

How Artificial Intelligence is Important for Brain Mapping: A Recent Research Review

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Abstract:

The integration of artificial intelligence (AI) into brain mapping has become increasingly pivotal, effectively translating complex neuroimaging data into clinically relevant insights for neurological and psychiatric disorders. This narrative review encompasses recent literature published between January 2015 and August 2026. It analyzes approximately 28 primary studies identified through a systematic search of databases including PubMed, Scopus, Web of Science, and IEEE Xplore. It seeks to examine the application of various AI methodologies, including convolutional neural networks, recurrent architectures, autoencoders, and graph neural networks, in both structural and functional neuroimaging. The discussion emphasizes the growing role of AI in diverse areas, such as the multimodal integration of MRI, fMRI, PET, and CT imaging; connectomics and functional-structural network mapping; and the classification of disorders, including Alzheimer's disease, Parkinson's disease, and schizophrenia.

Additionally, it considers applications in preoperative planning and predicting neurostimulation responses. The review also highlights the significance of explainable AI techniques, such as saliency maps and Grad-CAM, as well as innovative strategies, including generative models for image synthesis and augmentation. Emerging themes, including foundation models and neuromorphic computing, are further explored. Nonetheless, significant challenges remain, including data scarcity, limited generalizability, limited interpretability, and the extensive computational demands of whole-brain connectomics. Ethical and regulatory considerations, particularly regarding data privacy, algorithmic fairness, and equitable representation, are vital for the responsible use of AI in clinical environments. Ultimately, the clinical efficacy of AI depends not only on technical performance but also on thorough validation, interdisciplinary collaboration, and governance measures that prioritize the needs of clinicians and patients in decision-making processes.

Keywords: *Artificial intelligence; Brain mapping; Neuroimaging; Connectomics; Machine learning*

1. Introduction:

Artificial intelligence plays an important role in brain mapping due to the unique complexity and scale of high-dimensional neuroimaging data, in large samples, which are typically transformed into clinically interpretable representations of brain structure/function and disease-related change. Recent reviews aptly characterize AI-based neuroimage analysis as a transformative advance in elucidating complex mechanisms of brain function and enhancing clinical diagnostic capabilities across multiple neurological and psychiatric disorders [1,2].

The heterogeneity and scale of data challenged the traditional approach to neuroimaging analysis, as it could not integrate multiple modalities, such as combining structural and functional information. The need for an integrative computational framework progressively led towards brain mapping, which relies more on computation. Recently, reports have shown how machine learning, deep learning, and advanced image processing are being integrated into complete workflows. These processes take raw imaging data and turn it into useful information for clinical use[2,3]. Recent literature illustrates that the application of artificial intelligence in neuroimaging has progressed beyond mere proof-of-concept image classification. A systematic review conducted in 2024, which examined 456 articles and included 104 studies, identified the predominant AI-enabled tasks in neuroimaging as disease classification, lesion segmentation, reconstruction, and prediction [1]. This evolution is clinically significant, as many disorders that jeopardize brain health may emerge long before visible symptoms become apparent. Consequently, machine learning is increasingly employed to extract non-invasive indicators of resilience, vulnerability, and early pathology from neuroimaging data[2].

In this context, brain mapping encompasses more than mere anatomical localization. It now also involves identifying structural pathways, functional networks, disease-related areas, connectomic organization, and cross-modal interactions. Notably, connectomics conceptualizes the brain as a structured network, which can be noninvasively mapped using functional and diffusion MRI techniques. Furthermore, advancements in machine learning facilitate this mapping process by aiding in classification, biomarker identification, severity assessment, treatment response prediction, and presurgical planning[4]. This review, therefore, examines how artificial intelligence enhances brain mapping through three interconnected roles: extracting significant imaging features, integrating diverse neuroimaging modalities, and translating identified patterns into clinically relevant predictions. Recent reviews have provided comprehensive summaries of artificial intelligence applications in neuroimaging, typically categorized by modality, disorder, or methodology[1–5]. However, the intersections among these areas have not been examined as thoroughly. The same architectures, such as convolutional neural networks, graph neural networks, autoencoders, and foundation models, are prevalent across various domains, including multimodal fusion, connectomics, disorder classification, and presurgical planning. Moreover, the challenges related to clinical translation, specifically interpretability, generalizability, and governance, are common to these domains rather than being confined to any single area. This review aims to offer an integrative perspective, synthesizing evidence that is often addressed in isolation to illuminate recurring methodological advancements and translational challenges. The focus is specifically on AI and machine-learning applications in adult human structural and functional neuroimaging, encompassing modalities such as MRI, fMRI, PET, CT, and diffusion imaging, while excluding studies centered solely on genetic, molecular, or non-imaging biomarkers elaborated in (Figure 1).

