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(Review Article)

Explainable AI-driven Deep Learning for Neurological Disease Diagnosis using MRI: A systematic review and future directions

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Abstract

This systematic literature review examines the transformative impact of deep learning and explainable AI (XAI) on neurological disease diagnosis using MRI. We analyzed 180 studies from prominent databases, including IEEE Xplore, ScienceDirect, Google Scholar, PubMed, and Scopus, focusing on the methodologies, applications, and emerging trends in diagnosing brain tumors, Alzheimer's disease, and Parkinson's disease. Our findings reveal the increasing use of XAI techniques like Grad-CAM, LIME, and SHAP to enhance model transparency and trustworthiness, a crucial step towards clinical adoption. While deep learning models demonstrate promising diagnostic accuracy, challenges persist, including limited datasets, high computational demands, and the need for robust clinical validation. This review highlights the potential of multimodal data integration and the importance of developing computationally efficient and interpretable models. We identify key future directions, emphasizing the need for larger, more diverse datasets, advancements in XAI methodologies, and the development of personalized treatment strategies guided by AI-driven insights. This comprehensive analysis serves as a valuable resource for researchers and clinicians, offering a roadmap for future research and the responsible implementation of AI in neurological disease diagnosis.

Keywords: Neurological Disease Diagnosis; MRI Imaging; Deep Learning; Explainable Artificial Intelligence (XAI); Brain Tumor; Alzheimer's Disease; Parkinson's Disease

1. Introduction

Neurological disorders, including brain tumors, Alzheimer's disease, and Parkinson's disease, pose significant diagnostic and therapeutic challenges. These conditions affect millions worldwide, impacting quality of life and straining healthcare systems [1,2]. The advent of deep learning and explainable artificial intelligence (XAI) has revolutionized medical imaging, particularly in the analysis of MRI scans for neurological disease diagnosis. These advancements offer the potential to enhance diagnostic precision, deepen our understanding of disease mechanisms, and pave the way for personalized treatment strategies [3,4].

1.1. Background

Deep learning techniques, particularly Convolutional Neural Networks (CNNs), have demonstrated remarkable success in image recognition tasks, making them well-suited for analyzing the complexities of medical imaging data [3]. Furthermore, XAI techniques like Gradient-weighted Class Activation Mapping (Grad-CAM) provide crucial insights into the decision-making processes of these AI models, increasing transparency and fostering trust within clinical settings [4,5]. This transparency is essential for building confidence among healthcare providers, which is crucial for the safe and effective integration of AI into medical practice [6].

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1.2. Statistics

The global burden of neurological diseases is substantial, with significant socio-economic ramifications. Alzheimer's disease and other dementias currently affect an estimated 57 million people worldwide, a number projected to triple to approximately 153 million by 2050 due to population aging and increased life expectancy [7,8]. Brain tumors, while less prevalent, represent approximately 1.4% of new cancer diagnoses in the United States [9]. Parkinson's disease affects over 10 million individuals globally, with prevalence expected to rise alongside global aging trends [8]. The economic burden of these conditions is immense. Alzheimer's disease alone is projected to cost over $1 trillion in the U.S. by 2050, while brain tumors and Parkinson's disease place further significant financial strain on healthcare systems [7,9].

1.3. Prior Literature Review

Existing literature has explored the application of various AI and machine learning (ML) techniques for diagnosing neurological diseases, especially Alzheimer's and Parkinson's disease. These reviews often highlight several key challenges:

- **Limited Datasets:** The scarcity of large, diverse datasets hinders the generalizability and robustness of developed AI models [12-21].
- **High Computational Demands:** Advanced AI and ML models often require substantial computational resources, posing a barrier to real-time applications and widespread clinical deployment [13,16,17,21].
- **Lack of Clinical Validation:** A significant gap exists in the clinical validation of these AI models, raising concerns about their real-world utility and reliability in medical settings [12,14,17,18].
- **Privacy Concerns:** The use of sensitive patient data in AI research necessitates careful consideration of privacy and ethical implications to ensure data security and patient confidentiality [12,14].

Despite these challenges, the literature also points to several notable achievements and future directions:

- **Systematic Reviews and Meta-Analyses:** Comprehensive reviews and meta-analyses have synthesized existing research, offering valuable insights into the current landscape of AI applications in neuroimaging and sensor data analysis [12,18].
- **Identification of Key Challenges:** These reviews have systematically identified and discussed key challenges, including data heterogeneity, model interpretability, and the need for standardized evaluation metrics [13,15,16].
- **Future Research Directions:** Recommendations for future research emphasize the development of more robust and interpretable models, the creation of larger and more diverse datasets, and the integration of AI models into clinical workflows to facilitate validation and adoption [14,17,20,21].

1.4. Justification for a New SLR

While deep learning and AI have made significant strides in medical imaging, a critical gap remains in the literature regarding the integration of explainable AI (XAI) for neurological disease diagnosis using MRI. This systematic literature review addresses this gap by providing a thorough analysis of current methodologies, their effectiveness, limitations, and potential future research directions. Specifically, this review focuses on the crucial role of XAI in enhancing the transparency and trustworthiness of deep learning models, a factor crucial for clinical acceptance and adoption. This review aims to bridge the gap between the exciting advancements in AI and their practical application in real-world clinical settings.

1.5. Objectives of this SLR

- Evaluate the effectiveness of deep learning models in diagnosing neurological diseases from MRI images.
- Analyze the role of XAI techniques in enhancing the transparency and trustworthiness of these models.
- Investigate the integration of multi-modal data to improve diagnostic accuracy.
- Identify challenges and future research directions in the application of AI in medical imaging, specifically concerning neurological diseases and the use of XAI.

2. Research Methodology

This systematic literature review (SLR) follows a structured and meticulous approach to comprehensively gather, evaluate, and synthesize research on the application of deep learning and explainable AI in diagnosing neurological diseases using MRI images. The methodology aims to ensure a robust exploration of existing studies while aligning with the objectives of assessing current methodologies, evaluating advancements, and identifying gaps in the field. The review process begins with the establishment of primary objectives, encompassing the evaluation of deep learning models' diagnostic capabilities, the integration of explainable AI techniques, the role of multi-modal data, and the identification of ongoing challenges and potential research avenues.

2.1. Question Formalization

To ensure a targeted and systematic approach, research questions were carefully formalized as a guiding framework for the review. These questions anchor the methodology and focus on examining critical themes such as model performance, interpretability, and innovation. The formalization process ensures that all aspects of the research are approached comprehensively, with a focus on addressing both technical and clinical perspectives.

Table 1 Research Questions**.**

Index	Question	Description	Discussion & Justification
RQ1	What are the primary neurological disorders examined in the study?	This question aims to establish the scope of the study by identifying the specific neurological disorders under investigation.	The study delves into three primary neurological disorders: brain tumors, Alzheimer's disease, and Parkinson's disease. These conditions significantly impact millions of individuals worldwide, imposing a substantial burden on healthcare systems and affecting patients' quality of life. The prevalence and severity of these disorders highlight the urgent need for innovative diagnostic tools that can improve early detection, accurate diagnosis, and timely intervention.
RQ2	How does the study approach the analysis of data and the selection of relevant research articles?	This question focuses on the systematic process of data analysis and article selection employed in the SLR.	The research methodology section details a structured approach involving a comprehensive literature search across multiple databases. It outlines the inclusion and exclusion criteria used to filter studies based on publication date, relevance, peer review status, and adherence to quality standards.
RQ3	How effective are deep learning models in diagnosing neurological diseases from MRI images?	This question aims to evaluate the diagnostic accuracy and reliability of various deep learning models. Understanding the effectiveness of these models is crucial for determining their potential to replace or augment traditional diagnostic methods.	Deep learning models, such as CNNs and hybrid models, have shown high accuracy in diagnosing neurological diseases like brain tumors and Alzheimer's disease, often outperforming traditional methods. For instance, models like ResNet and EfficientNet have achieved accuracies above 95% in various studies.
RQ4	How can the integration of multi-modal data improve diagnostic accuracy?	This question investigates the benefits of combining MRI with other imaging modalities or clinical data. Multi-modal data integration can provide a more comprehensive view of a patient's condition, potentially leading to more accurate diagnoses.	Integrating multi-modal data, such as combining MRI with PET scans or clinical data, has been shown to improve diagnostic accuracy. Studies have demonstrated that multi-modal approaches can capture more comprehensive information about the disease, leading to better diagnostic performance and early detection.
RQ5	What role do explainable AI techniques play in enhancing the transparency and	This question focuses on the impact of explainable AI on the interpretability and clinical acceptance of AI models. Explainable AI techniques are	Explainable AI techniques, such as Grad-CAM and SHAP, have been integrated into deep learning models to provide visual and interpretable explanations of model decisions. These techniques help in identifying important

	trustworthiness of these models?	essential for gaining the trust of healthcare professionals and ensuring that AI-driven decisions can be understood and validated.	features and regions in MRI images, thereby enhancing the trustworthiness and clinical acceptance of AI models.
RQ6	What are the potential benefits of using AI-based diagnostic tools for neurological diseases in clinical practice?	This question focuses on the potential impact of AI-based diagnostic tools on healthcare delivery and patient care, emphasizing the positive contributions AI can make to the field of neurology.	Several potential benefits of AI in clinical practice are implied, including improved diagnostic accuracy, early disease detection, personalized treatment planning, and reduced workload for healthcare professionals. The studies discuss the development of AI-powered systems that assist clinicians in making more informed decisions, leading to better patient outcomes.
RQ7	What are the current challenges and future research directions in the application of AI in medical imaging?	This question aims to identify existing barriers and propose areas for future research to advance the field. Understanding the challenges and opportunities in AI-driven medical imaging can help guide future studies and improve the implementation of these technologies in clinical practice.	Current challenges include the need for large annotated datasets, addressing data imbalance, and ensuring model generalizability across different populations. Future research directions involve developing more robust and interpretable models, integrating AI with clinical workflows, and exploring the use of AI in personalized medicine.

2.2. Analyzing Data and Selecting Articles

The literature search was conducted across databases like IEEE Xplore, ScienceDirect, Google Scholar, PubMed, and Scopus to ensure comprehensive coverage. Relevant keywords and tailored search strings were used to retrieve peer-reviewed studies aligned with the research objectives. Inclusion criteria focused on publication date, relevance, and methodological rigor, while studies lacking peer review or relevance were excluded.

Data extraction involved systematically gathering information on study design, findings, and limitations. Synthesized data was analyzed to identify trends, patterns, and research gaps, forming the basis for conclusions and recommendations. The review process was documented to ensure transparency and reproducibility.

2.2.1. Keywords & Search Strategy

The search utilized advanced filters and keyword combinations across databases to ensure inclusion of high-quality, relevant studies. Details of databases and search strategies are presented in Table 3.

Table 2 Research Paper Database and Search Strategy Details.

Database	Keyword / String	Count/ Results	Explored	Downloaded	Total Results	Total Explored	Total Downloaded	Final Total
IEEE Xplore	Neurological Disease Diagnosis using Artificial Intelligence Machine Learning Deep Learning Neural Networks	48	48	34	122	122	95	544
	Brain Tumor Disease	43	43	37				

	Classification identification Segmentation							
	Alzheimer's Disease Classification identification Segmentation	14	14	11				
	Parkinson's Disease Classification identification Segmentation	2	2	1				
	Neurological Disease Diagnosis using Cam Grad	3	3	3				
	Neurological Disease Diagnosis using Explainable AI	12	12	9				
Science Direct	Neurological Disease Diagnosis using Artificial Intelligence Machine Learning Deep Learning Neural Networks	2,685	350	103	22,114	1,500	230	
	Brain Tumor Disease Classification identification Segmentation	4,285	200	44				
	Alzheimer's Disease Classification identification Segmentation	2,521	200	39				
	Parkinson's Disease Classification identification Segmentation	1,679	150	31				
	Neurological Disease Diagnosis using Cam Grad	339	50	5				
	Neurological Disease Diagnosis using Explainable AI	10,605	100	8				

Google Scholar	Neurological Disease Diagnosis using Artificial Intelligence Machine Learning Deep Learning Neural Networks	47,800	260	30	246,100	1,070	123	
	Brain Tumor Disease Classification identification Segmentation	93,000	150	39				
	Alzheimer's Disease Classification identification Segmentation	34,600	170	20				
	Parkinson's Disease Classification identification Segmentation	26,300	200	18				
	Neurological Disease Diagnosis using Cam Grad	20,800	160	5				
	Neurological Disease Diagnosis using Explainable AI	23,600	130	11				
PubMed	Neurological Disease Diagnosis using Artificial Intelligence Machine Learning Deep Learning Neural Networks	2,230	150	20	2,793	298	50	
	Brain Tumor Disease Classification identification Segmentation	14	14	4				
	Alzheimer's Disease Classification identification Segmentation	13	13	5				
	Parkinson's Disease Classification	11	11	4				

	identification Segmentation							
	Neurological Disease Diagnosis using Cam Grad	57	57	7				
	Neurological Disease Diagnosis using Explainable AI	468	53	10				
Scopus	Neurological Disease Diagnosis using Artificial Intelligence Machine Learning Deep Learning Neural Networks	6,555	110	9	32,488	740	46	
	Brain Tumor Disease Classification identification Segmentation	11,433	120	13				
	Alzheimer's Disease Classification identification Segmentation	8,581	160	9				
	Parkinson's Disease Classification identification Segmentation	4,833	130	3				
	Neurological Disease Diagnosis using Cam Grad	299	110	5				
	Neurological Disease Diagnosis using Explainable AI	787	110	7				

