International Research Journal of Multidisciplinary Scope (IRJMS), 2025; 6(2): 1-20

Review Article | ISSN (O): 2582-631X DOI: 10.47857/irjms.2025.v06i02.01953

Integrating Deep Learning in Brain Connectome Mapping: Insights from a Systematic Review

Udayakumar P, Subhashini R*

School of Computer Science Engineering and Information Systems (SCORE), Vellore Institute of Technology, Vellore, India. *Corresponding Author's Email: rsubhashini@vit.ac.in

Abstract

Deep learning, a subset of artificial intelligence in computer science, has become crucial in understanding the structural and functional connectivity of the human brain connectome. It offers novel insights into the comprehensive probabilistic modeling of the brain. This study aims to provide an overview of various deep learning techniques applied to the human brain connectome and to review significant structural and functional connectivity findings using MRI images for different brain diseases. A detailed literature search was conducted using the PRISMA model across databases such as Scopus, web of Science, and PubMed. The primary search terms included "Brain," "Connectome," "Deep Learning," and "Neuroimaging or MRI." This search identified 113 relevant studies out of a total of 882. The systematic review found that deep learning algorithms are rapidly widely used in neuroscience. Traditional neural network approaches, such as convolutional neural networks (CNN), graph neural networks (GNN), and artificial neural networks (ANN), remain prevalent. These algorithms are often tailored to address specific tasks, with MRI images serving as the primary data source for brain imaging. Deep learning has significant potential to enhance the understanding of structural and functional brain models in neuroscience applications. However, several challenges must be addressed to utilize deep learning more effectively in brain mapping. Accumulating detailed data is crucial for developing intelligible DL algorithms to achieve this goal.

Keywords: Connectome, Deep Learning, Human Brain, MRI, Neuroscience, PRISMA.

Introduction

Artificial Intelligence has played a major role in the health care sector especially in Neuroscience in the last two decades. The Brain is the body's natural primary control system, where neurons accomplish all of these processes in the brain (1). Neurons are the neurological program's basic structural and functional units; myriad kinds of neurons are present in the brain. These neurons are connected through special connections called synapses. In contrast to neurons, the brain consists of supportive cells known as nerve fiber cells. The human brain is estimated to have 86 to 100 billion neurons (nerve cells) and 125 trillion synapses alone, more than 1000 trillion synapses on average (2). Brain interconnectivity enables neurons to exhibit a variety of physiological reactions, and also create and disseminate information collaborate their activities over short and large ranges, and maintain an architectural legacy of past incidents. The pattern connection is connected and impacts almost every aspect of the visual cortex resulting in a strong (3). The connectome, which details the full network of neuron and brain area connections, is central to understanding brain connectivity. Using these techniques, it is possible for the first time to collect detailed whole-brain data sets from multiple human participants and compare them to personal information regarding neural activity, cognition, behavior, and genealogy (4). Quantifying, analyzing, and modeling these challenging data sets necessitates employing the mathematical and theoretical principles of complex networks (5). As a result of theoretical and technical advancements, a new explanation of the human brain is emerging; one that sees cognitive functions as the result of jointly synchronized mechanisms in a network of complex relationships (6). A connectome is primarily concerned with structure, or the physical connections between brain components in large numbers but at a limited number. A consistent anatomical description should eventually result from empirically mapping structural connections since structural connectivity serves as a crucial point of methodo- logical convergence (7). There are multiple nested spatial scales of structural

(Received 08th August 2024; Accepted 22nd January 2025; Published 14th April 2025)

connectivity in the human brain. The organization can be broadly categorized into three levels: the microscale involving synapses and individual neurons, the macroscale encompassing anatomically distinct brain regions, and the mesoscale comprising neuronal populations and their connections (8). In the structural network, functional connectivity fluctuates considerably over time, indicating shifts in internal states or neural reactions to stimuli or tasks (9). A functional correlation typically refers to the statistical link between distant neural components and can be assessed through various methods, each providing unique insights into brain function. Mapping the human connectome is a major focus of contemporary research. Measurements help establish the pairwise connections between nodes once these nodes are categorized as structural, functional, or effective connectivity. A series of pairwise associations can be arranged into a connection matrix, which illustrates the structure of the graph or network. The connections between nodes form the graph's adjacency structure, identifying which nodes are direct neighbors. Depending on the method used to define these connections, graphs can be categorized as binary (edges are either present or absent), weighted (edges have varying values), undirected (edges indicate a symmetrical relationship), or directed (edges indicate an asymmetrical relationship, 10). Medical Imaging (MI) data, as well as spatial and temporal data, were created in large quantities by healthcare institutions. Health researcher's and clinicians' approaches to detecting, interpreting, and evaluating structural, and functional connectivity of the brain for degenerative diseases, as well as assessing risk and reactions to medicines, have drastically changed as a result of the study of such data (11). Moreover, "physically" processing medical data, especially brain imaging, is time-demanding, and the probability of interpretation inaccuracies isn't insignificant. Day-to-day accuracies and variances in diagnostic imaging, for example, are estimated to be greater than 5% (12). This led to the development of fresh approaches to assist clinicians' inefficiently and properly processing information. The use of advanced algorithms has increased in popularity as computational power has expanded and medical data quality has improved (13). Deep Learning (DL), a branch of AI, has revolutionized a range of neurosurgical activities in recent years. DL algorithms especially have received attention in computer vision, exceeding other techniques on a variety of high-profile image analysis assessments (14). Unlike traditional machine learning models, deep learning automatically learns useful representations and features directly from raw data, eliminating the need for manually calculating and selecting potentially relevant variables (15). Due to major advancements in computing power, such as the use of Graphics Processing Units (GPUs), these algorithms have become efficient for learning from 3D and 2D images commonly used in the medical field. Although these algorithms have achieved remarkable results over the years, many traditional computer-based methods and algorithms are now impractical in real-world scenarios because of the increased data complexity and volume (16). In medical imaging, structures like tumors and tissues can be too intricate for conventional equations or models to capture effectively. Furthermore, it's often difficult for specialists to establish clear guidelines, particularly in tasks like disease monitoring and processing (17). Over the past ten years, deep learning (DL) has garnered significant attention in brain imaging and cognitive neuroscience fields (18). Deep learning (DL) has shown great promise in diagnostic tasks, particularly in theoretical and practical studies of physiological and pathological components. DL methods have been applied to brain data processing for diagnosing conditions such as hypertension, dementia, neurodegenerative disorders, and tumors (19). However, it is indeed important to emphasize that, owing to the difficulty and quantity of brain data, DL algorithms typically require many stages to accomplish things. Image preprocessing, feature selection and classification, and image segmentation, for example, are frequently required as preliminary steps to increase the performance of the algorithms to reasonable standards. This research delves into recent endeavors to map the intricate neural pathways within the human brain. By employing diverse methods, preliminary brain maps are emerging, offering glimpses into the brain's organizational structure. While current insights are limited and fragmented, the journey to fully charting the human connectome has undeniably commenced, marked by rapid advancements. Our research tackles key gaps in understanding the human connectome and its role in neuroscience. While many studies focus on either structural or functional connectivity, we emphasize the need to integrate multimodal data for a fuller picture. Traditional machine learning often falls short due to the complexity and high dimensionality of brain data. Despite progress in deep learning for medical imaging, mapping the connectome for diseases like Alzheimer's and schizophrenia remains challenging. We also see a lack of exploration in combining different types of connectivity for personalized diagnoses. Lastly, current methods often lack robust preprocessing pipelines, which our work aims to address. A primary focus of this article is on providing an overview of deep learning algorithms that can directly contribute to mapping the human brain connectome. This paper aims to explore the central concepts and practical applications of Machine Learning and Deep Learning, alongside their connections to neuroscience. First, we introduce the search strategy employed in this study, which follows the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework. Secondly, this paper summarizes the key elements utilized in connectome-based deep learning studies. It also provides an extensive review of recent methods for connectome classification based on brain structural and functional connectivity. Considering the latest developments and the growing potential of deep learning in understanding brain disorders and pathologies, we review current advances in this field. Finally, we conclude with research gap and potential using connectome with Neural network model effective in future for better undersanding of neuroimaging data.

Search Strategy

The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) standards were used to conduct a systematic literature review. With the assistance of a professional librarian, the search queries were carefully constructed, incorporating deep learning and Connectome-related search phrases. Using the key terms "Brain", "Connectome", "Deep Learning" and "Machine Learning" A comprehensive literature search was performed across major databases, including Scopus, Web of Science, and PubMed, up until August 30, 2024. Table 1 provides a detailed list of the search keywords used. Additional references were gathered through cross-referencing key articles. Out of 882 studies, 113 were identified that utilized deep learning algorithms for various purposes. The search strategy flow chart and the annual publication statistics are depicted in Figure 1.