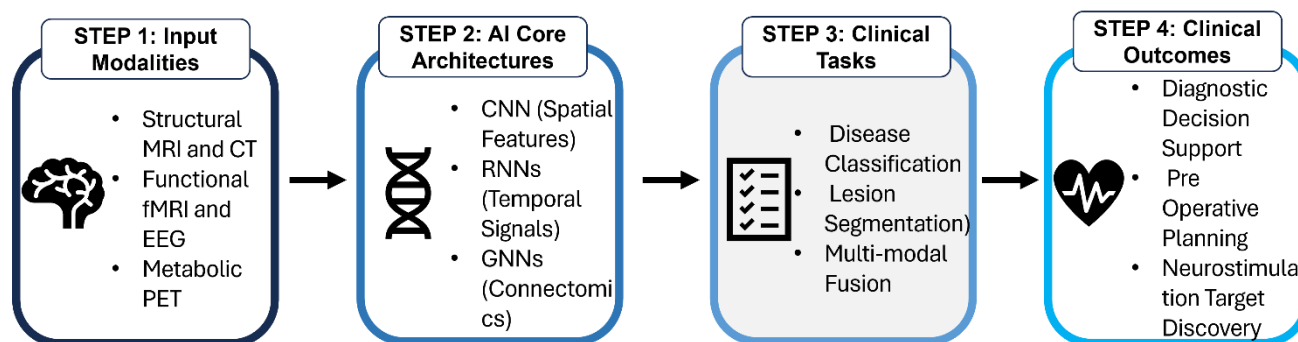


Figure 1: The AI-driven Brain Mapping Workflow

2. Methods:

This review presents an overview of recent developments in the application of artificial intelligence (AI) to brain mapping, neuroimaging, and related fields in neuroscience. Due to the wide variety of imaging modalities (see Figure 3), targeted diseases, and AI architectures involved, a narrative synthesis approach was chosen over a systematic review or meta-analysis. Nevertheless, the identification and selection of studies were conducted in accordance with the PRISMA 2020 guidelines (see Figure 2). A comprehensive literature search was conducted using databases such as PubMed, Scopus, Web of Science, and IEEE Xplore. This search encompassed the period from January 2015 to August 2026 and was enhanced by backward citation tracking of pertinent articles. A combination of controlled vocabulary and free-text terms—namely, "artificial intelligence," "machine learning," "deep learning," "brain mapping," "neuroimaging," "connectome," and other related terms—was utilized, linked by Boolean operators. The inclusion criteria specified that eligible records must be peer-reviewed articles or reviews published in English, specifically reporting an application of AI or machine learning in the context of human brain mapping or neuroimaging. Excluded from the review were conference abstracts, books, non-English publications, and those records lacking a clear AI or machine learning application. The database search yielded a total of 595 records (PubMed = 182, Scopus = 176, Web of Science = 141, IEEE Xplore = 96). After removing 124 duplicates, 471 unique records were screened based on title and abstract, resulting in the exclusion of 356 as out of scope. Subsequently, the remaining 115 full-text reports were assessed for eligibility, with none deemed unretrievable. A final selection of 28 studies was made for narrative synthesis. The extracted data, including author, year, modality, AI method, and key findings, are summarized in Table 1 and organized thematically according to application domain, reflecting the diversity of methods and outcomes observed across the studies.