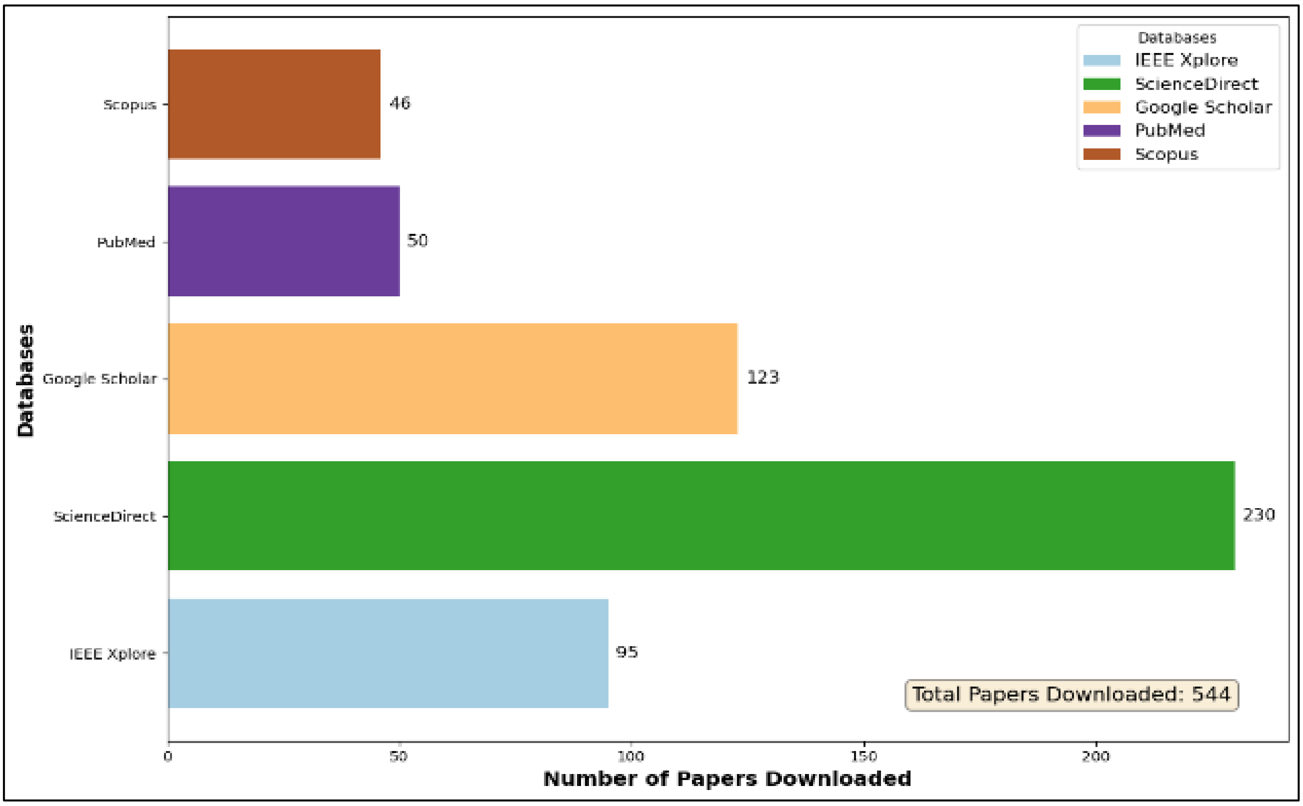

Figure 1 Number of Papers Downloaded vs. Databases.

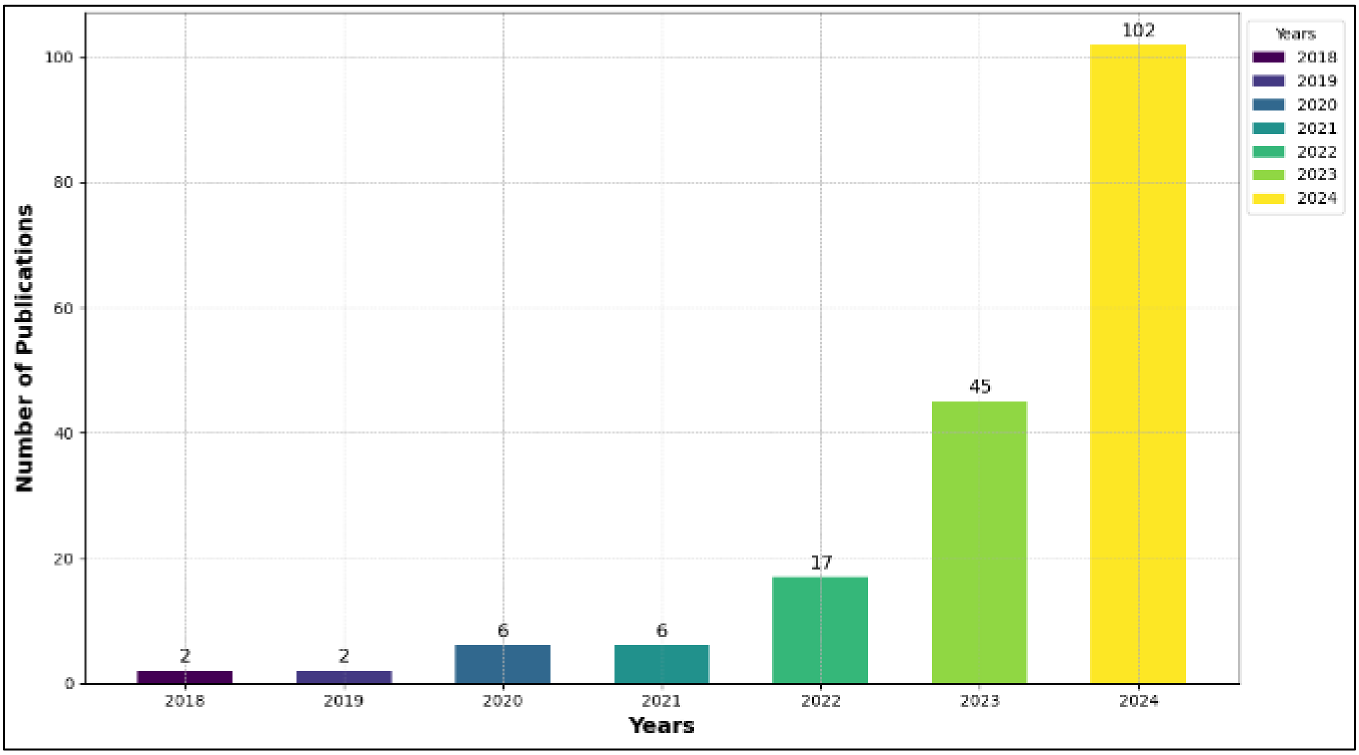

Figure 2 Number of Included articles per year (2018–2024).

2.2.2. Inclusion and Exclusion Criteria

To ensure the quality and relevance of the studies included in the SLR, specific inclusion and exclusion criteria are established. These criteria help in filtering out studies that do not meet the required standards and focus on those that provide valuable insights into the research questions.The following Table 4 Shows the Details About Inclusion and Exclusion criteria.

Table 3 Details about Inclusion and Exclusion Criteria**.**

Total Papers	**544**
Included	180
Distinct	180
Repeated	0
Excluded	364
Distinct	327
Repeated	37
Exclusion Reason	
Unpublished	0
Not accessible	0
Nothing about TOPIC	364

3. Related Work

In recent years, AI and ML applications in diagnosing and classifying Alzheimer's disease (AD) have gained significant attention. Ikram Bazarbekov et al. reviewed AI methods for AD diagnosis, identifying challenges such as limited datasets, lack of clinical evaluation, and privacy concerns [12]. Similarly, Mohsen Ghorbian et al. analyzed ML techniques for brain tumor classification, noting limitations like small sample sizes, lack of generalizability, and high computational demands [13].Arshdeep Kaur et al. focused on ML and DL techniques for predicting AD using neuroimaging and sensor data, emphasizing issues like dataset scarcity and privacy concerns [14]. In explainable AI, Savin Madapatha et al. reviewed MRI-based approaches for brain disease detection, highlighting challenges such as limited datasets and time-consuming manual segmentation [15]. Ravikumar Sajjanar et al. explored hybrid ML-DL approaches for brain tumor segmentation, noting high computational costs and model complexity [16].

Eqtidar M. Mohammed et al. reviewed DL models for AD detection, addressing dataset limitations, computational complexity, and regional medical record gaps [17]. Jing Wang et al. conducted a review and meta-analysis of AI-assisted PET imaging for Parkinson's disease, identifying issues of heterogeneity and lack of external validation [18]. M. Menagadevi et al. discussed ML and DL methods for detecting AD via MRI, noting challenges like low-quality images and dataset scarcity [19]. Wided Hechkel et al. focused on early AD detection using imaging techniques, highlighting problems of class imbalance and data leakage [20]. Lastly, Maleika Heenaye-Mamode Khan et al. reviewed transfer learning models for AD detection, addressing limitations like insufficient annotated datasets and interpretability challenges [21].

Table 4 Comparison of Existing Reviews.

Author	**Main Focus**	**Limitations**	**Achievements**
Ikram Bazarbekov et al. [12]	Review of AI methods for Alzheimer's disease diagnosis using neuroimaging and sensor data	Limited access to large and diverse datasets. Lack of clinical evaluation. Privacy concerns.	Systematic review of AI methods for Alzheimer's disease diagnosis. Identification of key challenges and future research directions.
Mohsen Ghorbian et al. [13]	Review of ML approaches in diagnosing and classifying brain tumors based on WHO classifications	Limited sample sizes, lack of generalizability, and high computational requirements.	Comprehensive analysis of ML techniques for brain tumor classification. Identification of key challenges and future research directions.

Arshdeep Kaur et al.[14]	Review of ML and DL techniques for predicting Alzheimer's disease using neuroimaging and sensor data	Limited access to large and diverse datasets. Lack of clinical evaluation. Privacy concerns.	Systematic review of ML and DL techniques for Alzheimer's disease prediction. Identification of key challenges and future research directions.
Savin Madapatha et al.[15]	Review of XAI-based approaches for brain disease detection using MRI images	Limited datasets, low anatomical contrast, and time-consuming manual segmentation.	Comprehensive review of MRI segmentation, classification, and XAI techniques for brain disease detection. Identification of key challenges and future research directions.
Ravikumar Sajjanar et al.[16]	Review of hybrid approaches for brain tumor segmentation in MRI using ML and DL techniques	Limited datasets, high computational time, and complexity of models.	Comprehensive review of hybrid techniques for MRI brain tumor segmentation. Identification of key challenges and future research directions.
Eqtidar M. Mohammed et al.[17]	Review of deep learning models for detecting Alzheimer's disease	Limited datasets, high computational complexity, and lack of comprehensive medical records in some regions.	Comprehensive review of deep learning techniques, imaging modalities, and preprocessing methods for Alzheimer's disease detection. Identification of key challenges and future research directions.
Jing Wang et al.[18]	Review of AI-assisted PET imaging for diagnosing Parkinson's disease	Limited datasets, high heterogeneity, and lack of external validation in some studies.	Comprehensive review and meta-analysis of AI algorithms in PET imaging for Parkinson's disease diagnosis. Identification of key challenges and future research directions.
M. Menagadevi et al.[19]	Review of machine and deep learning approaches for detecting Alzheimer's disease using MRI	Low quality of medical images, lack of large datasets, and complexity of medical images.	Comprehensive review of image preprocessing, segmentation, feature extraction, and classification techniques for Alzheimer's disease detection. Identification of key challenges and future research directions.
Wided Hechkel et al.[20]	Review of machine learning and imaging techniques for early detection of Alzheimer's disease	Limited datasets, class imbalance, and data leakage issues.	Comprehensive review of visual biomarkers, datasets, imaging techniques, and machine learning models for Alzheimer's disease detection. Identification of key challenges and future research directions.
Maleika Heenaye-Mamode Khan et al.[21]	Review of transfer learning models for detecting Alzheimer's disease using pre-trained deep learning models	Limited annotated datasets, computational resource requirements, and challenges in model interpretability.	Comprehensive review of transfer learning models, neuroimaging techniques, datasets, data augmentation, preprocessing techniques, and input data management for Alzheimer's disease detection. Identification of key challenges and future research directions.

4. Neurological Disorders

Neurological disorders encompass conditions affecting the central and peripheral nervous systems, including a range of diseases such as epilepsy, Alzheimer's disease, Parkinson's disease, multiple sclerosis, and brain tumors. These disorders impact the brain, spinal cord, and nerves, leading to various symptoms depending on the specific condition and affected areas of the nervous system [12-21].

4.1. Types of Neurological Disorders

- **Neurodegenerative Diseases:** This category includes conditions like Alzheimer's and Parkinson's disease, characterized by the progressive loss of nerve cells [38,40,43,207].
- **Cerebrovascular Diseases:** Conditions such as stroke that affect the blood supply to the brain can lead to significant neurological impairment [208].
- **Demyelinating Diseases:** Multiple sclerosis is an example, where the myelin sheath surrounding nerve fibers is damaged, leading to disrupted nerve signaling [209,210].
- **Infections:** Diseases such as meningitis and encephalitis, which infect the brain and spinal cord, can cause severe neurological symptoms [211].
- **Functional Disorders:** These include conditions like epilepsy, marked by abnormal electrical discharges in the brain that result in seizures [212].
- **Brain Tumors:** Abnormal cell growths within the brain, either benign or malignant, also fall under neurological disorders [39,42].

4.2. Stages of Neurological Disorders

- **Early Stage:** Symptoms may be subtle and hard to notice, making early diagnosis essential for effective intervention [213].
- **Middle Stage:** Symptoms become more pronounced and can affect daily life.
- **Late Stage:** Severe symptoms drastically impact quality of life, often requiring comprehensive care.

5. Brain Tumor

Brain tumors are abnormal cell growths within the brain or central spinal canal, and they can be benign or malignant. Tumors can either originate in the brain (primary) or spread from other parts of the body (secondary or metastatic) [39,42].

5.1. Types of Brain Tumors

- **Gliomas:** Tumors arising from glial cells, including astrocytomas and glioblastomas [214].
- **Meningiomas:** Develop from the meninges, the protective layers around the brain and spinal cord [215].
- **Pituitary Tumors:** Affect the pituitary gland, which regulates hormonal functions [216].
- **Schwannomas:** Tumors from Schwann cells that produce the myelin sheath surrounding nerves [217].
- **Medulloblastomas:** Often found in children, these tumors arise in the cerebellum [218].

