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REVIEW ARTICLE

Revealing hidden neuroanatomical patterns of the brain for diagnosis and personalized therapy using artificial intelligence and neuroimaging

Ana Starcevic[1], Aleksandar Malikovic[1]

[1] University of Belgrade, Faculty of Medicine, Institute of Anatomy, Belgrade, Serbia

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Correspondence to:
Ana Starcevic
University of Belgrade, Faculty of Medicine
Belgrade, Serbia
Email: ana.starcevic22@gmail.com

Summary

The integration of artificial intelligence with advanced neuroimaging techniques represents one of the most important developments in contemporary neuroscience and clinical neuroanatomy. This narrative review summarizes how machine learning and deep learning methods can be applied to neuroimaging data to reveal hidden anatomical and functional brain patterns with direct clinical relevance. Neuroanatomy plays a central role in this process, providing the structural framework for interpreting functional, metabolic, and electrophysiological signals. Artificial intelligence-based analysis enables the detection of subtle alterations in gray and white matter, the analysis of brain networks and pathways, and the integration of multimodal imaging data beyond the limits of human perception and conventional statistical approaches. In addition to aiding physicians in establishing the correct diagnosis, these capabilities contribute to earlier and more accurate diagnoses, improved disease differentiation, identification of affected structures within specific health conditions or diseases, and more reliable prognostic assessment. In addition to diagnostic applications, artificial intelligence supports the development of personalized therapeutic strategies, including targeted neuromodulation, neuroimaging-guided surgery, adaptive brain–computer interfaces, and an individualized approach in further disease monitoring. Despite existing challenges related to data heterogeneity, model interpretability, and ethical regulation, the synergy between AI and neuroimaging represents a critical step toward personalized medicine. By leveraging detailed neuroanatomical information, artificial intelligence-driven approaches enable therapies tailored to the unique brain structure and network organization of each individual.

Keywords: neuroanatomy, neuroimaging, artificial intelligence, machine learning, personalized medicine

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INTRODUCTION

The human brain is considered to be one of the most complex biological systems. One of the most significant characteristics is the specific, yet still not fully understood, neuroanatomical organization and dynamic functional interactions across multiple spatial and temporal scales (1,2). There are approximately billions of neurons organized into different cortical layers, subcortical nuclei, and white matter tracts that together enable functions such as cognition, behavior, adaptive responses to the environment, and resilience. One of the biggest challenges in neuroscience is to reveal pathological processes that impair this neural architecture. Modern neuroimaging techniques, including structural magnetic resonance imaging (MRI), functional MRI (fMRI), diffusion tensor imaging (DTI), positron emission tomography (PET), electroencephalography (EEG), and magnetoencephalography (MEG), provide in vivo access to both the brain's structure and function (3). Neuroanatomy provides the essential interpretative framework for these modalities, as all functional, metabolic, and electrophysiological signals are spatially related to specific anatomical substrates, such as cortical gyri, sulci, subcortical nuclei, and cerebral white matter pathways (4,5). Rapidly increasing dimensionality and complexity of neuroimaging data often exceed the capacity of conventional statistical approaches to detect clinically meaningful patterns (6). Artificial intelligence (AI), particularly through machine learning (ML) and deep learning (DL) tools, has emerged as a transformative analytical paradigm capable of modeling complex, nonlinear relationships within large-scale biomedical, clinical, and neuroanatomical datasets (7). Also, when applied across different neuroimaging modalities, AI can perform automated segmentation and quantification of subtle neuroanatomical variations, analysis of brain connectivity, its dynamics, and integration and translation of multimodal information from different neurovisualisation modalities into clinically relevant biomarkers (8,9). This convergence has redefined neuroanatomy from a basic, descriptive medical-scientific discipline into a quantitative, predictive, and translational science.

This narrative review aims to incorporate current evidence on the role of AI-assisted neuroimaging in revealing hidden neuroanatomical and connectivity patterns of the brain and to discuss how these advances improve diagnosis, prognosis, and the development of personalized therapeutic strategies in clinical neuroscience.