Table 1: Keywords Used for Systematics Review

Database	Keywords
Scopus	TITLE-ABS-KEY ("Brain" AND "Connectome" AND ("Deep Learning" OR "Machine Learning")) AND (LIMIT-TO (PUBSTAGE , "final")) AND (LIMIT-TO (DOCTYPE , "ar")) AND (LIMIT-TO (LANGUAGE , "English")) AND (LIMIT-TO (SRCTYPE , "j"))
Web of Science	"Brain" AND "Connectome" (Abstract) AND "Machine Learning" OR "Deep Learning" (All Fields)
Pubmed	"Brain"[Title/Abstract] AND "Connectome"[Title/Abstract] AND ("Deep Learning"[Title/Abstract] OR "Machine Learning"[Title/Abstract])

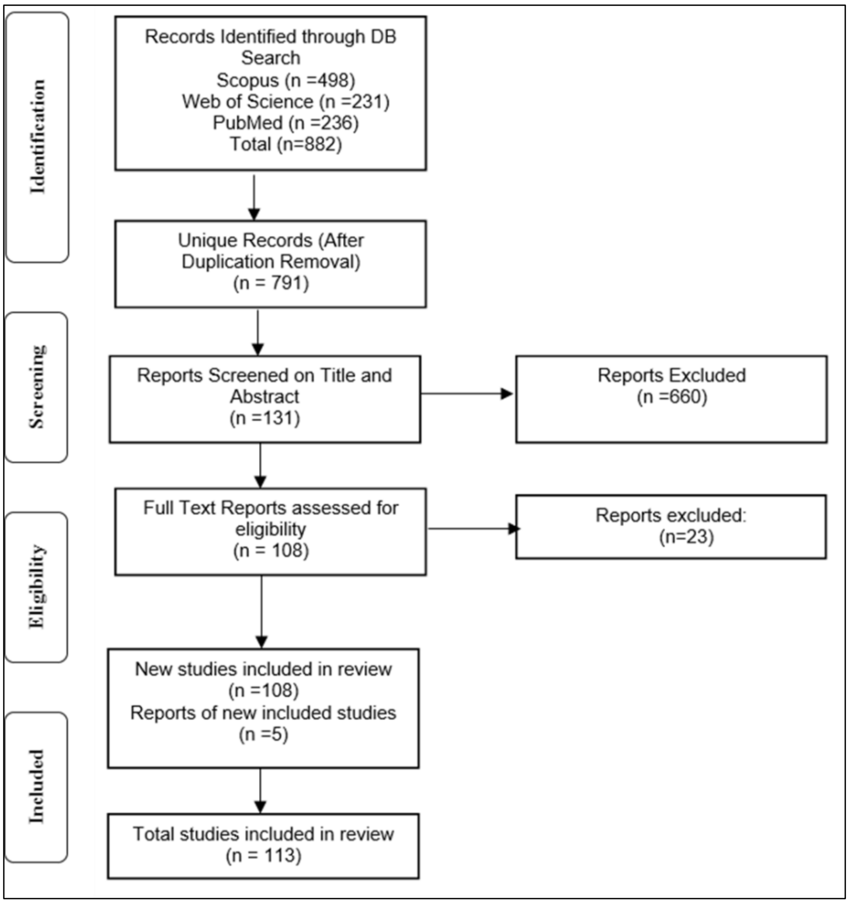

Figure 1: The Diagram Depicts the PRISMA-Based Selection Process, Narrowing 882 Papers to 113 for the Final Analysis

After eliminating duplicates and irrelevant titles and abstracts, the remaining papers were meticulously screened to identify those pertinent to our research topic. The screening process involved evaluating each paper against a set of exclusion criteria are There is no full-text available, No machine learning or deep learning applications, Abstracts of conferences, Papers presented at conferences, Textbooks, Book chapters and Languages other than English. Any paper that met at least one of these criteria was excluded from further consideration. After thoroughly examining a vast collection of articles and their supporting references, we meticulously selected 113 pieces of research that met our strict criteria for inclusion in this systematic review. Every article deemed relevant to our investigation was incorporated and categorized accordingly. The findings extracted from each study were carefully considered for our analysis are Name of the first author, Publication year, Primary objective, Methodology, Type of Data, Dataset, AI/ML/DL methodology and Benchmark measurement. Based on our reasoning, we assessed the distribution of all published articles across areas like structural connectivity, functional connectivity, deep learning algorithms, and types of input data. Given the varied applications, we concluded that a quantitative synthesis was inappropriate. As a consequence, a narrative method is used to give a qualitative synthesis of the data. Given the enormous number of articles in the literature and the current results, categorization tasks have been thoroughly investigated, both statistically and qualitatively. Finally, we differentiated structural and functional connectivity-based categorization tasks. Indeed, given the encouraging findings produced by these methodologies, we consider the latter to be a developing problem that requires further investigation. Figure 2 represent complete flow of the systematic review process on brain connectome research using deep learning models. It outlines each step from the initial literature search to the final selection and analysis of relevant studies.

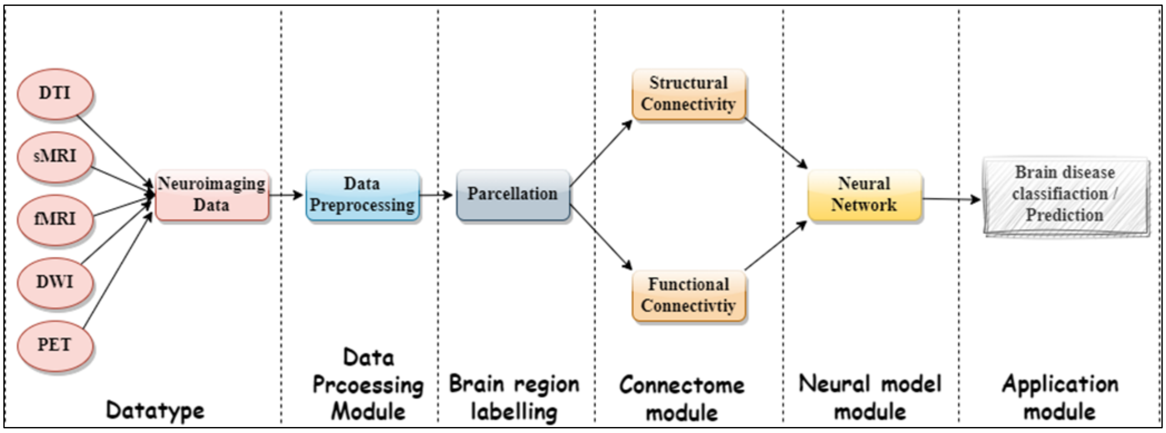

Figure 2: Complete Flow of Systematic Review on Connectome Using Deep Learning Mode

Data type

In recent years, multiple technologies have emerged to study the brain's structure without invasive neurosurgery. The introduction of Computed Tomography (CT) imaging and magnetic resonance imaging (MRI) has allowed for more effective identification and management of neurological disorders (20). A CT image is a depiction of cross-sectional views generated by computer-processed combinations of numerous X-ray measurements taken from different angles (21). Using Positron Emission Tomography (PET), metabolic processes can be observed at the cellular level. High-quality images of biological structures are achieved using MRI by using a strong magnetic field and radio waves (22).The magnetic characteristics of MRI are determined by the properties of atomic nuclei. During the test, the protons are aligned inside the water molecules of the tissue being studied by a high, homogeneous external magnetic field. The injection of external Radio Frequency (RF) radiation perturbs or disrupts this alignment (or magnetization). RF radiation is released as the nucleus restores to its resting arrangement through various relaxation processes. The emitted signals are recorded after a certain time has elapsed since the initial RF. Diffusion Tensor Imaging (DTI) is a neuroimaging technique that uses magnetic resonance to evaluate the location, direction, and anisotropy of the brain's white matter tracts. Instead of solely using this data to assign contrast or colors to pixels in a cross-sectional image, it can be employed to measure the restricted diffusion of water in tissue, allowing for the creation of neural tract images (23). Diffusion-weighted imaging (DWI) is a method for detecting random movements of water protons. Water molecules generally move freely in the extracellular space, but their movement is significantly restricted within the intracellular environment. In ischemic brain tissue, diffusion, or spontaneous movement, becomes severely limited (24). During ischemia, the sodium-potassium pump ceases to function, leading to an intracellular accumulation of sodium. The resulting osmotic difference causes water to move from the extracellular to the intracellular space (25). Subcellular water mobility becomes restricted, producing a very high signal on DWI. Consequently, DWI is a highly sensitive method for detecting strokes; Table 2 contains all of the reviewed article's input data.

Table 2: Type of Brain Image

Brain Image	Definition
MRI	MRI provides detailed images of the brain, spinal cord, and vascular structures, and allows visualization in all three planes: axial, sagittal, and coronal.
MRI T1 Weighted Image	Short TE and TR timings are used to create T1-weighted images. The contrast and brightness of these images are primarily influenced by the T1 properties of the tissue.
MRI T2 Weighted Image	Longer TE and TR periods are used to produce T2-weighted images. The contrast and brightness of these images are primarily influenced by the T2 properties of the tissue.
MRI Flair	The Flair sequence is similar to a T2-weighted image but uses much longer TE and TR periods.

Diffusion-weighted imaging (DWI)	This MR imaging technique is based on detecting the random Brownian motion of water molecules within a tissue voxel. Generally, highly cellular tissues or those with cellular swelling exhibit lower diffusion coefficients. Diffusion imaging is particularly useful in identifying tumors and cerebral ischemia.
Diffusion Tensor Imaging	Diffusion tensor data is used in tractography, which enables 3D imaging of particular white matter pathways. With the use of DTI Tractography, one may locate the thalamocortical tract or the corticospinal tract, for instance.