5.2. Stages of Brain Tumors

- **Grade I:** Benign and slow-growing.
- **Grade II:** Relatively slow-growing, with potential to become malignant.
- **Grade III:** Malignant and actively growing.
- **Grade IV:** Highly malignant and aggressive, as in glioblastoma multiforme [219]

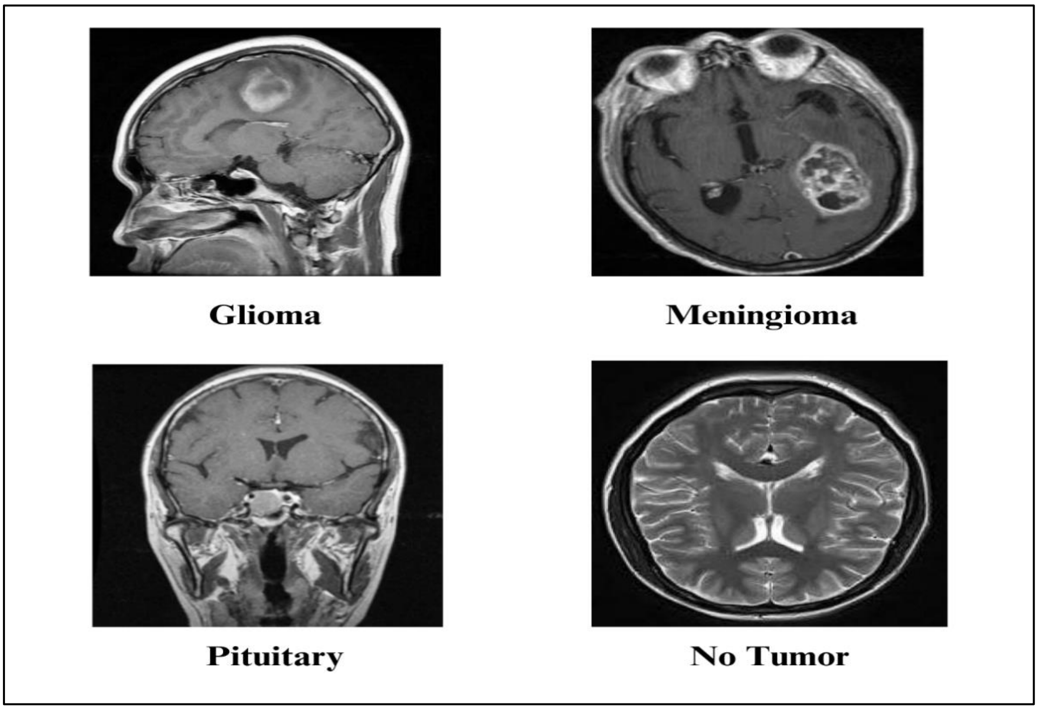

Figure 3 MRI images for Brain Tumor classes [59].

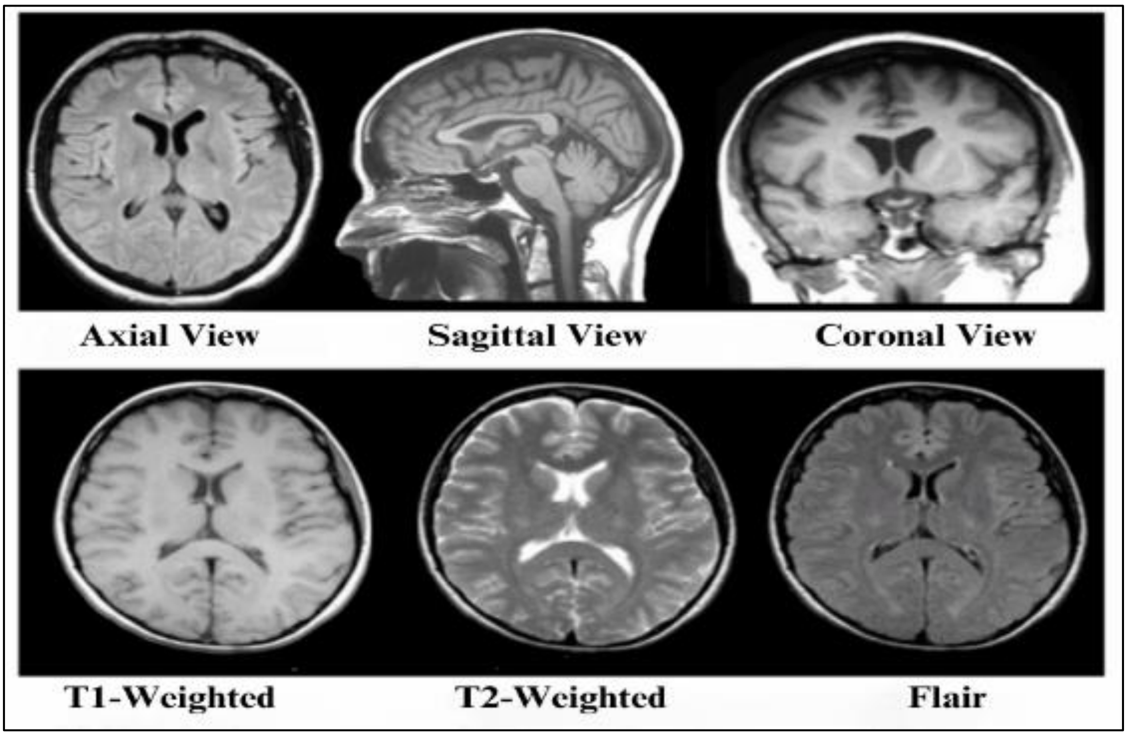

Figure 4 The three prominent views of MRI scanning: axial, sagittal, coronal (Top), and brain MRI slices of T1-weighted vs. T2-weighted and flair (Bottom) [34].

5.3. Approaches used for Brain Tumor Diagnosis

Shekhar et al. [27] proposed a method using discrete wavelet transform and SVM for effective brain tumor identification and classification from MRI images. Sultan et al. [28] developed a CNN-based deep learning model for multi-classification of brain tumors, achieving high accuracies. Mehrotra et al. [29] introduced a scheme using DWT for feature extraction and SVM for classification, achieving high accuracy. Divyamary et al. [30] utilized Naive Bayes classifier for brain tumor detection with moderate accuracy. Shafana et al. [31] provided an overview of AI-based techniques for brain tumor segmentation, detection, and diagnosis, highlighting MRI's effectiveness. Kibriya et al. [32] used CNN models and SVM for brain tumor classification, achieving high accuracy. Khairandish et al. [33] proposed a hybrid CNN-SVM model for tumor detection and classification, achieving significant accuracy improvements. Jena et al. [34] highlighted the use of radiogenomics combined with AI for brain tumor characterization, emphasizing personalized treatment benefits.

Fernando et al. [35] reviewed statistical, deep learning, and probabilistic models for MRI-based brain tumor segmentation. Gao et al. [36] developed a deep learning system for automated identification and classification of 18 types of brain tumors from MRI data, achieving higher accuracy and sensitivity compared to neuroradiologists. Agrawal et al. [37] presented a framework for brain tumor segmentation and classification using deep learning techniques, showing improved performance with the 3D-UNet model. Aggarwal et al. [38] proposed an improved ResNet model for brain tumor segmentation, addressing gradient issues in DNNs. Talukder et al. [39] introduced a deep learning approach based on transfer learning for brain tumor classification, achieving high accuracy. Tseng et al. [40] optimized the XGBoost technique for brain tumor detection using feature selection and image segmentation, achieving high accuracy and precision. Shourie et al. [41] proposed a VGG-16 model for brain tumor detection using MRI scans, demonstrating high sensitivity and specificity. Shyamala et al. [42] developed a method for brain tumor classification using MRI images, involving preprocessing, feature extraction, and classification with a GRNN, achieving high accuracy. Ranjbarzadeh et al. [43] proposed an optimized CNN model for brain tumor segmentation using an Improved Chimp Optimization Algorithm, achieving high precision and recall.

Ruba et al. [44] introduced a novel JGate-AttResUNet model for brain tumor segmentation, achieving high mean dice values. Amritraj et al. [45] proposed a deep learning model using CNN and ResNet50 for brain tumor diagnosis, achieving high training and validation accuracies. Liu et al. [46] developed a multi-task learning transformer for brain tumor segmentation and classification, achieving high accuracy. Song et al. [47] reviewed deep learning techniques for noninvasive grading of glioma brain tumors using MRI. Nanda et al. [48] proposed a classification model using a hybrid saliency-K-mean segmentation technique and SSO in RBNN, achieving high accuracies. Saboor et al. [49] introduced an AI-based CAD system using attention-gated recurrent units for brain tumor detection, achieving high accuracy. Srinivasan et al. [50] developed three CNN models for multi-classification of brain tumors using MRI images, achieving high accuracies. Roy et al. [51] proposed an explainable ensemble-based pipeline for brain tumor classification using a Dual-GAN mechanism, achieving high accuracy. Khalighi et al. [52] explored the role of AI in neuro-oncology, focusing on gliomas and highlighting AI's superiority in accuracy and specificity. Almufareh et al. [53] evaluated YOLO-based deep learning models for brain tumor segmentation and classification using MRI scans, achieving high performance. Sarada et al. [54] presented a modified ResNet50V2 deep learning model for multi-classification of brain tumors, achieving high accuracy.

Bhimavarapu et al. [55] proposed an improved FCM segmentation algorithm and an enhanced ELM classifier for brain tumor detection, achieving high accuracy and precision. Jakhar et al. [56] introduced a novel brain tumor segmentation approach using multi-scale pixel segmentation and fractal feature extraction, achieving high accuracy and sensitivity. Kalaiselvi et al. [57] proposed a brain tumor detection method using a Boosted Multi-Gradient SVM classifier, achieving high accuracy. Xu et al. [58] presented a novel approach for brain tumor diagnosis using MRI scans, leveraging Mobilenetv2 optimized by the Contracted Fox Optimization Algorithm, achieving high precision and accuracy. Byeon et al. [60] introduced the ICU-Net model for brain tumor segmentation, leveraging dynamic convolution and a non-local attention mechanism, achieving high performance. Jagadeesh et al. [61] proposed the EA-DFFTU-Net model for effective brain tumor segmentation with missing MRI modalities, achieving better performance. Rashid et al. [62] proposed a method for brain tumor detection using anisotropic filtering, SVM classifier, and morphological operations, achieving moderate accuracy.

Gürsoy et al. [63] proposed a fused deep learning model combining GNN and CNN for brain tumor detection, achieving high classification accuracy. Ullah et al. [64] proposed an efficient system based on deep learning and evolutionary optimization for classifying brain tumor modalities, achieving high accuracy. Singh et al. [65] proposed an automated solution using a CNN for brain tumor classification, achieving high accuracy and concordance with ground truth. Ashafuddula et al. [66] proposed a novel thresholding-based MRI image segmentation approach with a transfer learning model for early-stage brain tumor detection, achieving high sensitivity and accuracy. Kordnoori et al. [67] proposed a multi-task learning model for segmentation and classification of supratentorial brain tumors, achieving high accuracy. Chauhan et al. [68] proposed a comparative analysis of deep learning models for brain tumor segmentation using multi-contrast MRI images, achieving high performance with the 3D U-Net model. Rajeswari et al. [69] proposed a Dense Fused Maxout Network for severity prediction of brain tumors, achieving high sensitivity, accuracy, and specificity. Zakariah et al. [70] proposed the Dual Vision Transformer-DSUNET model for brain tumor segmentation, achieving high Dice

Coefficient values and overall accuracy. Yang et al. [71] proposed a method combining GRU networks and the Enhanced Hybrid Dwarf Mongoose Optimization algorithm for brain tumor detection, achieving high sensitivity and specificity.

Musthafa et al. [72] introduced an integrated approach using ResNet50 combined with Grad-CAM for brain tumor detection, achieving high accuracy and interpretability. Yu et al. [74] proposed HSA-Net, a novel segmentation method utilizing SWDC and HDense modules, achieving high Dice coefficient and classification accuracy. Aboussaleh et al. [75] proposed Inception-UDet, an improved U-Net architecture for brain tumor segmentation, achieving high DSC on various datasets. Malakouti et al. [76] utilized machine learning and transfer learning techniques for brain tumor classification, achieving high accuracy with LightGBM and GoogLeNet models. Basha et al. [77] proposed a method for brain tumor detection using R-CNN masks, Grad-CAM, and transfer learning, achieving high sensitivity and accuracy. Yalamanchili et al. [78] proposed using VGG-16 and Efficient NetB7 models for brain tumor classification and segmentation, achieving high classification accuracy. Nelson et al. [79] utilized the EfficientNetB3 model for multiclass brain tumor detection using MRI scans, achieving high overall accuracy.

Priyadarshini et al. [80] proposed a fine-tuned EfficientNetV2S model for classifying brain tumors into multiple grades, achieving high test accuracy, recall, precision, and sensitivity. Zeineldin et al. [81] introduced NeuroIGN, an AI-based system for image-guided neurosurgery, achieving high accuracy in tumor segmentation. Haque et al. [82] proposed NeuroNet19, a deep neural network model using VGG19 and an Inverted Pyramid Pooling Module for brain tumor classification, achieving high accuracy and precision. Rasool et al. [83] proposed TransResUNet, a hybrid architecture combining ResNet U-Net with Transformer blocks for glioma brain tumor segmentation, achieving high dice scores and overall accuracy. Hossain et al. [84] proposed an ensemble model called IVX16, combining VGG16, InceptionV3, and Xception for multiclass brain tumor classification, achieving high accuracy. Iriawan et al. [85] proposed a YOLO-UNet architecture combining YOLO for detection and UNet for segmentation of MRI brain tumor images, achieving a high correct classification ratio.

6. Alzheimer’s Disease

Alzheimer’s disease is a progressive neurodegenerative disorder causing memory loss, cognitive decline, and behavioral changes, making it the leading cause of dementia in older adults [12,14,17,19-21].

6.1. Types of Alzheimer’s Disease

- **Early-Onset Alzheimer’s:** Occurs before age 65, often with a genetic basis [220].
- **Late-Onset Alzheimer’s:** The more common form, occurring after age 65 [221].

6.2. Stages of Alzheimer’s Disease

- **Preclinical Stage:** Brain changes occur without noticeable symptoms.
- **Mild Cognitive Impairment (MCI):** Early memory and thinking impairments appear.
- **Mild Alzheimer’s:** Cognitive challenges begin to interfere with daily life.
- **Moderate Alzheimer’s:** Memory loss, confusion, and language difficulties intensify.
- **Severe Alzheimer’s:** Severe decline, with inability to communicate or perform daily tasks [222].