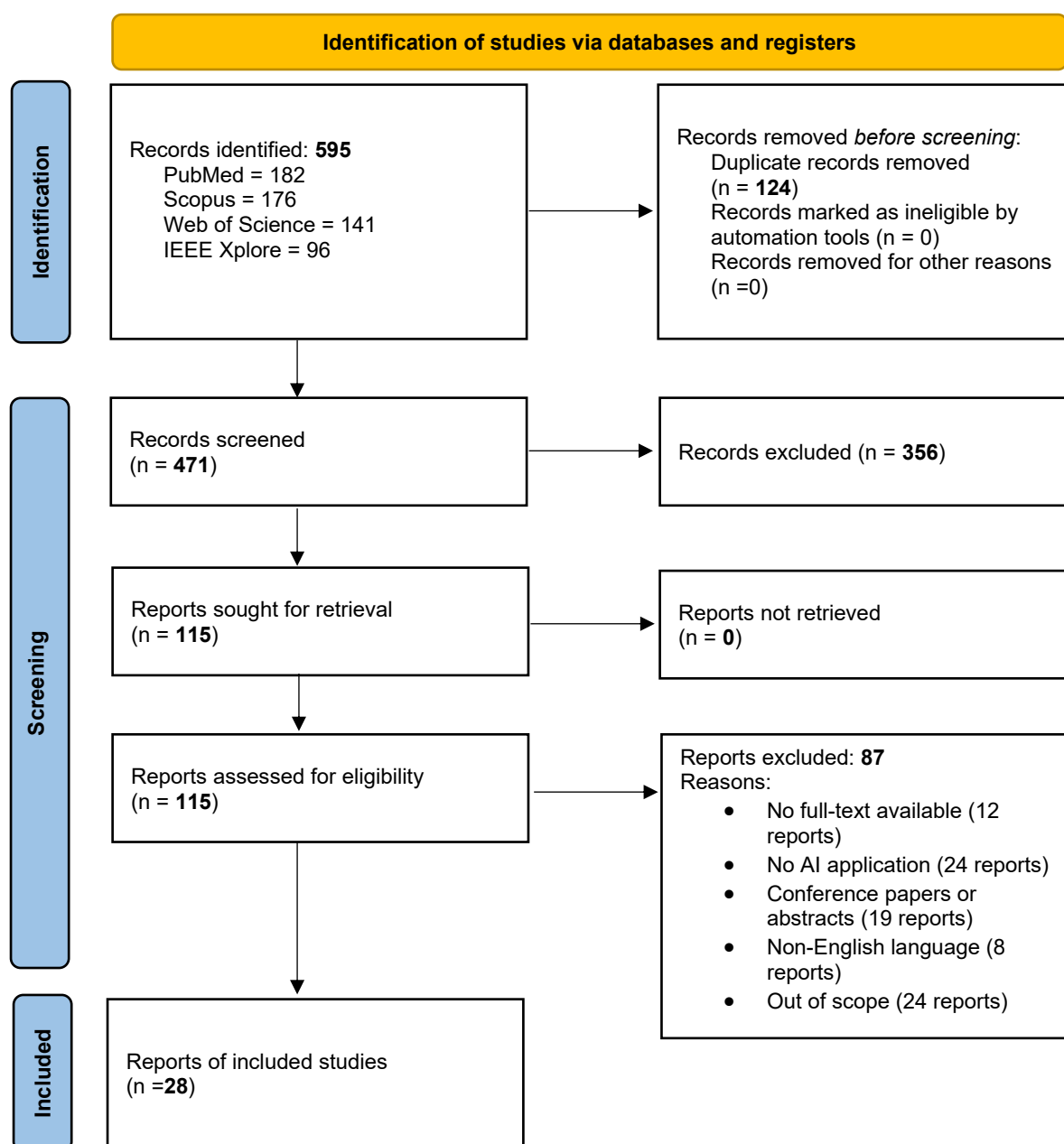


Figure 2: PRISMA Flow Diagram

Table 1: Characteristics of Included Studies

No.	Author(s)	Title	Year	Modality	AI Method	Key Finding
1	Luckett PH et al.	Data-Efficient Resting State Functional MRI Brain Mapping with Deep Learning	2023	RS-fMRI	3D CNN	Mapped language and motor networks with 96% out-of-sample accuracy and similar results from 2.5 vs 10 min of data; remained accurate in glioblastoma cases for presurgical planning[6]
2	Luckett PH et al.	Resting state network mapping in individuals using deep learning	2023	RS-fMRI	3D CNN	Generated individual voxelwise RSN maps that were resistant to noisy or short acquisitions and clinically suitable for automated presurgical localization[7]
3	Zhu Z et al.	From sMRI to task-fMRI: A unified geometric deep learning framework for cross-modal brain anatomo-functional mapping	2023	sMRI → task-fMRI	Geometric deep learning with graph encoding and attention	Predicted individual task-fMRI maps from anatomy alone across seven HCP task datasets, addressing anatomo-functional mapping with uncertainty-filtered learning[8]
4	Wang et al.	Decoding and mapping task states of the human brain via deep learning	2020	Task-fMRI	Deep neural network	Classified seven task states from HCP fMRI with 93.7% average accuracy and automatically identified task-relevant brain areas[9]
5	Tang et al.	Deep multimodal model for autism diagnosis	2020	fMRI connectomics	Deep multimodal model	Learned joint representations from two connectomic views and achieved 74% accuracy with 95% recall, outperforming single-view functional data[10]
6	Li et al.	Deep transfer learning neural network for whole-brain functional connectivity classification	2018	RS-fMRI connectome	Deep transfer learning NN	Improved classification of whole-brain functional connectivity patterns and addressed small-sample limitations by transferring knowledge from healthy datasets[11]
7	Pinaya et al.	Deep autoencoders for normative structural deviation mapping	2019	Structural MRI	Deep autoencoder	Built a normative model from 1,113 healthy scans and detected disease-specific neuroanatomical deviations in schizophrenia and autism[12]
8	Kam et al.	Static and dynamic functional network features for eMCI classification	2020	RS-fMRI	Joint static–dynamic network model	Showed that dynamic functional-network features complement static features and improved early MCI diagnostic performance by about 10%[13]
9	Niu et al.	Multimodal brain-age prediction	2020	MRI, DTI, rs-fMRI	Multiple ML and deep learning models	Compared 36 feature–model combinations in 839 subjects and proposed bias correction for the brain-age gap using age and sex interactions[14]
10	Rajendran S et al.	Automated Segmentation of Brain Tumor MRI Images Using Deep Learning	2023	Structural multimodal MRI	U-Net + 3D CNN ensemble	Combined segmentation networks to improve tumor delineation, reporting validation accuracies near 99% across the whole tumor, enhanced tumor, and tumor core[15]

11	Wen L et al.	A deep ensemble learning framework for glioma segmentation and grading prediction	2025	Multimodal MRI	U-Net–based ensemble attention	deep with	Used four MRI modalities from BraTS2020 and achieved Dice scores of 91.28% WT and 85.88% ET, outperforming recent multimodal baselines[16]
12	van der Voort SR et al.	Combined molecular subtyping, grading, and segmentation of glioma using multi-task deep learning	2023	Preoperative structural MRI	3D Multi-task CNN		Simultaneously predicted IDH, 1p/19q, and grade while segmenting tumor; generalized to an independent 13-institute test cohort[17]
13	Zhu Z et al.	OMT and tensor SVD–based deep learning model for segmentation and predicting genetic markers of glioma	2025	Preoperative MRI	OMT + tensor SVD deep learning		Analyzed 3,565 patients across 16 datasets, achieved a lesion Dice of 0.880, and outperformed four radiologists for WHO grade, IDH, and 1p/19q prediction on TCGA[18]
14	Naser M	Brain tumor segmentation and grading of lower-grade glioma using deep learning in MRI images	2020	MRI (T1pre, FLAIR, T1post)	U-Net + transfer learning VGG16		Delivered 0.84 Dice for segmentation and 0.95 patient-level grading accuracy for lower-grade glioma[19]
15	Isensee et al.	HD-BET brain extraction	2019	MRI preprocessing	Artificial neural network		Improved a critical preprocessing step for neuroimaging and outperformed six public skull-stripping tools across multicenter datasets, including neuro-oncology imaging[20]
16	Partamian H et al.	Machine learning on interictal intracranial EEG predicts surgical outcome in drug-resistant epilepsy	2025	iEEG + MRI/CT coregistration	Unsupervised with DMD and NNMF	ML	Converted interictal iEEG into interpretable spatiotemporal epileptogenic networks that delineated EZ and predicted surgical outcome without waiting for seizures[21]
17	Pilet J et al.	Predicting seizure onset zones from interictal intracranial EEG using functional connectivity and machine learning	2025	Interictal iEEG	SVM on FC graph features		Predicted seizure onset zones with AUC 0.91 in node-level CV, and gamma-band AEC graph features outperformed spikes and HFOs with equal feature counts[22]
18	Ren S et al.	CNN-Autoformer: Automated EEG-Based Seizure Detection and Localization Using Hybrid Deep Learning	2026	Multi-channel EEG	CNN + Autoformer		Reached 98.34% accuracy on CHB-MIT and generated seizure-onset heatmaps aligned with expert annotations for localization[23]
19	Liu G et al.	Efficient Group Cosine Convolutional Neural Network for EEG-Based Seizure Identification	2025	Multi-channel EEG	Group CosCNN		Preserved channel spatial information and enabled real-time seizure onset channel localization, with 91.30% individual-level localization accuracy on CHB-MIT[24]
20	Phang et al.	EEG-derived brain connectome classification in schizophrenia	2020	EEG connectome	Multi-domain CNN		Combined connectivity features with decision-level fusion and achieved 91.69% accuracy for schizophrenia classification[25]
21	Qamar WUR et al.	Deep learning in intracranial EEG for seizure detection: advances, challenges, and clinical applications	2025	iEEG review	CNN, LSTM, transformer review		Synthesized that recent models localize EZ through probabilistic mapping, but still face major challenges in interpretability, generalization, and real-time deployment[26]
22	Leone A et al.	Preoperative mapping techniques for brain tumor surgery: a systematic review	2025	fMRI, nTMS, MEG	Systematic review of mapping methods		Found fMRI useful but limited by false positives/negatives and highlighted that ML is being explored to distinguish eloquent from co-activated non-eloquent areas, though routine use remains limited[27]
23	Haddad AF et al.	Preoperative Applications of Navigated Transcranial Magnetic Stimulation	2021	nTMS	Image-guided stimulation mapping		Reported that nTMS provides highly accurate non-invasive cortical mapping, with motor mapping best validated and useful for operative planning and risk stratification[28]