Some modern optimization frameworks aim to predict clinical severity from resting-state fMRI (rs-fMRI) data. These frameworks decompose correlation matrices into a sparse set of representative subnetworks, forming a network manifold. The steps in a competitive environment are combined using patient-specific non-negative coefficients and a linear regression model that utilizes these coefficients to estimate clinical severity (26). Recent innovations introduce Image Quality Transfer (IQT), a cutting-edge computational imaging technique. IQT uses machine learning to translate the rich data obtained from specialized experimental medical imaging devices to the more extensive but lower-quality data collected in routine scans. Some research has examined the individual and combined strengths and weaknesses of various measurements, using resting-state fMRI data from the UK Biobank and the Human Connectome Project. They tested over 9000 different pipeline versions on a total of 14000 participants to identify the optimal one NBS-Predict is a novel machine learning method that integrates the capabilities of machine learning with the ease of the Network-Based Statistic (NBS). This innovative technique uses ML models to swiftly and accurately identify neuroimaging biomarkers by embedding the models within a cross-validation framework. NBS-Predict utilized 1200 brain scans from the Human Connectome Project to make predictions about brain function.

Deep Learning

Deep learning approaches are successful in vision, voice, and language processing, and there is rising interest in applying them to high-impact application fields such as healthcare. While most of the success has been in dealing with clinical pictures and volumes, as well as textual reports, more recent attempts have concentrated on difficult data sources, such as integrated health records, knowledge graphs, and so on. These initiatives have depended on applying basic formalisms like convolutional neural networks to data that is arbitrarily arranged. Graph Neural Networks (GNNs), are known for their tremendous expressive capabilities with graph-structured data and are highly effective with population graphs in clinical diagnoses, such as autism (27). Table 3 contains all of the deep learning methods used in this study.

Table 3: Deep Learning Algorithms

Algorithm	Mechanism
Convolutional Neural Network(CNN)	Form of artificial neural network that has different layers and is mostly used for image processing and object detection in image recognition and processing. They are especially intended to analyze pixel input (28).
Recurrent Neural Network(RNN)	The LSTM output is used as an input in the current phase, and it has internal memory that allows it to recall previous inputs. The use of RNNs to caption images, analyze time series, process natural language, know handwriting, and translate is widespread (28).
Multilayer Perceptron(MLP)	A form of feedforward artificial neural network (ANN), the multi-layer perceptron is often referred to as the deep learning architecture. The most popular algorithm, "Backpropagation," is employed by Train MLP (28).
Self-Organizing Map(SOM)	Its type of unsupervised learning is the Self-Organizing Map (SOM), often known as the Kohonen Map. It's known as a dimensionality reduction approach based on neural networks. The fundamental merit of using a SOM is that it simplifies the visualization of high-dimensional data (28).
Deep Belief Network(DBN)	It's a multi-layer generative graphical model that incorporates several unsupervised networks into one. In order to achieve the ultimate goal, we

	must develop an unsupervised training method for each contrastive divergence-dependent subnetwork that is more efficient (28).
Restricted Boltzmann Machine(RBM)	A Restricted Boltzmann Machine (RBM) is a type of generative probabilistic neural network that can generate a probability distribution across a large number of inputs. RBMs have been instrumental in reducing data, categorizing, predicting, content-based filtering, pattern recognition, template matching, and many more applications (28).
Autoencoders	The auto-encoder is a significant unsupervised learning technique in which neural circuits are utilized to learn representations (AE) (28).
Generative Adversarial Network(GAN)	A Generative Adversarial Network (GAN) is a neural network architecture that uses generative modeling. GANs are constructed from two neural networks: the generator and the discriminator (28).

Machine and deep learning techniques have the potential to enhance the accuracy of fiber tracking and connectome reconstruction. These methods have recently shown success in understanding the relationship between dMRI data and local fiber orientations (29). This led to the idea of machine and deep learning tractography, where a neural network is trained to predict the direction of streamlining propagation based on dMRI signal patterns. Deep learning algorithms offer the advantage of not requiring a specific diffusion model or signal parameterization, which can provide greater robustness to variations in data collection methods and noise. Various network topologies, such as recurrent convolutional networks and multi-layer perceptron architectures, have been explored about this new fiber-tracking approach.

Qualitative Metrics

Performance measurement is a fundamental part of all ML and DL applications. In assessing machine learning and deep learning classification tasks, accuracy, precision, sensitivity, and specificity are commonly used measures. The accuracy and precision of a test indicate its fundamental reliability, while specificity and sensitivity reveal its likelihood of producing false negatives and false positives. Despite their widespread use, these characteristics are not always a meaningful measure in certain situations, as previous assessments have noted. These features are commonly used, even though, as earlier analyses have pointed out, they may not be a relevant metric in some situations. In individuals with mesial temporal lobe epilepsy, researchers investigated whether deep learning applied to whole-brain structural connectomes could accurately predict postoperative seizure outcomes, As a result, more research is including the Positive Predictive Value (PPV) and Negative Predictive Value (NPV) in their analyses (NPV, 30). Recent studies examine Gray Matter (GM) network topology in people with Paradoxical Kinesigenic Dyskinesia (PKD) to determine if GM network characteristics may serve to identify the disorder, one of the most commonly used assessment metrics for testing or visualizing the performance of a machine learning classification problem is the Area Under the Curve (AUC) of a Receiver Operating Characteristics (ROC) curve. As the AUC increases, so does the model's ability to predict (31).Lastly, researchers should be commended for their efforts to test their methodologies to minimize human error and manage variances in brain data The development of validation approaches to this end is essential (32). In terms of cross-validation, leave-one-out, and leave-one-group-out procedures continue to be the most practical (33). Through these techniques, we can enhance the accuracy of ML and DL algorithms and eliminate biases that may be present in singular datasets (34).

Results and Discussion

In the past 10 years, the number of studies analyzing deep learning models has increased exponentially. The annual publication statistics are depicted in Figure 3 as a supporting tool for various paradigms of brain care; such methodologies include Structural and Functional connectivity information and deep Learning-assisted brain care in patients with epilepsy, brain tumors, neurological disorders, Vascular dementia, neurological damage, and cerebrovascular abnormalities. There was also a tendency toward customized solutions and fewer machine learning methods. The most often utilized input data types were MRI, MRI T1 Weighted Image, MRI T2 Weighted Image, MRI Flair, Diffusion-weighted imaging (DWI), Diffusion Tensor Imaging, and MRI data. The most commonly examined applications were radiological brain tumor segmentation and classification. Below this section, we summarized in the form of qualitative, quantities of recent research publications and methods proposed by the various researchers in Human brain connectome mapping using deep learning methods.

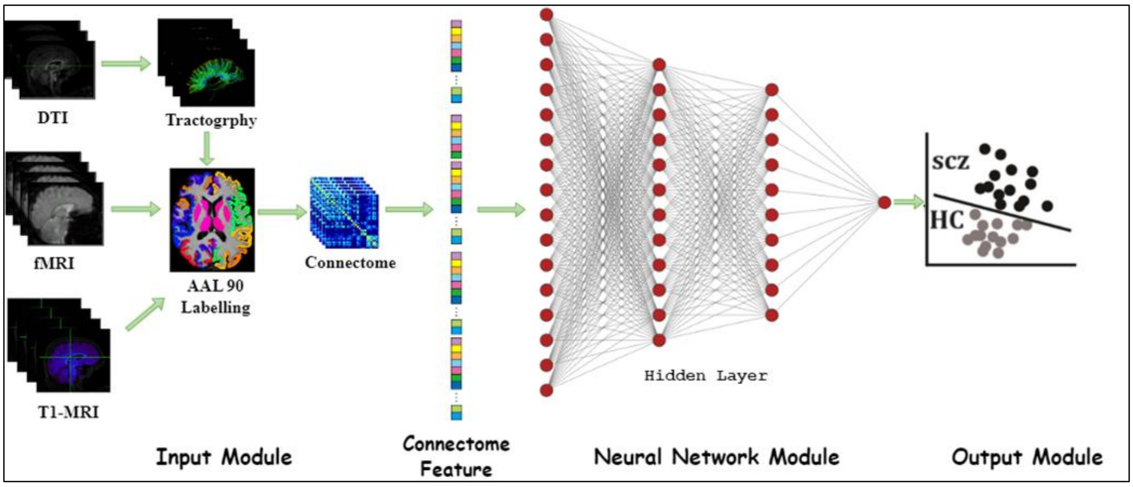

Figure 3: Arctiture of Connectome Using Deep Learning

Deep Learning for Connectome

Recent studies of deep learning-based methods in neuroimaging models like the fiber Orientation Distribution Function(fODF) peaks are directly segmented by CNNs, eliminating the need for tractography, image registration, or Parcellation (35) and Lacking anatomical data or multi-registration, the technique can predict tissue segmentation straight from fresh dMRI data, including data gathered with diverse collection procedures (36). Toolbox for image processing in neuroscience in recent advancements like "Brain Network Construction and Classification (BrainNetClass)" toolkit to push more advanced brain network construction approaches to the field, including many state-of-the-art techniques created lately to capture complicated and high-order interactions across brain areas. Table 4 summarizes recent studies concerning Deep Learning or Machine learning techniques with human brain connectome mapping. Among various approaches proposed in recent years in a combination of neuroscience and Machine Intelligence to solve brain connectivity function and various brain diseases in the Human brain with datatype, dataset, and source of the dataset.

