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# Deep learning frameworks for MRI-based diagnosis of neurological disorders: a systematic review and meta-analysis

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**Abstract**
The automatic diagnosis of neurological disorders using Magnetic Resonance Imaging (MRI) is a widely researched problem. MRI is a non-invasive and highly informative imaging modality, which is one of the most widely accepted and used neuroimaging modalities for visualizing the human brain. The advent of tremendous processing capabilities, multi-modal data, and deep-learning techniques has enabled researchers to develop intelligent, sufficiently accurate classification methods. A comprehensive literature review has revealed extensive research on the automatic diagnosis of neurological disorders. However, despite numerous studies, a systematically developed framework is lacking, that relies on a sufficiently robust dataset or ensures reliable accuracy. To date, no consolidated framework has been established to classify multiple diseases and their subtypes effectively based on various types and their planes of orientation in structural and functional MR images. This systematic review provides a detailed and comprehensive analysis of research reported from 2000 to 2023. Systems developed in prior art have been categorized according to their disease diagnosis capabilities. The datasets employed and the tools developed are also summarized to assist researchers to conduct further studies in this crucial domain. The contributions of this research include facilitating the design of a unified framework for multiple neurological disease diagnoses, resulting in the development of a generic assistive tool for hospitals and neurologists to diagnose disorders precisely and swiftly thus potentially saving lives, in addition to increasing the quality of life of patients suffering from neurodegenerative disorders.

**Keywords** Brain MRI · Classification · Computer aided diagnosis · Deep learning · Neurological diseases

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## 1 Introduction

Neurological disorders are among the most common causes of death worldwide. Even in developed countries with adequate medical facilities, disorders such as Alzheimer's disease (AD) and stroke are among the top three biggest killers (WHO 2020). With timely diagnoses, neurological disorders can be cured or contained (Minz and Mahobiya 2017; Yagis et al. 2021), thereby saving lives and the quality of life could be improved for patients with non-curable neurodegenerative disorders (Nandpuru et al. 2014; Minz and Mahobiya 2017;Mikolas et al. 2018; Majib et al. 2021; Ocasio and Duong 2021; Zhang 2022; Alhassan et al. 2022; Garcia-Gutierrez et al. 2022; Wood et al. 2022 ). Diagnosing neurological disorders based solely on clinical findings is difficult (Nandpuru et al. 2014), because hallmark symptoms may not always be present, especially in the early phase of a disease (Nemoto et al. 2021). Conventional computer vision (CV) algorithms are generally not capable to process vast datasets and assimilate classification features from them. Artificial Intelligence (AI) proved to be a game changer in this direction, with the capabilities to analyze massive data and tune millions of learnable parameters adaptively in real-time. This resulted in an exponential increase in classification accuracies, though at the cost of computational intensiveness. This issue was resolved by the marvels the graphics processing unit (GPU) technology has achieved over the past decade in terms of computational speed (Boeken et al. 2023). The recent massive data storage and processing capabilities of machines paved the way for AI to be an integral part of our lives in the world today. AI in healthcare (Miotto et al. 2018) and medical imaging (Greenspan et al. 2016) has played a pivotal role in the past decade, resulting in the development of fast, accurate, and automatic systems for assisting in the diagnosis, treatment, and monitoring of patients. Neurological disorders are no exception (Ahmed et al. 2018). A tremendous amount of research has used multi-modal brain signals to assist doctors and patients in the diagnosis, prognosis, and management of neurological disorders (Yang et al. 2018). Among the numerous available biomedical imaging modalities, Magnetic Resonance Imaging (MRI) is often considered the most versatile and non-invasive imaging tool for examining the human body. MRI offers high spatial resolution, high soft tissue contrast, tomographic imaging, multidirectional scans, and the integration of anatomical, physiological, metabolic, and functional imaging features. These have assisted neurologists in diagnosing a vast number of disorders Tian et al. (2021). MRI measurements vary widely depending on the technology used, brain scan orientation, and magnetic strength. In addition to planar data that deal with 2D brain images (slices), 3D volumetric MRI data of the entire brain are available for expert and machine examination. Brain MRI images possess similar features, especially in the case of neurodegenerative disorders that contain subtle and intricate changes (Tomson 2006; Avants et al. 2008; Mikolas et al. 2018; Yagis et al. 2019) rendering the diagnostic process very challenging (Noor et al. 2019). Manual inspection of such images by experts produces diagnoses based on personal expertise (Kanmani and Marikkannu 2018; Majib et al. 2021), with a probability of misdiagnosis owing to subtle changes in such images depending on the disease stage and overlapping features (Mathkunti and Rangaswamy 2020; Talai et al. 2021), among other factors (Raghavaiah and Varadarajan 2022). In the case of experts being unavailable in remote areas, accurate and timely diagnosis can be a problem. From the perspective of Computer Aided Diagnosis (CAD), due to the similarity of features in MRI data, Deep Learning (DL) has outperformed traditional Machine Learning (ML) in classifying neurological disorders

Jo et al. (2019); Zhu et al. (2019); Rashid et al. (2020); Salehi et al. (2020); Zhang et al. (2020); Zhao and Zhao (2021); Abrol et al. (2021). With the help of DL, the structural (Mateos-Pérez et al. 2018; Bhatele and Bhadauria 2020; Falkai et al. 2022 ) and functional Rashid et al. (2020) states of the brain MRI can very well be examined and analyzed (Kumar and Karnan 2014; Liu et al. 2014; Somasundaram and Genish 2015; Miranda et al. 2016; Arora and Dhir 2017; Valliani et al. 2019; Mazurowski et al. 2019; Francis and Babu 2019; Tyagi 2019; DS 2019; Yao et al. 2020; Zhang et al. 2020; Wang et al. 2021; Zhao and Zhao 2021; Lima et al. 2022; Behrad and Abadeh 2022; Wang et al. 2022 ), assisting neurologists to reach an optimal diagnosis (Arbabshirani et al. 2017; Calhoun and Sui 2016). Substantial research has already been done toward the development of CAD systems to assist neurologists in reaching precise diagnoses (Mårtensson et al. 2020). Most proposed systems can diagnose a single disease but very few comprehensive frameworks have been proposed with the ability to diagnose multiple diseases. However, the models have been trained with very limited data and hence confidence in their accuracy is lacking.

Many studies have been conducted in this area; however, almost 64% of the work deals with the diagnosis of a single disease or with the binary normal/abnormal MRI classification, and only 36% of the research has presented or developed systems capable of handling the diagnosis of two or more diseases. In a thorough literature survey of more than 1200 research articles, postgraduate theses, and patents from 2000 to December 10, 2023, as presented in Fig. 1, only approximately 1% effectively diagnosed five or more neurological disorders using a single framework, but they too, with extremely limited training datasets achieved questionable performance accuracy (Khani et al. 2013; Aggarwal et al. 2021; Maleki et al. 2022; Castiglioni et al. 2021 ).

Along with the traditional treatment regimens for neurological disorders, many non-invasive intervention techniques also exist, including Transcranial Magnetic Stimulation (TMS) and transcranial Direct Current Stimulation (tDCS) (Wang et al. 2023;Camacho-Conde et al. 2023). Employing such techniques, very precise and well-controlled stimulation of cortical and subcortical brain areas can result in improvements in symptoms of major depression, AD, Parkinson's Disease (PD), Attention Deficit Hyperactivity Disorder (ADHD), and other neurological disorders Camacho-Conde et al. (2022). But in order to choose an appropriate intervention method or treatment course, the first and foremost step is the accurate diagnosis. The intervention techniques are beyond the purview of this work as this paper focuses primarily on the CAD systems.

This review provides the prior art selection criteria in Sect. 2. Sect. 2.5 describes the details pertaining to MRI-based neurological disorder diagnosis systems designed since 2000, ranging from two- to multiple-disease diagnosis frameworks. This section describes the capabilities and deficits of these diagnoses, assists in research, and builds on the motivation for developing a unified framework capable of assisting neurologists in accurately diagnosing multiple neurological diseases. The following two sections succinctly provide information on certain publicly available datasets and developed tools. This will be followed by challenges and future research in this area.

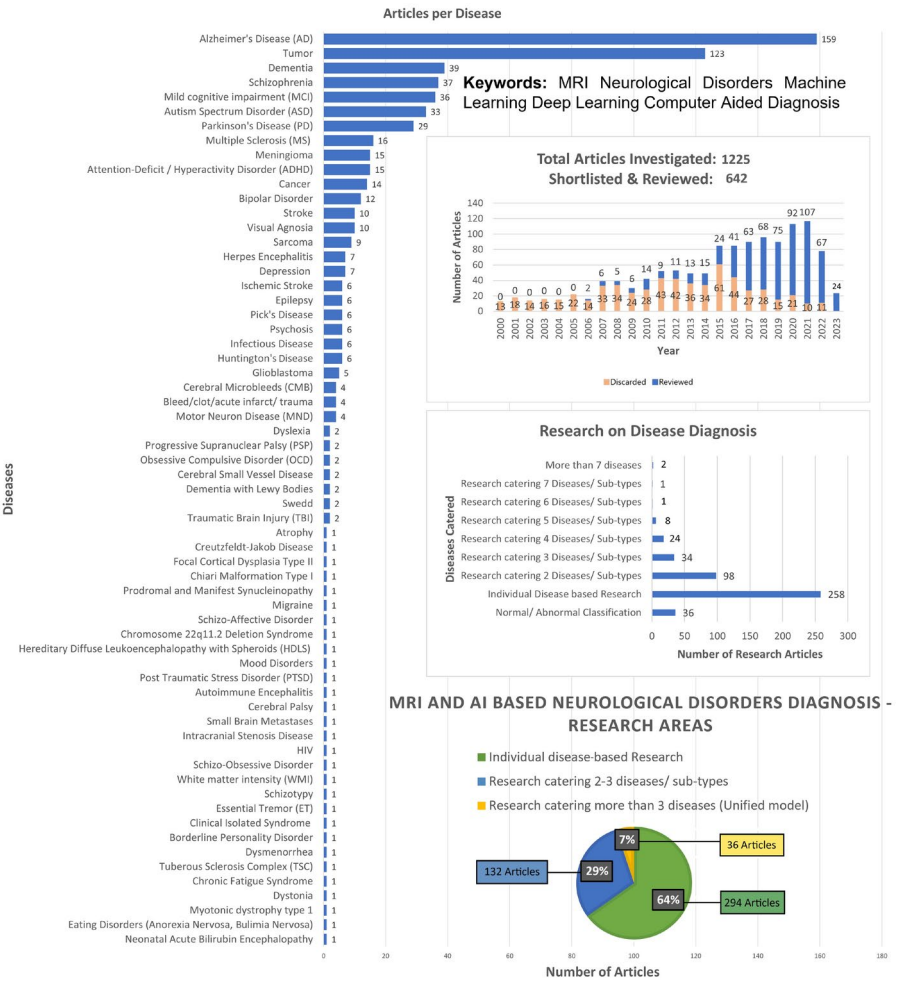


**Fig. 1** Statistics—Diseases studied for CAD using brain MRI (Left), total articles investigated, shortlisted and reviewed (Top), number of diseases catered per article (Center), individual to multiple disease CAD research (Bottom)

## 2 Materials and methods

### 2.1 Study selection

The host databases Scopus, Web of Science, and Google Scholar underwent keyword searches for articles published until 10 December 2023. The search phrases included "MRI and neurological disorder diagnosis using deep learning." The filters were set for each year from 2000 to 2023. The search returns per year were individually scanned, and the titles of articles included in the first 10 pages were examined. Only the most relevant articles with full-text access were downloaded. After removing the duplicates, these articles were later screened for abstracts, and only approximately half of the original number was retained.

This was followed by a thorough examination of the full texts, and the details of further disqualifications of articles are provided in subsequent sections and Fig. 2. We followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines.

## 2.2 Inclusion criteria

Research related to the CAD of neurological disorders using ML with MRI as the sole data modality was included in this review. The CAD of neurodegenerative disorders was also included, along with congenital malformations, trauma, stroke and vascular malformations, neoplasms, infectious or inflammatory diseases, and demyelinating diseases. Models that handle multiple types of MRI data, including structural and functional MRI data, were also considered in this review.

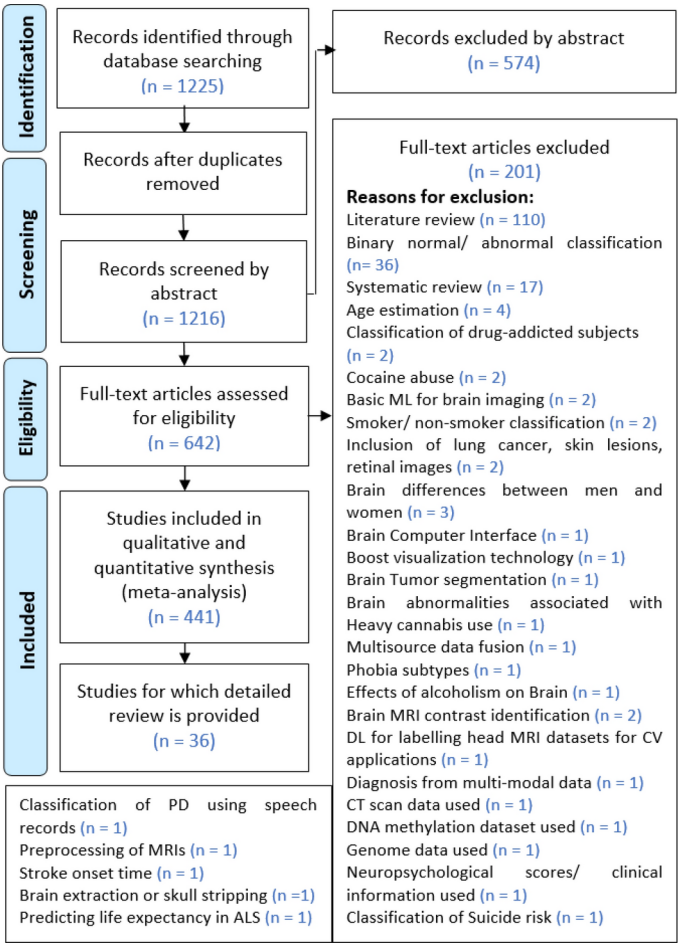


**Fig. 2** PRISMA study selection diagram—of the 1225 articles identified, 441 were included in the qualitative and quantitative analysis. Details of the articles excluded are briefly stated

### 2.3 Exclusion criteria

Various articles were excluded from this review based on certain criteria, they are enumerated here.

1. **Normal/abnormal brain classification** Studies dealing with normal/abnormal brain classifications without a diagnosis of a specific disease were excluded, since such systems do not have the capability to serve as CAD tools.
2. **One to three disease diagnosis** Single-, two-, and three-disease diagnosis systems were studied and included in the meta-analysis; however, their details were excluded for brevity. This was done due to the overwhelming number of research articles (390).
3. **Literature Reviews** Systematic and Literature reviews have also been excluded from this review.
4. **Age/Gender Prediction** Research to infer age and sex information from MRI images was also excluded. Although such age inference can be useful in obtaining maximum information about the patient and reaching a concrete diagnosis if a patient's history is unavailable.
5. **Drug, alcohol abuse/addiction classification** Studies identifying drug abuse from brain MRIs have also been excluded but could be considered if a generic unified framework must be designed for the complete assessment of a patient using a single modality, that is a brain MRI. Patients with smoking status, alcoholism, cocaine abuse, and brain abnormalities associated with heavy cannabis use were excluded from this category.
6. **Phobia identification** Classification of Phobia types was excluded, although this category could also be included in a robust CAD system.
7. **Multi-modal Data** Cases of CAD using modalities other than brain MRI were also excluded. Such modalities include Computed Tomography (CT), speech, Deoxyribonucleic acid (DNA), genome information, data acquired from other sensors, questionnaires, neuropsychological scores, and other clinical information. The reason for this was to keep the CAD system as simple and economical as possible and to identify the potential of MRI data alone for accurate diagnosis.
8. **Brain MRI contrast identification, Brain extraction, Skull stripping** Research falling under this section could also be useful in developing an omnipotent CAD tool but has been excluded here for brevity.
9. **Life expectancy prediction, inference of onset times** Yet another important aspect which a powerful CAD tool must have, excluded here.
10. **Miscellaneous** Studies on brain segmentation, basic ML for brain imaging, and preprocessing of MRIs, among others, were excluded to limit the scope of this review. The main reasons are given in Fig. 2.

### 2.4 Highlights and information extracted

The following information was extracted and summarized from the articles reviewed in this study.