24	Setlak M et al.	Navigated Transcranial Magnetic Stimulation (nTMS): From Functional Brain Mapping to Clinical Applications in Neurosurgery and Neurology	2026	nTMS	Narrative review	Concluded evidence is strongest for preoperative motor mapping, while language mapping remains more heterogeneous and needs standardized protocols and multicenter validation[29]
25	Yamao Y et al.	Intraoperative Brain Mapping by Cortico-Cortical Evoked Potential	2021	Intraoperative electrophysiology	CCEP network mapping	Showed that CCEP can map and monitor large-scale cortical networks intraoperatively, including dorsal and ventral language pathways and frontal motor connectivity[30]
26	Al-Adli N et al.	Technical Aspects of Motor and Language Mapping in Glioma Patients	2023	Intraoperative mapping	Review of stimulation mapping	Reinforced that intraoperative stimulation mapping remains the gold standard for safe maximal resection when gliomas are near the eloquent cortex[31]
27	Zhao L	Advances in functional magnetic resonance imaging-based brain function mapping: a deep learning perspective	2025	fMRI review	CNN, transformers, RNN, self-supervised models	Identified fMRI embeddings, foundation models, and brain-inspired AI as the main next steps for more precise and efficient brain mapping[32]
28	Zhu T et al.	Mapping Functional Brain Organization Using Artificial Intelligence	2026	rs-fMRI multimodal integration	with Supervised, unsupervised, self-supervised AI	Reviewed AI parcellation methods and concluded future progress depends on multimodal integration, explainable AI, and foundation models for individualized functional atlases[33]

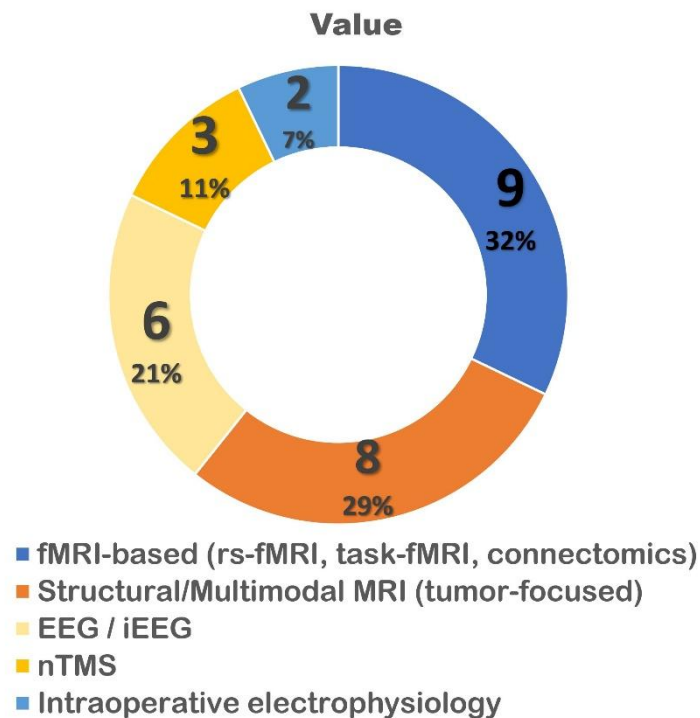


Figure 3: Studies by Imaging Modality

3. AI Methods for Neuroimaging Analysis

The methodological significance of artificial intelligence in brain mapping lies in its ability to identify complex patterns in neuroimaging data that traditional analyses often overlook. Comprehensive reviews indicate that convolutional neural networks have emerged as the preferred architecture for both structural and functional image analysis, owing to their proficiency in feature extraction and classification of MRI data[3,5]. Additionally, survey evidence suggests that deep learning techniques frequently surpass conventional analytical methods in neuroimaging, thereby facilitating their rapid integration into clinical and translational imaging practices [1,2]. Various artificial intelligence architectures contribute uniquely to the field of brain mapping. Convolutional neural networks (CNNs) are primarily employed for spatial feature extraction from both structural and functional brain images.

In contrast, recurrent neural networks and similar sequential models are particularly valuable when analyzing the temporal structure of fMRI or EEG signals[3,5]. Autoencoders represent an additional unsupervised approach, adept at generating compact latent representations from intricate inputs, which is essential when labeled neuroimaging datasets are scarce[34,35]. A significant challenge in brain mapping stems from the inherently spatiotemporal nature of functional neuroimaging. Many earlier models addressed either spatial organization or temporal dynamics, but rarely both. To overcome this limitation, deep sparse recurrent autoencoders were developed to simultaneously learn spatial patterns and temporal fluctuations of connectome-scale brain networks from 4D fMRI data. Such comprehensive modeling is crucial, as accurately depicting neural organization requires understanding both the spatial locations of activity and its temporal evolution [36].

Graph-based deep learning has gained significant prominence, particularly when the focus is on networks of interconnected brain regions rather than on individual voxels or slices. Resting-state fMRI captures the temporal dynamics of intrinsic functional networks, leading to the proposal of spatio-temporal graph convolutional networks. Earlier deep learning methods often overlooked crucial aspects such as inter-

regional dependencies and temporal non-stationarity [37]. In analyses using extensive datasets from the Human Connectome Project and the National Consortium on Alcohol and Neuro Development in Adolescence (NCANDA), these graph-based models demonstrated enhanced predictive accuracy. They successfully identified brain regions and functional connections that correspond to established neuroscience markers [37].

Furthermore, there is a methodological shift from narrowly focused supervised models to more versatile self-supervised and foundation-model approaches. Traditional supervised analysis of brain imaging data requires large labeled datasets and often yields task-specific models, thereby limiting scalability and generalizability. In contrast, foundation models trained using self-supervised objectives across diverse public datasets are beginning to mitigate these limitations, achieving competitive results in segmentation, lesion detection, denoising, and brain age estimation while requiring less labeled data [35]. These advancements underscore the critical role of artificial intelligence in contemporary brain mapping. AI provides architectures optimized for image structure, temporal dynamics, and graph organization, facilitating both supervised diagnostic efforts and unsupervised exploration. Nonetheless, challenges such as computational demands, high dimensionality, insufficient annotation, and interpretability continue to affect model performance and clinical applicability [3].