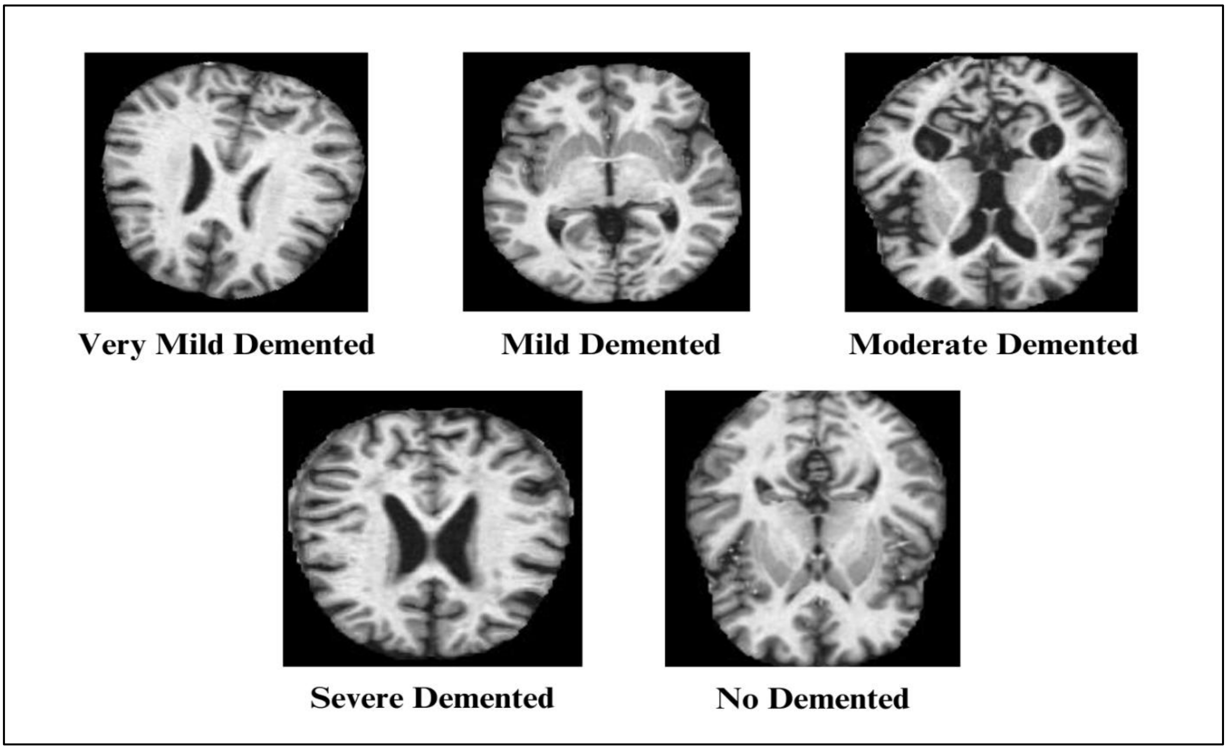

Figure 5 MRI images for Alzheimer's Disease classes [73].

6.3. Approaches used for Alzheimer's Diagnosis

Islam et al. [86] proposed an ensemble of deep convolutional neural networks for diagnosing Alzheimer's disease using brain MRI data, achieving high accuracy and precision. Zhang et al. [87] developed a multi-modal deep learning model combining MRI, PET, and clinical assessments for auxiliary diagnosis, improving diagnostic accuracy. Salehi et al. [88] reviewed deep learning algorithms for diagnosing Alzheimer's, highlighting the effectiveness of CNNs in analyzing MRI brain images. Feng et al. [89] proposed a method using wavelet transformation energy features from structural MRI images to identify Alzheimer's disease, outperforming state-of-the-art methods. Basher et al. [90] combined CNN and DNN for diagnosing Alzheimer's using volumetric features from structural MRI data, achieving high classification accuracy. Hazarika et al. [91] evaluated deep learning models for classifying Alzheimer's using MRI scans, with DenseNet-121 achieving the highest performance. Mahendran et al. [92] presented a deep learning-based classification model with an embedded feature selection approach for early detection using DNA methylation data. Cheung et al. [93] developed a deep learning algorithm to detect Alzheimer's using retinal photographs, showing high sensitivity and specificity. Fareed et al. [94] proposed ADD-Net, a CNN architecture for detecting Alzheimer's using MRI scans, achieving high accuracy and AUC values.

Pedrero-Sánchez et al. [95] developed a multi-branch CNN to classify healthy individuals and those with Alzheimer's and Parkinson's using smartphone sensor data, achieving 100% classification accuracy. Khan et al. [96] developed a three-tiered cognitive-based machine learning algorithm for predicting Alzheimer's and Mild Cognitive Impairment, achieving high accuracy. Zhou et al. [97] developed an interpretable Graph Convolutional Network framework using multi-modality brain imaging data for Alzheimer's diagnosis, identifying important biomarkers. Alorf et al. [98] developed methods for multi-label classification of Alzheimer's stages using resting-state fMRI data and deep learning, achieving high accuracies. Velazquez et al. [99] developed a multimodal ensemble model to predict conversion from Early Mild Cognitive Impairment to Alzheimer's, achieving high accuracy. Rahim et al. [100] proposed a hybrid multimodal deep-learning framework to predict Alzheimer's progression, achieving high accuracy and introducing a novel explainability approach. Chen et al. [101] proposed a U-Net based GAN to synthesize FDG-PET from MRI-T1WI for Alzheimer's diagnosis, achieving high performance. Fathi et al. [102] proposed an ensemble method using CNN-based classifiers for early diagnosis using MRI images, achieving high accuracy rates. Zhang et al. [103] proposed a Weakly Supervised Deep Learning model incorporating attention mechanisms for Alzheimer's diagnosis, achieving high performance. Zhou et al. [104] developed an Alzheimer's segmentation and classification pipeline using machine learning, achieving high performance. Klepl et al. [105] proposed an Adaptive Gated Graph Convolutional Network for diagnosing Alzheimer's using EEG data, achieving high accuracy and providing consistent explanations.

Enumula et al. [106] proposed a method for predicting and classifying Alzheimer's using CT images and machine learning, achieving high accuracy. Jenifel et al. [107] proposed an Alzheimer's detection system using an eight-layered CNN called AlexNet, achieving high accuracy. Liu et al. [108] proposed a method for Alzheimer's classification using MRI images of the hippocampus and whole brain, achieving high accuracy. Boyapati et al. [109] proposed a method for predicting Alzheimer's using a combination of CNN and GAN, achieving high accuracy. Shetty et al. [110] proposed a method for detecting Alzheimer's using a CNN, achieving high accuracy. Asgharzadeh-Bonab et al. [111] proposed fusion schemes to combine deep features from brain MRI and its transforms, achieving high accuracy. Saleh et al. [112] proposed a method for classifying Alzheimer's using DenseNet and transfer learning, achieving high accuracy and AUC values. Hazarika et al. [113] proposed a hybrid deep neural network model for classifying Alzheimer's using MRI scans, achieving high performance. Yao et al. [114] reviewed AI methodologies for diagnosing Alzheimer's using brain MRI images, highlighting the effectiveness of deep learning models. Nagarathna et al. [115] proposed a hybrid model for classifying Alzheimer's stages using MRI data, achieving high accuracy and AUC values. Mahendran et al. [116] proposed a Deep Belief Network model for predicting Alzheimer's using multi-omics data, achieving better performance compared to traditional models. Sekhar et al. [117] proposed a novel approach for classifying Alzheimer's using EEG data by combining GANs and the Marine Predators Algorithm, achieving superior classification performance.

Nguyen et al. [118] proposed a deep learning-based approach for the differential diagnosis of Alzheimer's and Frontotemporal Dementia using structural MRI, achieving high performance. Wang et al. [119] evaluated heatmap methods for capturing Alzheimer's patterns using deep neural networks, with Integrated Gradients producing the best overlap with meta-analysis maps. Jahan et al. [120] proposed an explainable AI model for predicting Alzheimer's using multimodal data, achieving high accuracy and providing explainability. AlMohimeed et al. [121] proposed a multi-level stacking ensemble model for detecting Alzheimer's using cognitive sub-scores, achieving high performance. Yao et al. [122] proposed Fuzzy-VGG for predicting Alzheimer's staging using brain MRI images, achieving high accuracy and performance. Yi et al. [123] proposed a deep learning model to identify patterns in Alzheimer's progression, predicting time-to-conversion and clustering distinct subgroups. Sharma et al. [124] proposed a CNN model based on InceptionV3 for classifying Alzheimer's stages using segmented MRI images, achieving high accuracy. Hwang et al. [125] utilized a deep generative model to predict amyloid positivity in cognitively normal individuals, achieving high accuracy. Zhang et al. [126] proposed sMRI-PatchNet, a patch-based deep learning network for Alzheimer's diagnosis using structural MRI, achieving high performance. Stoleru et al. [127] evaluated transfer learning and deep learning algorithms for diagnosing Alzheimer's using MRI scans, with ResNet-152 achieving the highest accuracy. Ozdemir et al. [128] proposed a CNN model for early diagnosis of Alzheimer's, achieving state-of-the-art accuracy and improved computing efficiency.

Biswas et al. [129] proposed a multi-class classification system for early diagnosis using 3D MRI images, achieving high accuracy. El-Assy et al. [130] proposed a CNN architecture for classifying Alzheimer's using MRI data, achieving high accuracies for multiple classifications. Ayus et al. [131] proposed hybrid models for Alzheimer's identification, achieving high accuracy and introducing an online interface for diagnosis. Nour et al. [132] proposed a Deep Ensemble Learning model for diagnosing Alzheimer's using EEG signals, achieving high accuracy. Ali et al. [133] proposed an integrated approach using Improved Fuzzy C-means clustering and a hybrid CNN-LSTM classifier, achieving high accuracy. Tripathy et al. [134] proposed an improved spatial attention guided depth separable CNN for Alzheimer's detection, achieving high accuracy. Mahmood et al. [135] introduced novel AD classification methods, achieving high performance and aiding in personalized treatment planning. Mahmud et al. [136] proposed an explainable AI-based approach for Alzheimer's diagnosis using deep transfer learning, achieving high accuracy and providing visual insights. Matlani [137] proposed a hybrid deep learning approach combining BiLSTM and ANN for early diagnosis, achieving high accuracy. Kiran et al. [138] introduced a personalized dynamically ensemble CNN for Alzheimer's diagnosis, improving classification accuracy. Malu et al. [139] introduced CirMNet, a hybrid feature extraction technique for Alzheimer's MRI classification, achieving high accuracy.

Bringas et al. [140] introduced CLADSI, a continual learning algorithm for identifying Alzheimer's stages using accelerometer data, achieving high accuracy. Rehman et al. [141] employed DenseNet-201 for diagnosing Alzheimer's stages using MRI scans, achieving high accuracy. Sorour et al. [142] proposed a novel AD-DL approach for early detection using MRI data and deep learning techniques, achieving high accuracy. Praveenkumar et al. [143] used transfer learning and pre-trained models to classify Alzheimer's using MRI data, achieving high performance. Yu et al. [144] integrated EEG signals and genetic data for Alzheimer's classification using machine learning models, achieving high performance. Parvin et al. [145] developed a framework using multimodal data to classify Alzheimer's, achieving high performance. Zuo et al. [146] proposed a deep learning-based approach using eye-tracking data for diagnosis, achieving high accuracy. Shukla et al. [147] proposed a model to enhance the explainability of AI in diagnosing Alzheimer's, achieving high performance. Kiss [148] discussed a mobile application algorithm for early detection, highlighting its accessibility and cost-effectiveness. Wong et al. [149] demonstrated using GANs for high classification accuracy with reduced data. Song et al. [150] applied Grad-CAM to a 3D-VGG16 network for diagnosis using fMRI data, achieving high accuracy. Conti et al. [151] used Raman spectroscopy and topological machine learning for detection via cerebrospinal fluid analysis, achieving high accuracy. Yuan et al. [152] proposed an improved multifeature squeeze-and-excitation-dilated residual network for predicting clinical scores and conversion probability, achieving high performance. Kamal et al. [153] introduced a multi-modal data-specific method using transformers for prediction, achieving high accuracy.

Hatami et al. [154] proposed a method combining reinforcement learning and deep learning for Alzheimer's disease classification, achieving higher accuracy than existing techniques. Alp et al. [155] proposed using Vision Transformer (ViT) for MRI processing in Alzheimer's diagnosis, achieving high accuracy and superior performance compared to other deep learning models. Fania et al. [156] used machine learning and explainable AI (XAI) to predict Alzheimer's disease mortality, highlighting the significant contribution of air pollution (O3 and NO2) to Alzheimer's mortality. Qian et al. [157] proposed a multi-task residual network (MMANet) for Alzheimer's classification and brain age prediction, achieving high accuracy and confirming the benefits of multi-task learning. Yousefzadeh et al. [158] proposed a novel explainable AI framework (LAVA) to assess Alzheimer's from retinal images, effectively identifying AD stages using retinal vasculature as a biomarker. Mahim et al. [159] proposed a hybrid model combining Vision Transformer (ViT) and Gated Recurrent Unit (GRU) for Alzheimer's detection from MRI images, achieving high accuracies and incorporating XAI techniques for enhanced interpretability.

7. Parkinson's Disease

Parkinson's disease is a chronic and progressive neurodegenerative disorder due to the loss of dopamine-producing neurons, leading to tremors, rigidity, and balance problems [18].

7.1. Types of Parkinson's Disease

- **Idiopathic Parkinson's Disease:** The most common type, with no identifiable cause [223].
- **Genetic Parkinson's Disease:** Linked to genetic mutations.
- **Secondary Parkinsonism:** Results from other conditions, such as stroke or medication effects.

7.2. Stages of Parkinson's Disease

- **Stage 1:** Symptoms are mild and do not interfere with daily activities.
- **Stage 2:** Symptoms worsen, making daily tasks more challenging.
- **Stage 3:** Loss of balance and coordination, with an increased risk of falls.
- **Stage 4:** Symptoms are severe, requiring assistance with daily activities.
- **Stage 5:** Advanced stage, with severe disability and dependence on caregivers [224].

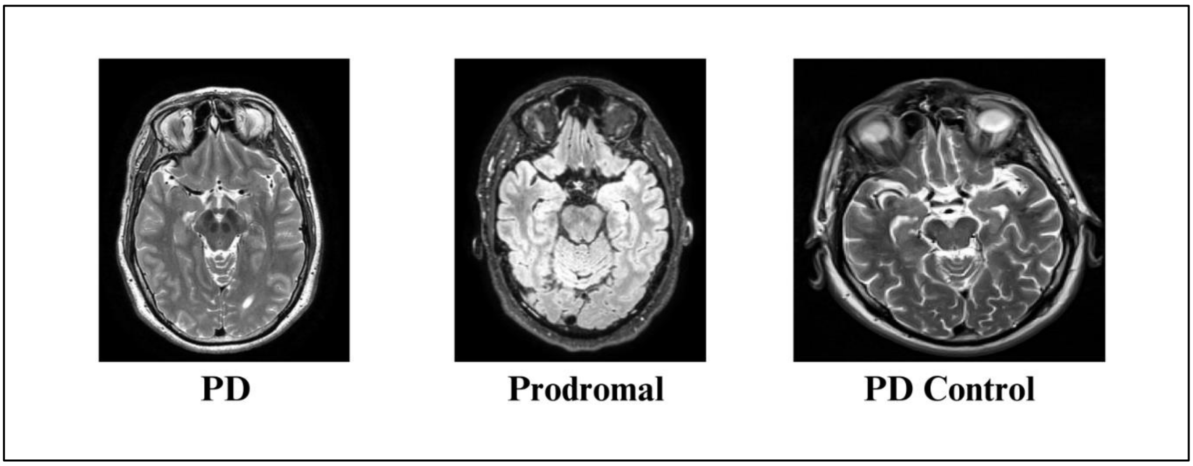

Figure 6 MRI images for Parkinson's Disease classes [226].