1. Year of study.
2. Diseases researched.

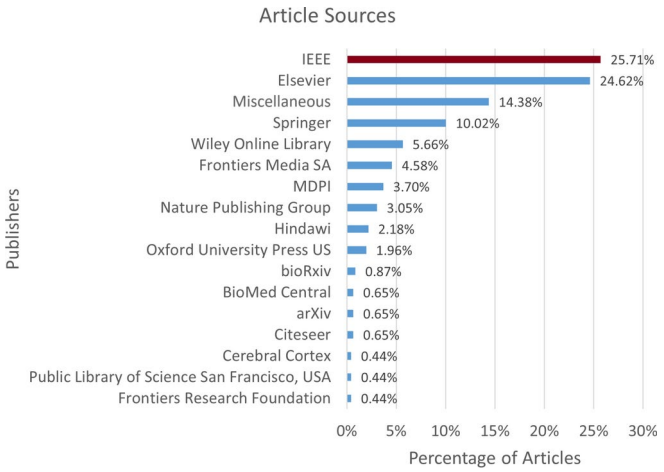


**Fig. 3** Article sources—percentages computed from a total of 441 articles. IEEE dominant

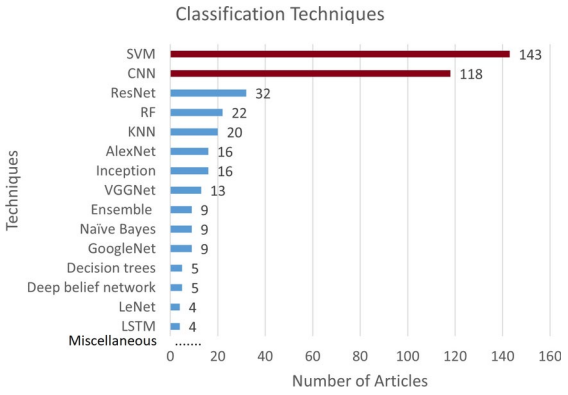


**Fig. 4** Classification methods used in articles—numbers computed from a total of 441 articles. Support Vector Machine (SVM) and Convolutional Neural Networks (CNN) dominant

3. Classification techniques used.
4. Accuracy of developed techniques.
5. Datasets used.
6. MRI types and orientations used.
7. Number of MRI images used for training.

Most articles were selected from IEEE, followed by Elsevier publications (Fig. 3). The top two classification techniques applied were Support Vector Machines (SVMs) and Convolutional Neural Networks (CNNs), followed by transfer learning (Fig. 4). The Alzheimer's Disease Neuroimaging Initiative (ADNI) dataset was the most commonly used (Fig. 5), with T1-weighted (T1W) structural MRI employed for diagnosis in the majority of studies (Fig. 6). Most researchers prefer the axial MRI planes (Fig. 7). Figure 8 shows the relationship between number of images used for training and the corresponding accuracy of the model developed for single-disease diagnosis, where as Fig. 9 shows the same for multiple

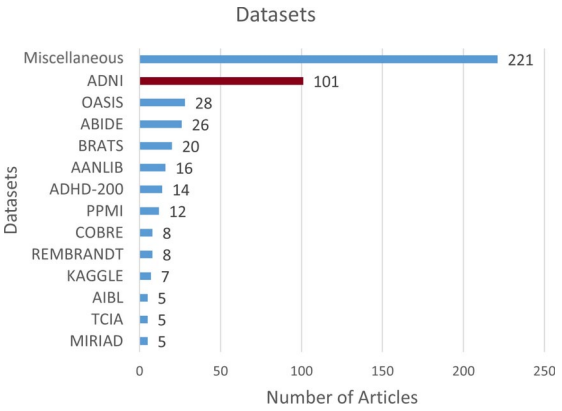


**Fig. 5** Publicly available Dataset Statistics—numbers computed from a total of 441 articles. Alzheimer's Disease Neuroimaging Initiative (ADNI) dominant since AD is the most widely researched disease in CAD systems

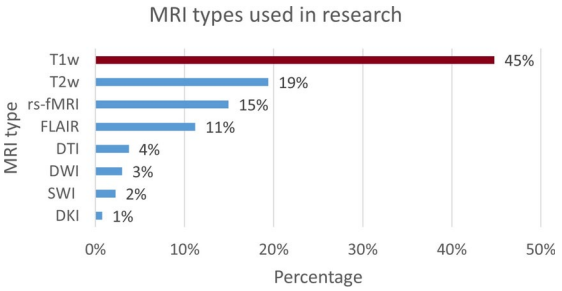


**Fig. 6** Brain MRI types, usage-percentages computed from a total of 441 articles. T1-weighted MRI dominant

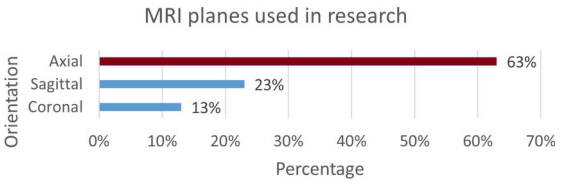


**Fig. 7** Brain MRI planes usage—percentages computed from a total of 441 articles. Axial orientation dominant

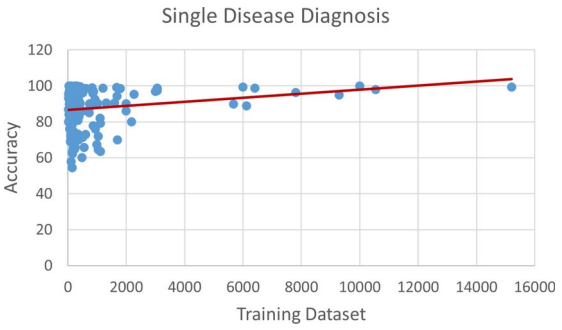


**Fig. 8** Training dataset vs. accuracy for single disease diagnosis—The blue dots represent individual studies, and the red line represents the trend

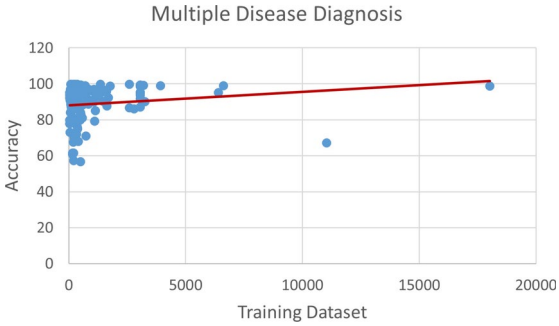


**Fig. 9** Training dataset vs. accuracy for multiple disease diagnosis—The blue dots represent individual studies, and the red line represents the trend

disease classification systems. This confirms that the larger the dataset, the better the system's accuracy.

### 2.5 The evolution of AI-based CAD approaches for neurological disorders

Research on computer-aided neurological disorder diagnosis using MRI started using ML approximately two decades ago Arimura et al. (2009), with algorithms such as the SVM dominating the classification aspect and support from techniques such as Principal Component Analysis (PCA) for dimensionality reduction and computational efficiency. This was followed by the advent of DL (Quaak et al. 2021) which has proven to be a faster, more accurate, and efficient approach (Qiu et al. 2018) because the feature extraction part, which was conducted separately in ML, is integrated, making it easier for scientists and researchers to extract latent features quickly and train, test, analyze, compare, tune, optimize, and deploy their models in real-time applications (Zegers et al. 2021). Aggressive research in the domain of DL has enabled such models to be deployed on machines with high computational capabilities and storage space (using TensorFlow (TF) as an example), on mobile devices (TFLite), and later, on low-power chips using TinyML. Research on CAD for neurological disorders has gradually grown to multiclass (multiple diseases) diagnosis from the simple binary (normal/abnormal) classification or identification of a single disease. A thorough literature survey was conducted, which consisted of more than 1200 articles (from conference/journal papers, theses, and patents). It was observed that a great deal of research has been conducted on single disease diagnosis as well as normal/abnormal classification, but only a very small fraction capable of handling the diagnosis of multiple diseases was found. Figure 1 shows the statistics of the literature survey along with the search keywords. Among more than 63 neurological disorders researched since 2000, most have been on the diagnosis of AD and its types. AD is a neurodegenerative disorder that starts with Mild Cognitive Impairment (MCI) and memory loss and may later progress into severe degradation in socializing traits. Extensive research has been conducted to diagnose AD Ahmed et al. (2018); Pellegrini et al. (2018); Yamanakkanavar et al. (2020);Altinkaya et al. (2020); Lazli et al. (2020); Al-Shoukry et al. (2020); Ebrahimighahnavieh et al. (2020); Ansart et al. (2021); Arafa et al. (2022); Frizzell et al. (2022); Loddo et al. (2022) with the majority focusing on SVMs and CNNs (Bernal et al. 2019 ) for classification. Systems that distinguish patients with AD from MCI and normal controls have also been studied and proposed in large numbers. The second most researched disease is brain tumors Kamboj et al. (2018); Somasundaram and Gobinath (2019); Shaver et al. (2019); Tandel et al. (2019); Gore and

Deshpande (2020) Nadeem et al. (2020); Abbood et al. (2021); Al-Galal et al. (2021); van Kempen et al. (2021); Nazir et al. (2021); Arabahmadi et al. (2022); Neromyliotis et al. (2022). Brain or central nervous system cancer is the twelfth leading cause of death in both men and women (Ilic and Ilic 2023; Tandel et al. 2020). Most studies deal with the classification of MRI scans with or without tumors. Others have classified tumors as benign or malignant, whereas a small fraction has worked to identify multiple types of tumors in a multi-class paradigm. Substantial research has been conducted on tumor segmentation. CAD systems using ML/DL and MRI for other neurological disorders predominantly Autism Spectrum Disorder (ASD) Khodatars et al. (2007); Yulianto et al. (2018); Parlett-Pelleriti et al. (2022), PD Noor et al. (2020), Multiple Sclerosis (MS) (Kontopodis et al. 2021;Shoeibi et al. 2021 ), ADHD Eslami et al. (2021), Stroke, Schizophernia Guney et al. (2021); Quaak et al. (2021), among others, have also been presented, but in relatively lower numbers. Additionally, research on inferring sex Xin et al. (2019); Yeung et al. (2022), age (Herent et al. 2018; Yeung et al. 2022 ) and smoking (Ding et al. 2015)/drug abuse has also been conducted, and the inferences of these models can be used in neurological disorder diagnosis models to make the best possible diagnosis from MRI. In some disorders, information pertaining to age, sex (Jang et al. 2022) and drug abuse (Yücel et al. 2008 ) can be useful in diagnosing the disease based on the features presented on MRI. In addition to the research mentioned above, a multitude of sensors (Krokidis et al. 2022) available in Android devices Krichen (2021) have been used for gathering information such as patient speech, facial expressions (Gola et al. 2017; Yolcu et al. 2017) and gait Chen et al. (2021), among others. Analysis of these supplementary data using various computer vision/image processing techniques, Natural Language Processing (NLP), statistical analysis algorithms, and thresholding have also been used in CAD. In addition, various standard questionnaires Prisnie et al. (2018) have been used to assist patients with CAD Lahmiri and Shmuel (2019). However, incorporating such methodologies in addition to MRI data may result in a computational time overhead for processing supplementary data. To simplify the framework and utilize the capabilities of DL to identify features and classify very similar MRIs with minor differences owing to disorders, supplementary sensor data were not incorporated in this research, aiming to infer multiple neurological disorders using only one modality as an input to the framework with adequate accuracy.

### 2.6 Review of multi-class CAD systems

The following section covers the crux of the survey with reference to a subset of the literature reviewed for brevity. The literature surveyed was categorized according to the number of diseases diagnosed. For brevity, four or more diseases/classes (Table 1) classification research is presented here. In the subsequent section, research catering to the MRI-based diagnosis of four or more diseases/classes (Table 1) is later discussed in detail, stating strengths and weaknesses, to build on the premise for future research directions.

**Table 1** ML- or DL-based research catering to CAD of four or more diseases/classes

| No | Paper | Disease | Technology | Accuracy | Dataset |
|---|---|---|---|---|---|
| 1 | Luts et al. (2007) | Normal tissue, Cerebrospinal Fluid (CSF), grade II diffuse astrocytomas, grade II oligoastrocytomas, grade II oligodendrogliomas, grade III astrocytomas, grade III oligoastrocytomas, grade III oligodendrogliomas, meningiomas, and grade IV gliomas | LS-SVMs, Linear Discriminant Analysis (LDA) | 92.05%—99.9% | MRI and Magnetic Resonance Spectroscopic Imaging (MRSI) data from the INTERPRET project database. 25 patients with a brain tumor and 4 volunteers |
| 2 | Khani et al. (2013) | AD, Alzheimer plus visual agnosia, Glioma, Huntington's Disease (HD), Meningioma, Pick, and Sarcoma | 2D Discrete Wavelet Transform (DWT), GARCH, PCA, LDA, SVM | Up to 100% | Harvard Medical School website—80 images, 10 images per category—T2-weighted (T2W) |
| 3 | Saritha et al. (2013) | Stroke, infectious disease, degenerative disease, brain tumor | Probabilistic neural network | Normal 100%, Stroke 91.3%, Degenerative disease 100%, Infectious disease 91.3%, Brain tumor 95.7% | Harvard Medical School website—T2W axial. 75 images, 15 in each category |
| 4 | Hemanth et al. (2014) | 4 Metastase, glioma, meningioma, and astrocytoma | Modified Counter Propagation Neural Network (MCPN), Modified Kohonen Neural Network (MKNN) | Up to 98% | 540 images—collected from radiologists |
| 5 | Sabuncu and Koglu (2015) | AD, Schizophrenia (SZ), ASD, ADHD; age, cerebrospinal fluid derived amyloid-$\beta$ levels and mini-mental state exam score | Multivariate Pattern Analysis (MVPA) | Up to 86 % | 2,800 subjects, from Harvard, ADNI, OASIS, ABIDE, ADHD-200 Consortium, COBRE, MCIC—T1W |
| 6 | Sooriya (2017) | Astrocytoma, Glioblastoma Multiforme, Oligodendroglioma, Healthy tissue, Unidentified tumor | CNN | 99.68% | REMBRANDT—Images of Normal Subjects (BRAINS) ImageBank repository of University of Edinburgh and from MIRIAD—axial, coronal and sagittal |

**Table 1** (continued)

| No | Paper | Disease | Technology | Accuracy | Dataset |
|---|---|---|---|---|---|
| 7 | Ion-Mărgin et al. (2017) | MS—Clinically Isolated Syndrome (CIS), Relapse Remitting (RR), Primary Progressive (PP), and Secondary Progressive (SP) | LDA, SVM, Random Forest (RF) | F1-score up to 87% | 87 MS patients (12 CIS, 30 RR, 17 PP, and 28 SP) and 18 Healthy Controls (HCs). Longitudinal data available for each MS patient included clinical (e.g., age, disease duration, Expanded Disability Status Scale), conventional MRI, T1W and spectroscopic imaging |
| 8 | Rachma et al. (2017) | White Matter Hyperintensity (WMH), Very Small (VS), Small (S), Medium (M), Large (L), Very Large (VL) | Deep Boltzmann Machine (DBM), Convolutional Encoder Network (CEN), patch-wise CNN (patch-CNN), SVM, RF | Dice Similarity Coefficient (DSC) up to 0.6489 | ADNI—60 MRI data from 20 subjects |
| 9 | Usman and Rajpoot (2017) | Brain tumor—background, necrosis, edema, enhancing tumor, and non-enhancing tumor | RF | 90% ± 3. 88% Dice overlap for the complete tumor region, 75% for the core tumor region and 95% for enhancing tumor region | MICCAI BraTS 2013—T1, T2, Gadolinium-Contrast-enhanced T1 (T1C) and Fluid-Attenuated Inversion Recovery (FLAIR) |
| 10 | Hemanth et al. (2018) | Metastasis, Meningioma, Glioma, and Astrocytoma | CNN | Up to 97.1% | Brain tumor images collected from M/s. Devaki Scan Centre. Total 220—T1, T2 and T2 FLAIR images |
| 11 | Kazemi and Hough (2018) | AD Stages—Normal Control (NC), significant memory concern (SMC), Early Mild Cognitive Impairment (EMCI), Late Mild Cognitive Impairment (LMCI), AD | AlexNet | 94.97% for AD, 95.64% for EMCI, 95.89% for LMCI, 98.34% for NC, and 94.55% for SMC | ADNI—Resting state-functional MRI (rs-fMRI) scans of 197 subjects |