3.1 Multimodal Brain Imaging Fusion

The significance of artificial intelligence in brain mapping stems from the limitations inherent in individual neuroimaging modalities, each of which fails to capture the brain's full biological intricacies. Techniques such as structural MRI, functional MRI, diffusion imaging, PET, and CT each offer distinct yet complementary insights. Analyzing these modalities in isolation often proves inadequate for a comprehensive understanding of the relationships among brain anatomy, connectivity, metabolism, and function [38,39]. This inherent complementarity has sparked considerable interest in the field of multimodal fusion. Reviews focused on fusion methods highlight that integrating different modalities can uncover valuable inter- and intra-modality information, enhance biomarker discovery, and facilitate predictions about behavior, brain aging, and disease progression [38]. Computational frameworks designed for neurological mapping emphasize that integrating MRI, fMRI, PET, and CT enhances resolution, interpretability, and diagnostic efficacy [3].

Several methodologies have been proposed to achieve this integration. Techniques such as canonical correlation analysis and multi-view learning are recognized as effective data fusion approaches that can enhance diagnostic accuracy. Furthermore, hybrid frameworks that incorporate imaging data alongside clinical and genetic variables are increasingly used to provide a more nuanced characterization of neurological diseases [3]. In studies of Alzheimer's disease, multimodal models integrating MRI and PET data have consistently outperformed unimodal strategies. Comprehensive systematic reviews suggest that complex models incorporating neuroimaging with clinical, cognitive, genetic, and behavioral data yield the most accurate predictions of progression from mild cognitive impairment to Alzheimer's dementia[40]. A significant advancement in multimodal brain mapping involves directly modeling the interplay between brain structure and function. For instance, diffusion MRI enables estimation of structural networks via white-matter connectivity, whereas fMRI captures time-varying BOLD activity without necessarily establishing anatomical connections between corresponding regions. Proposed bidirectional mapping frameworks aim to mitigate the biases inherent in one-way mappings by concurrently modeling structure-to-function and function-to-structure dynamics and employing contrastive learning methods to align latent representations across modalities [39].

Efforts to enhance interpretability within multimodal models have also been made. Integrated gradients have been used to generate saliency maps from multimodal bidirectional mapping systems, facilitating the identification of brain regions associated with predicted disease states or phenotypes [39]. This

interpretability is crucial; as the complexity of multimodal fusion increases, the clinical utility of these integrated brain maps hinges not only on their predictive accuracy but also on their ability to relate mapped features to discernible neurobiological phenomena. Nevertheless, the practical implementation of multimodal brain mapping remains technically challenging. Variations in resolution, imaging acquisition protocols, and noise profiles complicate the integration process, while the computational demands of large multimodal datasets can hinder real-time applications[3]. Even as multimodal systems improve performance, harmonizing data across centers remains a formidable challenge [3]. Thus, it is essential to highlight in clinically oriented discussions that the strength of multimodal AI lies not merely in aggregating more data but in its capacity to reconstruct a more comprehensive representation of the brain under study.

3.2 AI in Connectomics and Network Mapping

Connectomics is a prime example of the pivotal role that artificial intelligence (AI) plays in brain mapping. Within this framework, the brain is understood as an intricate network comprising regions that are both structurally and functionally interconnected. Researchers are increasingly employing machine learning techniques to extract clinically relevant insights from extensive relational datasets[4]. Reviews on translation research highlight how the use of machine learning in connectomics has not only enhanced the understanding and classification of neurological disorders but has also facilitated the identification of biomarkers, allowed for assessments of disease severity, improved predictions regarding treatment outcomes and responses, aided in pinpointing targets for brain stimulation, and optimized presurgical connectome mapping[4].

Graph neural networks (GNNs) are particularly well-suited to this domain, given their ability to preserve the inherent network structure of connectivity data. A noteworthy primary study utilizing a sample of 998 participants from the Human Connectome Project demonstrated that a GNN could accurately predict mean functional connectivity from structural connectivity, accounting for 89% of the explained variance, and mean functional centrality, with an impressive 99% of the variance explained [41]. This model importantly acknowledged significant individual-level variability, illustrating AI's ability to discern essential aspects of brain function from its anatomical structure. This finding reinforces the argument that effective brain mapping should integrate considerations of both network topology and dynamic neural activity[41].

In addition, another pivotal study showed that graph-based methods provide crucial insights into the temporal instability of resting-state networks. Specifically, spatio-temporal graph convolutional networks, trained and validated using large cohorts from both the Human Connectome Project and the National Consortium on Alcohol and Neuro Development in Adolescence (NCANDA), conceptualized functional connectivity as a dynamic graph. This representation was derived from brief BOLD subsequences and successfully captured non-stationary connectivity patterns while illuminating the significance of specific neural connections [37]. This approach not only enhanced predictive accuracy across broad cohorts but also highlighted regions and connections known for their neurobiological importance[37]. The translational potential of AI in connectomics is particularly significant in neurosurgical and interventional contexts. Research using machine learning has aimed to noninvasively localize temporal lobe epilepsy foci with resting-state fMRI and diffusion MRI, thereby significantly reducing reliance on invasive confirmation methods [4]. Moreover, deep learning methodologies have been employed to differentiate the language and primary motor cortices from resting-state fMRI data and to delineate eloquent regions in proximity to tumors, thereby demonstrating how network-level mapping can greatly improve preoperative planning [4].

Nonetheless, connectomic brain mapping presents considerable computational challenges. For instance, high-resolution synaptic mapping of a single cubic millimeter of human cortex can generate approximately 1.4 petabytes of data[42]. The demands of whole-brain mapping necessitate sophisticated processes for data acquisition, alignment, cleaning, and visualization, as well as infrastructure capable of managing zettabyte-scale data [42,43]. As a solution, neuromorphic computing is being explored as a potential avenue for continuous, low-power engagement with brain signals in closed-loop interfaces[43,44].