7.3. Approaches used for Parkinson's Diagnosis

Magesh et al. [160] proposed a machine learning model using LIME for early detection of Parkinson's disease from DaTSCAN images, achieving high accuracy and interpretability. Nilashi et al. [161] presented a method for remote tracking of Parkinson's progression using Deep Belief Network and Self-Organizing Map, improving UPDRS prediction accuracy. Mounika et al. [162] evaluated various machine learning models for diagnosing Parkinson's, with KNN achieving the highest accuracy. Karaman et al. [163] developed a CNN model using transfer learning for detecting Parkinson's from voice signals, achieving high performance. Nogales et al. [164] proposed using BERT to analyze EEG data for diagnosing Parkinson's, demonstrating the potential of NLP techniques in medical diagnostics. Pahuja et al. [165] presented deep learning frameworks for Parkinson's detection using multi-modal features, achieving high accuracy. Chen et al. [166] used DCNNs optimized by the chimp optimization algorithm for diagnosing Parkinson's from speech signals, achieving high accuracy. Yao et al. [167] used DCNNs optimized by the whale optimization algorithm for diagnosing Parkinson's from speech signals, achieving high accuracy. Rana et al. [168] evaluated machine learning algorithms for diagnosing Parkinson's using voice features, with ANN achieving the highest accuracy. Sangeetha et al. [169] used CNNs to detect Parkinson's from brain MRI images, achieving high accuracy.

Guatelli et al. [170] used spectrograms of voice recordings and ELM random weight neural networks to detect Parkinson's, achieving high accuracy. Nilashi et al. [171] combined DBN and ANFIS for early diagnosis of Parkinson's, improving UPDRS prediction accuracy. Camacho et al. [172] developed a CNN model trained on T1-weighted MRI datasets to classify Parkinson's, achieving high accuracy and providing explainable classifications. Akram et al. [173] discussed various methods for diagnosing Parkinson's using AI, machine learning, and deep learning techniques, emphasizing early diagnosis. Bhandari et al. [174] integrated gene expression data to diagnose Parkinson's using machine learning and explainable AI, identifying significant gene biomarkers. Hireš et al. [175] evaluated the generalization performance of machine learning models for detecting Parkinson's from voice recordings, highlighting the need for diverse datasets. Kumar et al. [176] used machine learning to identify miRNA biomarkers for diagnosing Parkinson's, achieving high accuracy. Krishna et al. [177] presented a model for detecting Parkinson's from speech signals using explainable AI techniques, achieving high accuracy. Majhi et al. [178] proposed deep learning models enhanced with a metaheuristic algorithm for early detection of Parkinson's using MRI and SPECT DaTscan datasets, achieving high accuracy. Roy et al. [179] presented a comprehensive analysis of AI-based methods for diagnosing Parkinson's, highlighting the potential of AI in early and accurate diagnosis. Priyadharshini et al. [180] presented a framework combining 3D MRI imaging and Gradient Boosting for early detection of Parkinson's, achieving high accuracy.

Yildirim et al. [181] presented a hybrid model for detecting Parkinson's from sound signals, achieving high accuracy. Habib et al. [182] proposed a framework using Deep Dual Attention Neural Network and Bi-LSTM for predicting Parkinson's from freezing of gait episodes, achieving high accuracy. Saleh et al. [183] proposed a hybrid CNN-KNN ensemble voting classifier for predicting Parkinson's from hand sketching images, achieving high accuracy. Teo et al. [184] introduced a multilayer BiLSTM network with explainable AI to distinguish between Parkinson's, essential tremor, and normal tremors, achieving high accuracy. Islam et al. [185] integrated clinical assessments and neuroimaging data to detect Parkinson's using machine learning and transfer learning techniques, achieving high accuracy. Veetil et al. [186] investigated data leakage and generalizability in MRI-based classification of Parkinson's using 2D CNNs, highlighting the importance of testing with heterogeneous populations. Mahendran et al. [187] used CNNs and transfer learning to classify Parkinson's using spiral and wave drawings, achieving high accuracy. Palakayala et al. [188] introduced AttentionLUNet, a hybrid model for Parkinson's detection using MRI, achieving high accuracy. Yang et al. [189] applied a deep learning neural network to video of finger tapping to distinguish Parkinson's from controls, achieving moderate accuracy. Wang et al. [190] proposed a deep learning-based method for cross-modality striatum segmentation using DaT SPECT and MR images, achieving high performance. Palakayala et al. [191] proposed a deep structured neural network to detect Parkinson's through voice samples, achieving high accuracy. Dentamaro et al. [192] investigated multimodal deep learning for early detection of Parkinson's using data from the PPMI database, achieving high accuracy. Al-Tam et al. [193] proposed a stacking ensemble-based approach for diagnosing Parkinson's, achieving high accuracy.

Desai et al. [194] presented a deep learning model using 3D MRI scans and data augmentation to classify Parkinson's, achieving high accuracy. Reddy et al. [195] proposed a classification model based on VGG19 with an attention mechanism to detect Parkinson's from spiral and wave drawings, achieving high accuracy. Kmiecik et al. [196] investigated the LRRK2 G2019S variant, identifying it as a common cause of monogenic Parkinson's and highlighting its risk factors. Zhao et al. [197] introduced an efficient diagnostic system for Parkinson's using smartphone videos of walking patterns, achieving high recognition rates. Deng et al. [198] introduced a video-based framework using machine learning to predict Parkinson's motor symptom severity, achieving high accuracy. Lv et al. [199] introduced a multimodal deep learning framework for Parkinson's detection using audio-visual data, achieving high accuracy. Di Cesare et al. [200] explored machine learning techniques for early detection of Parkinson's through speech analysis, achieving high accuracy. Zhang et al. [201] introduced mP-Gait, a system using mmWave radar to assess gait impairment in Parkinson's patients, achieving high accuracy. Huang et al. [202] introduced an explainable 3D multi-head attention residual convolution network for evaluating Parkinson's severity, achieving high performance. Kim et al. [203]

introduced the TULIP dataset for assessing Parkinson's motor symptoms using multi-camera video data, aiming to improve assessment precision. Ahmadi et al. [204] proposed a hybrid approach combining LS-SVR and Fuzzy Clustering for early diagnosis of Parkinson's, achieving high performance. Raj et al. [205] introduced a method using visibility graphs to classify Parkinson's severity, achieving high accuracy. Reddy et al. [206] investigated machine learning algorithms for diagnosing Parkinson's from speech analysis, achieving high accuracy.

8. Explainable AI (XAI) in Medical Imaging

The inherent opacity of deep learning models, often referred to as the "black box" problem, poses a significant challenge to their adoption in healthcare. While these models can achieve high accuracy in medical image analysis, understanding how they arrive at their predictions is crucial for building trust among clinicians and ensuring responsible implementation [15, 17]. Explainable AI (XAI) addresses this challenge by providing insights into the decision-making processes of these models, enhancing transparency and trustworthiness. This transparency is particularly critical in neurological disease diagnosis, where understanding the rationale behind a diagnostic decision is paramount for patient care and treatment planning [18].

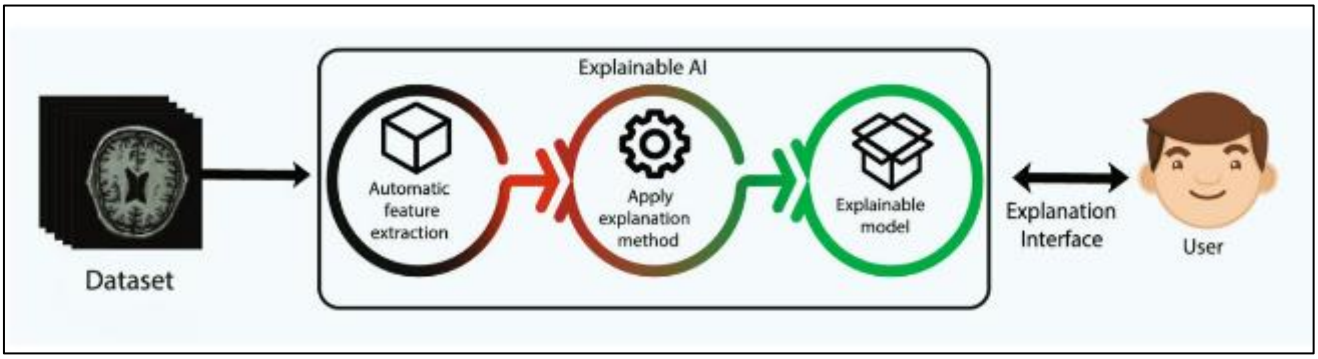

Figure 7 XAI Workflow for Medical Image Analysis [225]

8.1. Examples of XAI Techniques

Several XAI techniques have emerged to shed light on the inner workings of deep learning models in medical imaging:

8.1.1. Grad-CAM (Gradient-weighted Class Activation Mapping)

Grad-CAM visually explains model predictions by generating "heatmaps" that highlight the regions of an image most influential to the model's decision [15]. This technique provides a visual representation of the model's focus when making a diagnosis.

8.1.2. Grad-CAM++

Building upon Grad-CAM, Grad-CAM++ offers improved localization and visualization of disease-affected regions, particularly in cases with multiple occurrences of the same pathology within an image, and addresses issues related to model scalability [15].

8.1.3. LIME (Local Interpretable Model-Agnostic Explanations)

LIME offers model-agnostic explanations by creating simplified, interpretable models around individual predictions [17]. This local approach provides insights into the model's behavior for specific cases, explaining why a particular prediction was made for a given input.

8.1.4. SHAP (SHapley Additive exPlanations)

Based on game theory, SHAP quantifies the contribution of each feature to a prediction, providing a more comprehensive understanding of feature importance [15]. This technique helps identify the key features driving the model's decisions, offering a global perspective on model behavior.

8.2. Benefits of XAI in Medical Imaging

The application of XAI in medical imaging offers several key advantages:

8.2.1. Enhanced Trust and Confidence

By revealing the decision-making processes of AI models, XAI fosters trust among clinicians, making them more comfortable relying on AI-driven insights for diagnosis and treatment planning [15, 17].

8.2.2. Improved Model Validation and Refinement:

XAI facilitates the identification of potential biases and flaws in AI models, enabling researchers to validate and refine these models for improved accuracy and reliability [15]. This iterative process leads to the development of more robust diagnostic tools.

8.2.3. New Insights and Discoveries

XAI can uncover hidden patterns and relationships in medical data that might be overlooked by human experts [15]. These discoveries can lead to new insights into disease mechanisms, the identification of potential biomarkers, and the development of personalized treatment strategies.

8.3. Challenges and Future Directions for XAI

While XAI holds immense promise, several challenges remain:

8.3.1. Need for More In-Depth Interpretability

Existing XAI techniques provide valuable insights, but further research is needed to develop methods that offer even more granular and comprehensive explanations, especially in complex diagnostic scenarios [15]. This includes moving beyond highlighting important regions to explaining the underlying features and patterns recognized by the model.

8.3.2. Integration with Clinical Workflows:

Seamless integration of XAI tools into existing clinical workflows is essential for practical adoption [15]. Future research should focus on developing user-friendly interfaces and tools that provide clinicians with actionable XAI insights in a clinically relevant context.

XAI is essential for the responsible and effective integration of AI into healthcare. By enhancing transparency and interpretability, XAI can improve diagnostic accuracy, build trust among clinicians, and ultimately contribute to better patient outcomes.

9. Research Limitations

This study has several limitations. Current research on neurological disease diagnosis often relies on limited and homogeneous datasets, affecting the generalizability of findings [12-21]. Data leakage can artificially inflate performance and needs to be addressed rigorously [13, 20]. The computational demands of deep learning models can be a barrier to clinical implementation [13, 16, 17, 21]. While XAI offers improvements, further work is needed to enhance model interpretability and facilitate better clinical understanding [15, 21].

10. Future Directions

Future research should prioritize developing larger, more representative datasets and integrating multimodal data for a holistic disease understanding. Creating computationally efficient models is vital for clinical deployment. Further development of XAI methods is crucial for enhancing transparency and trust, and research should focus on personalized medicine and tailored treatments based on individual patient profiles.

11. Conclusion

This review examined AI-driven methodologies for diagnosing neurological diseases, highlighting the transformative potential of deep learning and explainable AI (XAI) in analyzing medical imaging data like MRI, CT, EEG, and clinical metrics. We synthesized findings from numerous studies, demonstrating AI's capacity to improve diagnostic accuracy, enable earlier detection of conditions such as brain tumors, Alzheimer's disease, and Parkinson's disease, and ultimately contribute to more informed clinical decision-making and the development of personalized treatment strategies.

However, significant challenges remain. Limited and homogeneous datasets often restrict the generalizability of AI models, while the computational demands of complex architectures can hinder their deployment in resource-constrained clinical settings. The "black box" nature of deep learning models necessitates ongoing research into XAI techniques to enhance transparency and build trust among healthcare professionals. Addressing these challenges through the development of robust, interpretable, and efficient models is crucial for realizing the full potential of AI in neurological disease diagnosis.

Future research should prioritize the creation of larger, more diverse datasets that accurately reflect the heterogeneity of these diseases. Integrating multimodal data, including genomic and proteomic information, will provide a more holistic understanding of disease mechanisms and potentially reveal novel biomarkers. Continued advancements in XAI are essential for not only improving model interpretability but also for uncovering hidden patterns and relationships within complex medical data. This, in turn, can lead to new insights into disease pathogenesis and personalized treatment approaches. By tackling these critical areas, we can pave the way for a future where AI-powered diagnostics play a central role in improving patient outcomes and transforming the landscape of neurological healthcare.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

References

[1] World Health Organization, "Neurological disorders: Public health challenges," 2017. [Online]. Available: https://www.who.int

[2] Alzheimer's Disease International (ADI), "Alzheimer's disease: global prevalence and impact," 2022. [Online]. Available: https://www.alzint.org

[3] G. Litjens, et al., "A survey on deep learning in medical image analysis," Medical Image Analysis, vol. 42, pp. 60-88, 2017.