Table 4: Recent Studies on Deep Learning for Connectome

Aim	ML / DL	Type of Data	Dataset - Source
Model-based Deep Learning architecture (37)	CNN	dMRI	7 subjects / HCP
Dice similarity coefficient (DSC) (38)	CNN	MRI	Healthy neonates / HCP
Functional Connectivity Pattern to Schizophrenic Control (39)	Auto Encoder	fMRI	734 Subjects / HCP
BrainNetCNN - structural brain networks (40)	CNN	DTI	168 DTI images / HCP
Angular correlation coefficient (ACC) (41)	DNN	DW-MRI	12 subjects / HCP
Deep Learning for Thalamus Segmentation (42)	CNN	dMRI	90 subjects / HCP
Structural connectomes (43)	CNN	dMRI and rs-f MRI	20 healthy adults / HCP

Connectome-based CNN model for early Alzheimer's detection (44)	BrainNetCNN	Structural MRI and DTI data	360 subjects
Brain connectivity to predict sex, age, cognition, and psychopathology accurately (45)	BrainNetCNN	Diffusion MRI	8183 connectomes

Machine learning techniques based on regional temporal dependence measures achieve a sex classification accuracy of up to 81 percent (46). Provide a unique, fast, and fully automated deep learning approach for segmenting OB tissue on T2-weighted (T2w) whole-brain MR images with sub-millimeter resolution. The researchers used three classic image-denoising approaches to study the impact of noise reduction on empirical data captured at a 0.6 mm isotropic resolution: utilizing a denoising convolutional neural network, block-matching and 4D filtering, and adaptive optimal non-local-means methods (47). Using deep learning, which is effective in a variety of big-data studies, the researchers combined clinical characteristics and MRI data to predict ALS patient survival. From the Human Connectome Project (HCP) dataset (GMV), gray matter volume was calculated using high-resolution magnetic resonance imaging data obtained from 100 healthy young adults. Tests of cognitive flexibility were conducted with Dimensional Change Card Sorts (DCCS). Relevance vector regression (RVR), a multivariate machine learning technique, was used to investigate the association between GMV and cognitive flexibility performance (48). Several investigators have trained the GAN algorithm using 1112 MRI images from the Human Connectome Project to create a generative model of a healthy human brain's T1-contrast 3D MRI image volume. A total of 1112 brains were removed from their skulls and mapped to a brain atlas and Utilizing 1000 s/mm^2 shell data from the Human Connectome Project (HCP), explored the potential of applying deep learning to the complete three-shell data sets (1000, 2000, and 3000 s/mm^2 from HCP) to estimate the information content obtained by 8th order MT-CSD. At present, most deep learning approaches represent data on a mesh surface, and the geometric CNN (gCNN) performs pattern recognition in a multi-shell mesh structure (49). DeepDTI uses data-driven supervised deep learning to determine the six unique unknowns in a diffusion tensor from six diffusion-weighted images (DWIs), decreasing the data requirements of DTI to six pictures (50). Interestingly, a deep neural network (DNN) was developed to decode various brain task states directly from fMRI data using support vector machine (SVM)-based multivariate pattern analysis (MVPA).

Deep Learning Based Structural Connectivity Analysis

In this section many current studies that structural brain connectivity does not determine cellular interactions rigidly. Instead, it reduces the dimensionality of the neuronal state space by creating constraints or skeletons. Recent studies on structural connectivity show the presence or absence of physical connections, such as synapses and pathways, as well as synaptic weight, time delay, and biophysical effectiveness is referred to as edge representation (synaptic weight). Microscopy is the reconstruction of tissue volume, Neuroanatomy is the tracing of pathways, and Neuroimaging is tractography. Networks can be weighted or unweighted, sparse and directed (projects), or sparse, undirected, etc., The anatomical structure is thought to be critical for understanding neural dynamics and, therefore, cognition and behavior, which is, in turn, a key rationale for assembling the human connectome. The dynamics of neural networks remain fluctuating and sensitive to dynamic perturbations in this reduced low-dimensional space. Many studies related to investigating structural brain anomalies associated with autism spectrum disorder (ASD), used Support Vector Machines (SVM) and many studies of children's brain PADs rely on a single MRI modality or a single ML algorithm. Based on brain modeling, AutoML predicts age differences and mental symptoms in children, with data derived from MRI samples of healthy and unhealthy children in different locations in New York City (51). Using network analyses of cerebral magnetic resonance imaging (MRI T1 and T2) data, disease propagation was predicted in 208 patients with amyotrophic lateral sclerosis (ALS) at Utrecht's outpatient clinic for motor neuron diseases (52). The developing Human Connectome Project (dHCP) produced automated claustrum segmentation in neonates using Transfer Learning of T2-weighted MRI of the claustrum in 558 newborn brains MRIs (53). Beyond T1-weighted scans, resting-state fMRI, and diffusion MRI data, models that combine multiple neuroimaging techniques enhance the ability to predict individual differences in cognitive performance and Resting-state fMRI employs sophisticated computational methods to investigate functional and structural distinctions between the brains of healthy individuals and those with various disorders; Examining T1-weighted MRI and diffusion-weighted imaging (DWI) reveals how surgical procedures modify the structural white matter network and how these network changes correlate with seizure outcomes post-epilepsy surgery (54). As reported in Table 5 studies consider Machine Learning or Deep Learning in the structural connectivity of various pathological and structural MRI data of current investigation are reported.

Table 5: Structural Connectivity: Aim, Pathology, Data Type, Dataset, ML/DL Method, Dataset, Data Source

Aim	Pathology / Anatomical	ML/ DL	Type of Data	Dataset	Dataset Source
Persistent Post–Concussion Symptoms (PPCS) in mTBI (55)	mild Traumatic Brain Injuries (mTBI)	SVM	MRI, rs-MRI	110 mixed recovery of mTBI	Alberta Children's Hospital
Brain connectivity and exploration of neurological dysfunction (56)	Fiber orientation Distribution Function (fODF)	CNN	MRI, DWIs	288 Subjects	HCP
Late-Life Depression (LLD) and Mild Cognitive Impairment (MCI) (57)	Alzheimer's Disease (AD)	SVM	MRI	91 Subjects	HCP
Identifying Diffuse Axonal Injury (DAI) with Traumatic Brain Injury (TBI) (58)	DAI and TBI	SVM	MRI	179 TBI patients	HBN neuroimaging data
Predicting surgical treatment outcomes in groups of patients with Temporal Lobe Epilepsy (TLE) (59)	TLE	SVM	MRI, DTI	35 with refractory TLE treated	The University of Bonn in Germany
Linkage/Association between multimodal brain imaging data (60)	Schizophrenia	FFNN	MRI	298 subjects	3-Tesla Siemens Trio scanner
Complexities of neurological and psychiatric disorders (61)	Schizophrenia	3D CNN / GNN	MRI	-	OpenVC dataset
Schizo-Net model for SCZ diagnosis (62)	Schizophrenia	Schizo-Net Neural Network	EEG	28 Subjects	Private

Deep Learning Based Functional Connectivity Analysis

Deep learning methods have attracted in analysis or segmentation of functional connectivity in the human brain in recent years; A recently developed machine learning approach, Connectome-Based Predictive Modeling (CPM), is adapted to whole-brain functional connectivity data ("Neural Fingerprints") with ANN and rs-functional MRI to develop a reliable prediction model of decision impulsivity; Researcher analyzed functional brain imaging (fMRI) data from 168 healthy people who had no history of neurological or psychiatric disorders and used machine learning to reconstruct trait narcissistic characteristics from whole-brain resting-state functional connectivity (RSFC, 63). Incorporating statistically regularized Dynamic Dictionary Learning (sr-DDL) and LSTM-ANN with resting-state functional MRI (rs-fMRI) connectivity and diffusion tensor imaging (DTI), construct a system for detecting brain connections associated with autism behavior (64).Connectivity is defined as the statistical correlation between neuronal time courses (for example, spikes, EEG, and BOLD) and Empirical Techniques such as Neurophysiology: The relationships between EEG/MEG BOLD signals include correlation, synchronization, coherence, and phase locking. The analysis also involves examining cross-correlations, partial correlations, and network characteristics, such as fully and weighted (or unweighted) connections after thresholding, focusing on undirected connectivity. As reported in Table 6 studies consider Machine Learning or Deep Learning in Functional Connectivity of various pathological and functional MRI data of current investigation are reported.