**Table 1** (continued)

| No | Paper | Disease | Technology | Accuracy | Dataset |
|---|---|---|---|---|---|
| 12 | Islam and Zhang (2018) | AD—Non-demented, very mild dementia, mild dementia, moderate dementia | Inception-v4, ResNet | 99% for non-demented stage, 75% for very mild stage, 62% for mild stage, and 33% for moderate stage | OASIS |
| 13 | Talo et al. (2019) | Normal, cerebrovascular, neoplastic, degenerative, and inflammatory diseases classes | Five pre-trained models including ResNet | 95.23% ± 0.6 | Harvard Medical School database—42 subjects used in five categories |
| 14 | Abrol et al. (2019) | Cognitively normal (CN) aging adults, MCI, AD, BD probands (BDP), schizoaffective disorder probands (SADP), and SZ probands (SZP) | ResNet | CN vs. AD 91%, sMCI vs. AD (86%), CN vs. pMCI (86%) and sMCI vs. pMCI (77%), CN vs. sMCI 65% and pMCI vs. AD 66% | ADNI and BSNIP—828 ADNI baseline scans, 1013 subjects from BSNIP |
| 15 | Khagi et al. (2019) | AD—non-demented for Clinical Dementia Rating (CDR) 0, very mild dementia for CDR 0.5, mild dementia for CDR 1 and moderate dementia for CDR 2 | CNN, Mutinffs, ReliefF, Laplacian and UDFS, SVM, k-nearest neighbors (kNN), Subspace ensemble | 99% | OASIS—sagittal view—18 subjects for CDR level 0, 16 subjects for CDR 0.5, 12 subjects for CDR 1 and 4 subjects for CDR 2, altogether 50 subjects with 5220 images |
| 16 | Nayak et al. (2020) | Degenerative disease, stroke, tumor, infectious disease, and normal | CNN | 97.50–100% | MD-1, 75 brain MRIs. MD-2, 200 brain MRIs. Harvard Medical School dataset—T2W axial |
| 17 | Rudie et al. (2020) | 35 Diseases | 3D-CNN | — | Multimodal brain MRI scans from 212 patients |
| 18 | Mehmod et al. (2020) | AD—CDR-0 (No Dementia), CDR−0.5 (Very Mild Dementia), CDR-1 (Mild-Dementia), and CDR-2 (Moderate AD) | Siamese CNN (SCNN) | 99.05% | OASIS—382 images. 167 CDR-0 (No Dementia), 87 CDR−0.5 (Very Mild Dementia), 105 CDR-1 (Mild-Dementia), and 23 CDR-2 (Moderate AD) |
| 19 | Ramzan et al. (2020) | AD Stages—CN, SMC, EMCI, MCI, LMCI, and AD | ResNet-18 | 97.92% | ADNI—A longitudinal cohort of resting-state fMRI of 138 subjects (25 CN, 25 SMC, 25 EMCI, 25 LMCI, 13 MCI, and 25 AD) |

**Table 1** (continued)

| No | Paper | Disease | Technology | Accuracy | Dataset |
|---|---|---|---|---|---|
| 20 | Bashyam et al. (2020) | Brain age and AD, MCI, SZ, and major depression | Inception-Resnet-v2 | Up to 86% | T1W brain MRI scans from NCs (n= 11,729). ADNI 1 and 2 (n= 1699, NC = 513, MCI = 833, AD = 353), SZ consortium (n= 835, NC = 448, schizophrenia = 387) and matched NC and major depression subjects from UK Biobank (n= 408, NC = 204, major depression = 204) |
| 21 | Deepa et al. (2021) | High-grade tumor, low-grade tumor, acute stroke, sub-acute stroke | Hybridized support vector-based RF classifier | 88.3% for brain tumor and 99.2% for stroke | BRATS 2013 and ISLES—1100 image, 600 tumor affected and 500 stroke affected images |
| 22 | Chagué et al. (2021) | Dementia—early-onset AD (EOAD), late-onset AD (LOAD), Frontotemporal Dementia (FTD), depression | SVM | Up to 82% | 3D T1 MRI—34 patients with EOAD, 49 with LOAD, 39 with FTD and 24 with depression from the pre-existing cohort CLIN-AD. Department of Neuroradiology at Pitie-Salpetriere Hospital |
| 23 | Mozhdeh et al. (2021) | PD stages—Control, Prodromal, as well as stages 1, 2 and 3 | CNN | 94% | PPMI—100 images, 20 subjects for each stage of PD and 20 NC |
| 24 | Poyraz et al. (2022) | Atrophy, normal, white matter intensity WMI, and ischemia | MobilNetV2, Iterative Neighborhood Component Analysis (INCA), SVM | 99.10% | 444 MR images. 100, 150, 92, and 102 brain MR images for atrophy, normal, white matter intensity WMI, and ischemia categories |
| 25 | Zhu et al. (2022) | Chronic SZ (ChSZ) from HCs, First-Episode Psychosis (FEP), ultra-high risk for psychosis (UHR), ASD | PCA, SVM | Up to 76% | Total 359 T1W MRI scans, 154 with SZ spectrum (UHR, n = 37; FEP, n = 24; and ChSZ, n = 93), 64 with ASD, and 141 HCs |
| 26 | Marwa et al. (2023) | AD, Non-Demented (ND), Moderately Demented (MoD), Mild Demented (MD), and Very Mild Demented (VMD) | CNN | 99.68% | OASIS—3200, 64, 896, and 2240 images for ND, MoD, MD, and VMD respectively |
| 27 | Yousaf et al. (2023) | Normal tissue, necrosis, edema, non-enhancing tumor, and enhancing tumor, acute and sub- acute stroke | Encoder-decoder architecture based UNET | 99.56% | BRATS 2015 and ISLES 2015 |
| 28 | Thangavel et al. (2023) | ND, VMD, MD, MoD | ResNet | 98% | 374 records from Github and Kaggle |
| 29 | Srinivasan et al. (2023) | Glioma, meningioma, no tumor, and pituitary tumor | RCNN | 98.17% | REMBRANDT dataset—620 MR images for testing, 2480 for training from 235 patients |

**Table 1** (continued)

| No | Paper | Disease | Technology | Accuracy | Dataset |
|---|---|---|---|---|---|
| 30 | El-Latif et al. (2023) | ND, VMD, MD, MoD | CNN | 95.93% | Alzheimer's 4 class Dataset—Kaggle 6400 images |
| 31 | Mujahid et al. (2023) | ND, VMD, MD, MoD | EfficientNet-B2 and VGG-16 | 97.35% | Kaggle—3200, 64, 896, and 2240 images for ND, MoD, MD, and VMD respectively |
| 32 | Yao et al. (2023) | ND, VMD, MD, MoD | Fuzzy-VGG | Up to 97% | 9109 2D MRI samples from Kaggle Alzheimer's classification dataset (KACD) and 749 3D MRI samples from the Recognition of Alzheimer's Disease dataset (ROAD) |
| 33 | Apostolopoulos et al. (2023) | Glioma, meningioma, and pituitary tumor. AD, PD, and HC. ND, VMD, MD, MoD | Attention Feature Fusion VGG19 (AFF-VGG19) | 93.53% for three brain tumor classes, 95.65% for AD and PD, and 94.97% in grading cases of dementia | Kaggle—Brain Tumors Dataset (26,249), Brain Disorders Dataset (7756), Dementia Grading Dataset (6400 images) |
| 34 | Allada et al. (2023) | AD, EMCI, LMCI, MCI, HC | VGG-19 | 91.05% | 1326 images in 5 classes from ADNI |
| 35 | Saeedi et al. (2023) | Glioma, meningioma, pituitary tumor, and HC | 2D-CNN, autoencoder, kNN, RF, SVM, Logistic Regression (LR), Stochastic Gradient Descent (SGD), Multi-Layer Perceptron (MLP) | 96.47% for 2D-CNN, 95.63% for autoencoder and 86% for kNN | Kaggle—3264 T1w contrast-enhanced MRI. glioma (926), meningioma (937), pituitary gland tumor (901), and healthy brain (500 images) |
| 36 | Ullah and Jamjoom (2023) | ND, VMD, MD, MoD | CNN | 99.38% | Kaggle—3200, 64, 896, and 2240 images for ND, MoD, MD, and VMD respectively |

The table provides the diagnosable diseases, DL/ML architecture used, accuracy of inference, and dataset (and number of subject scans) used to train the system

## 3 Discussion

Luts et al. (2007) studied pattern recognition methods using MRI to assist medical experts in the CAD of brain tumors. Although a multiclass classification system, it only considers different types of tumors and no other diseases. Two modalities are used instead of one, rendering the data computationally intensive. In addition, the dataset used was very limited, rendering the accuracy of 99.9% questionable. Sabuncu et al. (2012) conducted an empirical benchmark MVPA study using structural neuroimaging. Although the datasets used in this study are reasonable, the disease set was limited. In addition, deep learning, which presents

a window for enhancing accuracy, has not been applied. The method proposed by Khani et al. (2013) classifies an MRI as normal or one of seven different diseases. The system was trained using a very limited dataset with only ten images per category, as well as from a single patient's volumetric MRI. This raises serious concerns regarding its performance. A similar limited dataset problem persists in studies by Ramzan et al. (2020),Chagué et al. (2021),Mozhdeh et al. (2021) and Hemanth et al. (2014). Saritha et al. (2013) combined wavelet-entropy-based spiderweb plots, probabilistic neural networks, and disease diagnosis using brain MRI. These diseases include stroke, degenerative diseases, infectious diseases, and brain tumors. They employed wavelet-entropy-based spiderweb plots for feature reduction, followed by a probabilistic neural network for classification. As expected, the sensitivity for detecting brain tumors was moderately good. However, degenerative and infectious diseases encompass a wide range of disorders and hence their system does not provide a pinpoint diagnosis. Sabuncu and Koglu (2015) used three classes of MVPA algorithms and structural measurements from brain MRIs to predict with varying degrees of accuracy, multiple parameters, including AD, Schizophrenia, Autism, as well as ADHD, age, cerebrospinal fluid-derived amyloid levels, and the Mini-Mental State Examination score. They claimed that although the choice of features has a considerable impact on prediction accuracy, clinical examination, and evaluation remain the gold standard determinants of diagnosis accuracy. Saritha et al. (2013) used only 15 images per class for a five-class classification system, catering for four diseases and a normal category. In addition, infectious and degenerative diseases were used as generalized categories, resulting in a system that lacks the capability for specific disease diagnosis. The accuracy of this study is questionable from the perspective of reliable diagnosis because of the small training dataset used. Sooriya (2017) proposed a CNN model to classify brain tumors into five classes using brain MRI. The model achieved an average F1-score of 99.46%. In addition, the proposed model's accuracy was 99.68%. Axial, coronal, and sagittal planes were used for training and testing. A limitation of this study was that it could only diagnose a single disease. Ion-Mărgin et al. (2017) presented the results for nine binary classification problems using clinical data, lesion loads, and metabolic features for MS. Their results indicated that metabolic features were better at differentiating between relapsing-remitting and primary progressive forms, whereas lesion loads were better at differentiating between relapsing-remitting and secondary progressive forms. They concluded that combining clinical data with magnetic resonance lesion loads and metabolic features could improve the discrimination between the relapsing-remitting and progressive forms. A modified DCNN was employed by Hemanth et al. (2018) to classify brain tumors into four classes using brain MRI. Only 20 images per category were used for training in this study, classifying brain tumors only. The accuracy was questionable because of the small dataset used for training. Kazemi and Hough (2018) applied the CNN-architecture AlexNet to fMRI datasets to classify five stages of AD. They successfully classified normal healthy controls, SMC, EMCI, LMCI, and AD however, the system is capable of handling only a single disease and its subtypes. Islam and Zhang (2018) proposed computer-aided early diagnosis of AD using brain MRI. Their study suggested that the non-demented stage can be predicted with very high accuracy, although the accuracy drastically decreases for very mild, mild, and moderate stages. Therefore, although the model has acceptable performance for non-demented patient classification, scope remains for improving the diagnosis of dementia. Training the proposed model with a dataset containing more samples from patients with dementia could help overcome this

limitation. Talo et al. (2019) compared the neurological disorder classification performances of different pretrained models. From among the five pre-trained models, they obtained the best classification accuracy of 95.23% ± 0.6 with the ResNet-50 model. The shortcomings of this study include the use of a limited dataset. In addition, very few neurological disorders were identified because the vaguely defined categories for Neoplastic, Cerebrovascular, Inflammatory and Degenerative diseases, encompass many disorders. Abrol et al. (2019) tested the diagnostic classification performance of the ResNet architecture. The diagnostic groups included cognitively normal aging adults, aging adults with MCI and neurodegenerative AD, and psychotic diagnostic groups such as bipolar disorder probands, schizoaffective disorder probands, and schizophrenia probands, which were studied in pairs; hence, several binary classification tasks were performed. The CN vs. AD classification task revealed the highest cross-validated accuracy of 91%, whereas the other tasks produced considerably lower accuracies. Khagi et al. (2019) utilized deep-layer features from a deep neural network architecture and trained ML architectures, such as SVM, kNN, and Subspace Ensemble, under different testing conditions for AD classification using those features. Nayak et al. (2020) employed a deep CNN-based approach to diagnose multi-class brain abnormalities. The proposed CNN model comprised five layers with learnable parameters: four convolutional layers and one fully connected layer. The limitations of this system include the limited dataset and few disease diagnoses. Multiple diseases are included in the generally defined categories of infectious and degenerative diseases, making diagnosis nonspecific. Only 165 images were used for training in the five categories, rendering the accuracy of up to 100% questionable. Rudie et al. (2020) used multimodal brain MRI scans of 212 patients with 35 neurological diseases. 3D CNN and atlas-based image processing were used to extract 11 imaging features. Expert-derived Bayesian networks incorporating domain knowledge were used for differential diagnosis. The system's performance was assessed by comparing its diagnostic accuracy with that of radiologists. A limited dataset was used in this study, with some categories being trained without images. Despite the significance of the disease pool, the system cannot serve as an assistive CAD tool for neurologists. Mehmod et al. (2020) developed a Siamese CNN model inspired by VGG-16 (also named OxfordNet) to classify dementia stages using augmentation to handle data imbalances. Although their system claimed acceptable accuracy, the disease pool for this CAD system was limited. Deepa et al. (2021) proposed a method for classifying tumors and strokes in MRI images using a hybrid ML algorithm. Texture-, intensity-, and shape-based features were used for classification. A maximum a priori (MAP)-based firefly algorithm was proposed for feature selection, and a hybridized support vector-based RF classifier was used for classification. This study used a reasonably sized dataset for training, but the diseases for which it caters are very few for it to act as a generic diagnostic assistance tool. The study deals only with tumors and stroke, with room for improving its 88.3% accuracy in classifying tumors. Poyraz et al. (2022) proposed an exemplar-based automated brain disease detection model using a computer vision technique with MobilNetV2 as the feature extractor and an SVM classifier. This study only dealt with three diseases. The training set was also limited, employing only 444 images in four categories, which resulted in questionable accuracy. Zhu et al. (2022) evaluated whether a model differentiating patients with chronic schizophrenia from healthy controls could be applied to earlier clinical stages, such as first-episode psychosis, ultra-high risk psychosis and ASD. A very limited number of diseases (ASD and types of SZ only) for diagnosis, only using 359 images in four categories

for training, and its low accuracy are the major weaknesses of this system. A similar trend was observed in the most recent research pertaining to CAD of multiple neurological disorders. Most of the multi-class research presented in 2024 was aimed at classifying brain tumors into gliomas, meningiomas, and pituitary gland tumors Zhou et al. (2024); Akter et al. (2024); Rastogi et al. (2024); Simo et al. (2024); Liu and Wang (2024); Haque et al. (2024); Agrawal and Maan (2024); Saboor et al. (2024), and different stages of AD Ayus and Gupta (2024); Li et al. (2024); Heidari and Ghazikhani (2024); El-Assy et al. (2024). These two diseases hold the most widely researched spot from CAD point of view. Although the accuracy claims in the proposed systems reach up to 99%, similar limitations including poor generalizability still persist, with capabilities to diagnose only a single disease and its subtypes or stages. Most research conducted in this domain lacks datasets of sufficient scale and deals with the diagnosis of a few diseases, mostly a single disease and its subtypes. This reflects the research gap that has attracted the attention of medical experts and data scientists.

### 3.1 Datasets

DL requires a substantial amount of training data to achieve optimal performance. Table 2 contains the details of the multiple datasets identified during the literature survey, including MRI data for various diseases. MRI data are available in Joint Photographic Experts Group (JPEG), Digital Imaging and Communications in Medicine (DICOM), or Neuroimaging Informatics Technology Initiative (NIfTI) data formats (Clayden et al. 2011). Most DICOM files involve a single slice for acquisition. Conversely, NIfTI files store volumetric data comprising multiple MRI slices that constitute the whole brain. In addition, axial, coronal, and sagittal views of the slices are available, which can serve as useful additional information sources for better diagnosis by analyzing multiple brain perspectives. After adequate pre-processing, these MRI signals can be used to train smart DL models using 2D slices and even 3D volumes, which produce the best results with minimum computational overhead.