[4] A. Esteva, et al., "A guide to deep learning in healthcare," Nature Medicine, vol. 25, pp. 24-29, 2019.

[5] Y. LeCun, Y. Bengio, and G. Hinton, "Deep learning," Nature, vol. 521, no. 7553, pp. 436–444, 2015.

[6] R. R. Selvaraju, et al., "Grad-CAM: Visual explanations from deep networks via gradient-based localization," in Proceedings of the IEEE International Conference on Computer Vision, 2017, pp. 618–626.

[7] Alzheimer's Disease International (ADI), "New study predicts the number of people living with Alzheimer's disease to triple by 2050," 2022. [Online]. Available: https://www.alzint.org

[8] World Health Organization, "Dementia: number of people affected to triple in next 30 years," 2017. [Online]. Available: https://www.who.int/news-room/fact-sheets/detail/dementia

[9] American Cancer Society, "Brain and spinal cord tumors in adults," n.d. [Online]. Available: https://www.cancer.org/cancer/brain-spinal-cord-tumors-adults/about/key-statistics.html

[10] P. Linardatos, V. Papastefanopoulos, and S. Kotsiantis, "Explainable AI: A review of machine learning interpretability methods," Entropy, vol. 23, no. 1, p. 18, 2021.

[11] E. J. Topol, "High-performance medicine: the convergence of human and artificial intelligence," Nature Medicine, vol. 25, pp. 44-56, 2019.

[12] I. Bazarbekov, A. Razaque, M. Ipalakova, J. Yoo, Z. Assipova, and A. Almisreb, "A review of artificial intelligence methods for Alzheimer's disease diagnosis: Insights from neuroimaging to sensor data analysis," Biomedical Signal Processing and Control, vol. 92, p. 106023, 2024.

[13] M. Ghorbian, S. Ghorbian, and M. Ghobaei-arani, "A comprehensive review on machine learning in brain tumor classification: taxonomy, challenges, and future trends," Biomedical Signal Processing and Control, vol. 98, p. 106774, 2024.

[14] A. Kaur, M. Mittal, J. S. Bhatti, S. Thareja, and S. Singh, "A systematic literature review on the significance of deep learning and machine learning in predicting Alzheimer's disease," Artificial Intelligence In Medicine, vol. 154, p. 102928, 2024.

[15] S. Madapatha and P. Fernando, "A systematic literature review of XAI-based approaches on brain disease detection using brain MRI images," in 2024 4th International Conference on Advanced Research in Computing (ICARC), 2024.

[16] R. Sajjanar, U. D. Dixit, and V. K. Vagga, "Advancements in hybrid approaches for brain tumor segmentation RI: a comprehensive review of machine learning and deep learning techniques," Multimedia Tools and Applications, vol. 83, pp. 30505-30539, 2024.

[17] E. M. Mohammed, A. M. Fakhrudeen, and O. Y. Alani, "Detection of Alzheimer's disease using deep learning models: A systematic literature review," Informatics in Medicine Unlocked, vol. 50, p. 101551, 2024.

[18] J. Wang, L. Xue, J. Jiang, F. Liu, P. Wu, J. Lu, H. Zhang, W. Bao, Q. Xu, Z. Ju, L. Chen, F. Jiao, H. Lin, J. Ge, C. Zuo, and M. Tian, "Diagnostic performance of artificial intelligence-assisted PET imaging for Parkinson's disease: a systematic review and meta-analysis," npj Digital Medicine, vol. 7, p. 17, 2024.

[19] M. Menagadevi, S. Devaraj, N. Madian, and D. Thiyagarajan, "Machine and deep learning approaches for Alzheimer disease detection using magnetic resonance images: An updated review," Measurement, vol. 226, p. 114100, 2024.

[20] W. Hechkel and A. Helali, "Unveiling Alzheimer's Disease Early: A Comprehensive Review of Machine Learning and Imaging Techniques," Archives of Computational Methods in Engineering, 2024. [Online]. Available: https://doi.org/10.1007/s11831-024-10179-3

[21] M. Heenaye-Mamode Khan, P. Reesaul, M. M. Auzine, and A. Taylor, "Detection of Alzheimer's disease using pre-trained deep learning models through transfer learning: a review," Artificial Intelligence Review, vol. 57, p. 275, 2024. [Online]. Available: https://doi.org/10.1007/s10462-024-10914-z

[22] IEEE Xplore Digital Library. [Online]. Available: https://ieeexplore.ieee.org/Xplore/home.jsp

[23] ScienceDirect. [Online]. Available: https://www.sciencedirect.com

[24] Google Scholar. [Online]. Available: https://scholar.google.com

[25] PubMed. [Online]. Available: https://pubmed.ncbi.nlm.nih.gov

[26] Scopus. [Online]. Available: https://www.scopus.com/home.uri

[27] S. Shekhar and M. A. Ansari, "Image Analysis for Brain Tumor Detection from MRI Images using Wavelet Transform," in International Conference on Power Energy, Environment and Intelligent Control (PEEIC), 2018.

[28] H. H. Sultan, N. M. Salem, and W. Al-Atabany, "Multi-Classification of Brain Tumor Images Using Deep Neural Network," IEEE Access, vol. 7, pp. 69215-69225, 2019. [Online]. Available: https://doi.org/10.1109/ACCESS.2019.2919122

[29] R. Mehrotra, M. A. Ansari, and R. Agrawal, "A Novel Scheme for Detection & Feature Extraction of Brain Tumor by Magnetic Resonance Modality Using DWT & SVM," in International Conference on Contemporary Computing and Applications (IC3A), 2020.

[30] D. Divyamary, S. Gopika, S. Pradeeba, and M. Bhuvaneswari, "Brain Tumor Detection from MRI Images using Naive Classifier," in 6th International Conference on Advanced Computing & Communication Systems (ICACCS), 2020.

[31] N. J. Shafana and A. SenthilSelvi, "Analysis of AI based Brain Tumor Detection and Diagnosis," in 4th International Conference on Computing and Communications Technologies (ICCCT), 2021. [Online]. Available: https://doi.org/10.1109/ICCCT53315.2021.9711914

[32] H. Kibriya, M. Masood, M. Nawaz, R. Rafique, and S. Rehman, "Multiclass Brain Tumor Classification Using Convolutional Neural Network and Support Vector Machine," in Mohammad Ali Jinnah University International Conference on Computing (MAJICC), 2021. [Online]. Available: https://doi.org/10.1109/MAJICC53071.2021.9526262

[33] M. O. Khairandish, M. Sharma, V. Jain, J. M. Chatterjee, and N. Z. Jhanjhi, "A Hybrid CNN-SVM Threshold Segmentation Approach for Tumor Detection and Classification of MRI Brain Images," IRBM, vol. 43, pp. 290-299, 2022. [Online]. Available: https://doi.org/10.1016/j.irbm.2021.06.003

[34] B. Jena, S. Saxena, G. K. Nayak, A. Balestrieri, N. Gupta, N. N. Khanna, J. R. Laird, M. K. Kalra, M. M. Fouda, L. Saba, and J. S. Suri, "Brain Tumor Characterization Using Radiogenomics in Artificial Intelligence Framework," Cancers, vol. 14, p. 4052, 2022. [Online]. Available: https://doi.org/10.3390/cancers14164052

[35] K. R. M. Fernando and C. P. Tsokos, "Deep and Statistical Learning in Biomedical Imaging: State of the Art in 3D MRI Brain Tumor Segmentation," Information Fusion, vol. 92, pp. 450-465, 2023. [Online]. Available: https://doi.org/10.1016/j.inffus.2022.12.013

[36] P. Gao, W. Shan, Y. Guo, Y. Wang, R. Sun, J. Cai, H. Li, W. S. Chan, P. Liu, L. Yi, S. Zhang, W. Li, T. Jiang, K. He, and Z. Wu, "Development and Validation of a Deep Learning Model for Brain Tumor Diagnosis and Classification Using Magnetic Resonance Imaging," JAMA Network Open, vol. 5, no. 8, p. e2225608, 2022. [Online]. Available: https://doi.org/10.1001/jamanetworkopen.2022.25608

[37] P. Agrawal, N. Katal, and N. Hooda, "Segmentation and classification of brain tumor using 3D-UNet deep neural networks," International Journal of Cognitive Computing in Engineering, vol. 3, pp. 199-210, 2022. [Online]. Available: https://doi.org/10.1016/j.ijcce.2022.11.001

[38] M. Aggarwal, A. K. Tiwari, M. P. Sarath, and A. Bjawan, "An early detection and segmentation of Brain Tumor using Deep Neural Network," BMC Medical Informatics and Decision Making, 2023. [Online]. Available: https://doi.org/10.1186/s12911-023-02174-8

[39] M. A. Talukder, M. M. Islam, M. A. Uddin, A. Akhter, M. A. J. Pramanik, S. Aryal, M. A. A. Almoyad, K. F. Hasan, and M. A. Moni, "An efficient deep learning model to categorize brain tumor using reconstruction and fine-tuning," Expert Systems With Applications, vol. 230, p. 120534, 2023. [Online]. Available: https://doi.org/10.1016/j.eswa.2023.120534

[40] C.-J. Tseng and C. Tang, "An optimized XGBoost technique for accurate brain tumor detection using feature selection and image segmentation," Healthcare Analytics, vol. 4, p. 100217, 2023. [Online]. Available: https://doi.org/10.1016/j.health.2023.100217

[41] P. Shourie, V. Anand, and S. Gupta, "An Intelligent VGG-16 Framework for Brain Tumor Detection Using MRI-Scans," in 2023 International Conference on Smart Systems for applications in Electrical Sciences (ICSSES), 2023. [Online]. Available: https://doi.org/10.1109/ICSSES58299.2023.10200833

[42] B. Shyamala and S. H. Brahmananda, "Brain tumor Classification using Optimized and Relief-based Feature Reduction and Regression Neural Network," Biomedical Signal Processing and Control, vol. 86, p. 105279, 2023. [Online]. Available: https://doi.org/10.1016/j.bspc.2023.105279

[43] R. Ranjbarzadeh, P. Zarbakhsh, A. Caputo, E. B. Tirkolaee, and M. Bendechache, "Brain tumor segmentation based on optimized convolutional neural network and improved chimp optimization algorithm," Computers in Biology and Medicine, vol. 168, p. 107723, 2024. [Online]. Available: https://doi.org/10.1016/j.compbiomed.2023.107723

[44] T. Ruba, R. Tamilselvi, and M. P. Beham, "Brain tumor segmentation using JGate-AttResUNet – A novel deep learning approach," Biomedical Signal Processing and Control, vol. 84, p. 104926, 2023. [Online]. Available: https://doi.org/10.1016/j.bspc.2023.104926

[45] S. Amritraj, J. Mahendra, and C. P. D. Cyril, "Brain Tumor Diagnosis Using CNN," in 2023 Third International Conference on Advances in Electrical, Computing, Communication and Sustainable Technologies (ICAECT), 2023. [Online]. Available: https://doi.org/10.1109/ICAECT57570.2023.10117616

[46] X. Liu, C. Yao, H. Chen, R. Xiang, H. Wu, P. Du, Z. Yu, W. Liu, J. Liu, and D. Geng, "BTSC-TNAS: A neural architecture search-based transformer for brain tumor segmentation and classification," Computerized Medical Imaging and Graphics, vol. 110, p. 102307, 2023. [Online]. Available: https://doi.org/10.1016/j.compmedimag.2023.102307

[47] G. Song, G. Xie, Y. Nie, M. S. Majid, and I. Yavari, "Noninvasive grading of glioma brain tumors using magnetic resonance imaging and deep learning methods," Journal of Cancer Research and Clinical Oncology, vol. 149, pp. 16293–16309, 2023. [Online]. Available: https://doi.org/10.1007/s00432-023-05389-4

[48] A. Nanda, R. C. Barik, and S. Bakshi, "SSO-RBNN driven brain tumor classification with Saliency-K-means segmentation technique," Biomedical Signal Processing and Control, vol. 81, p. 104356, 2023. [Online]. Available: https://doi.org/10.1016/j.bspc.2022.104356

[49] A. Saboor, J. P. Li, A. U. Haq, U. Shehzad, S. Khan, R. M. Aotaibi, and S. A. Alajlan, "DDFC: deep learning approach for deep feature extraction and classification of brain tumors using magnetic resonance imaging in E-healthcare system," Scientific Reports, vol. 14, p. 6425, 2024. [Online]. Available: https://doi.org/10.1038/s41598-024-56983-6

[50] S. Srinivasan, D. Francis, S. K. Mathivanan, H. Rajadurai, B. D. Shivahare, and M. A. Shah, "A hybrid deep CNN model for brain tumor image multi-classification," BMC Medical Imaging, 2024. [Online]. Available: https://doi.org/10.1186/s12880-024-01195-7

[51] P. Roy, F. M. S. Srijon, and P. Bhowmik, "An explainable ensemble approach for advanced brain tumor classification applying Dual-GAN mechanism and feature extraction techniques over highly imbalanced data," PLOS ONE, vol. 19, no. 9, p. e0310748, 2024. [Online]. Available: https://doi.org/10.1371/journal.pone.0310748

[52] S. Khalighi, K. Reddy, A. Midya, K. B. Pandav, A. Madabhushi, and M. Abedalthagafi, "Artificial intelligence in neuro-oncology: advances and challenges in brain tumor diagnosis, prognosis, and precision treatment," npj Precision Oncology, vol. 8, p. 80, 2024. [Online]. Available: https://doi.org/10.1038/s41698-024-00575-0

[53] M. F. Almufareh, M. Imran, A. Khan, M. Humayun, and M. Asim, "Automated Brain Tumor Segmentation and Classification in MRI Using YOLO-Based Deep Learning," IEEE Access, vol. 12, pp. 16189-16207, 2024. [Online]. Available: https://doi.org/10.1109/ACCESS.2024.3359418

[54] B. Sarada, K. N. Reddy, M. Singh, R. Babu, and B. R. Babu, "Brain Tumor Classification Using Modified ResNet50V2 Deep Learning Model," International Journal of Computing and Digital Systems, 2024.

