI can uncover novel relationships between structural and functional changes, aiding in the identification of disease-specific patterns that may serve as diagnostic or prognostic indicators [3].

In the realm of clinical applications, AI-driven PET neuroimaging has shown particular promise in the early diagnosis and prognosis of neurodegenerative diseases. For Alzheimer's disease, machine learning models trained on amyloid and tau PET data can distinguish between healthy aging, mild cognitive impairment, and early Alzheimer's with high accuracy. Predictive models can also estimate the likelihood of disease progression, assisting in clinical decision-making and patient counseling. In movement disorders such as Parkinson's disease, AI can enhance the interpretation of dopaminergic PET imaging, enabling more precise differentiation between Parkinson's and atypical parkinsonian syndromes. In psychiatric disorders like major depression and schizophrenia, AI analysis of PET tracers targeting neurotransmitter systems has provided insights into altered neurochemistry and treatment response prediction, paving the way for more personalized therapeutic strategies [4].

Despite its transformative potential, the application of AI in PET neuroimaging faces several challenges. A major limitation is the availability of large, high-quality annotated datasets for training robust AI models, particularly for rare neurological and psychiatric conditions. Data harmonization across imaging centers is critical to mitigate variability in PET acquisition protocols, scanner hardware, and tracer kinetics. Another challenge lies in the interpretability of AI models, especially deep learning systems, which are often perceived as "black boxes." Developing explainable AI methods that can provide transparent and biologically meaningful justifications for their predictions is essential for clinical adoption. Furthermore, rigorous validation on independent datasets, prospective clinical trials, and regulatory approval processes are necessary to ensure the reliability and safety of AI-driven PET applications in real-world settings [5].

Conclusion

Artificial intelligence is transforming PET neuroimaging by enhancing image quality, automating quantitative analysis, and enabling early detection and precise characterization of neurological and psychiatric disorders. Through innovations in deep learning-based reconstruction, denoising, segmentation, and multimodal data integration, AI is expanding the diagnostic and research potential of PET. These advancements are fostering personalized approaches to treatment and improving our understanding of disease mechanisms at the molecular level. While challenges related to data availability, harmonization, interpretability, and clinical validation remain, ongoing research and collaboration between AI developers, neuroimaging scientists, and clinicians are steadily addressing these barriers. As AI technologies continue to mature, they are poised to become integral to PET neuroimaging workflows, driving new discoveries and improving patient care in neurology and psychiatry.

References

1. Iacob G, Dinca EB. Current data and strategy in glioblastoma multiforme.. J Med Life. 2009;2(4):386..
2. Cao Y, Sundgren PC, Tsien CI, et al. Physiologic and metabolic magnetic resonance imaging in gliomas. J Clin Oncol. 2006;24(8):1228-35.
3. Jan CI, Tsai WC, Harn HJ, et al. Predictors of response to autologous dendritic cell therapy in glioblastoma multiforme . Front Immunol. 2018;9:727
4. Singh SK, Hawkins C, Clarke ID, et al. Identification of human brain tumour initiating cells. nature. 2004;432(7015):396-401.
5. Ye L, Wang L, Yang JA, et al. . Identification of tumor antigens and immune landscape in glioblastoma for mRNA vaccine development.. Front Genet. 2021;12:701065.

Citation: Grant E. Artificial intelligence in PET neuroimaging: Applications in neurological and psychiatric disorders. J NeuroInform Neuroimaging. 2025;10(1):185.