### 3.2 Tools

Very few CAD tools have been developed to assist neurologists in differential diagnosis. Of the 441 articles analyzed, only four embedded their trained networks into publicly accessible tools. The tool developed by Deepa et al. (2021) classifies tumors and stroke only, dealing with two types of each, using the MATLAB Graphical User Interface (GUI). Helaly et al. (2021) developed a web-based application to diagnose AD and its types. Collective information on these tools and a few other tools is presented in Table 3.

### 3.3 Key findings

Binary normal/abnormal brain classification systems have very little impact on differential diagnosis and, therefore, cannot serve as CAD tools in medical practice. Most CAD research has revolved around single-disease diagnosis, with a few extensions to cater to their subtypes. Very few CAD systems have been proposed that are capable of handling multiple disorders. The major shortcoming of such systems is the inadequacy of the training data, rendering them unreliable. Some systems trained with substantial datasets have low

**Table 2** Publicly available datasets containing brain MR scans with different pathologies

| No | Dataset | Details |
|---|---|---|
| 1 | OpenNeuro https://openneuro.org/search/modality/mri | 538 Public Datasets |
| 2 | fastMRI (Zbontar et al. 2018) https://fastmri.med.nyu.edu/ | 6,970 fully sampled brain MRIs |
| 3 | The MICCAI 2008 MS Lesion Segmentation Challenge Dataset https://www.nitrc.org/projects/msseg | MS |
| 4 | The MICCAI 2016 MS Lesion Segmentation Challenge Dataset (Commowick et al. 2021) https://shanoir.irisa.fr/shanoir-ng/challenge-request | MS |
| 5 | ISBI 2015 Longitudinal MS Lesion Segmentation Challenge Dataset (Carass et al. 2017 ) https://smart-stats-tools.org/lesion-challenge | MS |
| 6 | eHealth Lab http://www.medinfo.cs.ucy.ac.cy/index.php/facilities/32-software/218-datasets | MS |
| 7 | UK Biobank and Human Connectome Project (Alfaro-Almagro et al. 2017 ) | - |
| 8 | Alzheimer's Disease Neuroimaging Initiative (ADNI) (Jack Jr et al. 2008 ) https://adni.loni.usc.edu/methods/mri-tool/standardized-mri-data-sets/ | AD |
| 9 | The Open Access Series of Imaging Studies (OASIS) database (Marcus et al. 2007) https://www.oasis-brains.org/ | AD |
| 10 | Parkinson's Progression Markers Initiative (PPMI) (Marek et al. 2011) https://www.ppmi-info.org/access-data-specimens/download-data | PD |
| 11 | Center for Biomedical Research Excellence (COBRE) https://tinyurl.com/fcon1000-cobre | Schizophrenia |
| 12 | The Minimal Interval Resonance Imaging in Alzheimer's Disease (MIRIAD) dataset (Malone et al. 2013) https://www.ucl.ac.uk/drc/research/research-methods/minimal-interval-resonance-imaging-alzheimers-disease-miriad | AD |
| 13 | National Alliance for Medical Image Computing (NAMIC) https://www.na-mic.org/wiki/Downloads | Schizophrenia, Autism, Lupus |
| 14 | The Federal Interagency Traumatic Brain Injury Research (FITBIR) informatics system datasets https://fitbir.nih.gov/ | Traumatic Brain Injury |
| 15 | Function Biomedical Informatics Research Network (FBIRN) Keator et al. (2016) http://www.schizconnect.org/https://www.nitrc.org/projects/hid | Schizophrenia |
| 16 | 1000 Functional Connectomes Project (FCP) Mennes et al. (2013) http://fcon_1000.projects.nitrc.org/ | 1200+ resting state functional MRI (R-fMRI) datasets |
| 17 | Human Connectome Project (HCP) http://www.humanconnectomeproject.org/data/inventory/ | |
| 18 | Medical School of Harvard University www.med.harvard.edu/aanlib/home.html | Normal Aging, Stroke, Tumors, Degenerative Diseases, Inflammatory or Infectious Diseases |
| 19 | The Multimodal Brain Tumor Image Segmentation Datasets BRATS 2014, 2015, 2016, 2017, 2018 https://paperswithcode.com/dataset/brats-2015-1, https://paperswithcode.com/dataset/brats-2018-1 | Brain Tumor |
| 20 | ISLES (Ischemic Stroke Lesion Segmentation) 2015 (Maier et al. 2017), 2016, 2017, 2018, 2022 https://www.isles-challenge.org/ | Stroke |
| 21 | Department of Radiology, Firat University Hospital Poyraz et al. (2022) https://www.kaggle.com/turkertuncer/brain-disorders-four-categories/ | Atrophy, Ischemia, WMI |
| 22 | ADHD-200 (Sasabe et al. 2014) http://fcon_1000.projects.nitrc.org/indi/adhd200/index.html | ADHD |

**Table 2** (continued)

| No | Dataset | Details |
|---|---|---|
| 23 | Bipolar and Schizophrenia Network for Intermediate Phenotypes BSNIP (Tamminga et al. 2014) | Psychosis, schizophrenia, schizoaffective disorder (SAD), and psychotic bipolar disorder (BDP) |
| 24 | Genetic Risk and Outcome of Psychosis (GROUP) (Korver et al. 2012) | Psychosis |
| 25 | Autism Brain Imaging Data Exchange (ABIDE I Di Martino et al. (2014) and ABIDE II Alexander et al. (2017) https://fcon_1000.projects.nitrc.org/indi/abide/ | Autism |
| 26 | FRONTIER (Frontotemporal Dementia Research Group) patient database https://www.sydney.edu.au/brain-mind/our-clinics/frontotemporal-dementia-clinic.html | Dementia |
| 27 | National Cancer Institute database (TCIA) Clark et al. (2013) http://cancerimagingarchive.net/ | Cancer |
| 28 | Machine Learning for Signal Processing (MLSP) 2014 Challenge Competition Silva et al. (2014) https://www.kaggle.com/c/mlsp-2014-mri | Schizophrenia |
| 29 | CADDementia Dataset (Bron et al. 2015) https://caddementia.grand-challenge.org/ | AD, MCI |
| 30 | MRI brain images collected from Brainix—Brain Tumour image collection from Pixmeo (Medical Imaging Software Company), Swiss and National Institutes of Health, USA | Brain Tumor |
| 31 | Mind Research Network (MRN) https://www.mrn.org/collaborate/data-community | Autism |
| 32 | Australian Schizophrenia Research Bank (ASRB) Loughland et al. (2010) https://www.neura.edu.au/discovery-portal/asrb/ | Schizophrenia |
| 33 | PREDICT-HD project https://www.ncbi.nlm.nih.gov/projects/gap/cgi-bin/document.cgi?study_id=phs000222.v1.p1&phd=2424 | Huntington Disease |
| 34 | Data from four separate SZ studies conducted at Johns Hopkins University (JHU), the Maryland Psychiatric Research Center (MPRC), the Institute of Psychiatry, London, UK (IOP), and the Western Psychiatric Institute and Clinic at the University of Pittsburgh (WPIC) | Schizophrenia |
| 35 | ADHD dataset for NYU, Neuro and OHSU fMRI data Bellec et al. (2017) http://fcon_1000.projects.nitrc.org/indi/adhd200/ | ADHD |
| 36 | AddNeuroMed cohort | AD |
| 37 | Adolescent Brain-Behavior Research Clinic (ABBRC) https://karlsgodtlab.psych.ucla.edu/abbrc/#:∼:text=Adolescent | - |
| 38 | INTERPRET project database http://azizu.uab.es/INTERPRET/ | - |
| 39 | https://www.fil.ion.ucl.ac.uk/spm/data/ fMRI | |
| 40 | https://www.ncbi.nlm.nih.gov/projects/gap/cgi-bin/dataset.cgi?study_id=phs000007.v13.p5&pht=690 | Dementia |
| 41 | Repository of Molecular Brain Neoplasia Data (REMBRANDT) https://wiki.cancerimagingarchive.net/display/Public/REMBRANDT | Glioma |
| 42 | https://www.kaggle.com/datasets/ahmedhamada0/brain-tumor-detection/metadata(Alanazi et al. 2022) | Brain Tumor |
| 43 | https://www.kaggle.com/datasets/sartajbhuvaji/brain-tumor-classification-mri (Alanazi et al. 2022 ) | Glioma tumor, Meningioma tumor, and Pituitary tumor |
| 44 | https://figshare.com/articles/dataset/brain_tumor_dataset/1512427 (Alanazi et al. 2022) | Brain Tumor |
| 45 | https://nda.nih.gov/ (Hall et al. 2012) | Autism |
| 46 | https://www.brainsimagebank.ac.uk/ | Normal Brain |

**Table 2** (continued)

| No | Dataset | Details |
|---|---|---|
| 47 | The Australian Imaging, Biomarker and Lifestyle Flagship Work of Ageing (AIBL) database (Ellis et al. 2009) https://aibl.csiro.au/ | AD |
| 48 | Baltimore Longitudinal Study of Aging (BLSA) https://blsa.nih.gov/ | Dementia |
| 49 | Multi-Ethnic Study of Atherosclerosis (MESA) (Bild et al. 2002; Olson et al. 2016) | Cerebral microbleeds |
| 50 | Dr. Andreia V. Faria (afaria1@jhmi.edu). The STIR data STIR/Vista Investigators—Dr. Marie Luby (lubym@ninds.nih.gov) Liu et al. (2021) | Stroke |
| 51 | Anatomical Tracings of Lesions After Stroke (ATLAS) Liew et al. (2018) https://fcon_1000.projects.nitrc.org/indi/retro/atlas.html | Stroke |
| 52 | MPI-Leipzig_Mind-Brain-Body https://legacy.openfmri.org/dataset/ds000221/ | Resting-state fMRI |
| 53 | Brain development website (IXI dataset) http://brain-development.org/ixi-dataset/ | Healthy Subjects |
| 54 | Kaggle Alzheimer's classification dataset (KACD) www.kaggle.com/tourist55/alzheimers-dataset-4-class-of-images | AD |
| 55 | Recognition of Alzheimer's Disease dataset (ROAD) https://www.datafountain.cn/competitions/369 | AD |

The Universal Resource Locators (URLs) to access them are also provided here, but in some cases permission may be required to access data

**Table 3** Publicly available tools for CAD of neurological disorders

| No | Tool | Disease |
|---|---|---|
| 1 | Stroke classification, MATLAB GUI Deepa et al. (2021) | Stroke |
| 2 | Tumor Classification, MATLAB GUI Deepa et al. (2021) | Tumor |
| 3 | AD stage prediction for MRI medical images Helaly et al. (2021) | AD |
| 4 | Tumor Ucuzal et al. (2019) | Tumor |
| 5 | MRI Predict Tool Salvador et al. (2017) | Psychosis |

accuracy. Sabuncu et al. (2012) employed data from 2800 subjects from multiple datasets to classify multiple disorders; however, their system failed to surpass 86% accuracy. However, systems developed to classify five to eight disorders and claim to reach an accuracy of 100%, such as those developed by Khani et al. (2013) and Saritha et al. (2013), use 10 to 15 images per class from a single online source. Such systems cannot be generalized and are failure-prone when tested using data from different sources. Publicly available CAD tools in this domain were very scarce. Furthermore, the majority of developed tools work with a single widely researched disease and its subtypes, including AD and tumors. However, open sharing in the neuroscience community has provided access to big MR data. Many publicly available datasets, ranging from structural to functional MRI data, have been identified in various studies for a wide spectrum of neurological disorders. This vast amount of data, such as 2D slices and 3D whole brain volumes is available in multiple sequences and orientations in JPEG, DICOM, NIfTI, and other formats. In addition to the datasets compiled for this study, numerous others are available that can assist the CAD pipeline using brain MRI, including preprocessing operations such as skull stripping or brain extraction Hoopes et al. (2022), brain lesion segmentation (Commowick et al. 2021) and substance abuse identification (Angeles-Valdez et al. 2022) from brain MRI. Despite the huge amount of publicly

available data, drastic uplift in storage and computational resources, and a multitude of complex, fast, and efficient DL architectures, to date, no study has encompassed them collectively to train an omnipotent CAD tool.

The development of DL frameworks for MRI-based diagnosis of neurological disorders has led to significant advancements in research and clinical applications. Here are some key highlights: 1. **Enhanced Access to Care and Empowerment through Technology:** Deep learning models, particularly CNNs, have shown remarkable improvements in detecting and classifying neurological disorders, such as AD, MS, and brain tumors. These models can analyze complex patterns in MRI images that are often imperceptible to the human eye (Shojaei et al. 2023). DL frameworks facilitate the automation of image interpretation, reducing the burden on radiologists and enabling faster diagnosis. This automation is particularly beneficial in settings with a high volume of scans. By improving diagnostic efficiency and accuracy, these technologies can help ensure that patients receive appropriate care quicker, potentially addressing past inadequacies in healthcare systems(Pinto-Coelho 2023). By utilizing advanced DL techniques, healthcare providers are better equipped to serve their patients, leading to improved treatment outcomes and empowering patients with informed choices regarding their health (Alowais et al. 2023). 2. **Reduction of Health Disparities Through Personalized Medicine:** DL enables the identification of specific disease subtypes, which can guide personalized treatment plans. By analyzing large datasets, researchers can uncover correlations between MRI findings and patient outcomes. Improved diagnostic techniques could help identify neurological disorders more effectively, especially in underserved populations, thus contributing to more equitable healthcare outcomes (Krishnan et al. 2023). Furthermore, early and precise diagnoses can provide families with answers and clearer pathways to management and support, helping to mitigate the emotional and psychological burden associated with uncertain diagnoses (Okoye et al. 2023).

### 3.4 The challenges

Brain imaging can be tremendously fruitful in visualizing structural and functional brain changes resulting from the underlying pathophysiological abnormalities. There are several non-invasive imaging techniques that can assist in the diagnosis and prognosis of neurological disorders. Structural MRI deals with morphometry of cortical structures whereas functional MRI can detect changes in blood flow resulting from brain activities (Garcia Santa Cruz et al. 2023). In clinical practice, medical experts typically fuse these modalities to reach concrete diagnosis (Shoeibi et al. 2023), making it an interesting approach for data scientists and engineers working on AI powered CAD tools to consider as well. This multimodal data fusion for CAD of neurological disorders comes with certain challenges. For optimum performance, DL requires massive, labelled datasets during training (Yang et al. 2022). The unavailability of such multi-modal data for multiple neurological disorders is the major challenge in CAD research in this domain, since the models trained using small datasets result in generalizability issues rendering them unusable in routine clinical practice (Viswan et al. 2024). Another similar challenge is the class imbalance issue Johnson and Khoshgoftaar (2019). The inference of the DL model trained on imbalanced data for different classes is observed to show a bias towards the dominant class Shoeibi et al. (2023). The choice of DL architectures as well as adequate hardware resources capable of handling massive multi-dimensional arrays have also been observed as bottlenecks in CAD research

catering to multi-class and multi-modal medical imaging data (Shoeibi et al. 2023). In addition to the current performance issues of the AI powered CAD regimens, including lack of robustness and generalizability, the major factor responsible for hindering the integration of such CAD tools in routine clinical practice is the lack of explainability (Jahan et al. 2023; Taşcı 2023). In the quest to increase the accuracies of CAD tools, the complexity of the AI system architectures increased exponentially. This resulted in a drastic reduction in interpretability and explainability. The DL architectures grew complex with hundreds of hidden layers and millions of trainable parameters, and despite their near-perfect performance Górriz et al. (2023); Farahani et al. (2022), the operations got wrapped in a "Black Box" Zeineldin et al. (2024); Qian et al. (2023); Borys et al. (2023); Tjoa and Guan (2020). This resulted in a decrease in trust of medical domain experts El-Sappagh et al. (2021), since in diagnostic radiology and clinical practice, precious human lives are on the line and a single error can lead to catastrophic consequences Viswan et al. (2024); Nazir et al. (2023); Jin et al. (2023); Van der Velden et al. (2022). This is one of the foremost reasons that despite the tremendous technological advancements Viswan et al. (2024), AI has not yet been able to secure a permanent placement in mainstream clinical diagnostic regimens. To bridge this gap between AI and medical experts, Explainable AI (XAI), a relatively new subdomain of AI, seems very promising Jin et al. (2022); Herent et al. (2018); Holzinger et al. (2017).