[55] U. Bhimavarapu, N. Chintalapudi, and G. Battineni, "Brain Tumor Detection and Categorization with Segmentation of Improved Unsupervised Clustering Approach and Machine Learning Classifier," Bioengineering, vol. 11, p. 266, 2024. [Online]. Available: https://doi.org/10.3390/bioengineering11030266

[56] S. P. Jakhar, A. Nandal, A. Dhaka, A. Alhudhaif, and K. Polat, "Brain Tumor Detection with Multi-Scale Fractal Feature Network and Fractal Residual Learning," Applied Soft Computing Journal, vol. 153, p. 111284, 2024. [Online]. Available: https://doi.org/10.1016/j.asoc.2024.111284

[57] S. Kalaiselvi and G. Thailambal, "Brain Tumor Diagnosis from MR Images Using Boosted Multi-Gradient Support Vector Machine Classifier," Measurement: Sensors, vol. 32, p. 101071, 2024. [Online]. Available: https://doi.org/10.1016/j.measen.2024.101071

[58] L. Xu and M. Mohammadi, "Brain Tumor Diagnosis from MRI Based on Mobilenetv2 Optimized by Contracted Fox Optimization Algorithm," Heliyon, vol. 10, p. e23866, 2024. [Online]. Available: https://doi.org/10.1016/j.heliyon.2023.e23866

[59] A. Rostami, "Labeled MRI Brain Tumor Dataset," Roboflow Universe, 2024. [Online]. Available: https://universe.roboflow.com/ali-rostami/labeled-mri-brain-tumor-dataset

[60] H. Byeon, M. Al-Kubaisi, A. K. Dutta, F. Alghayadh, M. Soni, M. Bhende, V. Chunduri, K. Suresh Babu, and R. Jeet, "Brain Tumor Segmentation Using Neuro-Technology Enabled Intelligence-Cascaded U-Net Model," Frontiers in Computational Neuroscience, vol. 18, p. 1391025, 2024. [Online]. Available: https://doi.org/10.3389/fncom.2024.1391025

[61] B. Jagadeesh and G. A. Kumar, "Brain tumor segmentation with missing MRI modalities using edge aware discriminative feature fusion based transformer U-net," Applied Soft Computing, vol. 161, p. 111709, 2024. [Online]. Available: https://doi.org/10.1016/j.asoc.2024.111709

[62] M. H. O. Rashid, M. A. Mamun, M. A. Hossain, and M. P. Uddin, "Brain Tumor Detection Using Anisotropic Filtering, SVM Classifier and Morphological Operation from MR Images," Applied Soft Computing Journal, vol. 161, p. 111709, 2024. [Online]. Available: https://doi.org/10.1016/j.asoc.2024.111709

[63] E. Gürsoy and Y. Kaya, "Brain-GCN-Net: Graph-Convolutional Neural Network for brain tumor identification," Computers in Biology and Medicine, vol. 180, p. 108971, 2024. [Online]. Available: https://doi.org/10.1016/j.compbiomed.2024.108971

[64] M. S. Ullah, M. A. Khan, N. A. Almujally, M. Alhaisoni, T. Akram, and M. Shabaz, "BrainNet: a fusion assisted novel optimal framework of residual blocks and stacked autoencoders for multimodal brain tumor classification," Scientific Reports, vol. 14, p. 5895, 2024. [Online]. Available: https://doi.org/10.1038/s41598-024-56657-3

[65] S. Singh and V. Saxena, "Classification and Segmentation of MRI Images of Brain Tumors Using Deep Learning and Hybrid Approach," International Journal of Electrical and Computer Engineering Systems, vol. 15, no. 2, pp. 163-172, 2024.

[66] N. I. Md. Ashafuddula and R. Islam, "ContourTL-Net: Contour-Based Transfer Learning Algorithm for Early-Stage Brain Tumor Detection," International Journal of Biomedical Imaging, vol. 2024, Article ID 6347920, 2024. [Online]. Available: https://doi.org/10.1155/2024/6347920

[67] S. Kordnoori, M. Sabeti, M. H. Shakoor, and E. Moradi, "Deep multi-task learning structure for segmentation and classification of supratentorial brain tumors in MR images," Interdisciplinary Neurosurgery: Advanced Techniques and Case Management, vol. 36, p. 101931, 2024. [Online]. Available: https://doi.org/10.1016/j.inat.2023.101931

[68] A. S. Chauhan, J. Singh, S. Kumar, N. Saxena, M. Gupta, and P. Verma, "Design and assessment of improved Convolutional Neural Network based brain tumor segmentation and classification system," Journal of Integrated Science and Technology, vol. 12, no. 4, p. 793, 2024.

[69] R. Rajeswari, S. Sahu, R. Tripathy, and M. S. Sesha Sai, "DFMN: Dense fused Maxout network for severity prediction of brain tumor using hybrid tumor segmentation algorithm," Biomedical Signal Processing and Control, vol. 92, p. 106029, 2024. [Online]. Available: https://doi.org/10.1016/j.bspc.2024.106029

[70] Zakariah M, Al-Razgan M, Alfakih T. Dual vision Transformer-DSUNET with feature fusion for brain tumor segmentation. Heliyon. 2024 Sep 14;10(18):e37804. doi: 10.1016/j.heliyon.2024.e37804. PMID: 39323802; PMCID: PMC11422567.

[71] Y. Yang, Chaoluomeng, and N. Razmjooy, "Early detection of brain tumors: Harnessing the power of GRU networks and hybrid dwarf mongoose optimization algorithm," Biomedical Signal Processing and Control, vol. 91, p. 106093, 2024. [Online]. Available: https://doi.org/10.1016/j.bspc.2024.106093

[72] M. M. Musthafa, T. R. Mahesh, V. V. Kumar, and S. Guuwad, "Enhancing brain tumor detection in MRI images through explainable AI using Grad-CAM with Resnet 50," BMC Medical Imaging, 2024. [Online]. Available: https://doi.org/10.1186/s12880-024-01292-7

[73] Deep Learning, "Alzheimer's Disease Detection Dataset," Roboflow Universe, 2023. [Online]. Available: https://universe.roboflow.com/deep-learning-xe457/alzheimer-s-disease-detection-ud5st

[74] Z. Yu, X. Li, J. Li, W. Chen, Z. Tang, and D. Geng, "HSA-net with a novel CAD pipeline boosts both clinical brain tumor MR image classification and segmentation," Computers in Biology and Medicine, vol. 170, p. 108039, 2024. [Online]. Available: https://doi.org/10.1016/j.compbiomed.2024.108039

[75] I. Aboussaleh, J. Riffi, A. M. Mahraz, and H. Tairi, "Inception-UDet: An Improved U-Net Architecture for Brain Tumor Segmentation," Annals of Data Science, vol. 11, no. 3, pp. 831–853, 2024. [Online]. Available: https://doi.org/10.1007/s40745-023-00480-6

[76] S. M. Malakouti, M. B. Menhaj, and A. A. Suratgar, "Machine learning and transfer learning techniques for accurate brain tumor classification," Clinical eHealth, vol. 7, pp. 106–119, 2024. [Online]. Available: https://doi.org/10.1016/j.ceh.2024.08.001

[77] N. K. Basha, C. Ananth, K. Muthukumaran, G. Sudhamsu, V. Mittal, and F. Gared, "Mask region-based convolutional neural network and VGG16 inspired brain tumor segmentation," Scientific Reports, vol. 14, p. 17615, 2024. [Online]. Available: https://doi.org/10.1038/s41598-024-66554-4

[78] S. Yalamanchili, P. Yenuga, N. Burla, H. Jonnadula, S. C. Bolem, V. R. R. Chirra, V. M. Ramana, P. Garnepudi, and N. R. Yamarthi, "MRI Brain Tumor Analysis on Improved VGG16 and Efficient NetB7 Models," Journal of Image and Graphics, vol. 12, no. 1, pp. 103-116, 2024. [Online]. Available: https://doi.org/10.18178/joig.12.1.103-116

[79] L. Nelson, S. Prasher, and D. Arumugam, "Multiclass Brain Tumor Detection using EfficientNet B3 Model with Magnetic Resonance Imaging," in International Conference on Circuit Power and Computing Technologies, 2024. [Online]. Available: https://doi.org/10.1109/ICCPCT61902.2024.10673377

[80] P. Priyadarshini, P. Kanungo, and T. Kar, "Multigrade brain tumor classification in MRI images using Fine tuned efficientnet," e-Prime - Advances in Electrical Engineering, Electronics and Energy, vol. 8, p. 100498, 2024. [Online]. Available: https://doi.org/10.1016/j.prime.2024.100498

[81] R. A. Zeineldin, M. E. Karar, O. Burgert, and F. Mathis-Ullrich, "NeuroIGN: Explainable Multimodal Image-Guided System for Precise Brain Tumor Surgery," Journal of Medical Systems, vol. 48, p. 25, 2024. [Online]. Available: https://doi.org/10.1007/s10916-024-02037-3

[82] R. Haque, M. M. Hassan, A. K. Bairagi, and S. M. S. Islam, "NeuroNet19: an explainable deep neural network model for the classification of brain tumors using magnetic resonance imaging data," Scientific Reports, vol. 14, p. 1524, 2024. [Online]. Available: https://doi.org/10.1038/s41598-024-51867-1

[83] N. Rasool, J. I. Bhat, N. A. Wani, N. Ahmad, and M. Alshara, "TransResUNet: Revolutionizing Glioma Brain Tumor Segmentation Through Transformer-Enhanced Residual UNet," IEEE Access, vol. 12, pp. 72105-72116, 2024. [Online]. Available: https://doi.org/10.1109/ACCESS.2024.3402947

[84] S. Hossain, A. Chakrabarty, T. R. Gadekallu, M. Alazab, and M. J. Piran, "Vision Transformers, Ensemble Model, and Transfer Learning Leveraging Explainable AI for Brain Tumor Detection and Classification," IEEE Journal of Biomedical and Health Informatics, vol. 28, no. 3, pp. 1261-1272, 2024. [Online]. Available: https://doi.org/10.1109/JBHI.2023.3266614

[85] N. Iriawan, A. A. Pravitasari, U. S. Nuraini, N. I. Nirmalasari, T. Azmi, M. Nasrudin, A. F. Fandisyah, K. Fithriasari, S. W. Purnami, Irhamah, and W. Ferriastuti, "YOLO-UNet Architecture for Detecting and Segmenting the Localized MRI Brain Tumor Image," Applied Computational Intelligence and Soft Computing, 2024. [Online]. Available: https://doi.org/10.1155/2024/3819801

[86] J. Islam and Y. Zhang, "Brain MRI analysis for Alzheimer’s disease diagnosis using an ensemble system of deep convolutional neural networks," Brain Informatics, 2018. [Online]. Available: https://doi.org/10.1186/s40708-018-0080-3

[87] F. Zhang, Z. Li, B. Zhang, H. Du, B. Wang, and X. Zhang, "Multi-modal deep learning model for auxiliary diagnosis of Alzheimer’s disease," Neurocomputing, vol. 361, pp. 185-195, 2019. [Online]. Available: https://doi.org/10.1016/j.neucom.2019.04.093

[88] A. W. Salehi, P. Baglat, and G. Gupta, "Alzheimer’s Disease Diagnosis using Deep Learning Techniques," International Journal of Engineering and Advanced Technology, vol. 9, no. 3, pp. 874-880, 2020. [Online]. Available: https://doi.org/10.35940/ijeat.C5345.029320

[89] J. Feng, S.-W. Zhang, L. Chen, and ADNI, "Identification of Alzheimer’s disease based on wavelet transformation energy feature of the structural MRI image and NN classifier," Artificial Intelligence in Medicine, vol. 108, p. 101940, 2020. [Online]. Available: https://doi.org/10.1016/j.artmed.2020.101940

[90] A. Basher, B. C. Kim, K. H. Lee, and H. Y. Jung, "Volumetric Feature-Based Alzheimer’s Disease Diagnosis From sMRI Data Using a Convolutional Neural Network and a Deep Neural Network," IEEE Access, vol. 9, pp. 29870-29882, 2021. [Online]. Available: https://doi.org/10.1109/ACCESS.2021.3059658

[91] R. A. Hazarika, D. Kandar, and A. K. Maji, "An Experimental Analysis of Different Deep Learning Based Models for Alzheimer’s Disease Classification Using Brain Magnetic Resonance Images," Journal of King Saud University – Computer and Information Sciences, vol. 34, pp. 8576-8598, 2021. [Online]. Available: https://doi.org/10.1016/j.jksuci.2021.09.003

[92] N. Mahendran and D. R. P. M. Vincent, "A deep learning framework with an embedded-based feature selection approach for the early detection of the Alzheimer’s disease," Computers in Biology and Medicine, vol. 141, p. 105056, 2022. [Online]. Available: https://doi.org/10.1016/j.compbiomed.2021.105056

[93] C. Y. Cheung, A. R. Ran, S. Wang, V. T. T. Chan, K. Sham, S. Hilal, N. Venketasubramanian, C.-Y. Cheng, C. Sabanayagam, Y. C. Tham, L. Schmetterer, G. J. McKay, M. A. Williams, A. Wong, L. W. C. Au, Z. Lu, J. C. Yam, C. C. Tham, J. J. Chen, O. M. Dumitrascu, P.-A. Heng, T. C. Y. Kwok, V. C. T. Mok, D. Milea, C. L.-H. Chen, and T. Y. Wong, "A deep learning model for detection of Alzheimer’s disease based on retinal photographs: a retrospective, multicentre case-control study," The Lancet Digital Health, vol. 4, no. 11, pp. e806-e815, 2022. [Online]. Available: https://doi.org/10.1016/S2589-7500(22)00169-8

[94] M. M. S. Fareed, et al., "ADD-Net: An Effective Deep Learning Model for Early Detection of Alzheimer Disease in MRI Scans," IEEE Access, vol. 10, pp. 96930-96951, 2022. [Online]. Available: https://doi.org/10.1109/ACCESS.2022.3204395

[95] J. F. Pedrero-Sánchez, et al., "Classification of Healthy, Alzheimer and Parkinson Populations with a Multi-Branch Neural Network," Biomedical Signal Processing and Control, vol. 75, p. 103617, 2022. [Online]. Available: https://doi.org/10.1016/j.bspc.2022.103617