Table 6: Functional Connectivity: Aim, Pathology, Data Type, Dataset, ML/DL Method, Dataset, Data Source

Aim	Pathology / Anatomical	ML/ DL	Type of Data	Dataset	Dataset Source
FC in Preterm Infants (65)	Neurodevelopment Disorders	SVM	rs- MRI, T2-d MRI	274 Subjects	Philips Medical Systems, Best, The Netherlands
Developmental Dyslexia in White Matter (66)	Developmental dyslexia	Linear SVM	MRI and DTI	528 Subjects	Center for Brain Research, Beijing Normal University
Brain features ASD from Typically Developing (TD, 67)	ASD	Conditional Random Forest (CRF)	MRI	93 Subjects	University of California San Diego
Brain Parcellations on ML Models (68)	ASD	CNN	rs-fMRI	539 Subjects	ABIDE
Functional connectivity patterns (69)	ASD	DTL-NN	rs-fMRI	regions of interest (ROIs)	ABIDE
DL predicts task-based contrast maps (70)	FC	CNN	fMRI	1200 Subjects	HCP

classification of individual independent-component (IC, 71)	FC	MLP	fMRI	1811 Participants	GIN-IMN
Brain network of anxiety (72)	OCD	ANN	fMRI	879 participants	HCP
Transdiagnostic predictive working memory model (73)	Schizophrenia, Bipolar disorder	ANN	rs-fMRI	242 subjects	HCP
Differentiate patients with Major Depressive Disorder (MDD) from healthy controls (74)	MDD	SVM and GCN	rs-fMRI	2338 Participants	REST-meta-MDD consortium
Directed structure learning Graph Neural Network (DSL-GNN) in the context of effective brain connectivity for distinguishing disease and healthy controls (HC, 75)	Alzheimer's disease (AD) and Parkinson's disease (PD)	GNN	electroencephalogram (EEG)	250 Subjects	Private

Recent research used fMRI and deep neural networks (DNNs) and kernel regression to predict individual phenotypes using whole-brain resting-state functional connectivity (RSFC) patterns in 10,000 subjects from the Human Connectome Project (HCP, 21); Using functional Magnetic Resonance Imaging (fMRI), researchers present M2D CNN, a unique multichannel 2D CNN model. A novel CNN framework was developed to train embedded features from BFNs for Alzheimer's disease diagnosis with resting-state functional MRI (rs-fMRI) of 351 samples (172 NCs and 179 eMCIs, respectively) from several Philips 3T scanners (76). However, a better understanding of how the organization of the human brain is influenced by cell-specific neurobiological gradients (77). Recurrent neural networks (RNNs) are used on both rat and human brains to anticipate the temporal development of rs-fMRI slow oscillations in the future (78). When examining a large-scale fMRI database containing eight state/task combinations, several state-unspecific individual differences in whole-brain connection patterns were discovered. These variants are known as Common Neural Modes (CNM, 4). Assess the contribution of distinct brain areas' Connectome measurements to the categorization task using SC, static FC, and dynamic FC (dFC, 79). Using 3D-CNN models with down-sampling techniques such as pooling and/or stride, feature tables created from the shifted and scaled neural activations of a single functional MRI (fMRI) volume might be utilized for the categorization of task information relating to the volume (80).

Brain Disorder, Disease Using Deep Learning

A total of 21 studies examined ML/DL for diseases in our studies. This includes categorization using structural and functional connectivity information to investigate neurological disorders. A classification algorithm was developed using MRI, SC, and FC data. We report on the distribution of data types, methods, and pathology in this section. It is worth noting that, due to the wide variety of subtasks discovered when employing anatomical information for categorization, a qualitative study strategy was chosen over a quantitative one. As reported in Table 7 studies consider Machine Learning or Deep Learning in Brain disorders, Disease using Deep Learning in the current investigation is reported.

Table 7: Brain Disease And Disorder Information: Aim, Pathology, Data Type, Dataset, ML/DL Method, Dataset, Data Source, and Performance Metrics

Aim	Pathology / Anatomical	Machine / Deep Learning Algorithms	Type of Data	Dataset	Dataset Source	Performance Metrics
Theory-of-Mind (ToM) (81)	autism	SVM	fMRI, DTI	15 Subjects	University of Alabama ASD Clinic	MVAR
ASD population using a random forest (RF) (82)	ASD	classification	rs-fMRI	105 children between the ages of 9 and 13	ADNI	random forest, k-fold cross-validation
High degree and High connection weights as hubs (83)	AD, ASD	DFF-NN	rs-fMRI	500 Subjects	HCP	5-fold cross-validation
Structural covariance matrices and functional connectivity matrices (84)	Schizophrenia	SVM	MRI	295 patients	HCP	10-fold cross-validation
Parkinson's disease progression pattern (85)	Parkinson's disease	RF, SVM	dMRI	21 Subjects	PPMI	Cross-Validation
Neural degenerative patterns in each TBI patient (86)	Traumatic brain injury (TBI)	ANN	dMRI	17 Subjects	Ghent University Hospital, Belgium.	Cross-Validation
CNN trained to segment normal optic chiasms (87)	Optic Chiasm	CNN	t1w - MRI	1049 Participants	HCP	
Classification of ASD patients (88)	ASD	Autoencoders	MRI	449 Subjects	ABIDE	10-fold cross-validation

Functional Connectivity Biomarkers (89)	PTSD and MDD	SVM	rs-fMRI	51 Individuals	NYSPI	10-fold cross-validation
Classification of mental disorder using structural connectivity data (90)	Schizophrenia	Sc-DGNN	DTI, DWI	88 Subjects		Accuracy

Recent Researchers used deep learning from MRI and diffusion tractography on 37 children (aged 11.8 to 3.1 years) with drug-resistant focal epilepsy to determine if current deep learning models detect epilepsy-related expressive and receptive language scores (91); Deep learning was investigated as a potential means of predicting the outcome of postsurgical seizures in patients with mesial temporal lobe epilepsy (TLE) using classification models with MRI data from hospitalized patients with 5-fold cross-validation of quantitative metrics using whole-brain structural connectomes. An alcohol severity assessment was conducted using the alcohol use disorders identification test (AUDIT) to evaluate problem drinking patterns in adults (age 22-60) who were subjected to a behavioral and neuroimaging protocol; generalizability of the model was checked in a validation sample (92). However, several investigations aimed to study the characteristics of brain Gray Matter (GM) network topologies in individuals with Paroxysmal Kinesigenic Dyskinesia (PKD) and analyze if the features of GM networks may have any diagnostic value and impact of epilepsy on the developing brain based on global metrics of network architecture generated by resting-state functional MRI (93). To determine the earliest detectable stage of dementia in simulated disease progression, the researcher developed dynamic models using data from the Nathan Kline Institute-Rockland Sample database (94). Evaluate whether Parkinson's disease (PD) can be differentiated from healthy controls by applying a deep learning approach to analyze parameter-weighted metrics and the number of streamlines (NOS) using a convolutional neural network (CNN, 95).

Challenge and Feature Scope

In the past few years, significant progress has been made toward mapping the human connectome. Connectomes will be built on the theoretical and empirical studies of the brain's system architecture and behavior. In our study total of 113 studies were identified out of 882, using Deep Learning algorithms for various purposes. We conducted a systematic and thorough literature search using the terms "Brain", "Connectome", "Deep Learning", and "Machine Learning". An analysis of 113 articles was conducted to find papers relevant to our research. A paper was screened for at least one of the following: No full-text available; No machine learning or deep learning applications; No AI/ML/DL applications; and No language other than English. A common measure of deep learning classification is accuracy, precision, sensitivity, and specificity. In the last ten years, there has been exponential growth in the huge studies evaluating deep learning models as an advanced and assisting tool specifically in connectome or neuroimaging. By using deep learning, CNNs segment fiber Orientation Distribution Function peaks in neuroimaging models using deep learning. With this technique, fresh dMRI data can be used to predict tissue segmentation. The researchers combined clinical characteristics with MRI data to predict the survival of ALS patients. According to many studies, structural connectivity in brain regions does not determine neuron (spatial) interactions rigidly. As a result, it decreases the dimensionality of the spatial state space by creating constraints or skeletons. However, neural networks remain fluctuating and sensitive to dynamic perturbations in this reduced low-dimensional space. One recent study examined the effectiveness of deep neural networks (DNNs) and kernel regression using fMRI of 10,000 participants. Researchers have created a novel multichannel 2D CNN model using functional magnetic resonance imaging (fMRI). An innovative CNN framework has been developed for Alzheimer's disease diagnosis. It is not always possible to measure these characteristics meaningfully in all situations. Researchers are incorporating the Positive Predictive Value (PPV) and the Negative Predictive Value (NPV) into their analyses. This includes categorization using structural and functional connectivity information to investigate neurological disorders. A classification algorithm was developed using MRI, SC, and FC data. Despite the impressive strides in using deep learning for brain connectome mapping, several challenges still need to be addressed. One major issue is the complexity and high dimensionality of neuroimaging data, which requires extensive preprocessing and advanced models to identify meaningful patterns. The dependence on large datasets, like those from the Human Connectome Project, reveals a lack of diverse and high-quality datasets that truly reflect different populations or include rare neurological conditions. While deep learning approaches such as CNNs and Auto Encoders show great potential, they often require extensive parameter tuning and can be hard to interpret, complicating their integration into clinical practice. Additionally, standardizing methods for mapping structural and functional connectivity is difficult due to variations in how data is collected and processed. Many studies also tend to focus on specific imaging modalities, missing out on the deeper insights that multimodal approaches could provide. These challenges highlight the urgent need for developing explainable and robust deep learning models that can effectively utilize diverse neuroimaging data for both clinical and research purposes.