METHODS

A narrative literature search was conducted using the PubMed/MEDLINE and Google Scholar databases. The search covered publications from January 2022 to January 2025, reflecting recent methodological and clinical developments. The following keywords and their combinations were used: artificial intelligence, machine learning, deep learning, neuroimaging, MRI, fMRI, DTI, PET, EEG, neuroanatomy, brain connectivity, biomarkers, diagnosis, personalized therapy, neuromodulation, and brain–computer interface. Only articles published in English were included. Original research articles, narrative and systematic reviews, and seminal methodological studies relevant to AI-based neuroimaging analysis were prioritized. Reference lists of key publications were manually screened to identify additional relevant sources.

Study Limitations

As a narrative review, this article does not employ a systematic methodology for literature search and data synthesis, which may introduce selection bias in the cited works. The rapid evolution of the AI field means that some recent advancements may not be captured within the specified search timeframe. Furthermore, the heterogeneity of study designs, neuroimaging protocols, and AI algorithms across the reviewed literature precludes quantitative meta-analysis and limits the generalizability of the findings.

AI-GUIDED DISCOVERY OF HIDDEN PATTERNS IN BRAIN STRUCTURE AND CONNECTIVITY

Identification of Microstructural and Anatomical Changes

Structural MRI remains the gold standard for in vivo neuroanatomical assessment, enabling visualization of brain morphology (total brain volume, cortical thickness, gray and white matter volumes, and subcortical morphology) (10). Precise segmentation of anatomical structures, such as the hippocampus, amygdala, thalamus, and various cortical areas, is highly important for understanding disease- or disorder-related changes (11). An overview of major neuroimaging modalities, the anatomical or functional features analyzed, and the commonly applied artificial intelligence methods is provided in **Table 1**.

Key hidden neuroanatomical and connectivity patterns identified using artificial intelligence across neurological and psychiatric disorders can be found in **Table 2**.

Deep learning architectures, particularly convolutional neural networks (CNNs) and U-Net–based models, have demonstrated high accuracy and reproducibility in automated brain segmentation and morphometric analysis (12). There are also commercial nonprofit software packages used to segment brain structures and preprocess neuroimaging data for further processing. Many previous investigations and ongoing ones have shown significant improvements and proof of concept in using

Table 1. Neuroimaging Modalities and Artificial Intelligence Methods

Neuroimaging Modality	Analyzed Anatomical/ Functional Aspect	Common AI Methods	Clinical Application	References
Structural MRI	Gray matter volume, cortical thickness, subcortical structures	CNN, U-Net, ViT	Neurodegeneration, neuro-oncology, developmental disorders	(10, 11, 12)
fMRI (rest/task)	Functional network connectivity	GNN, SVM, LSTM	Psychiatric disorders, epilepsy	(18, 19, 20)
DTI	White matter microstructure, tractography	Random Forest, CNN	MS, TBI, neurodegeneration	(15, 16)
PET	Metabolic and protein pathology	CNN, multimodal DL	Alzheimer's disease, tumors	(29)
EEG/MEG	Time-frequency patterns	SVM, XGBoost, RNN	Epilepsy, BCI, neurofeedback	(30)

Abbreviations: MRI – Magnetic Resonance Imaging, fMRI – functional Magnetic Resonance Imaging, DTI – Diffusion Tensor Imaging, PET – Positron Emission Tomography, EEG – Electroencephalography, MEG – Magnetoencephalography, CNN – Convolutional Neural Network, U-Net – U-shaped Network, ViT – Vision Transformer, GNN – Graph Neural Network, SVM – Support Vector Machine, LSTM – Long Short-Term Memory, DL – Deep Learning, RNN – Recurrent Neural Network, XGBoost – eXtreme Gradient Boosting, MS – Multiple Sclerosis, TBI – Traumatic Brain Injury, ASD – Autism Spectrum Disorder, BCI – Brain-Computer Interface

Table 2. Hidden Patterns and Associated Disorders

Pattern Type	Neuroanatomical Substrate	Detected Disorders	Clinical Significance	References
Subtle Atrophy	Hippocampus, Medial Temporal Lobe	Alzheimer's disease	Early diagnosis, prognosis	(13)
Network Disconnectivity	DMN, Executive Networks	Schizophrenia	Differential diagnosis	(20)
Microstructural Damage	White Matter (FA, MD)	MS, TBI	Early biomarkers	(16)
Local Hyper-Connectivity	Cortical Networks	Autism Spectrum Disorder (ASD)	Disease subtyping	(21)

Abbreviations: DMN – Default Mode Network, FA – Fractional Anisotropy, MD – Mean Diffusivity, MS – Multiple Sclerosis, TBI – Traumatic Brain Injury, ASD - Autism Spectrum Disorders