### 3.5 The future

AI has revolutionized the world and will continue to do so in the near future, thus enabling new applications that were previously considered science fiction. Simple, robust, and efficient systems can be developed in every field, and medicine is no exception. It would not be over-optimistic to anticipate a single generic framework for the diagnosis of multiple neurological disorders using MRI becoming available to neurologists and radiologists, to assist in quickly reaching concrete diagnoses of intricate neurological disorders. From a broader perspective, a single application capable of diagnosing every medical condition worldwide using a vast variety of human biomarkers, including speech, gait, facial expressions, MRI, X-rays, ultrasound, blood work, and other medical reports as well as patient history, physical interactions, and activities, does not seem far-fetched. Given the huge amount of data and tremendous readily available processing capabilities, such an application could contain a massive network ensemble of multiple modalities used concurrently to achieve a pinpoint diagnosis. The integration of XAI Ker et al. (2017); Miotto et al. (2018); Lundervold and Lundervold (2019) would be the crowning achievement, affording confidence to patients and doctors by providing the reasons for diagnoses, rather than the conventional "Black box" approach Zhang et al. (2021). This omnipotent network would dynamically update its training and disease pool databases with new data, making it the complete physician's assistant and serving humanity by alleviating diseases.

Recently techniques including Fuzzy logic and Quantum transfer learning have also been observed to gain momentum in CAD research for neurological disorders. Alsharabi et al. (2023) proposed an integration of quantum computing phenomena with deep neural networks for the differential diagnosis of AD and PD using brain MRI. Their AlexNet-quantum transfer learning approach achieved a classification accuracy of 97% and 96% for PD and AD respectively, with high-speed computational power as an added benefit for real time deployment and use. Yao et al. (2023) used Fuzzy theory to reorder and prioritize pixels

based on their most significant local information. This was followed by a VGG architecture for training. The results of their study claim to have an accelerated model convergence along with improvements in classification performance of AD stages using brain MRI. Sharma et al. (2022) also proposed a system to distinguish between AD, MCI and HC. They used a DL model for feature extraction and fuzzy hyperplane based least square twin support vector machine (FLS-TWSVM) for the classification of the extracted features for early diagnosis of AD, with an accuracy of up to 97.29%. Iqbal et al. (2024) addressed the issues of noise and fuzzy boundaries in brain MRI, and interpretability, by proposing a combination of Hybrid Parallel Fuzzy CNN (HP-FCNN) with Adaptive Class Activation Mapping (AD-CAM). Their system claims to outperform classical architectures including ResNet, DenseNet, VGG, and EfficientNet, with an accuracy of 96.81%, along with the valuable addition of explainability which is an indispensable requirement of the hour for such CAD tools to enter routine healthcare regimens.

Data scientists and radiologists have diverse and sometimes contradictory opinions on AI and its potential, particularly in medical applications. During this study, a survey was conducted by radiologists, and expert opinions were requested on whether AI-based tools to examine MR images would be helpful in diagnosing multiple neurological disorders. Their interests and anticipation were found to be overwhelming, with many concerns pertaining to the accuracy of such frameworks, if developed. Skepticism has also been expressed. As an example, the comments from Dr. Shahabuddin Siddiqui, Specialist in Diagnostic Radiology, at the Pakistan Institute of Medical Sciences Hospital, Islamabad, Pakistan, are as follows: "*It is a good idea to develop an app that can read images of the brain and diagnose certain diseases. However, in practice, I do not think it will work for all diseases. Most diseases do not exhibit typical imaging patterns. The signal characteristics and location of the disease process can vary significantly among patients. Therefore, more than one image reader application is required to diagnose a disease accurately. Having background knowledge and experience in clinical neurology and radiology remains the most important factor in patient diagnosis.*" However, radical opposition has emerged and stern comments from data scientists have been noted. Zaharchuk et al. (2018) found that "*DL has the potential to revolutionize all industries, including medical imaging. Given the centrality of neuroimaging in the diagnosis and treatment of neurological diseases, DL is likely to affect neuroradiologists first and most profoundly. One concern is that, if these approaches are successful, some of the work that radiologists have traditionally performed may become obsolete.*" Korfiatis and Erickson (2019) present an even stronger statement: "*There has been a revolution in the world of computer science with new formulations of DL technology achieving performance that exceeds humans in identifying the content in images. This revolution has led some researchers to predict that computers will replace radiologists.*" Others Bakator and Radosav (2018); Zhang and Sejdić (2019); Chauhan and Choi (2019); Mazurowski et al. (2019); Yao et al. (2020); Lima et al. (2022) believe more in a meet-in-the-middle approach, stating "*Despite the limitations, the advantages of DL far outweigh its shortcomings, and thus, it will become an essential tool for diagnosis and prognosis in the era of precision medicine. Future research teams in medical imaging should integrate DL experts in addition to clinical scientists in their teams to fully harness the potential of DL.*" Kim et al. (2018) and "*With the clearer pathogenesis of human brain disorders, the further development of DL techniques, and larger open source datasets, a human–machine collaboration for medical diagnosis and treatment will ultimately become a symbiosis in the*

*future.*" Zhang et al. (2020) This undoubtedly presents a wide window of opportunity and invites research into the development of a unified framework capable of classifying multiple neurological disorders with reasonable accuracy to function as a robust and reliable assistive tool for neurologists. To minimize misdiagnoses, the combination of their experience and the machines' capabilities for analyzing humanly imperceptible pixel-level differences in images would reduce invalid diagnoses for diseases with overlapping MRI abnormalities and features.

## 4 Conclusion

This review provides an in-depth exploration and synthesis of existing CAD research on neurological disorders, with a particular focus on DL-based frameworks. Our analysis reveals several key insights:

1. **Current State of DL-based CAD Systems:** Most DL-based CAD systems are designed to diagnose a single neurological disease or its subtypes with a reasonable degree of accuracy. However, these systems often fall short when applied to multiple neurological disorders, primarily due to limitations in the datasets used for training and the complexity of the conditions. Statistically, around 64% articles presented systems for single disease diagnosis, whereas a meager 7% experimented with CAD of more than 3 disorders. Out of the 36 multiple disease diagnosis articles discussed in this paper, 26 articles worked with the sub-types or stages of a single disease. Moreover, no publicly available tool capable of diagnosing multiple neurological disorders using brain MRI was found.
2. **Challenges in Multimodal Diagnosis:** We highlight a significant gap in the ability of current CAD systems to handle a wide range of neurological disorders concurrently. Systems capable of diagnosing multiple diseases are either restricted by the number of diseases they can handle or by the limited and often biased datasets used for training, which in turn hampers their effectiveness in clinical settings.
3. **Potential of DL Frameworks:** Despite these challenges, there is promising evidence that a DL-based framework could be developed to function as an assistive tool for neurologists. Such a framework could facilitate the timely and accurate diagnosis of complex neurological conditions from MRI signals, thus improving patient outcomes. We point out that leveraging massive, publicly available datasets across multiple diseases could enable the development of more generic and robust models.
4. **Future Directions:** To address the current limitations, researchers should focus on creating CAD systems that are trained on diverse and extensive datasets, allowing them to be more generalizable across different neurological conditions. Additionally, the implementation of these systems in real-time frameworks could pave the way for their commercial use, making them accessible to a broader range of medical practitioners.
5. **Impact on Clinical Practice:** The deployment of a universally accessible, single imaging modality for the diagnosis of a broad spectrum of neurological disorders could significantly enhance the early detection and treatment of these conditions. This would not only improve the accuracy of diagnoses but also increase the chances of curing or containing the diseases, ultimately leading to a better quality of life for many patients.

In summary, while the current state of DL-based CAD systems shows great potential, there remains a need for further research and development to create more comprehensive and reliable diagnostic tools. The findings from this review, coupled with insights from medical experts, suggest that these advancements are within reach and could revolutionize the way neurological disorders are diagnosed and treated.

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## Declarations

**Conflict of interest** The authors have no conflict of interest to declare.



## References

Abbood AA, Shallal QM, Fadhel MA (2021) Automated brain tumor classification using various deep learning models: a comparative study. Indonesian Journal of Electrical Engineering and Computer Science 22(1): 252–259https://doi.org/10.11591/ijeecs.v22.i1.pp252-259

Abrol A, Fu Z, Salman M, Silva R, Du Y, Plis S, Calhoun V (2021) Deep learning encodes robust discriminative neuroimaging representations to outperform standard machine learning. Nat Commun 12(1):1–17. https://doi.org/10.1038/s41467-020-20655-6

Abrol A, Rokham H, Calhoun VD (2019) Diagnostic and prognostic classification of brain disorders using residual learning on structural MRI data. In: 2019 41St Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), pp 4084–4088. IEEE. https://doi.org/10.1109/EMBC.2019.8857902

Aggarwal R, Sounderajah V, Martin G, Ting DS, Karthikesalingam A, King D, Ashrafian H, Darzi A (2021) Diagnostic accuracy of deep learning in medical imaging: a systematic review and meta-analysis. NPJ Digit Med 4(1):65

Agrawal A, Maan V (2024) Brain tumor classification of mri scans using deep learning techniques. In: 2024 International Conference on Communication, Computer Sciences and Engineering (IC3SE), pp 1128–1133. IEEE

Ahmed MR, Zhang Y, Feng Z, Lo B, Inan OT, Liao H (2018) Neuroimaging and machine learning for dementia diagnosis: recent advancements and future prospects. IEEE Rev Biomed Eng 12:19–33. https://doi.org/10.1109/RBME.2018.2886237

Akter A, Nosheen N, Ahmed S, Hossain M, Yousuf MA, Almoyad MAA, Hasan KF, Moni MA (2024) Robust clinical applicable CNN and U-net based algorithm for MRI classification and segmentation for brain tumor. Expert Syst Appl 238:122347

Al-Galal SAY, Alshaikhli IFT, Abdulrazzaq M (2021) MRI brain tumor medical images analysis using deep learning techniques: a systematic review. Health Technol 11(2):267–282. https://doi.org/10.1007/s12553-020-00514-6

Al-Shoukry S, Rassem TH, Makbol NM (2020) Alzheimer's diseases detection by using deep learning algorithms: a mini-review. IEEE 8:77131–77141. https://doi.org/10.1109/ACCESS.2020.2989396

Alanazi MF, Ali MU, Hussain SJ, Zafar A, Mohatram M, Irfan M, AlRuwaili R, Alruwaili M, Ali NH, Albarrak AM (2022) Brain tumor/mass classification framework using magnetic-resonance-imaging-based isolated and developed transfer deep-learning model. Sensors 22(1):372. https://doi.org/10.3390/s22010372

Alexander LM, Escalera J, Ai L, Andreotti C, Febre K, Mangone A, Vega-Potler N, Langer N, Alexander A, Kovacs M et al (2017) An open resource for transdiagnostic research in pediatric mental health and learning disorders. Scientific data 4(1):1–26. https://doi.org/10.1038/sdata.2017.181

Alfaro-Almagro F, Jenkinson M, Bangerter N, Andersson J, Griffanti L, Douaud G, Sotiropoulos S, Jbabdi S, Hernández-Fernández M, Vallee E, et al (2017) Image processing and quality control for the first 10000 brain imaging datasets. bioRxiv

Alhassan AM, Initiative ADN, Biomarkers AI, Ageing LFS (2022) Enhanced fuzzy elephant herding optimization-based OTSU segmentation and deep learning for Alzheimer's disease diagnosis. Mathematics 10(8):1259. https://doi.org/10.3390/math10081259

Allada A, Bhavani R, Chaduvula K, Priya R (2023) Early diagnosis of Alzheimer disease from MRI using deep learning models. J Inform Technol Manag 15:52–71

Alowais SA, Alghamdi SS, Alsuhebany N, Alqahtani T, Alshaya AI, Almohareb SN, Aldairem A, Alrashed M, Bin Saleh K, Badreldin HA et al (2023) Revolutionizing healthcare: the role of artificial intelligence in clinical practice. BMC Med Educ 23(1):689

Alsharabi N, Shahwar T, Rehman AU, Alharbi Y (2023) Implementing magnetic resonance imaging brain disorder classification via ALEXNET-quantum learning. Mathematics 11(2):376

Altinkaya E, Polat K, Barakli B (2020) Detection of Alzheimer's disease and dementia states based on deep learning from MRI images: a comprehensive review. J Institut Electron Comput 1(1):39–53

Angeles-Valdez D, Rasgado-Toledo J, Issa-Garcia V, Balducci T, Villicaña V, Valencia A, Gonzalez-Olvera JJ, Reyes-Zamorano E, Garza-Villarreal EA (2022) The Mexican magnetic resonance imaging dataset of patients with cocaine use disorder: Sudmex conn. Sci Data 9(1):133

Ansart M, Epelbaum S, Bassignana G, Bône A, Bottani S, Cattai T, Couronné R, Faouzi J, Koval I, Louis M et al (2021) Predicting the progression of mild cognitive impairment using machine learning: a systematic, quantitative and critical review. Med Image Anal 67:101848. https://doi.org/10.1016/j.media.2020.101848

Apostolopoulos ID, Aznaouridis S, Tzani M (2023) An attention-based deep convolutional neural network for brain tumor and disorder classification and grading in magnetic resonance imaging. Information 14(3):174

Arabahmadi M, Farahbakhsh R, Rezazadeh J (2022) Deep learning for smart healthcare-a survey on brain tumor detection from medical imaging. Sensors 22(5):1960. https://doi.org/10.3390/s22051960

Arafa DA, Moustafa HE-D, Ali-Eldin AM, Ali HA (2022) Early detection of Alzheimer's disease based on the state-of-the-art deep learning approach: a comprehensive survey. Multimed Tools Appl. https://doi.org/10.1007/s11042-022-11925-0

Arbabshirani MR, Plis S, Sui J, Calhoun VD (2017) Single subject prediction of brain disorders in neuroimaging: promises and pitfalls. Neuroimage 145:137–165. https://doi.org/10.1016/j.neuroimage.2016.02.079

Arimura H, Magome T, Yamashita Y, Yamamoto D (2009) Computer-aided diagnosis systems for brain diseases in magnetic resonance images. Algorithms 2(3):925–952. https://doi.org/10.3390/a2030925

Arora T, Dhir R (2017) Correlation-based feature selection and classification via regression of segmented chromosomes using geometric features. Med Biol Eng Comput 55(5):733–745. https://doi.org/10.1007/s11517-016-1553-2

Avants BB, Epstein CL, Grossman M, Gee JC (2008) Symmetric diffeomorphic image registration with cross-correlation: evaluating automated labeling of elderly and neurodegenerative brain. Med Image Anal 12(1):26–41. https://doi.org/10.1016/j.media.2007.06.004

Ayus I, Gupta D (2024) A novel hybrid ensemble based Alzheimer's identification system using deep learning technique. Biomed Signal Process Control 92:106079

Bakator M, Radosav D (2018) Deep learning and medical diagnosis: a review of literature. Multimodal Technol Interact 2(3):47. https://doi.org/10.3390/mti2030047

Bashyam VM, Erus G, Doshi J, Habes M, Nasrallah IM, Truelove-Hill M, Srinivasan D, Mamourian L, Pomponio R, Fan Y et al (2020) Mri signatures of brain age and disease over the lifespan based on a deep brain network and 14 468 individuals worldwide. Brain 143(7):2312–2324. https://doi.org/10.1093/brain/awaa160

Behrad F, Abadeh MS (2022) An overview of deep learning methods for multimodal medical data mining. Exp Syst Appl. https://doi.org/10.1016/j.eswa.2022.117006

Bellec P, Chu C, Chouinard-Decorte F, Benhajali Y, Margulies DS, Craddock RC (2017) The neuro bureau ADHD-200 preprocessed repository. Neuroimage 144:275–286. https://doi.org/10.1016/j.neuroimage.2016.06.034

Bernal J, Kushibar K, Asfaw DS, Valverde S, Oliver A, Martí R, Lladó X (2019) Deep convolutional neural networks for brain image analysis on magnetic resonance imaging: a review. Artif Intell Med 95:64–81. https://doi.org/10.1016/j.artmed.2018.08.008

Bhatele KR, Bhadauria SS (2020) Brain structural disorders detection and classification approaches: a review. Artif Intell Rev 53(5):3349–3401. https://doi.org/10.1007/s10462-019-09766-9

Bild DE, Bluemke DA, Burke GL, Detrano R, Diez Roux AV, Folsom AR, Greenland P, JacobsJr DR, Kronmal R, Liu K et al (2002) Multi-ethnic study of atherosclerosis: objectives and design. Am J Epidemiol 156(9):871–881. https://doi.org/10.1093/aje/kwf113

Boeken T, Feydy J, Lecler A, Soyer P, Feydy A, Barat M, Duron L (2023) Artificial intelligence in diagnostic and interventional radiology: where are we now? Diagn Int Imaging 104(1):1–5