3.3 Clinical Applications in Disorder Classification

The foremost clinical application of artificial intelligence (AI) in brain mapping is the classification of neurological disorders. Systematic reviews and surveys reveal that the classification of disorders is the primary emphasis in AI neuroimaging studies, with a particular focus on neurological rather than psychiatric conditions [5].

Among neurodegenerative disorders, Alzheimer's disease has garnered significant attention in a pivotal study conducted by [45]. Researchers developed a parameter-efficient three-dimensional convolutional neural network (CNN) that successfully predicted the progression from mild cognitive impairment to Alzheimer's disease, achieving a commendable 86% cross-validated accuracy, 87.5% sensitivity, and 85% specificity (area under the curve [AUC] = 0.925). At the review level, CNNs demonstrated superior performance to support vector machines for this prediction task, with multimodal MRI-PET models outshining single-modality approaches [40].

In the context of Parkinson's disease, connectome-based deep learning exemplifies AI's valuable capabilities in both classifying the disorder and visualizing disrupted neural circuits. In a primary study involving a prospective cohort of 115 patients and 115 controls, [46] revealed that CNNs utilizing parameter-weighted structural connectome matrices achieved AUCs of 0.895, 0.801, and 0.836, depending on the diffusion-derived weighting. These models surpassed streamline-count-based approaches, with gradient-weighted class activation mapping effectively highlighting alterations in the connections between the basal ganglia and cerebellum.

The application of AI in psychiatric disorders remains comparatively limited. A notable primary resting-state study on major depressive disorder conducted by [47] analyzed datasets comprising 2,338 and 1,039 participants. The study found that machine learning and graph convolutional networks achieved only a mean accuracy of 61% in distinguishing patients from controls, which was lower than the accuracy of sex classification on the same data. This finding suggests that whole-brain connectivity may serve as a weak yet reproducible biomarker, likely reflecting disease heterogeneity, although consistent thalamic hyperconnectivity was observed across datasets.

Additionally, brain tumor imaging represents another significant application of AI. In a recent study [34] involving 3,264 MRI images, a two-dimensional CNN achieved a training accuracy of 96.47%, with average recall around 95% and ROC areas near 0.99-1.0, thereby outperforming traditional machine learning techniques while exhibiting lower complexity than a comparator autoencoder.

4. Presurgical Planning and Brain Stimulation

Artificial intelligence (AI) has emerged as a significant tool in presurgical brain mapping, demonstrating the ability to extract clinically relevant network information from both resting-state and structural imaging techniques when direct, task-based mapping is either limited or impractical [2–4]. In the field of translational connectomics, machine learning is increasingly employed not only for classification but also for the discovery of biomarkers, assessment of disease severity, prediction of outcomes, forecasting responses to interventions, identification of stimulation targets, and mapping of connectomes prior to neurosurgical procedures [2,4]. The clinical implications are profound, as precise brain mapping is crucial for the success of epilepsy surgery, the management of movement disorders, tumor surgery, and planning for neuromodulation interventions [3] (see Table 2)

Numerous studies have demonstrated that AI-enhanced connectomic analysis can significantly improve the localization and stratification of neurological conditions relevant to intervention planning. For instance, in cases of temporal lobe epilepsy, machine learning techniques have been used to localize epileptogenic foci by analyzing resting-state functional MRI (fMRI) and diffusion MRI. This approach provides a non-invasive

alternative to traditional invasive confirmation methods[4]. Furthermore, in the context of mild traumatic brain injury, dynamic functional connectivity models have identified individualized abnormal connectomic patterns, correlating them with outcomes related to anxiety, depression, episodic memory, executive function, and language. This progression suggests that presurgical or interventional mapping can transcend static lesion localization, advancing toward an understanding of patient-specific network dysfunction[4]. Notably, decision-level fusion techniques have proven particularly advantageous, as they can effectively manage high-dimensional multimodal features by integrating multiple internal expert estimators into a single predictive model [4]. Resting-state network mapping is also becoming increasingly relevant for patients who are unable to engage in reliable task paradigms. Novel machine learning approaches in translational imaging are being developed to enhance early detection, prediction, and treatment outcomes, culminating in workflows that yield clinically actionable quantitative metrics[2]. Frameworks designed for multimodal neurological mapping have reported enhancements in interpretability and computational efficiency, with the potential for real-time applications, which is especially pertinent in intraoperative or rapid presurgical contexts [3].

In the realm of brain stimulation, the literature suggests that connectomic AI serves primarily as a tool for target discovery and response prediction, rather than as a substitute for clinical expertise. Reviews of macroscale connectomics consistently highlight the identification of potential stimulation targets and the evaluation of stimulation effects on the connectome as current applications[4]. More broadly, while AI is being investigated to optimize treatment selection and anticipate responses in neurological care, recent clinical reviews caution that the evidence remains limited. Many studies suffer from small sample sizes, selection bias, and a lack of external validation[48]. The most compelling conclusion is that AI has significant potential to augment presurgical and stimulation planning through the integration of connectomics; however, prospective validation in actual clinical workflows is imperative [48,49].

Table 2: Representative clinical roles of AI in presurgical planning and brain stimulation.

Clinical Use	AI Input	Main Role	Performance / Evidence	Evidence Level
Epilepsy lateralisation	rs-fMRI, dMRI	Non-invasive focus localization	Performance varies by cohort/pipeline; it is not uniformly reported in the reviewed literature	Retrospective, small-to-moderate cohorts[4]
mTBI network assessment	Static + dynamic FC, regional entropy (ML model fusion)	Individualized dysfunction mapping	75% accuracy (77% precision, 74% sensitivity, 76% specificity)	Retrospective, single-center cohort[4,50]
Brain stimulation planning	Structural/functional connectomes	Target and response prediction	Evidence is largely descriptive; prospective validation is lacking	Narrative/translational review[4,48]

Rapid clinical mapping	Multimodal MRI/fMRI/PET/CT	Efficient, interpretable mapping	Real-time potential reported; head-to-head performance data not yet available.	Narrative review[3,4]
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4.1 Explainable AI and Interpretability