Conclusion

A review of current literature on Deep learning methods that assist in mapping the human brain's connectome was presented in this study. Over the past decade, the rapid advancement of Deep Learning (DL) methodologies has profoundly impacted the field of brain care, particularly in the analysis of structural and functional connectivity. These innovative approaches have provided significant insights and improvements in the diagnosis and management of various neurological conditions, including epilepsy, brain tumors, vascular dementia, and other neurological disorders. The application of DL models, such as Convolutional Neural Networks (CNNs) and Deep Neural Networks (DNNs), has revolutionized the way we analyze brain connectivity. These models have demonstrated exceptional capability in processing complex neuroimaging data, leading to more accurate segmentation, classification, and prediction outcomes. The development of tools like the Brain Network Construction and Classification (Brain Net Class) toolkit exemplifies the progress in constructing and analyzing advanced brain networks. Functional connectivity analysis has also benefited greatly from DL advancements. Techniques like Connectome-Based Predictive Modeling (CPM) and the integration of ANN-based methods have enabled researchers to develop reliable prediction models for various cognitive and behavioral traits. The use of statistically regularized Dynamic Dictionary Learning (sr-DDL) and LSTM-ANN has further enhanced the detection of brain connections associated with conditions such as autism and other developmental disorders. DL has proven to be a powerful tool in diagnosing and understanding brain disorders. Numerous studies have shown that DL models can effectively classify and predict outcomes for conditions like autism, schizophrenia, Alzheimer's disease, and traumatic brain injuries. These models have provided valuable insights into the structural and functional anomalies associated with these disorders, thereby improving diagnostic accuracy and informing treatment strategies. Despite these advancements, there are still challenges to overcome. Future research should focus on enhancing the generalizability of DL models across diverse populations and neuroimaging modalities. Additionally, the development of more comprehensive datasets that include a broader range of patient demographics and conditions is crucial for the continued improvement of these models. In conclusions, the integration of DL models in neuroimaging and brain care has significantly advanced our understanding and management of neurological conditions. These methodologies offer promising potential for more precise diagnosis, better understanding of disease mechanisms, and improved patient outcomes. Key findings show that both structural and functional connectivity data gathered from various imaging techniques like MRI, DTI, fMRI, and diffusion-weighted imaging are crucial for improving brain care. These approaches are being used to diagnose and predict conditions such as epilepsy, brain tumors, Alzheimer's, and vascular dementia. Customized deep learning models, including CNNs and AutoEncoders, have proven effective for tasks like segmentation and classification. Innovative tools like the BrainNetClass toolkit are also emerging, making it easier to construct and analyze brain networks. However, challenges persist, such as the need for better integration of different data types, improved model generalizability, and enhanced interpretability. Looking ahead, research should aim to create unified frameworks that utilize multi-modal neuroimaging, focus on explainable AI, and improve the scalability of deep learning methods in connectome research. As research continues to evolve, the application of DL in brain care is expected to further enhance our ability to diagnose, treat, and manage neurological disorders, ultimately leading to better healthcare and quality of life for patients. In the future, deep learning in brain connectome mapping will likely emphasize personalized and multimodal approaches to better address brain disorders. By integrating structural and functional connectivity, we can enhance diagnostics and treatments for conditions like epilepsy and brain tumors. Advanced neuroimaging techniques, such as T1- and T2-weighted MRI and diffusion imaging, will improve the accuracy of connectome models. Emerging methods, including CNNs and geometric CNNs, will streamline analyses by estimating connectomic features more directly. Overall, future research will focus on integrating diverse data sources and developing automated processing pipelines to better link neuroimaging with clinical applications.

Abbreviations

dHCP: developing Human Connectome Project, ABIDE: Autism Brain Imaging Data Exchange, ADNI: Alzheimer's Disease Neuroimaging Initiative, PPMI: Parkinson's Progression Markers Initiative, ACC: Angular correlation coefficient, DSC: Dice Similarity Coefficient, BM4D: Block Matching 4-Dimensional, DCCS: Dimensional Change Card Sorts, RVR: Relevance Vector Regression, MT-CSD: Multi-Tissue Constrained Spherical Deconvolution, MVPA: Multi Variate Pattern Analysis, CPM: Connectome-Based Predictive Modeling, srDDL: statistically regularized Dynamic Dictionary Learning, ToM: Theory of Mind, NYSPI: New York State Psychiatric Institute, NHIS-IH: National Health Insurance Service Ilsan Hospital.

Acknowledgement

Nil.

Author Contributions

All authors made an equal contribution.

Conflict of Interest

There is no conflict of interest with the content of this article.

Ethics Approval

Not applicable.

Funding

The current research has not received any specific grant from funding agencies that belong to public, not-for-profit, or commercial sectors.

References

1. Sporns O. Networks of the Brain. USA: MIT press. https://mitpress.mit.edu/9780262528986/networks-of-the-brain/ 2016.
2. Zhang J. Basic neural units of the brain: neurons, synapses and action potential. arXiv:1906.01703. 2019 May 30.
3. Wang X, Liang X, Jiang Z, Nguchu BA, Zhou Y, Wang Y, *et al.* Decoding and mapping task states of the human brain via deep learning. Hum Brain Mapp. 2020;41(6):1505-19.
4. Takagi Y, Hirayama JI, Tanaka SC. State-unspecific patterns of whole-brain functional connectivity from resting and multiple task states predict stable individual traits. Neuroimage. 2019;201:116036.
5. Liu L, Zhang H, Wu J, Yu Z, Chen X, Rekik I, *et al.* Overall survival time prediction for high-grade glioma patients based on large-scale brain functional networks. Brain Imaging and Behavior. 2019;13(5):1333-51.
6. Sporns O. The human connectome: a complex network. Annals of the new York Academy of Sciences. 2011 Apr;1224(1):109-25.
7. Rasero J, Sentis AI, Yeh FC, Verstynen T. Integrating across neuroimaging modalities boosts prediction accuracy of cognitive ability. PLoS computational biology. 2021 Mar 5;17(3):e1008347.
8. Irimia A, Lei X, Torgerson CM, Jacokes ZJ, Abe S, Van Horn JD. Support vector machines, multidimensional scaling and magnetic resonance imaging reveal structural brain abnormalities associated with the interaction between autism spectrum disorder and sex. Frontiers in Computational Neuroscience. 2018 Nov 26;12:93.
9. Miranda-Dominguez O, Feczko E, Grayson DS, Walum H, Nigg JT, Fair DA. Heritability of the human connectome: A connectotyping study. Network Neuroscience. 2018;2(2):175-99.