Borys K, Schmitt YA, Nauta M, Seifert C, Krämer N, Friedrich CM, Nensa F (2023) Explainable AI in medical imaging: an overview for clinical practitioners-beyond saliency-based XAI approaches. Eur J Radiol 162:110786

Bron EE, Smits M, Van Der Flier WM, Vrenken H, Barkhof F, Scheltens P, Papma JM, Steketee RM, Orellana CM, Meijboom R et al (2015) Standardized evaluation of algorithms for computer-aided diagnosis of dementia based on structural MRI: the Caddementia challenge. NeuroImage 111:562–579. https://doi.org/10.1016/j.neuroimage.2015.01.048

Calhoun VD, Sui J (2016) Multimodal fusion of brain imaging data: a key to finding the missing link (s) in complex mental illness. Biol Psychiatry Cogn Neurosci Neuroimaging 1(3):230–244. https://doi.org/10.1016/j.bpsc.2015.12.005

Camacho-Conde JA, Gonzalez-Bermudez MDR, Carretero-Rey M, Khan ZU (2022) Brain stimulation: a therapeutic approach for the treatment of neurological disorders. CNS Neurosci Ther 28(1):5–18

Camacho-Conde JA, Rosario Gonzalez-Bermudez M, Carretero-Rey M, Khan ZU (2023) Therapeutic potential of brain stimulation techniques in the treatment of mental, psychiatric, and cognitive disorders. CNS Neurosci Ther 29(1):8–23

Carass A, Roy S, Jog A, Cuzzocreo JL, Magrath E, Gherman A, Button J, Nguyen J, Bazin P-L, Calabresi PA et al (2017) Longitudinal multiple sclerosis lesion segmentation data resource. Data Brief 12:346–350. https://doi.org/10.1016/j.dib.2017.04.004

Castiglioni I, Rundo L, Codari M, Di Leo G, Salvatore C, Interlenghi M, Gallivanone F, Cozzi A, D'Amico NC, Sardanelli F (2021) AI applications to medical images: from machine learning to deep learning. Phys Med 83:9–24

Chagué P, Marro B, Fadili S, Houot M, Morin A, Samper-González J, Beunon P, Arrivé L, Dormont D, Dubois B et al (2021) Radiological classification of dementia from anatomical MRI assisted by machine learning-derived maps. J Neuroradiol 48(6):412–418. https://doi.org/10.1016/j.neurad.2020.04.004

Chauhan N, Choi B-J (2019) Performance analysis of classification techniques of human brain MRI images. Int J Fuzzy Logic Intell Syst 19(4):315–322. https://doi.org/10.5391/IJFIS.2019.19.4.315

Chen F, Fan X, Li J, Zou M, Huang L (2021) Gait analysis based Parkinson's disease auxiliary diagnosis system. J Internet Technol 22(5):991–999

Clark K, Vendt B, Smith K, Freymann J, Kirby J, Koppel P, Moore S, Phillips S, Maffitt D, Pringle M et al (2013) The cancer imaging archive (TCIA): maintaining and operating a public information repository. J Digit Imaging 26(6):1045–1057. https://doi.org/10.1007/s10278-013-9622-7

Clayden JD, Maniega SM, Storkey AJ, King MD, Bastin ME, Clark CA (2011) Tractor: magnetic resonance imaging and tractography with R. J Stat Softw 44:1–18

Commowick O, Kain M, Casey R, Ameli R, Ferré J-C, Kerbrat A, Tourdias T, Cervenansky F, Camarasu-Pop S, Glatard T et al (2021) Multiple sclerosis lesions segmentation from multiple experts: the MICCAI 2016 challenge dataset. NeuroImage 244:118589. https://doi.org/10.1016/j.neuroimage.2021.118589

DS BJKKA Valverde (2019) Soliver A Martí x lladóo r deep convolutional neural networks for brain image analysis on magnetic resonance imaging: a review. Artif Intell Med 95: 64–81

Deepa B, Murugappan M, Sumithra M, Mahmud M, Al-Rakhami MS (2021) Pattern descriptors orientation and map firefly algorithm based brain pathology classification using hybridized machine learning algorithm. IEEE Access 10:3848–3863. https://doi.org/10.1109/ACCESS.2021.3100549

Ding X, Yang Y, Stein EA, Ross TJ (2015) Multivariate classification of smokers and nonsmokers using SVM-RFE on structural MRI images. Human Brain Map 36(12):4869–4879. https://doi.org/10.1002/hbm.22956

Di Martino A, Yan C-G, Li Q, Denio E, Castellanos FX, Alaerts K, Anderson JS, Assaf M, Bookheimer SY, Dapretto M et al (2014) The autism brain imaging data exchange: towards a large-scale evaluation of the intrinsic brain architecture in autism. Mol Psychiatry 19(6):659–667. https://doi.org/10.1038/mp.2013.78

Ebrahimighahnavieh MA, Luo S, Chiong R (2020) Deep learning to detect Alzheimer's disease from neuroimaging: A systematic literature review. Comput Methods Programs Biomed 187:105242. https://doi.org/10.1016/j.cmpb.2019.105242

El-Assy A, Amer HM, Ibrahim H, Mohamed M (2024) A novel CNN architecture for accurate early detection and classification of Alzheimer's disease using MRI data. Sci Rep 14(1):3463

El-Latif AAA, Chelloug SA, Alabdulhafith M, Hammad M (2023) Accurate detection of Alzheimer's disease using lightweight deep learning model on MRI data. Diagnostics 13(7):1216

El-Sappagh S, Alonso JM, Islam SR, Sultan AM, Kwak KS (2021) A multilayer multimodal detection and prediction model based on explainable artificial intelligence for Alzheimer's disease. Sci Rep 11(1):2660

Ellis KA, Bush AI, Darby D, De Fazio D, Foster J, Hudson P, Lautenschlager NT, Lenzo N, Martins RN, Maruff P et al (2009) The Australian imaging, biomarkers and lifestyle (AIBL) study of aging: methodology and baseline characteristics of 1112 individuals recruited for a longitudinal study of Alzheimer's disease. Int Psychogeriatr 21(4):672–687. https://doi.org/10.1017/S1041610209009405

Eslami T, Almuqhim F, Raiker JS (2021) Saeed F Machine learning methods for diagnosing autism spectrum disorder and attention-deficit/hyperactivity disorder using functional and structural MRI: a survey. Front Neuroinform 14:575999. https://doi.org/10.3389/fninf.2020.575999

Falkai P, Schmitt A, Andreasen N (2022) Forty years of structural brain imaging in mental disorders: is it clinically useful or not? Dial Clin Neurosci https://doi.org/10.31887/DCNS.2018.20.3/pfalkai

Farahani FV, Fiok K, Lahijanian B, Karwowski W, Douglas PK (2022) Explainable AI: a review of applications to neuroimaging data. Front Neurosci 16:906290

Francis BK, Babu SS (2019) Predicting academic performance of students using a hybrid data mining approach. J Med Syst 43(6):1–15. https://doi.org/10.1007/s10916-019-1295-4

Frizzell TO, Glashutter M, Liu CC, Zeng A, Pan D, Hajra SG, D'Arcy RC, Song X (2022) Artificial intelligence in brain MRI analysis of Alzheimer's disease over the past 12 years: a systematic review. Ageing Res Rev. https://doi.org/10.1016/j.arr.2022.101614

Garcia Santa Cruz B, Husch A, Hertel F (2023) Machine learning models for diagnosis and prognosis of Parkinson's disease using brain imaging: general overview, main challenges, and future directions. Front Aging Neurosci 15:1216163

Garcia-Gutierrez F, Delgado-Alvarez A, Delgado-Alonso C, Díaz-Álvarez J, Pytel V, Valles-Salgado M, Gil MJ, Hernández-Lorenzo L, Matías-Guiu J, Ayala JL et al (2022) Diagnosis of Alzheimer's disease and behavioural variant frontotemporal dementia with machine learning-aided neuropsychological assessment using feature engineering and genetic algorithms. Int J Geriat Psychiatry 37(2)

Gola KA, Shany-Ur T, Pressman P, Sulman I, Galeana E, Paulsen H, Nguyen L, Wu T, Adhimoolam B, Poorzand P et al (2017) A neural network underlying intentional emotional facial expression in neurodegenerative disease. NeuroImage Clin 14:672–678. https://doi.org/10.1016/j.nicl.2017.01.016

Gore DV, Deshpande V (2020) Comparative study of various techniques using deep learning for brain tumor detection. In: 2020 International Conference for Emerging Technology (INCET), IEEE. pp 1–4. https://doi.org/10.1109/INCET49848.2020.9154030

Greenspan H, Van Ginneken B, Summers RM (2016) Guest editorial deep learning in medical imaging: overview and future promise of an exciting new technique. IEEE Transact Med Imaging 35(5):1153–1159. https://doi.org/10.1109/TMI.2016.2553401

Guney G, Yigin BO, Guven N, Alici YH, Colak B, Erzin G, Saygili G (2021) An overview of deep learning algorithms and their applications in neuropsychiatry. Clin Psychopharmacol Neurosci 19(2):206. https://doi.org/10.9758/cpn.2021.19.2.206

Górriz JM, Álvarez-Illán I, Álvarez-Marquina A, Arco JE, Atzmueller M, Ballarini F, Barakova E, Bologna G, Bonomini P, Castellanos-Dominguez G et al (2023) Computational approaches to explainable artificial intelligence: advances in theory, applications and trends. Inform Fusion 100:101945

Hall D, Huerta MF, McAuliffe MJ, Farber GK (2012) Sharing heterogeneous data: the national database for autism research. Neuroinformatics 10(4):331–339. https://doi.org/10.1007/s12021-012-9151-4

Haque R, Hassan MM, Bairagi AK, Shariful Islam SM (2024) Neuronet19: an explainable deep neural network model for the classification of brain tumors using magnetic resonance imaging data. Sci Rep 14(1):1524

Heidari S, Ghazikhani A (2024) Diagnosis and classification of Alzheimer's disease from MRI images using parallel deep convolutional neural networks. J Telemed 1(2):1–13

Helaly HA, Badawy M, Haikal AY (2021) Deep learning approach for early detection of Alzheimer's disease. Cogn Comput. https://doi.org/10.1007/s12559-021-09946-2
Hemanth DJ, Anitha J, Naaji A, Geman O, Popescu DE et al (2018) A modified deep convolutional neural network for abnormal brain image classification. IEEE Access 7:4275–4283. https://doi.org/10.1109/ACCESS.2018.2885639
Hemanth DJ, Vijila CKS, Selvakumar AI, Anitha J (2014) Performance improved iteration-free artificial neural networks for abnormal magnetic resonance brain image classification. Neurocomputing 130:98–107. https://doi.org/10.1016/j.neucom.2011.12.066
Herent P, Jegou S, Wainrib G, Clozel T (2018) Brain age prediction of healthy subjects on anatomic mri with deep learning: Going beyond with an "Explainable AI" mindset. bioRxiv 413302
Holzinger A, Biemann C, Pattichis CS, Kell DB (2017) What do we need to build explainable AI systems for the medical domain? Preprint at arXiv:1712.09923
Hoopes A, Mora JS, Dalca AV, Fischl B, Hoffmann M (2022) Synthstrip: Skull-stripping for any brain image. Neuroimage 260:119474
Ilic I, Ilic M (2023) International patterns and trends in the brain cancer incidence and mortality: An observational study based on the global burden of disease. Heliyon 9(7)
Ion-Mărgin A, Kocevar G, Stamile C, Sima DM, Durand-Dubief F, Van Huffel S, Sappey-Marinier D (2017) Machine learning approach for classifying multiple sclerosis courses by combining clinical data with lesion loads and magnetic resonance metabolic features. Front Neurosci 11:398. https://doi.org/10.3389/fnins.2017.00398
Iqbal S, Qureshi AN, Aurangzeb K, Alhussein M, Wang S, Anwar MS, Khan F (2024) Hybrid parallel fuzzy CNN paradigm: Unmasking intricacies for accurate brain MRI insights. IEEE Transactions on Fuzzy Systems
Islam J, Zhang Y (2018) Early diagnosis of Alzheimer's disease: A neuroimaging study with deep learning architectures. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops, pp 1881–1883. https://doi.org/10.1109/CVPRW.2018.00247
Jack Jr, CR, Bernstein, MA, Fox, NC, Thompson, P, Alexander, G, Harvey, D, Borowski, B, Britson, PJ, L Whitwell, J, Ward, C, et al (2008) The Alzheimer's disease neuroimaging initiative (ADNI): MRI methods Journal of Magnetic Resonance Imaging: An Official Journal of the International Society for Magnetic Resonance in Medicine 27(4), 685–691 https://doi.org/10.1002/jmri.21049
Jahan S, Abu Taher K, Kaiser MS, Mahmud M, Rahman MS, Hosen AS, Ra I-H (2023) Explainable AI-based Alzheimer's prediction and management using multimodal data. PLoS ONE 18(11):0294253
Jang I, Li B, Riphagen JM, Dickerson BC, Salat DH, Initiative ADN et al (2022) Multiscale structural mapping of Alzheimer's disease neurodegeneration. NeuroImage Clin 33:102948. https://doi.org/10.1016/j.nicl.2022.102948
Jin W, Li X, Fatehi M, Hamarneh G (2023) Guidelines and evaluation of clinical explainable AI in medical image analysis. Med Image Anal 84:102684
Jin W, Li X, Hamarneh G (2022) Evaluating explainable ai on a multi-modal medical imaging task: Can existing algorithms fulfill clinical requirements? In: Proceedings of the AAAI Conference on Artificial Intelligence 36:11945–11953
Jo T, Nho K, Saykin AJ (2019) Deep learning in Alzheimer's disease: diagnostic classification and prognostic prediction using neuroimaging data. Front Aging Neurosci 11:220. https://doi.org/10.3389/fnagi.2019.00220
Johnson JM, Khoshgoftaar TM (2019) Survey on deep learning with class imbalance. J Big Data 6(1):1–54
Kamboj A, Rani R, Chaudhary J (2018) Deep leaming approaches for brain tumor segmentation: a review. In: 2018 First International Conference on Secure Cyber Computing and Communication (ICSCCC), IEEE. pp 599–603. https://doi.org/10.1109/ICSCCC.2018.8703202
Kanmani P, Marikkannu P (2018) MRI brain images classification: a multi-level threshold based region optimization technique. J Med Syst 42(4):1–12. https://doi.org/10.1007/s10916-018-0915-8
Kazemi Y, Hough S (2018) A deep learning pipeline to classify different stages of alzheimer's disease from fmri data. In: 2018 IEEE Conference on Computational Intelligence in Bioinformatics and Computational Biology (CIBCB), pp 1–8. IEEE https://doi.org/10.1109/CIBCB.2018.8404980
Keator DB, Erp TG, Turner JA, Glover GH, Mueller BA, Liu TT, Voyvodic JT, Rasmussen J, Calhoun VD, Lee HJ et al (2016) The function biomedical informatics research network data repository. Neuroimage 124:1074–1079. https://doi.org/10.1016/j.neuroimage.2015.09.003
Kempen EJ, Post M, Mannil M, Kusters B, Ter Laan M, Meijer FJ, Henssen DJ (2021) Accuracy of machine learning algorithms for the classification of molecular features of gliomas on MRI: a systematic literature review and meta-analysis. Cancers 13(11):2606. https://doi.org/10.3390/cancers13112606
Ker J, Wang L, Rao J, Lim T (2017) Deep learning applications in medical image analysis. IEEE Access 6:9375–9389. https://doi.org/10.1109/ACCESS.2017.2788044

Khagi B, Kwon G-R, Lama R (2019) Comparative analysis of Alzheimer's disease classification by CDR level using CNN, feature selection, and machine-learning techniques. Int J Imaging Syst Technol 29(3):297–310. https://doi.org/10.1002/ima.22316

Khani H, Shayesteh MG, Zali-Vargahan B (2013) Robust algorithm for brain magnetic resonance image (MRI) classification based on Garch variances series. Biomed Signal Process Control 8(6):909–919. https://doi.org/10.1016/j.bspc.2013.09.001

Khodatars M, Shoeibi A, Ghassemi N, Jafari M, Khadem A, Sadeghi D, Moridian P, Hussain S, Alizadehsani R, Zare A, et al (2007) Deep learning for neuroimaging-based diagnosis and rehabilitation of autism spectrum disorder: a review. arxiv. 2020. Preprint at arXiv:2007.01285. https://doi.org/10.1016/j.compbiomed.2021.104949

Kim J, Hong J, Park H (2018) Prospects of deep learning for medical imaging. Precision Future Med 2(2):37–52. https://doi.org/10.23838/pfm.2018.00030