Explainability is a crucial factor in the clinical acceptance of artificial intelligence (AI) applications in brain mapping. The inherent opacity of deep learning models presents significant challenges within healthcare settings, where trust is paramount. Typically, these models provide only the input data and the final output, failing to offer transparent reasoning within their internal mechanisms, as highlighted in [51,52]. Such a lack of clarity is particularly concerning in brain imaging, where predictive outcomes can significantly impact diagnosis, treatment strategies, and surgical decisions[51–53]. Consequently, explainable AI is increasingly regarded not as an optional enhancement but as a fundamental necessity for fostering clinician trust, facilitating human-AI collaboration, and securing regulatory approval[51,54]. Current methods of explainable AI (XAI) applied in neuroimaging encompass a range of techniques, including Local Interpretable Model-agnostic Explanations (LIME), Shapley Additive Explanations (SHAP), Gradient-weighted Class Activation Mapping (Grad-CAM), saliency maps, occlusion analysis, attention-based visualizations, and intrinsically interpretable models[52–54]. NeuroXAI is a class of post hoc interpretation methods for pre-trained neural networks, enabling the generation of multiple visualization maps and the demonstration of activation flow through internal convolutional neural network (CNN) filters in both classification and segmentation tasks. In the context of brain tumor imaging, these techniques are being positioned as essential tools to aid radiologists and enhance the interpretation of routine clinical data, rather than merely improving technical transparency [51].

Recent investigations into brain tumors underscore the growing expectation for clinically relevant interpretations. A survey of neuro-oncologists revealed that 82% would consider using AI tools only if clear, intuitive visual explanations accompanied them. Occlusion sensitivity methods have been recognized for their ability to pinpoint tumor-discriminative regions with greater spatial precision than certain gradient-based alternatives, while Grad-CAM and SHAP provide complementary visual and quantitative insights [55]. A novel interpretable deep learning model for brain tumor prediction has also incorporated uncertainty-aware decision support alongside XAI, enabling explanations that assess the model's readiness for deployment or the need for refinement [56]. Despite these advancements, the field remains methodologically immature. Reviews of explainable clinical decision support systems demonstrate that while radiology, oncology, and neurology are spearheading the adoption of XAI, only a limited number of studies incorporate usability testing, clinician feedback, or human-in-the-loop evaluations[54]. Furthermore, the evaluation of explanations remains inconsistent, and standardized metrics for interpretability in brain models continue to be underdeveloped[54,57]. Future research is anticipated to focus on quantitative assessment of explanations, anatomical overlap metrics, concept-based mapping, and multimodal, language-linked explanations that translate model outputs into clinically comprehensible rationales [51,57].

4.2 Generative Models and Data Augmentation

Generative models have emerged as significant tools in brain mapping, particularly given the frequent limitations of neuroimaging datasets. Challenges such as acquisition costs, privacy mandates, class imbalances, and the absence of certain imaging modalities can impede research and clinical practice[58–60]. In this context, generative adversarial networks (GANs) have primarily been employed to generate synthetic

images for data augmentation. However, this family of models also serves a variety of other purposes, including segmentation, super-resolution, denoising, and cross-modal translation[52,61]. These applications are critical to brain mapping, as they enhance training diversity, facilitate reconstruction of missing data, and standardize input for downstream classifiers or segmenters [58,61]. A particularly significant application of these technologies lies in completing missing modalities. In the imaging of Alzheimer's disease, positron emission tomography (PET) provides vital metabolic information that complements magnetic resonance imaging (MRI), yet it poses challenges related to cost, radiation exposure, and limited availability [59]. The 3D GAN framework known as BPGAN has successfully synthesized PET images from MRI obtained from the Alzheimer's Disease Neuroimaging Initiative (ADNI). This model demonstrated an approximately 1% improvement in multi-class Alzheimer's diagnosis compared to MRI alone, while producing synthetic scans that quantitatively outperformed those generated by alternative models. While this improvement may appear modest, it underscores the potential for synthetic modalities to provide complementary information rather than serving solely as visual approximations[59].

Another notable use case involves sequence synthesis in tumor workflows. When certain MRI sequences are unavailable, GAN-generated T1-weighted or FLAIR images can effectively replace missing data in multi-sequence lesion-segmentation pipelines [60]. Research published in Radiology reported that the median structural similarity for generated T1-weighted scans ranged between 0.82 and 0.92, while the median for FLAIR scans was between 0.76 and 0.92. Additionally, lesion segmentation using these generated inputs achieved median Dice scores as high as 0.97 across various lesion components [60]. Recent advancements in 3D GAN pipelines focus on producing generalized whole-brain MRI volumes rather than solely disease-specific scans, employing synthesis techniques alongside augmentation and SMOTE-based balancing to enhance classifier consistency in the context of scarce real-world data, as reported in one conference-stage study [58]. Despite these advancements, the clinical translation of GANs remains constrained. Evidence from scoping reviews indicates that while GANs can enhance the performance of artificial intelligence on brain MRI, further refinements are necessary before these systems can be integrated into routine clinical practice [61]. A recent review of multimodal precision medicine highlights pressing issues such as training instability, mode collapse, quality control challenges, validation complexities, and ethical considerations regarding synthetic data [52]. Thus, while generative models represent a valuable research infrastructure for augmentation and modality completion, they require further validation, quality assessment, and governance to facilitate their broader deployment in clinical settings.

5. Emerging Frontiers

The forthcoming evolution of artificial intelligence in brain mapping is marked by a transition from task-specific models to overarching foundation models, federated learning, and hybrid multimodal systems, with their clinically scalable deployment [49,57,62]. Foundation models, as defined in this context, are large-scale, pretrained systems adept at processing noisy and heterogeneous neural data. They are designed to generalize across various tasks, modalities, and experimental settings. The potential of these models lies not only in enhanced predictive performance but also in their applicability across diverse activities, including decoding, segmentation, simulation, and discovery, according to a recent preprint survey [57].