10. Bullmore E, Sporns O. Complex brain networks: graph theoretical analysis of structural and functional systems. Nat Rev Neurosci. 2009;10(3):186-98.
11. Zhou Z, Chen X, Zhang Y, Hu D, Qiao L, Yu R, *et al.* A toolbox for brain network construction and classification (BrainNetClass). Human Brain Mapping. 2020;41(10):2808-26.
12. Zhu Y, Qi S, Zhang B, He D, Teng Y, Hu J, Wei X. Connectome-based biomarkers predict subclinical depression and identify abnormal brain connections with the lateral habenula and thalamus. Frontiers in psychiatry. 2019 Jun 12;10:371.
13. Pervaiz U, Vidaurre D, Woolrich MW, Smith SM. Optimising network modelling methods for fMRI. Neuroimage. 2020;211:116604.
14. Nath V, Pathak SK, Schilling KG, Schneider W, Landman BA. Deep learning estimation of multi-tissue constrained spherical deconvolution with limited single shell DW-MRI. InMedical Imaging 2020: Image Processing 2020 Mar 10 (Vol. 11313, pp. 162-171). SPIE.
15. Chong CK, Ho ETW. Synthesis of 3D MRI Brain Images with Shape and Texture Generative Adversarial Deep Neural Networks. IEEE Access. 2021; 9:64747-60.
16. Alexander DC, Zikic D, Ghosh A, Tanno R, Wottschel V, Zhang J, *et al.* Image quality transfer and applications in diffusion MRI. NeuroImage. 2017;152:283-98.
17. Serin E, Zalesky A, Matory A, Walter H, Kruschwitz JD. NBS-Predict: A prediction-based extension of the network-based statistic. Neuroimage. 2021;244:118625.
18. Zhang Y, Tetrel L, Thirion B, Bellec P. Functional annotation of human cognitive states using deep graph convolution. Neuroimage. 2021;231:117847.
19. van der Burgh HK, Schmidt R, Westeneng HJ, de Reus MA, van den Berg LH, van den Heuvel MP. Deep learning predictions of survival based on MRI in amyotrophic lateral sclerosis. NeuroImage: Clinical. 2017;13:361-9.
20. Barron DS, Gao S, Dadashkarimi J, Greene AS, Spann MN, Noble S, *et al.* Transdiagnostic, Connectome-Based Prediction of Memory Constructs Across Psychiatric Disorders. Cereb Cortex. 2021;31(5):2523-33.
21. He T, Kong R, Holmes AJ, Nguyen M, Sabuncu MR, Eickhoff SB, et al. Deep neural networks and kernel regression achieve comparable accuracies for functional connectivity prediction of behavior and demographics. Neuroimage. 2020;206:116276.
22. Cai H, Chen J, Liu S, Zhu J, Yu Y. Brain functional connectome-based prediction of individual decision impulsivity. Cortex. 2020;125:288-98.
23. Zhang F, Karayumak SC, Hoffmann N, Rathi Y, Golby AJ, O'Donnell LJ. Deep white matter analysis (DeepWMA): fast and consistent tractography segmentation. Medical Image Analysis. 2020 Oct 1;65:101761.
24. RaviPrakash H, Anwar SM, Biassou NM, Bagci U. Morphometric and functional brain connectivity differentiates chess masters from amateur players. Frontiers in neuroscience. 2021 Feb 19;15:629478.
25. Estrada S, Lu R, Diers K, Zeng W, Ehses P, Stöcker T, *et al.* Automated olfactory bulb segmentation on high resolutional T2-weighted MRI. Neuroimage. 2021;242:118464.
26. D'Souza NS, Nebel MB, Wymbs N, Mostofsky SH, Venkataraman A. A joint network optimization framework to predict clinical severity from resting state functional MRI data. NeuroImage. 2020 Feb 1;206:116314.
27. Jahedi A, Nasamran CA, Faires B, Fan J, Müller RA. Distributed Intrinsic Functional Connectivity Patterns Predict Diagnostic Status in Large Autism Cohort. Brain Connectivity. 2017;7(8):515-25.
28. Sarker IH. Deep Learning: A Comprehensive Overview on Techniques, Taxonomy, Applications and Research Directions. SN Comput Sci. 2021;2(6):420.
29. Brown CJ, Miller SP, Booth BG, Zwicker JG, Grunau RE, Synnes AR, *et al.* Predictive connectome subnetwork extraction with anatomical and connectivity priors. Comput Med Imaging Graph. 2019;71:67-78.
30. Gleichgerrcht E, Munsell B, Bhatia S, Vandergrift WA, Rorden C, McDonald C, *et al.* Deep learning applied to whole-brain connectome to determine seizure control after epilepsy surgery. Epilepsia. 2018;59(9):1643-54.
31. Li X, Lei D, Niu R, Li L, Suo X, Li W, *et al.* Disruption of gray matter morphological networks in patients with paroxysmal kinesigenic dyskinesia. Human Brain Mapping. 2021;42(2):398-411.
32. Amoroso N, La Rocca M, Bruno S, Maggipinto T, Monaco A, Bellotti R, Tangaro S. Multiplex networks for early diagnosis of Alzheimer's disease. Frontiers in Aging Neuroscience. 2018 Nov 14;10:365.
33. Rubbert C, Mathys C, Jockwitz C, Hartmann CJ, Eickhoff SB, Hoffstaedter F, Caspers S, Eickhoff CR, Sigl B, Teichert NA, Südmeyer M. Machine-learning identifies Parkinson's disease patients based on resting-state between-network functional connectivity. The british journal of radiology. 2019 Sep 1;92(1101):20180886.
34. Wang Y, Xu C, Park JH, Lee S, Stern Y, Yoo S, Kim JH, Kim HS, Cha J, Alzheimer's Disease Neuroimaging Initiative. Diagnosis and prognosis of Alzheimer's disease using brain morphometry and white matter connectomes. NeuroImage: Clinical. 2019 Jan 1;23:101859.
35. Wasserthal J, Neher P, Maier-Hein KH. TractSeg - Fast and accurate white matter tract segmentation. NeuroImage. 2018;183:239-53.
36. Zhang F, Breger A, Cho KI, Ning L, Westin CF, O'Donnell LJ, Pasternak O. Deep learning based segmentation of brain tissue from diffusion MRI. Neuroimage. 2021 Jun 1;233:117934.
37. Aggarwal HK, Mani MP, Jacob M. Modl-mussels: Model-based deep learning for multishot sensitivity-encoded diffusion mri. IEEE Transactions on Medical Imaging. 2020;39(4):1268-77.
38. Ding Y, Acosta R, Enguix V, Suffren S, Ortmann J, Luck D, *et al.* Using Deep Convolutional Neural Networks for Neonatal Brain Image Segmentation. Front Neurosci. 2020;14:207.
39. Hu J, Kuang Y, Liao B, Cao L, Dong S, Li P. A multichannel 2D convolutional neural network model for task-evoked fMRI data classification. Computational intelligence and neuroscience. 2019;2019(1):5065214.

40. Kawahara J, Brown CJ, Miller SP, Booth BG, Chau V, Grunau RE, *et al.* BrainNetCNN: Convolutional neural networks for brain networks; towards predicting neurodevelopment. NeuroImage. 2017;146:1038-49.
41. Nath V, Schilling KG, Parvathaneni P, Hansen CB, Hainline AE, Huo Y, *et al.* Deep learning reveals untapped information for local white-matter fiber reconstruction in diffusion-weighted MRI. Magnetic Resonance Imaging. 2019;62:220-7.
42. Pinheiro GR, Brusini L, Bajrami A, Pizzini FB, Calabrese M, Reis F, Appenzeller S, Menegaz G, Rittner L. Diffusion MRI and silver standard masks to improve CNN-based thalamus segmentation. InMedical Imaging 2021: Image Processing 2021 Feb 15;11596:692-698.
43. Sarwar T, Seguin C, Ramamohanarao K, Zalesky A. Towards deep learning for connectome mapping: A block decomposition framework. NeuroImage. 2020 May 15;212:116654.
44. Kolahkaj S, Zare H. A connectome-based deep learning approach for Early MCI and MCI detection using structural brain networks. Neuroscience Informatics. 2023;3(1):100118.
45. Yeung HW, Stolicyn A, Buchanan CR, Tucker-Drob EM, Bastin ME, Luz S, *et al.* Predicting sex, age, general cognition and mental health with machine learning on brain structural connectomes. Human Brain Mapping. 2023;44(5):1913-33.
46. Dhamala E, Jamison KW, Sabuncu MR, Kuceyeski A. Sex classification using long-range temporal dependence of resting-state functional MRI time series. Hum Brain Mapp. 2020;41(13):3567-79.
47. Tian Q, Zaretskaya N, Fan Q, Ngamsombat C, Bilgic B, Polimeni JR, *et al.* Improved cortical surface reconstruction using sub-millimeter resolution MPRAGE by image denoising. Neuroimage. 2021;233:117946.
48. Zhu J, Zhu DM, Zhang C, Wang Y, Yang Y, Yu Y. Quantitative prediction of individual cognitive flexibility using structural MRI. Brain Imaging and Behavior. 2019;13(3):781-8.
49. Seong SB, Pae C, Park HJ. Geometric Convolutional Neural Network for Analyzing Surface-Based Neuroimaging Data. Front Neuroinform. 2018; 12:42.
50. Tian Q, Bilgic B, Fan Q, Liao C, Ngamsombat C, Hu Y, Witzel T, Setsompop K, Polimeni JR, Huang SY. DeepDTI: High-fidelity six-direction diffusion tensor imaging using deep learning. NeuroImage. 2020 Oct 1;219:117017.
51. Luna A, Bernanke J, Kim K, Aw N, Dworkin JD, Cha J, *et al.* Maturity of gray matter structures and white matter connectomes, and their relationship with psychiatric symptoms in youth. Human Brain Mapping. 2021;42(14):4568-79.
52. Meier JM, van der Burgh HK, Nitert AD, Bede P, de Lange SC, Hardiman O, *et al.* Connectome-Based Propagation Model in Amyotrophic Lateral Sclerosis. Annals of Neurology. 2020;87(5):725-38.
53. Neubauer A, Li HB, Wendt J, Schmitz-Koep B, Menegaux A, Schinz D, Menze B, Zimmer C, Sorg C, Hedderich DM. Efficient claustrum segmentation in T2-weighted neonatal brain MRI using transfer learning from adult scans. Clinical Neuroradiology. 2022 Sep;32(3):665-76.
54. Taylor PN, Sinha N, Wang Y, Vos SB, de Tisi J, Miserocchi A, *et al.* The impact of epilepsy surgery on the structural connectome and its relation to outcome. NeuroImage: Clinical. 2018;18:202-14.
55. Iyer KK, Zalesky A, Barlow KM, Cocchi L. Default mode network anatomy and function is linked to pediatric concussion recovery. Annals of Clinical and Translational Neurology. 2019;6(12):2544-54.
56. Lin Z, Gong T, Wang K, Li Z, He H, Tong Q, *et al.* Fast learning of fiber orientation distribution function for MR tractography using convolutional neural network. Medical Physics. 2019;46(7):3101-16.
57. Mai N, Wu Y, Zhong X, Chen B, Zhang M, Ning Y. Determining the effects of LLD and MCI on brain decline according to machine learning and a structural covariance network analysis. Journal of Psychiatric Research. 2020 Jul 1;126:43-54.
58. Mitra J, Shen KK, Ghose S, Bourgeat P, Fripp J, Salvado O, *et al.* Statistical machine learning to identify traumatic brain injury (TBI) from structural disconnections of white matter networks. NeuroImage. 2016;129:247-59.
59. Munsell BC, Wee CY, Keller SS, Weber B, Elger C, da Silva LA, Nesland T, Styner M, Shen D, Bonilha L. Evaluation of machine learning algorithms for treatment outcome prediction in patients with epilepsy based on structural connectome data. Neuroimage. 2015 Sep 1;118:219-30.
60. Plis SM, Amin MF, Chekroud A, Hjelm D, Damaraju E, Lee HJ, *et al.* Reading the (functional) writing on the (structural) wall: Multimodal fusion of brain structure and function via a deep neural network based translation approach reveals novel impairments in schizophrenia. NeuroImage. 2018;181:734-47.
61. Caznok Silveira AC, Antunes AS, Athié MC, da Silva BF, Ribeiro dos Santos JV, Canateli C, Fontoura MA, Pinto A, Pimentel-Silva LR, Avansini SH, de Carvalho M. Between neurons and networks: investigating mesoscale brain connectivity in neurological and psychiatric disorders. Frontiers in Neuroscience. 2024 Feb 20;18:1340345.
62. Grover N, Chharia A, Upadhyay R, Longo L. Schizo-Net: A novel Schizophrenia Diagnosis Framework Using Late Fusion Multimodal Deep Learning on Electroencephalogram-Based Brain Connectivity Indices. IEEE Transactions on Neural Systems and Rehabilitation Engineering. 2023;31:464-73.
63. Feng C, Yuan J, Geng H, Gu R, Zhou H, Wu X, *et al.* Individualized prediction of trait narcissism from whole-brain resting-state functional connectivity. Human Brain Mapping. 2018;39(9):3701-12.
64. D'Souza NS, Nebel MB, Crocetti D, Robinson J, Wymbs N, Mostofsky SH, Venkataraman A. Deep sr-DDL: Deep structurally regularized dynamic dictionary learning to integrate multimodal and dynamic functional connectomics data for multidimensional clinical characterizations. NeuroImage. 2021 Nov 1;241:118388.
65. Ball G, Aljabar P, Arichi T, Tusor N, Cox D, Merchant N, *et al.* Machine-learning to characterise neonatal functional connectivity in the preterm brain. NeuroImage. 2016;124:267-75.
66. Cui Z, Xia Z, Su M, Shu H, Gong G. Disrupted white matter connectivity underlying developmental