Kontopodis EE, Papadaki E, Trivizakis E, Maris TG, Simos P, Papadakis GZ, Tsatsakis A, Spandidos DA, Karantanas A, Marias K (2021) Emerging deep learning techniques using magnetic resonance imaging data applied in multiple sclerosis and clinical isolated syndrome patients. Exp The Med 22(4):1–17. https://doi.org/10.3892/etm.2021.10583

Korfiatis P, Erickson B (2019) Deep learning can see the unseeable: predicting molecular markers from MRI of brain gliomas. Clin Radiol 74(5):367–373. https://doi.org/10.1016/j.crad.2019.01.028

Korver N, Quee PJ, Boos HB, Simons CJ, Haan L, Investigators G (2012) Genetic risk and outcome of psychosis (group), a multi site longitudinal cohort study focused on gene-environment interaction: objectives, sample characteristics, recruitment and assessment methods. Int J Methods Psychiatr Res 21(3):205–221. https://doi.org/10.1002/mpr.1352

Krichen M (2021) Anomalies detection through smartphone sensors: a review. IEEE Sens J 21(6):7207–7217. https://doi.org/10.1109/JSEN.2021.3051931

Krishnan G, Singh S, Pathania M, Gosavi S, Abhishek S, Parchani A, Dhar M (2023) Artificial intelligence in clinical medicine: catalyzing a sustainable global healthcare paradigm. Front Artif Intell 6:1227091

Krokidis MG, Dimitrakopoulos GN, Vrahatis AG, Tzouvelekis C, Drakoulis D, Papavassileiou F, Exarchos TP, Vlamos P (2022) A sensor-based perspective in early-stage Parkinson's disease: current state and the need for machine learning processes. Sensors 22(2):409. https://doi.org/10.3390/s22020409

Kumar RS, Karnan M (2014) Review of MRI image classification techniques. Int J Res Stud Comput Sci Eng 1(1):21–28

Lahmiri S, Shmuel A (2019) Performance of machine learning methods applied to structural MRI and ADAS cognitive scores in diagnosing Alzheimer's disease. Biomed Signal Process Control 52:414–419. https://doi.org/10.1016/j.bspc.2018.08.009

Lazli L, Boukadoum M, Mohamed OA (2020) A survey on computer-aided diagnosis of brain disorders through MRI based on machine learning and data mining methodologies with an emphasis on Alzheimer disease diagnosis and the contribution of the multimodal fusion. Appl Sci 10(5):1894. https://doi.org/10.3390/app10051894

Li S, Qu H, Dong X, Dang B, Zang H, Gong Y (2024) Leveraging deep learning and xception architecture for high-accuracy MRI classification in Alzheimer diagnosis. Preprint at arXiv:2403.16212

Liew S-L, Anglin JM, Banks NW, Sondag M, Ito KL, Kim H, Chan J, Ito J, Jung C, Khoshab N et al (2018) A large, open source dataset of stroke anatomical brain images and manual lesion segmentations. Sci data 5(1):1–11. https://doi.org/10.1038/sdata.2018.11

Lima AA, Mridha MF, Das SC, Kabir MM, Islam MR, Watanobe Y (2022) A comprehensive survey on the detection, classification, and challenges of neurological disorders. Biology 11(3):469. https://doi.org/10.3390/biology11030469

Liu C-F, Hsu J, Xu X, Ramachandran S, Wang V, Miller MI, Hillis AE, Faria AV (2021) Deep learning-based detection and segmentation of diffusion abnormalities in acute ischemic stroke. Commun Med 1(1):1–18. https://doi.org/10.1038/s43856-021-00062-8

Liu Y, Xu C, Cheung S-C, Lü J (2014) Greendroid: automated diagnosis of energy inefficiency for smartphone applications. IEEE Transact Softw Eng 40(9):911–940

Liu X, Wang Z (2024) Deep learning in medical image classification from MRI-based brain tumor images. Preprint at arXiv:2408.00636

Loddo A, Buttau S, Di Ruberto C (2022) Deep learning based pipelines for Alzheimer's disease diagnosis: a comparative study and a novel deep-ensemble method. Comput Biol Med 141:105032. https://doi.org/10.1016/j.compbiomed.2021.105032

Loughland C, Draganic D, McCabe K, Richards J, Nasir A, Allen J, Catts S, Jablensky A, Henskens F, Michie P et al (2010) Australian schizophrenia research bank: a database of comprehensive clinical, endophenotypic and genetic data for Aetiological studies of schizophrenia, Australian & New Zealand. J Psychiatry 44(11):1029–1035

Lundervold AS, Lundervold A (2019) An overview of deep learning in medical imaging focusing on MRI. Z Med Phys 29(2):102–127. https://doi.org/10.1016/j.zemedi.2018.11.002
Luts J, Heerschap A, Suykens JA, Van Huffel S (2007) A combined MRI and MRSI based multiclass system for brain tumour recognition using LS-SVMS with class probabilities and feature selection. Artif Intell Med 40(2):87–102. https://doi.org/10.1016/j.artmed.2007.02.002
Maier O, Menze BH, Gablentz J, Häni L, Heinrich MP, Liebrand M, Winzeck S, Basit A, Bentley P, Chen L, et al (2017) ISLES 2015-a public evaluation benchmark for ischemic stroke lesion segmentation from multispectral MRI. Med Image Anal 35:250–269 https://doi.org/10.1016/j.media.2016.07.009
Majib MS, Rahman MM, Sazzad TS, Khan NI, Dey SK (2021) VGG-SCNET: A VGG net-based deep learning framework for brain tumor detection on MRI images. IEEE Access 9: 116942–116952 https://doi.org/10.1109/ACCESS.2021.3105874
Maleki F, Ovens K, Gupta R, Reinhold C, Spatz A, Forghani R (2022) Generalizability of machine learning models: quantitative evaluation of three methodological pitfalls. Radiol Artif Intell 5(1):220028
Malone IB, Cash D, Ridgway GR, MacManus DG, Ourselin S, Fox NC, Schott JM (2013) MIRIAD-public release of a multiple time point Alzheimer's MR imaging dataset. NeuroImage 70:33–36. https://doi.org/10.1016/j.neuroimage.2012.12.044
Marcus DS, Wang TH, Parker J, Csernansky JG, Morris JC, Buckner RL (2007) Open access series of imaging studies (oasis): cross-sectional MRI data in young, middle aged, nondemented, and demented older adults. J Cogn Neurosci 19(9):1498–1507. https://doi.org/10.1162/jocn.2007.19.9.1498
Marek K, Jennings D, Lasch S, Siderowf A, Tanner C, Simuni T, Coffey C, Kieburtz K, Flagg E, Chowdhury S et al (2011) The Parkinson progression marker initiative (PPMI). Prog Neurobiol 95(4):629–635
Marwa E-G, Moustafa HE-D, Khalifa F, Khater H, AbdElhalim E (2023) An MRI-based deep learning approach for accurate detection of Alzheimer's disease. Alex Eng J 63:211–221
Mateos-Pérez JM, Dadar M, Lacalle-Aurioles M, Iturria-Medina Y, Zeighami Y, Evans AC (2018) Structural neuroimaging as clinical predictor: a review of machine learning applications. NeuroImage Clin 20:506–522
Mathkunti NM, Rangaswamy S (2020) Machine learning techniques to identify dementia. SN Comput Sci 1(3):1–6. https://doi.org/10.1007/s42979-020-0099-4
Mazurowski MA, Buda M, Saha A, Bashir MR (2019) Deep learning in radiology: an overview of the concepts and a survey of the state of the art with focus on MRI. J Magn Resonance Imaging 49(4):939–954. https://doi.org/10.1002/jmri.26534
Mehmod A, Maqsood M, Bashir M, Shuyuan Y (2020) A deep Siamese convolution neural network for multi-class classification of Alzheimer disease. Brain Sci 10(2):84. https://doi.org/10.3390/brainsci10020084
Mennes M, Biswal BB, Castellanos FX, Milham MP (2013) Making data sharing work: the FCP/INDI experience. Neuroimage 82:683–691. https://doi.org/10.1016/j.neuroimage.2012.10.064
Mikolas P, Hlinka J, Skoch A, Pitra Z, Frodl T, Spaniel F, Hajek T (2018) Machine learning classification of first-episode schizophrenia spectrum disorders and controls using whole brain white matter fractional anisotropy. BMC Psychiatry 18(1):1–7. https://doi.org/10.1186/s12888-018-1678-y
Minz A, Mahobiya C (2017) Mr image classification using adaboost for brain tumor type. In: 2017 IEEE 7th International Advance Computing Conference (IACC), IEEE. pp 701–705. https://doi.org/10.1109/IACC.2017.0146
Miotto R, Wang F, Wang S, Jiang X, Dudley JT (2018) Deep learning for healthcare: review, opportunities and challenges. Brief Bioinform 19(6):1236–1246. https://doi.org/10.1093/bib/bbx044
Miranda E, Aryuni M, Irwansyah E (2016) A survey of medical image classification techniques. In: 2016 International Conference on Information Management and Technology (ICIMTech), IEEE. pp 56–61. https://doi.org/10.1109/ICIMTech.2016.7930302
Mozhdeh A, Chitsazian S, Chakrabarti P, Chakrabarti T, Kateb B, Nami M (2021) An MRI-based deep learning model to predict Parkinson's disease stages. medRxiv
Mujahid M, Rehman A, Alam T, Alamri FS, Fati SM, Saba T (2023) An efficient ensemble approach for Alzheimer's disease detection using an adaptive synthetic technique and deep learning. Diagnostics 13(15):2489
Mårtensson G, Ferreira D, Granberg T, Cavallin L, Oppedal K, Padovani A, Rektorova I, Bonanni L, Pardini M, Kramberger MG et al (2020) The reliability of a deep learning model in clinical out-of-distribution MRI data: a multicohort study. Med Image Anal 66:101714. https://doi.org/10.1016/j.media.2020.101714
Nadeem MW, Ghamdi MAA, Hussain M, Khan MA, Khan KM, Almotiri SH, Butt SA (2020) Brain tumor analysis empowered with deep learning: a review, taxonomy, and future challenges. Brain Sci 10(2):118. https://doi.org/10.3390/brainsci10020118
Nandpuru HB, Salankar S, Bora V (2014) MRI brain cancer classification using support vector machine. In: 2014 IEEE Students' Conference on Electrical, Electronics and Computer Science, IEEE. pp 1–6. https://doi.org/10.1109/SCEECS.2014.6804439

Nayak DR, Dash R, Majhi B (2020) Automated diagnosis of multi-class brain abnormalities using MRI images: a deep convolutional neural network based method. Pattern Recogn Lett 138:385–391. https://doi.org/10.1016/j.patrec.2020.04.018

Nazir S, Dickson DM, Akram MU (2023) Survey of explainable artificial intelligence techniques for biomedical imaging with deep neural networks. Comput Biol Med 156:106668

Nazir M, Shakil S, Khurshid K (2021) Role of deep learning in brain tumor detection and classification (2015 to 2020): a review. Comput Med Imaging Graph 91:101940. https://doi.org/10.1016/j.compmedimag.2021.101940

Nemoto K, Sakaguchi H, Kasai W, Hotta M, Kamei R, Noguchi T, Minamimoto R, Arai T, Asada T (2021) Differentiating dementia with Lewy bodies and Alzheimer's disease by deep learning to structural MRI. J Neuroimaging 31(3):579–587. https://doi.org/10.1111/jon.12835

Neromyliotis E, Kalamatianos T, Paschalis A, Komaitis S, Fountas KN, Kapsalaki EZ, Stranjalis G, Tsougos I (2022) Machine learning in meningioma MRI: past to present. a narrative review. J Magn Resonance Imaging 55(1), 48–60 https://doi.org/10.1002/jmri.27378

Noor MBT, Zenia NZ, Kaiser MS, Mamun SA, Mahmud M (2020) Application of deep learning in detecting neurological disorders from magnetic resonance images: a survey on the detection of alzheimer's disease, parkinson's disease and schizophrenia. Brain Inform 7(1):1–21. https://doi.org/10.1186/s40708-020-00112-2

Noor MBT, Zenia NZ, Kaiser MS, Mahmud M, Mamun SA (2019) Detecting neurodegenerative disease from MRI: a brief review on a deep learning perspective. In: International Conference on Brain Informatics, Springer. pp 115–125. https://doi.org/10.1007/978-3-030-37078-7_12

Ocasio E, Duong TQ (2021) Deep learning prediction of mild cognitive impairment conversion to Alzheimer's disease at 3 years after diagnosis using longitudinal and whole-brain 3D MRI. Peer J Computer Science 7: 560 https://doi.org/10.7717/peerj-cs.560

Okoye C, Obialo-Ibeawuchi CM, Obajeun OA, Sarwar S, Tawfik C, Waleed MS, Wasim AU, Mohamoud I, Afolayan AY, Mbaezue RN (2023) Early diagnosis of autism spectrum disorder: a review and analysis of the risks and benefits. Cureus 15(8)

Olson JL, Bild DE, Kronmal RA, Burke GL (2016) Legacy of mesa. Global Heart 11(3):269–274. https://doi.org/10.1016/j.gheart.2016.08.004

Parlett-Pelleriti CM, Stevens E, Dixon D, Linstead EJ (2022) Applications of unsupervised machine learning in autism spectrum disorder research: a review. Rev J Autism Develop Dis. https://doi.org/10.1007/s40489-021-00299-y

Pellegrini E, Ballerini L, Hernandez MdCV, Chappell FM, González-Castro V, Anblagan D, Danso S, Muñoz-Maniega S, Job D, Pernet C et al (2018) Machine learning of neuroimaging for assisted diagnosis of cognitive impairment and dementia: a systematic review Alzheimer's & dementia: diagnosis. Assess Dis Monitor 10:519–535. https://doi.org/10.1016/j.dadm.2018.07.004

Pinto-Coelho L (2023) How artificial intelligence is shaping medical imaging technology: a survey of innovations and applications. Bioengineering 10(12):1435

Poyraz AK, Dogan S, Akbal E, Tuncer T (2022) Automated brain disease classification using exemplar deep features. Biomed Signal Process Control 73:103448

Prisnie JC, Sajobi TT, Wang M, Patten SB, Fiest KM, Bulloch AG, Pringsheim T, Wiebe S, Jette N (2018) Effects of depression and anxiety on quality of life in five common neurological disorders. Gen Hosp Psychiatry 52:58–63. https://doi.org/10.1016/j.genhosppsych.2018.03.009

Qian J, Li H, Wang J, He L (2023) Recent advances in explainable artificial intelligence for magnetic resonance imaging. Diagnostics 13(9):1571

Qiu S, Chang GH, Panagia M, Gopal DM, Au R, Kolachalama VB (2018) Fusion of deep learning models of MRI scans, mini-mental state examination, and logical memory test enhances diagnosis of mild cognitive impairment. Alzheimer's & Dementia: Diagnosis. Assess Dis Monitor 10:737–749. https://doi.org/10.1016/j.dadm.2018.08.013

Quaak M, Mortel L, Thomas RM, Wingen G (2021) Deep learning applications for the classification of psychiatric disorders using neuroimaging data: systematic review and meta-analysis. NeuroImage Clin 30:102584. https://doi.org/10.1016/j.nicl.2021.102584

Rachma MF, Valdés-Hernández MdC, Agan MLF, Komura T (2017) Deep learning vs. conventional machine learning: pilot study of wmh segmentation in brain mri with absence or mild vascular pathology. J Imaging 3(4):66 https://doi.org/10.3390/jimaging3040066

Raghavaiah P, Varadarajan SA (2022) CAD system design for Alzheimer's disease diagnosis using temporally consistent clustering and hybrid deep learning models. Biomed Signal Process Control 75:103571. https://doi.org/10.1016/j.bspc.2022.103571

Ramzan F, Khan MUG, Rehmat A, Iqbal S, Saba T, Rehman A, Mehmood Z (2020) A deep learning approach for automated diagnosis and multi-class classification of Alzheimer's disease stages using resting-state fmri and residual neural networks. J Med Syst 44(2):1–16. https://doi.org/10.1007/s10916-019-1475-2

Rashid M, Singh H, Goyal V (2020) The use of machine learning and deep learning algorithms in functional magnetic resonance imaging-a systematic review. Expert Syst 37(6):12644. https://doi.org/10.1111/exsy.12644

Rastogi D, Johri P, Tiwari V, Elngar AA (2024) Multi-class classification of brain tumour magnetic resonance images using multi-branch network with inception block and five-fold cross validation deep learning framework. Biomed Signal Process Control 88:105602

Rudie JD, Rauschecker AM, Xie L, Wang J, Duong MT, Botzolakis EJ, Kovalovich A, Egan JM, Cook T, Bryan RN, et al (2020) Subspecialty-level deep gray matter differential diagnoses with deep learning and bayesian networks on clinical brain MRI: a pilot study. Radiol Artif Intell 2(5) https://doi.org/10.1148/ryai.2020190146