AI tools to map the neuromorphological substrates, positioning the aforementioned as a powerful potential diagnostic tool. It was stated that in neurodegenerative disorders, AI-based morphometric analysis can detect subtle atrophy patterns in the medial temporal lobe that precede overt cognitive symptoms, enabling early diagnosis and prognostic stratification in Alzheimer's disease (13). These patterns are not random voxel-level changes but anatomically coherent sequences that follow known neuroanatomical pathways of disease progression. In neuro-oncology, AI-driven quantitative analysis of tumor morphology, encompassing lesion shape, heterogeneity, edema, and spatial relationships to specific cortical areas, enables tumor classification and prediction of treatment response (14). White-matter brain integrity is another crucial neuroanatomical dimension. Diffusion tensor imaging (DTI) may characterize axonal microstructure through metrics such as fractional anisotropy and mean diffusivity (15). AI-based analysis of diffusion data improves sensitivity to early microstructural brain damage in medical conditions such as multiple sclerosis, traumatic brain injury, and neurodegenerative disorders by identifying tract-specific alterations from normal anatomical organization (16). These findings underscore the central role of neuroanatomy as the reference framework for AI-driven discovery.

Analysis of Functional and Effective Brain Networks

Brain function arises from coordinated activity across disseminated white-matter neuronal networks rather than isolated cortical or deep-brain regions (17). Resting-state and task-based fMRI reveal functional brain connectivity, reflecting temporal synchronization between neuroanatomically distinct brain areas (18). By combining graph theory with AI, the brain can be modeled as a complex network in which nodes represent anatomically defined regions and edges represent functional or structural connections (19). AI-based network analysis has revealed disease- or disorder-specific patterns of dysconnectivity. For example, in schizophrenia, altered connections between the default mode network and executive control brain networks pinpoint disrupted integration of internally and externally directed cognition (20). In autism spectrum disorders, AI studies identify patterns of local hyper-connectivity combined with reduced long-range connectivity, supporting the concept of an altered brain network (21-25). All these highlight the impact of AI tools in revealing hidden functional connections within the neuroanatomical organization.

Beyond functional connectivity, effective connectivity analysis addresses causal interactions between brain regions. Methods such as dynamic causal modeling and Granger causality, enhanced by AI-based optimization,

Table 3. Diagnostic and Prognostic Applications of Artificial Intelligence

Clinical Task	Input Data	AI Approach	Outcome	References
Early Diagnosis	MRI, EEG	Supervised Learning	Pre-symptomatic detection	(13, 32)
Differential Diagnosis	MRI, fMRI	SVM, XGBoost	Distinguishing similar entities	(20)
Subtyping	Multimodal Data	Clustering	Identification of biotypes	(33, 34)
Prognosis	Longitudinal Data	LSTM, Regression	Prediction of disease course	(14, 30)

Abbreviations: MRI – Magnetic Resonance Imaging, EEG – Electroencephalography, fMRI – functional Magnetic Resonance Imaging, SVM – Support Vector Machine, XGBoost – eXtreme Gradient Boosting, LSTM – Long Short-Term Memory

allow inference of directed information flow within neuroanatomically defined brain white matter circuits (26). This approach has proven specifically important in mapping epileptogenic foci and cortico-basal ganglia-thalamocortical loops implicated in Parkinson's disease (27). Each identified network abnormality shows clinical translation implications only when interpreted within its precise anatomical context.

Multimodal Data Fusion and Integrative Biomarkers

The most powerful applications of AI algorithms in neuroimaging involve multimodal data fusion. These algorithms can summarize morphological and electrophysiological data, creating biomarkers that may generate a blueprint for multiple dimensions of brain disorders (28). This integrative approach is essential in complex neurological disorders such as Alzheimer's disease, where structural atrophy, functional disconnection, and molecular pathophysiological momentum interact (29). One of the main goals of specific multimodal AI frameworks is to align neuroanatomical, physiological, and microanatomical and micromolecular data within a unified blueprint of the brain, enabling more precise diagnosis than single modality (30,31). This integrative approach pinpoints the neuroanatomical biomarkers toward a systems-level understanding of disease or disorder.