dyslexia: A machine learning approach. Human Brain Mapping. 2016;37(4):1443-58.
67. Eill A, Jahedi A, Gao Y, Kohli JS, Fong CH, Solders S, *et al.* Functional Connectivities Are More Informative Than Anatomical Variables in Diagnostic Classification of Autism. Brain Connectivity. 2019;9(8):604-12.
68. Khosla M, Jamison K, Kuceyeski A, Sabuncu MR. Ensemble learning with 3D convolutional neural networks for functional connectome-based prediction. NeuroImage. 2019;199:651-62.
69. Li H, Parikh NA, He L. A novel transfer learning approach to enhance deep neural network classification of brain functional connectomes. Frontiers in neuroscience. 2018 Jul 24;12:491.
70. Ngo GH, Khosla M, Jamison K, Kuceyeski A, Sabuncu MR. Predicting individual task contrasts from resting-state functional connectivity using a surface-based convolutional network. Neuroimage. 2022;248:118849.
71. Nozais V, Boutinaud P, Verrecchia V, Gueye MF, Hervé PY, Tzourio C, *et al.* Deep Learning-based Classification of Resting-state fMRI Independent-component Analysis. Neuroinformatics. 2021;19(4):619-37.
72. Takagi Y, Sakai Y, Abe Y, Nishida S, Harrison BJ, Martínez-Zalacaín I, *et al.* A common brain network among state, trait, and pathological anxiety from whole-brain functional connectivity. Neuroimage. 2018;172:506-16.
73. Zhu J, Li Y, Fang Q, Shen Y, Qian Y, Cai H, *et al.* Dynamic functional connectome predicts individual working memory performance across diagnostic categories. NeuroImage: Clinical. 2021;30.
74. Gallo S, El-Gazzar A, Zhutovsky P, Thomas RM, Javaheripour N, Li M, *et al.* Functional connectivity signatures of major depressive disorder: machine learning analysis of two multicenter neuroimaging studies. Molecular Psychiatry. 2023;28(7):3013-22.
75. Cao J, Yang L, Sarrigiannis PG, Blackburn D, Zhao Y. Dementia classification using a graph neural network on imaging of effective brain connectivity. Computers in Biology and Medicine. 2024;168:107701.
76. Kam TE, Zhang H, Jiao Z, Shen D. Deep Learning of Static and Dynamic Brain Functional Networks for Early MCI Detection. IEEE Transactions on Medical Imaging. 2020;39(2):478-87.
77. Paquola C, Seidlitz J, Benkarim O, Royer J, Klimes P, Bethlehem RA, Larivière S, Vos de Wael R, Rodríguez-Cruces R, Hall JA, Frauscher B. A multi-scale cortical wiring space links cellular architecture and functional dynamics in the human brain. PLoS biology. 2020 Nov 30;18(11):e3000979.
78. Sobczak F, He Y, Sejnowski TJ, Yu X. Predicting the fMRI Signal Fluctuation with Recurrent Neural Networks Trained on Vascular Network Dynamics. Cereb Cortex. 2021;31(2):826-44.
79. Tozlu C, Jamison K, Gauthier SA, Kuceyeski A. Dynamic functional connectivity better predicts disability than structural and static functional connectivity in people with multiple sclerosis. Frontiers in neuroscience. 2021 Dec 13;15:763966.
80. Vu H, Kim HC, Jung M, Lee JH. fMRI volume classification using a 3D convolutional neural network robust to shifted and scaled neuronal activations. Neuroimage. 2020;223:117328.
81. Deshpande G, Libero LE, Sreenivasan KR, Deshpande HD, Kana RK. Identification of neural connectivity signatures of autism using machine learning. Frontiers in human neuroscience. 2013 Oct 17;7:670.
82. Feczko E, Balba NM, Miranda-Dominguez O, Cordova M, Karalunas SL, Irwin L, *et al.* Subtyping cognitive profiles in Autism Spectrum Disorder using a Functional Random Forest algorithm. NeuroImage. 2018;172:674-88.
83. Gupta S, Rajapakse JC, Welsch RE, Alzheimer's Disease Neuroimaging Initiative. Ambivert degree identifies crucial brain functional hubs and improves detection of alzheimer's disease and autism spectrum disorder. NeuroImage: Clinical. 2020 Jan 1;25:102186.
84. Lei D, Pinaya WHL, Young J, van Amelsvoort T, Marcelis M, Donohoe G, *et al.* Integrating machining learning and multimodal neuroimaging to detect schizophrenia at the level of the individual. Human Brain Mapping. 2020;41(5):1119-35.
85. Peña-Nogales Ó, Ellmore TM, de Luis-García R, Suescun J, Schiess MC, Giancardo L. Longitudinal connectomes as a candidate progression marker for prodromal Parkinson's disease. Frontiers in Neuroscience. 2019 Jan 9;12:967.
86. Poudel GR, Dominguez D JF, Verhelst H, Vander Linden C, Deblaere K, Jones DK, *et al.* Network diffusion modeling predicts neurodegeneration in traumatic brain injury. Annals of Clinical and Translational Neurology. 2020;7(3):270-9.
87. Puzniak RJ, Prabhakaran GT, Hoffmann MB. Deep Learning-Based Detection of Malformed Optic Chiasms From MRI Images. Front Neurosci. 2021;15:755785.
88. Rakić M, Cabezas M, Kushibar K, Oliver A, Lladó X. Improving the detection of autism spectrum disorder by combining structural and functional MRI information. NeuroImage: Clinical. 2020 Jan 1;25:102181.
89. Zilcha-Mano S, Zhu X, Suarez-Jimenez B, Pickover A, Tal S, Such S, *et al.* Diagnostic and Predictive Neuroimaging Biomarkers for Posttraumatic Stress Disorder. Biological Psychiatry: Cognitive Neuroscience and Neuroimaging. 2020;5(7):688-96.
90. Udayakumar P, Subhashini R. Connectome-based schizophrenia prediction using structural connectivity-Deep Graph Neural Network (sc-DGNN). Journal of X-Ray Science and Technology. 2024 May 29(Preprint): 1 Jan. 2024; 32(4) : 1041-1059.
91. Jeong JW, Lee MH, O'Hara N, Juhász C, Asano E. Prediction of baseline expressive and receptive language function in children with focal epilepsy using diffusion tractography-based deep learning network. Epilepsy & Behavior. 2021 Apr 1;117:107909.
92. Fede SJ, Grodin EN, Dean SF, Diazgranados N, Momenan R. Resting state connectivity best predicts alcohol use severity in moderate to heavy alcohol users. NeuroImage Clinical. 2019;22:101782. doi:10.1016/j.nicl.2019.101782.
93. Paldino MJ, Zhang W, Chu ZD, Golriz F. Metrics of brain network architecture capture the impact of

disease in children with epilepsy. NeuroImage: Clinical. 2017;13:201-8.
94. Peraza LR, Díaz-Parra A, Kennion O, Moratal D, Taylor JP, Kaiser M, *et al.* Structural connectivity centrality changes mark the path toward Alzheimer's disease. Alzheimer's and Dementia: Diagnosis, Assessment and Disease Monitoring. 2019;11:98-107.
95. Yasaka K, Kamagata K, Ogawa T, Hatano T, Takeshige-Amano H, Ogaki K, *et al.* Parkinson's disease: deep learning with a parameter-weighted structural connectome matrix for diagnosis and neural circuit disorder investigation. Neuroradiology. 2021;63(9):1451-62.