Saboor A, Li JP, Ul Haq A, Shehzad U, Khan S, Aotaibi RM, Alajlan SA (2024) DDFC: deep learning approach for deep feature extraction and classification of brain tumors using magnetic resonance imaging in e-healthcare system. Sci Rep 14(1):6425

Sabuncu M, Buckner R, Smoller J, Lee P, Fischl B, Sperling R (2012) Alzheimer's disease neuroimaging initiative the association between a polygenic Alzheimer score and cortical thickness in clinically normal subjects. Cereb Cortex 22:2653–2661

Sabuncu MR, Koglu E (2015) Clinical prediction from structural brain MRI scans: a large-scale empirical study. Neuroinformatics 13(1):31–46. https://doi.org/10.1007/s12021-014-9238-1

Saeedi S, Rezayi S, Keshavarz H, Niakan Kalhori R, S. (2023) MRI-based brain tumor detection using convolutional deep learning methods and chosen machine learning techniques. BMC Med Inform Decision Making 23(1):16

Salehi AW, Baglat P, Sharma BB, Gupta G, Upadhya AA (2020) CNN model: earlier diagnosis and classification of Alzheimer disease using MRI. In: 2020 International Conference on Smart Electronics and Communication (ICOSEC), IEEE. pp 156–161. https://doi.org/10.1109/ICOSEC49089.2020.9215402

Salvador R, Radua J, Canales-Rodríguez EJ, Solanes A, Sarró S, Goikolea JM, Valiente A, Monté GC, Natividad MdC, Guerrero-Pedraza A et al (2017) Evaluation of machine learning algorithms and structural features for optimal MRI-based diagnostic prediction in psychosis. PLoS One 12(4):0175683. https://doi.org/10.1371/journal.pone.0175683

Saritha M, Joseph KP, Mathew AT (2013) Classification of MRI brain images using combined wavelet entropy based spider web plots and probabilistic neural network. Pattern Recogn Lett 34(16):2151–2156. https://doi.org/10.1016/j.patrec.2013.08.017

Sasabe J, Suzuki M, Imanishi N, Aiso S (2014) Activity of D-amino acid oxidase is widespread in the human central nervous system. Front Synap Neurosci 6:14. https://doi.org/10.3389/fnsyn.2014.00014

Sharma R, Goel T, Tanveer M, Murugan R (2022) FDN-ADNET: Fuzzy LS-TWSVM based deep learning network for prognosis of the Alzheimer's disease using the sagittal plane of MRI scans. Appl Soft Comput 115:108099

Shaver MM, Kohanteb PA, Chiou C, Bardis MD, Chantaduly C, Bota D, Filippi CG, Weinberg B, Grinband J, Chow DS et al (2019) Optimizing neuro-oncology imaging: a review of deep learning approaches for glioma imaging. Cancers 11(6):829. https://doi.org/10.3390/cancers11060829

Shoeibi A, Khodatars M, Jafari M, Ghassemi N, Moridian P, Alizadehsani R, Ling SH, Khosravi A, Alinejad-Rokny H, Lam H-K et al (2023) Diagnosis of brain diseases in fusion of neuroimaging modalities using deep learning: a review. Inform Fusion 93:85–117

Shoeibi A, Khodatars M, Jafari M, Moridian P, Rezaei M, Alizadehsani R, Khozeimeh F, Gorriz JM, Heras J, Panahiazar M et al (2021) Applications of deep learning techniques for automated multiple sclerosis detection using magnetic resonance imaging: A review. Comput Biol Med 136:104697. https://doi.org/10.1016/j.compbiomed.2021.104697

Shojaei S, Abadeh MS, Momeni Z (2023) An evolutionary explainable deep learning approach for Alzheimer's MRI classification. Expert Syst Appl 220:119709

Silva RF, Castro E, Gupta CN, Cetin M, Arbabshirani M, Potluru VK, Plis SM, Calhoun VD (2014) The tenth annual MLSP competition: Schizophrenia classification challenge. In: 2014 IEEE International Workshop on Machine Learning for Signal Processing (MLSP), IEEE, pp 1–6. https://doi.org/10.1109/MLSP.2014.6958889

Simo AMD, Kouanou AT, Monthe V, Nana MK, Lonla BM (2024) Introducing a deep learning method for brain tumor classification using MRI data towards better performance. Inform Med Unlocked 44:101423

Somasundaram K, Genish T (2015) An atlas based approach to segment the hippocampus from MRI of human head scans for the diagnosis of Alzheimers disease. Int J Comput Intell Inform 5(1)

Somasundaram S, Gobinath R (2019) Current trends on deep learning models for brain tumor segmentation and detection–a review. In: 2019 International Conference on Machine Learning, Big Data, Cloud and Parallel Computing (COMITCon), IEEE. pp 217–221. https://doi.org/10.1109/COMITCon.2019.8862209

Sooriya RD Narmada (2017) A sophisticated convolutional neural network model for brain tumor classification. In: 2017 IEEE International Conference on Industrial and Information Systems (ICIIS), pp 1–5. IEEE https://doi.org/10.1109/ICIINFS.2017.8300364

Srinivasan S, Bai PSM, Mathivanan SK, Muthukumaran V, Babu JC, Vilcekova L (2023) Grade classification of tumors from brain magnetic resonance images using a deep learning technique. Diagnostics 13(6):1153

Talai AS, Sedlacik J, Boelmans K, Forkert ND (2021) Utility of multi-modal MRI for differentiating of Parkinson's disease and progressive supranuclear palsy using machine learning. Front Neurol. https://doi.org/10.3389/fneur.2021.648548

Talo M, Yildirim O, Baloglu UB, Aydin G, Acharya UR (2019) Convolutional neural networks for multi-class brain disease detection using MRI images. Comput Med Imaging Graph 78:101673. https://doi.org/10.1016/j.compmedimag.2019.101673

Tamminga CA, Pearlson G, Keshavan M, Sweeney J, Clementz B, Thaker G (2014) Bipolar and schizophrenia network for intermediate phenotypes: outcomes across the psychosis continuum. Schizophrenia bulletin 40(Suppl–2):131–137. https://doi.org/10.1093/schbul/sbt179

Tandel GS, Balestrieri A, Jujaray T, Khanna NN, Saba L, Suri JS (2020) Multiclass magnetic resonance imaging brain tumor classification using artificial intelligence paradigm. Comput Biol Med 122:103804. https://doi.org/10.1016/j.compbiomed.2020.103804

Tandel GS, Biswas M, Kakde OG, Tiwari A, Suri HS, Turk M, Laird JR, Asare CK, Ankrah AA, Khanna N et al (2019) A review on a deep learning perspective in brain cancer classification. Cancers 11(1):111. https://doi.org/10.3390/cancers11010111

Taşcı B (2023) Attention deep feature extraction from brain MRIS in explainable mode: DGXAINET. Diagnostics 13(5):859

Thangavel P, Natarajan Y, Preethaa KS (2023) EAD-DNN: Early Alzheimer's disease prediction using deep neural networks. Biomed Signal Process Control 86:105215

Tian M, He X, Jin C, He X, Wu S, Zhou R, Zhang X, Zhang K, Gu W, Wang J et al (2021) Transpathology: molecular imaging-based pathology. Eur J Nuclear Med Mol Imaging 48:2338–2350

Tjoa E, Guan C (2020) A survey on explainable artificial intelligence (XAI): toward medical XAI. IEEE Transact Neural Netw Learn Syst 32(11):4793–4813

Tomson T (2006) Excess mortality in epilepsy in developing countries. Lancet Neurol 5(10):804–805. https://doi.org/10.1016/S1474-4422(06)70555-5

Tyagi V (2019) A review on image classification techniques to classify neurological disorders of brain MRI. In: 2019 International Conference on Issues and Challenges in Intelligent Computing Techniques (ICICT), vol 1, IEEE. pp 1–4. https://doi.org/10.1109/ICICT46931.2019.8977658

Ucuzal, H., YAŞAR, Ş., Çolak, C (2019) Classification of brain tumor types by deep learning with convolutional neural network on magnetic resonance images using a developed web-based interface. In: 2019 3rd International Symposium on Multidisciplinary Studies and Innovative Technologies (ISMSIT), IEEE. pp 1–5. https://doi.org/10.1109/ISMSIT.2019.8932761

Ullah Z, Jamjoom M (2023) Deep learning for Alzheimer's stages detection using brain images. Comput Mater Continua 74(1)

Usman K, Rajpoot K (2017) Brain tumor classification from multi-modality MRI using wavelets and machine learning. Pattern Anal Appl 20(3):871–881. https://doi.org/10.1007/s10044-017-0597-8

Valliani AA-A, Ranti D, Oermann EK (2019) Deep learning and neurology: a systematic review. Neurol Ther 8:351–365. https://doi.org/10.1007/s40120-019-00153-8

Velden BH, Kuijf HJ, Gilhuijs KG, Viergever MA (2022) Explainable artificial intelligence (XAI) in deep learning-based medical image analysis. Med Image Anal 79:102470

Viswan V, Shaffi N, Mahmud M, Subramanian K, Hajamohideen F (2024) Explainable artificial intelligence in Alzheimer's disease classification: a systematic review. Cogn Comput 16(1):1–44

Wang CS-M, Chang W-H, Yang Y-K, Cheng K-S (2023) Comparing transcranial direct current stimulation (TDCS) with other non-invasive brain stimulation (NIBS) in the treatment of Alzheimer's disease: a literature review. J Med Biol Eng 43(4):362–375

Wang L, Wang H, Huang Y, Yan B, Chang Z, Liu Z, Zhao M, Cui L, Song J, Li F (2022) Trends in the application of deep learning networks in medical image analysis: evolution between 2012 and 2020. Eur J Radiol 146:110069. https://doi.org/10.1016/j.ejrad.2021.110069

Wang J, Zhu H, Wang S-H, Zhang Y-D (2021) A review of deep learning on medical image analysis. Mobile Netw Appl 26(1):351–380. https://doi.org/10.1007/s11036-020-01672-7

WHO: WHO Global Health Estimates. https://www.who.int/news-room/fact-sheets/detail/the-top-10-causes-of-death Accessed 8 Aug 2023

Wood DA, Kafiabadi S, Al Busaidi A, Guilhem E, Montvila A, Lynch J, Townend M, Agarwal S, Mazumder A, Barker GJ et al (2022) Deep learning models for triaging hospital head MRI examinations. Med Image Anal 78:102391. https://doi.org/10.1016/j.media.2022.102391

Xin J, Zhang Y, Tang Y, Yang Y (2019) Brain differences between men and women: evidence from deep learning. Front Media SA. https://doi.org/10.3389/fnins.2019.00185

Yagis E, De Herrera AGS, Citi L (2019) Generalization performance of deep learning models in neurodegenerative disease classification. In: 2019 IEEE International Conference on Bioinformatics and Biomedicine (BIBM), IEEE. pp 1692–1698. https://doi.org/10.1109/BIBM47256.2019.8983088

Yagis E, De Herrera AGS, Citi L (2021) Convolutional autoencoder based deep learning approach for alzheimer's disease diagnosis using brain mri. In: 2021 IEEE 34th International Symposium on Computer-Based Medical Systems (CBMS), IEEE. pp 486–491. https://doi.org/10.1109/CBMS52027.2021.00097

Yamanakkanavar N, Choi JY, Lee B (2020) MRI segmentation and classification of human brain using deep learning for diagnosis of Alzheimer's disease: a survey. Sensors 20(11):3243. https://doi.org/10.3390/s20113243

Yang G, Ye Q, Xia J (2022) Unbox the black-box for the medical explainable ai via multi-modal and multi-centre data fusion: a mini-review, two showcases and beyond. Inform Fusion 77:29–52

Yang H, Zhang J, Liu Q, Wang Y (2018) Multimodal MRI-based classification of migraine: using deep learning convolutional neural network. Biomed Eng Online 17(1):1–14. https://doi.org/10.1186/s12938-018-0587-0

Yao AD, Cheng DL, Pan I, Kitamura F (2020) Deep learning in neuroradiology: a systematic review of current algorithms and approaches for the new wave of imaging technology. Radiol Artif Intellig. https://doi.org/10.1148/ryai.2020190026

Yao Z, Mao W, Yuan Y, Shi Z, Zhu G, Zhang W, Wang Z, Zhang G (2023) Fuzzy-VGG: A fast deep learning method for predicting the staging of Alzheimer's disease based on brain MRI. Inf Sci 642:119129

Yeung HW, Stolicyn A, Buchanan CR, Tucker-Drob EM, Bastin ME, Luz S, Whalley HC, Cox SR, Smith KM (2022) Predicting sex, age, general cognition and mental health with machine learning on brain structural connectomes. medRxiv. https://doi.org/10.1002/hbm.26182

Yolcu G, Oztel I, Kazan S, Oz C, Palaniappan K, Lever TE, Bunyak F (2017) Deep learning-based facial expression recognition for monitoring neurological disorders. In: 2017 IEEE International Conference on Bioinformatics and Biomedicine (BIBM), IEEE. pp 1652–1657. https://doi.org/10.1109/BIBM.2017.8217907

Yousaf F, Iqbal S, Fatima N, Kousar T, Rahim MSM (2023) Multi-class disease detection using deep learning and human brain medical imaging. Biomed Signal Process Control 85:104875

Yulianto A, et al (2018) Pengaruh literasi keuangan syariah terhadap keputusan penggunaan produk atau layanan lembaga keuangan syariah

Yücel M, Solowij N, Respondek C, Whittle S, Fornito A, Pantelis C, Lubman DI (2008) Regional brain abnormalities associated with long-term heavy cannabis use. Arch General Psychiatry 65(6):694–701. https://doi.org/10.1001/archpsyc.65.6.694

Zaharchuk G, Gong E, Wintermark M, Rubin D, Langlotz C (2018) Deep learning in neuroradiology. Am J Neuroradiol 39(10):1776–1784. https://doi.org/10.3174/ajnr.A5543

Zbontar J, Knoll F, Sriram A, Murrell T, Huang Z, Muckley MJ, Defazio A, Stern R, Johnson P, Bruno M, et al (2018) FASTMRI: An open dataset and benchmarks for accelerated MRI. Preprint at arXiv:1811.08839

Zegers C, Posch J, Traverso A, Eekers D, Postma A, Backes W, Dekker A (2021) Current applications of deep-learning in neuro-oncological MRI. Phys Med 83:161–173. https://doi.org/10.1016/j.ejmp.2021.03.003

Zeineldin RA, Karar ME, Elshaer Z, Coburger J, Wirtz CR, Burgert O, Mathis-Ullrich F (2024) Explainable hybrid vision transformers and convolutional network for multimodal glioma segmentation in brain MRI. Sci Rep 14(1):3713

Zhang Z (2019) Radiological images and machine learning: trends, perspectives, and prospects. Comput Biol Med 108:354–370. https://doi.org/10.1016/j.compbiomed.2019.02.017

Zhang J (2022) Mining imaging and clinical data with machine learning approaches for the diagnosis and early detection of Parkinson's disease. NPJ Parkinson's Dis 8(1):1–15. https://doi.org/10.1038/s41531-021-00266-8

Zhang X, Han L, Zhu W, Sun L, Zhang D (2021) An explainable 3D residual self-attention deep neural network for joint atrophy localization and Alzheimer's disease diagnosis using structural MRI. IEEE J Biomed Health Inform. https://doi.org/10.1109/JBHI.2021.3066832

Zhang L, Wang M, Liu M, Zhang D (2020) A survey on deep learning for neuroimaging-based brain disorder analysis. Front Neurosci 14:779. https://doi.org/10.3389/fnins.2020.00779

Zhao X, Zhao X-M (2021) Deep learning of brain magnetic resonance images: a brief review. Methods 192:131–140. https://doi.org/10.1016/j.ymeth.2020.09.007

Zhou L, Wang M, Zhou N (2024) Distributed federated learning-based deep learning model for privacy MRI brain tumor detection. Preprint at arXiv:2404.10026

Zhu G, Jiang B, Tong L, Xie Y, Zaharchuk G, Wintermark M (2019) Applications of deep learning to neuro-imaging techniques. Front Media SA. https://doi.org/10.3389/fneur.2019.00869

Zhu Y, Nakatani H, Yassin W, Maikusa N, Okada N, Kunimatsu A, Abe O, Kuwabara H, Yamasue H, Kasai K et al (2022) Application of a machine learning algorithm for structural brain images in chronic schizophrenia to earlier clinical stages of psychosis and autism spectrum disorder: A multiprotocol imaging dataset study. Schizophr Bull 48(3):563–574. https://doi.org/10.1093/schbul/sbac030



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