FROM PATTERN RECOGNITION TO DIAGNOSIS AND PROGNOSIS

Early and Differential Diagnosis

The classification or stratification that AI models may provide is pretty solid, objective, and reproducible, offering clinicians diagnostic support for various neuropsychiatric conditions nowadays. Although not yet widely accepted, with its main role in medical professional societies, supervised learning approaches applied across almost all data modalities of neurovisualisation may enable the detection of disease- or disorder-specific morphological and functional patterns before the clinical manifestation of a specific medical condition (32). For example, AI-derived EEG analysis can differentiate epileptic from non-epileptic events, while MRI-based models improve differential diagnosis among neurodegenerative syndromes with overlapping clinical manifestations. This transition from descriptive pattern recognition to decision support presents a paradigm shift, in which AI tools and their algorithms augment clinical expertise by identifying neuroanatomical brain signatures that may remain hidden during routine clinical examination.

Disease Subtyping and Biomarker Identification

Their clinical manifestations best illustrate the biological heterogeneity of different medical disorders. Unsupervised machine learning techniques and algorithms, including clustering and dimensionality reduction, allow the identification of neurobiologically distinct types within various diagnostic categories, and this kind of stratification has been shown to be very useful in depression and schizophrenia, revealing specific neuroanatomical and connectivity-based types correlated with treatment response (33,34). By grounding these subtypes in neuroanatomical and network-level variables, AI tools can bridge the gap from a few clinical symptom-based classifications to full, clinically informed, and proposed diagnostic frameworks.

Prognosis and Modeling Disease Trajectory

Longitudinal neuroimaging datasets may provide insight into disease progression but their complexity implicate very complex analytical challenges. Recurrent neural networks, AI-driven, predict individual and precise disease or disorder trajectories, including rates of cognitive decline or lesion progression in neurodegenerative disorders (30,14). The predictive capacity of AI tools supports proactive clinical management of a patient, allowing clinicians to tailor monitoring, intervention, and treatment strategies based on the anticipated course of the medical condition. Major diagnostic and prognostic applications of artificial intelligence in neuroimaging are outlined in **Table 3**.

Enabling Personalized Therapeutic Strategies

The role of artificial intelligence in supporting personalized therapeutic strategies based on individual neuroanatomical and connectivity profiles is illustrated in **Figure 1**.

Figure 1. Role of artificial intelligence in personalized therapeutic strategies. AI-driven analysis supports individualized neuromodulation targeting, neuroimaging-guided surgery, adaptive brain–computer interfaces, and personalized neurofeedback protocols (*The image is an original work of authorship, generated using the DALL·E (OpenAI) tool and further edited by the author for the purposes of this work*)

Targeted Neuromodulation

Personalized neuromodulation is one of the most clinically impactful applications of AI-assisted neuroimaging tools (28). Techniques such as transcranial magnetic stimulation (TMS) and deep brain stimulation (DBS) have traditionally relied on standardized neuroanatomical targets. AI-based connectomic analysis enables the identification of individualized brain stimulation targets based on each patient's unique structural and functional connectivity profile, improving medical professionals' efficacy and at the same time minimizing side effects.

Neuroimaging-Guided Surgery and Radiotherapy

In neurosurgery and radiotherapy, AI algorithms integrate structural and functional maps in order to optimize intervention planning. (22) Automated delineation of tumors, specific areas of brain cortex and specific white matter brain pathways advances preprocessing of datasets precision and reduces the risk of postoperative deficits. These advances demonstrate how AI operationalizes neuroanatomical knowledge in high-demand clinical contexts.

Brain–Computer Interfaces and Neurofeedback

Adaptive brain–computer interfaces and personalized neurofeedback systems rely on AI algorithms to decode individual neural signatures, or blueprints, from EEG or fMRI data. These closed-loop systems dynamically adjust in response to ongoing brain activity, supporting neurorehabilitation and treatment of specific neuropsychiatric disorders. Their success depends on accurate mapping between functional signals and underlying neuroanatomical brain substrates.

Personalized Drug Discovery

Integration of neuroimaging biomarkers with diverse omics data, such as genetic and clinical data, using AI tools enhances patient stratification during clinical trials and supports the development of targeted therapies. This approach refers to fully personalized, individual pharmacotherapy by relating drug response to specific neuroanatomical and network substrates in the brain within a specific medical condition.