Recent advancements in neuroimaging underscore the technical viability of this approach. The BrainSegFounder project, for instance, employed a two-stage self-supervised pretraining strategy on multimodal MRI data sourced from 41,400 participants. This method, which first encoded general anatomical features and then disease-specific characteristics, outperformed earlier fully supervised methods in segmenting tumor and stroke lesions. The study attributes these improved outcomes to scaling both model complexity and the volume of unlabelled data, which collectively enhanced sample efficiency and predictive accuracy [62]. This advancement signals a strategic shift away from reliance on limited manually labeled datasets. Federated learning effectively addresses the significant challenge of achieving generalization across

multiple centers without requiring the direct exchange of sensitive data. A peer-reviewed study conducted across three international centers demonstrated that federated training of a brain-age model using MRI data from multiple sclerosis patients outperformed centralized training, achieving a mean absolute error of 6.08 years compared to 7.02 years [49]. This innovative approach enables the use of distributed imaging databases while eliminating the need to transfer raw data. Nevertheless, federated systems may retain center-specific scanner and testing biases, which could hinder optimal convergence for individual institutions. Future research directions suggest adopting a foundation-model-plus-transfer-learning strategy, allowing multicenter data to create a robust, center-independent base model that can be subsequently refined at the local level[49].

Table 3: Current Landscape vs. Future Frontiers of AI in Brain Mapping

DIMENSIONAL FOCUS	CURRENT CORE METHODOLOGIES	NEXT-GENERATION FRONTIERS
MODEL SCOPE	Task-specific, supervised models trained on small, labeled cohorts	Large-scale Foundation Models (e.g., BrainSegFounder) [62] self-supervised Models (e.g.,
DATA PRIVACY	Centralized data storage is prone to re-identification risks	Privacy-preserving Learning across sites[49] Federated international
NETWORK SCALE	Macroscale region-to-region functional/structural connectomics	Synaptic-resolution Zettabyte-scale connectomics[42,43]
CLINICAL TRUST	"Black box" neural networks lack transparent reasoning	Explainable AI (XAI) metrics (Grad-CAM, SHAP, Saliency Maps)[52,53]

6. Challenges and Limitations

Recent advancements in artificial intelligence (AI) for brain mapping are notable; however, several critical limitations persist, including issues with data quality, generalizability, bias, interpretability, and readiness for clinical deployment [3,48,52]. Neurological AI studies frequently exhibit methodological weaknesses, such as small sample sizes, selection bias, inadequate external validation, and insufficient evidence supporting model robustness in real-world clinical settings [48]. Despite optimistic reviews of translational imaging, the transition from model development to integration into clinical workflows remains fraught with technical and organizational challenges [2]. Among these challenges, bias emerges as a significant barrier, as it can covertly undermine safety and fairness. In the context of medical imaging, AI has the potential to mitigate human cognitive biases; however, it may also incorporate systematic errors present in the training data, thereby perpetuating these issues in clinical practice [63]. The review on imaging bias emphasizes the need to proactively identify biases at each stage of the AI pipeline to ensure models maintain their clinical applicability across diverse populations and settings [63]. This concern is particularly pronounced in brain imaging, given that factors such as center effects, scanner characteristics, demographic imbalances, and modality-specific inconsistencies can all disrupt model performance.

7. Ethical and Regulatory Considerations

The application of artificial intelligence in brain mapping raises several significant ethical considerations, notably regarding privacy and consent, bias and fairness, and transparency and accountability. Neuroimaging data is inherently sensitive; the integration of AI technologies exacerbates privacy concerns, as the potential for misuse or re-identification of brain images, behavioral data, and associated biomarkers increases, particularly in environments with insufficient governance [64–66]. Traditional methods of de-identification

are no longer fully effective, given advances in reconstruction algorithms that can identify participants from imaging data. This reality necessitates implementing tiered access protocols and enhanced technical safeguards [66]. Moreover, ethical governance should conceptualize consent as an ongoing process throughout the data lifecycle, rather than merely a single event at the time of data collection. It must also seek to mitigate both individual harms, such as re-identification, and collective harms, including the stigmatization of populations associated with specific neuroimaging biomarkers[67].

Regarding regulatory frameworks, the need for AI in brain mapping demands stringent validation, adaptive oversight, and cohesive governance across different jurisdictions. The current landscape of AI regulation in healthcare and medical imaging is fragmented, and existing frameworks frequently lag behind adaptive systems that are responsive to newly gathered real-world data post-deployment [53,68–70]. Merely obtaining regulatory clearance is insufficient; AI applications must undergo thorough clinical validation, realistic testing during deployment, and continuous post-market monitoring to ensure safety, fairness, and clinical relevance over time [63,65,71,72]. Effective governance models should prioritize principles of fairness, explainability, and accountability, ensuring that staff are adequately trained and that multidisciplinary oversight is incorporated. Importantly, patients and the public should be actively involved in decisions regarding the adoption of these systems rather than being relegated to passive recipients[72].

8. Future Directions

Next steps break down into improving data and models, scaling up while protecting privacy, and making large-scale connectomics more computationally practical.

- Researchers need to focus on multimodal fusion, tracking changes over time, testing models on datasets beyond the original, and modeling individuals in greater depth. These issues still stand in the way of real-world neuroimaging prediction[52,73].
- Federated learning and similar privacy-focused methods are crucial for multicenter brain imaging studies (see Table 3). These approaches enable collaboration and data sharing without moving raw, sensitive data between sites [52,64].
- There's a lot of momentum behind brain foundation models, hybrid generative-discriminative systems, and smarter ways to fuse data from different sensors. These approaches drive early biomarker discovery and precision medicine forward [52,74,75].
- But scaling up connectomics brings a mountain of hurdles. Just mapping 1 mm³ of cortex has already produced about 1.4 petabytes of data. If we push toward mapping an entire brain, the storage and ethical questions reach the zettabyte scale—and the field needs brand-new infrastructure to handle them efficiently [42,43].

Conclusion

Artificial intelligence has taken center stage in brain mapping. It sharpens our analysis of complex neuroimaging data, helps catch problems earlier, and even enables predictions tailored to individuals—pushing precision neurology forward [64,73]. Still, AI delivers the most clinical value when we blend multimodal imaging with predictive modeling and ensure that the outputs make sense to clinicians. All this must happen within systems that keep humans in charge and ethical principles front and center [53,64,67].

But breakthroughs don't just hinge on better algorithms. The real progress comes from tackling deeper challenges: getting data quality right, safeguarding privacy, building in fairness, and thoroughly validating results—then ensuring strong governance supports everything [64,71,76]. In the end, AI's true impact on brain mapping isn't only about how well it performs technically. What really matters is whether we can use it responsibly, fairly, and in ways that genuinely help patients.

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