Table 4. Challenges and Future Directions

Domain	Main Challenges	Proposed Solutions	References
Data	Heterogeneity, small samples	Harmonization, federated learning	(32)
Interpretability	Black box" models	Explainable AI (XAI), attention mechanisms	(28)
Fairness	Population bias	Diverse datasets	(33, 34)
Implementation	Computational resources	Edge AI, workflow integration	(22)
Future Directions	System complexity	Digital twins, closed loops	(28, 30)

Challenges and Limitations

AI-tools assisted neuroimaging analysis has several challenges. Data heterogeneity in technical propositions and protocols across different neuroimaging centers limits the generalizability of models. The "black box" nature of many deep learning systems locks interpretability and clinical trust. Bias arising from unrepresentative training datasets raises concerns about fairness and equity. Ethical and regulatory issues related to data privacy, informed consent, and clinical accountability remain unresolved. Finally, integrating AI tools into clinical workflows and everyday practice requires substantial technical infrastructure, interdisciplinary collaboration, and teamwork among medical doctors. Each of these challenges highlights the need for explainable AI, standardized data harmonization and robust external validation as seen in **Table 4**.

Future Directions

Emerging AI algorithms such as transformers, graph neural networks, and generative models promise improved modeling of complex brain networks. Multimodal and multiscale integration of neuroimaging data with all possible omics and exposome data will enable the development of specific, individualized, comprehensive digital phenotypes. Real-time closed-loop systems will further individualize therapy by intervening at the steps of medical care when and if needed. The concept of "digital brain twins," computational replicas of individual brains, offers a visionary framework for in silico testing of therapeutic strategies before real-world application. Human–AI collaboration and interaction will define the future of clinical neuroscience and clinical practice, with AI augmenting rather than replacing clinical judgment.

CONCLUSION

The integration of artificial intelligence with neuroimaging is already fundamentally transforming neuroanatomy and clinical neuroscience by revealing hidden neuroanatomical and connectivity patterns. Artificial intelligence enhances diagnostic accuracy, provides prognostic insights, and supports the development of personalized therapeutic strategies. Neuroanatomy remains the essential and inevitable variable of this process, providing the spatial and organizational context for AI-driven discovery.

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OTKRIVANJE SKRIVENIH NEUROANATOMSKIH OBRAZACA MOZGA ZA DIJAGNOZU I PERSONALIZOVANU TERAPIJU KORIŠĆENJEM VEŠTAČKE INTELIGENCIJE I NEUROIMIDŽINGA

Ana Starčević[1], Aleksandar Maliković[1]

Sažetak

Integracija veštačke inteligencije sa savremenim neuroimidžing tehnikama predstavlja jedno od najznačajnijih dostignuća u savremenoj neuronauci i kliničkoj neuroanatomiji. Ovaj narativni pregled ima za cilj da prikaže kako se metode mašinskog i dubokog učenja primenjuju u analizi neuroimidžing podataka radi otkrivanja skrivenih neuroanatomskih i funkcionalnih obrazaca mozga koji su od kliničkog značaja. Neuroanatomija ima ključnu ulogu u interpretaciji neuroimidžing nalaza, jer obezbeđuje okvir za mapiranje morfoloških i funkcionalnih signala. Primena veštačke inteligencije omogućava detekciju suptilnih promena u sivoj i beloj masi mozga, analizu moždanih mreža i puteva, i integraciju podataka iz više modaliteta vizualizacije moždanih struktura. Pored potencijalne pomoći lekaru u postavljanju prave dijagnoze, ovakav pristup doprinosi ranijoj i preciznijoj dijagnozi, boljoj diferencijaciji bolesti, identifikaciji zahvaćenih struktura u okviru specifičnog zdravstvenog stanja ili bolesti i pouzdanijoj proceni prognoze. Pored dijagnostičkih aplikacija, veštačka inteligencija omogućava razvoj personalizovanih terapijskih strategija, uključujući ciljanu neuromodulaciju, neuroimidžing-vođene hirurške intervencije, adaptivne moždano-računarske interfejse i individualizovani pristup u daljem praćenju bolesti. Uprkos izazovima vezanim za standardizaciju podataka, razumevanja logike odlučivanja modela i etičku regulativu, sinergija veštačke inteligencije i neuroimidžinga predstavlja ključni korak ka preciznoj medicini i terapiji prilagođenoj jedinstvenoj neuroanatomskoj organizaciji svakog pojedinca.

Ključne reči: neuroanatomija, neuroimidžing, veštačka inteligencija, mašinsko učenje, personalizovana medicina

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