[96] A. Khan and S. Zubair, "Development of a Three-Tiered Cognitive Hybrid Machine Learning Algorithm for Effective Diagnosis of Alzheimer’s Disease," Journal of King Saud University – Computer and Information Sciences, vol. 34, pp. 8000-8018, 2022. [Online]. Available: https://doi.org/10.1016/j.jksuci.2022.07.016

[97] H. Zhou, et al., "Interpretable Graph Convolutional Network of Multi-Modality Brain Imaging for Alzheimer’s Disease Diagnosis," in IEEE 19th International Symposium on Biomedical Imaging (ISBI), 2022. [Online]. Available: https://doi.org/10.1109/ISBI52829.2022.9761449

[98] A. Alorf and M. U. G. Khan, "Multi-Label Classification of Alzheimer’s Disease Stages from Resting-State fMRI-Based Correlation Connectivity Data and Deep Learning," Computers in Biology and Medicine, vol. 151, p. 106240, 2022. [Online]. Available: https://doi.org/10.1016/j.compbiomed.2022.106240

[99] M. Velazquez and Y. Lee, "Multimodal Ensemble Model for Alzheimer's Disease Conversion Prediction from Early Mild Cognitive Impairment Subjects," Computers in Biology and Medicine, vol. 151, p. 106201, 2022. [Online]. Available: https://doi.org/10.1016/j.compbiomed.2022.106201

[100] N. Rahim, et al., "Prediction of Alzheimer's Progression Based on Multimodal Deep-Learning-Based Fusion and Visual Explainability of Time-Series Data," Information Fusion, vol. 92, pp. 363-388, 2023. [Online]. Available: https://doi.org/10.1016/j.inffus.2022.11.028

[101] K. Chen, et al., "A Comparative Study of GNN and MLP Based Machine Learning for the Diagnosis of Alzheimer's Disease Involving Data Synthesis," Neural Networks, vol. 169, pp. 442-452, 2024. [Online]. Available: https://doi.org/10.1016/j.neunet.2023.10.040

[102] S. Fathi, et al., "A Deep Learning-Based Ensemble Method for Early Diagnosis of Alzheimer's Disease using MRI Images," Neuroinformatics, vol. 22, pp. 89-105, 2024. [Online]. Available: https://doi.org/10.1007/s12021-023-09646-2

[103] X. Zhang, et al., "A New Weakly Supervised Deep Neural Network for Recognizing Alzheimer's Disease," Computers in Biology and Medicine, vol. 163, p. 107079, 2023. [Online]. Available: https://doi.org/10.1016/j.compbiomed.2023.107079

[104] K. Zhou, et al., "A Novel Cascade Machine Learning Pipeline for Alzheimer's Disease Identification and Prediction," Frontiers in Aging Neuroscience, vol. 14, p. 1073909, 2023. [Online]. Available: https://doi.org/10.3389/fnagi.2022.1073909

[105] D. Klepl, et al., "Adaptive Gated Graph Convolutional Network for Explainable Diagnosis of Alzheimer's Disease Using EEG Data," IEEE Transactions on Neural Systems and Rehabilitation Engineering, vol. 31, pp. 3978-3987, 2023. [Online]. Available: https://doi.org/10.1109/TNSRE.2023.3321634

[106] R. R. Enumula and R. K. Rao, "Alzheimer's Disease Prediction and Classification Using CT Images Through Machine Learning," Bratislava Medical Journal, vol. 124, no. 5, pp. 337-344, 2023. [Online]. Available: https://doi.org/10.4149/BLL_2023_051

[107] M. G. Jenifel, M. S. Devi, and D. Umanandhini, "Alzheimer Disease Detection System using AlexNet a novel Eight Layered Convolutional Neural Network," in Global Conference on Information Technologies and Communications (GCITC), 2023. [Online]. Available: https://doi.org/10.1109/GCITC60406.2023.10426374

[108] B. Liu, "Alzheimer's Disease Classification Using Hippocampus and Improved DenseNet," in International Conference on Image Processing, Computer Vision and Machine Learning (ICICML), 2023. [Online]. Available: https://doi.org/10.1109/ICICML60161.2023.10424926

[109] N. Boyapati, et al., "Alzheimer's Disease Prediction using Convolutional Neural Network (CNN) with Generative Adversarial Network (GAN)," in International Conference on Data Science, Agents, and Artificial Intelligence (ICDSAAI), 2023. [Online]. Available: https://doi.org/10.1109/ICDSAAI59313.2023.10452539

[110] H. Shetty, H. Surlekar, and G. Nagare, "Alzheimer's Diseases Detection by using Convolution Neural Network," in International Conference on Information Systems and Computer Networks (ISCON), 2023. [Online]. Available: https://doi.org/10.1109/ISCON57294.2023.10112095

[111] A. Asgharzadeh-Bonab, H. Kalbkhani, and S. Azarfardian, "An Alzheimer's Disease Classification Method Using Fusion of Features from Brain Magnetic Resonance Image Transforms and Deep Convolutional Networks," Healthcare Analytics, vol. 4, p. 100223, 2023. [Online]. Available: https://doi.org/10.1016/j.health.2023.100223

[112] A. W. Saleh, et al., "An Alzheimer's Disease Classification Model Using Transfer Learning DenseNet with Embedded Healthcare Decision Support System," Decision Analytics Journal, vol. 9, p. 100348, 2023. [Online]. Available: https://doi.org/10.1016/j.dajour.2023.100348

[113] R. A. Hazarika, et al., "An Approach for Classification of Alzheimer's Disease Using Deep Neural Network and Brain Magnetic Resonance Imaging (MRI)," Electronics, vol. 12, no. 676, 2023. [Online]. Available: https://doi.org/10.3390/electronics12030676

[114] Z. Yao, et al., "Artificial Intelligence-Based Diagnosis of Alzheimer's Disease with Brain MRI Images," European Journal of Radiology, vol. 165, p. 110934, 2023. [Online]. Available: https://doi.org/10.1016/j.ejrad.2023.110934

[115] N. C. R., et al., "Classifying the Stages of Alzheimer's Disease by Using Multi Layer Feed Forward Neural Network," Procedia Computer Science, vol. 218, pp. 1845-1856, 2023. [Online]. Available: https://doi.org/10.1016/j.procs.2023.01.162

[116] N. Mahendran and D. R. P. M. Vincent, "Deep Belief Network-Based Approach for Detecting Alzheimer's Disease Using the Multi-Omics Data," Computational and Structural Biotechnology Journal, vol. 21, pp. 1651-1660, 2023. [Online]. Available: https://doi.org/10.1016/j.csbj.2023.02.021

[117] J. C. Sekhar, et al., "Deep Generative Adversarial Networks with Marine Predators Algorithm for Classification of Alzheimer's Disease Using Electroencephalogram," Journal of King Saud University - Computer and Information Sciences, vol. 35, p. 101848, 2023. [Online]. Available: https://doi.org/10.1016/j.jksuci.2023.101848

[118] H.-D. Nguyen, et al., "Deep Grading for MRI-Based Differential Diagnosis of Alzheimer's Disease and Frontotemporal Dementia," Artificial Intelligence In Medicine, vol. 144, p. 102636, 2023. [Online]. Available: https://doi.org/10.1016/j.artmed.2023.102636

[119] D. Wang, et al., "Deep Neural Network Heatmaps Capture Alzheimer's Disease Patterns Reported in a Large Meta-Analysis of Neuroimaging Studies," NeuroImage, vol. 269, p. 119929, 2023. [Online]. Available: https://doi.org/10.1016/j.neuroimage.2023.119929

[120] S. Jahan, et al., "Explainable AI-Based Alzheimer's Prediction and Management Using Multimodal Data," PLOS ONE, vol. 18, no. 11, p. e0294253, 2023. [Online]. Available: https://doi.org/10.1371/journal.pone.0294253

[121] A. AlMohimeed, et al., "Explainable Artificial Intelligence of Multi-Level Stacking Ensemble for Detection of Alzheimer's Disease Based on Particle Swarm Optimization and the Sub-Scores of Cognitive Biomarkers," IEEE Access, vol. 11, pp. 123173-123193, 2023. [Online]. Available: https://doi.org/10.1109/ACCESS.2023.3328331

[122] Z. Yao, W. Mao, Y. Yuan, Z. Shi, G. Zhu, W. Zhang, Z. Wang, and G. Zhang, "Fuzzy-VGG: A fast deep learning method for predicting the staging of Alzheimer's disease based on brain MRI," Information Sciences, vol. 642, p. 119129, 2023. [Online]. Available: https://doi.org/10.1016/j.ins.2023.119129

[123] F. Yi, Y. Zhang, J. Yuan, Z. Liu, F. Zhai, A. Hao, F. Wu, J. Somekh, M. Peleg, Y.-C. Zhu, and Z. Huang, "Identifying underlying patterns in Alzheimer's disease trajectory: a deep learning approach and Mendelian randomization analysis," eClinicalMedicine, vol. 64, p. 102247, 2023. [Online]. Available: https://doi.org/10.1016/j.eclinm.2023.102247

[124] G. Sharma, V. Anand, R. Chauhan, N. Garg, and S. Gupta, "Multi-Class Alzheimer's Disease Classification using a Fine-Tuned InceptionV3 Pretrained Model: A Step Towards Diagnosis and Prediction," in 2nd International Conference on Futuristic Technologies (INCOFT), 2023. [Online]. Available: https://doi.org/10.1109/INCOFT60753.2023.10425243

[125] U. Hwang, S.-W. Kim, D. Jung, S.-W. Kim, H. Lee, S. W. Seo, J.-K. Seong, and S. Yoon, "Real-world prediction of preclinical Alzheimer's disease with a deep generative model," Artificial Intelligence In Medicine, vol. 144, p. 102654, 2023. [Online]. Available: https://doi.org/10.1016/j.artmed.2023.102654

[126] X. Zhang, L. Han, L. Han, H. Chen, D. Dancey, and D. Zhang, "sMRI-PatchNet: A novel efficient explainable patch-based deep learning network for Alzheimer's disease diagnosis with structural MRI," IEEE Access, vol. 11, pp. 108603-108616, 2023. [Online]. Available: https://doi.org/10.1109/ACCESS.2023.3321220

[127] G. I. Stoleru and A. Iftene, "Transfer Learning for Alzheimer's Disease Diagnosis from MRI Slices: A Comparative Study of Deep Learning Models," Procedia Computer Science, vol. 225, pp. 2614-2623, 2023. [Online]. Available: https://doi.org/10.1016/j.procs.2023.10.253

[128] C. Ozdemir and Y. Dogan, "Advancing early diagnosis of Alzheimer's disease with next-generation deep learning methods," Biomedical Signal Processing and Control, vol. 96, p. 106614, 2024. [Online]. Available: https://doi.org/10.1016/j.bspc.2024.106614

[129] R. Biswas and R. J. Gini, "Multi-class classification of Alzheimer's disease detection from 3D MRI images using ML techniques and its performance analysis," Multimedia Tools and Applications, vol. 83, pp. 33527-33554, 2024. [Online]. Available: https://doi.org/10.1007/s11042-023-16519-y

[130] A. M. El-Assy, H. M. Amer, H. M. Ibrahim, and M. A. Mohamed, "A novel CNN architecture for accurate early detection and classification of Alzheimer's disease using MRI data," Scientific Reports, vol. 14, p. 3463, 2024. [Online]. Available: https://doi.org/10.1038/s41598-024-53733-6

[131] I. Ayus and D. Gupta, "A novel hybrid ensemble based Alzheimer's identification system using deep learning technique," Biomedical Signal Processing and Control, vol. 92, p. 106079, 2024. [Online]. Available: https://doi.org/10.1016/j.bspc.2024.106079

[132] M. Nour, U. Senturk, and K. Polat, "A novel hybrid model in the diagnosis and classification of Alzheimer's disease using EEG signals: Deep ensemble learning (DEL) approach," Biomedical Signal Processing and Control, vol. 89, p. 105751, 2024. [Online]. Available: https://doi.org/10.1016/j.bspc.2023.105751

[133] E. H. Ali, S. Sadek, G. Z. El Nashef, and Z. F. Makki, "Advanced Integration of Machine Learning Techniques for Accurate Segmentation and Detection of Alzheimer's Disease," Algorithms, vol. 17, p. 207, 2024. [Online]. Available: https://doi.org/10.3390/a17050207

[134] S. K. Tripathy, R. K. Nayak, K. S. Gadupa, R. D. Mishra, A. K. Patel, S. K. Satapathy, A. K. Bhoi, and P. Barsocchi, "Alzheimer's Disease Detection via Multiscale Feature Modelling Using Improved Spatial Attention Guided Depth Separable CNN," International Journal of Computational Intelligence Systems, vol. 17, p. 113, 2024. [Online]. Available: https://doi.org/10.1007/s44196-024-00502-y

[135] T. Mahmood, A. Rehman, T. Saba, Y. Wang, and F. S. Alamri, "Alzheimer's disease unveiled: Cutting-edge multi-modal neuroimaging and computational methods for enhanced diagnosis," Biomedical Signal Processing and Control, vol. 97, p. 106721, 2024.

[136] T. Mahmud, K. Barua, S. U. Habiba, N. Sharmen, M. S. Hossain, and K. Andersson, "An Explainable AI Paradigm for Alzheimer's Diagnosis Using Deep Transfer Learning," Diagnostics, vol. 14, p. 345, 2024.

[137] P. Matlani, "BiLSTM-ANN: Early Diagnosis of Alzheimer's Disease Using Hybrid Deep Learning Algorithms," Multimedia Tools and Applications, vol. 83, pp. 60761-60788, 2024.

[138] A. Kiran, M. Alsaadi, A. K. Dutta, M. Raparthi, M. Soni, S. Alsubai, H. Byeon, M. H. Kulkarni, and E. Asenso, "Bio-inspired Deep Learning-Personalized Ensemble Alzheimer's Diagnosis Model for Mental Well-being," SLAS Technology, vol. 29, p. 100161, 2024.

[139] G. Malu, N. Uday, E. Sherly, A. Abraham, and N. K. Bodhey, "CirMNet: A Shape-Based Hybrid Feature Extraction Technique Using CNN and CMSMD for Alzheimer's MRI Classification," IEEE Access, vol. 12, pp. 80491-80504, 2024.

[140] S. Bringas, R. Duque, C. Lage, and J. L. Montaña, "CLADSI: Deep Continual Learning for Alzheimer's Disease Stage Identification Using Accelerometer Data," IEEE Journal of Biomedical and Health Informatics, vol. 28, no. 6, pp. 3401-3410, 2024.

[141] Zia-ur-Rehman, M. K. Awang, J. Rashid, G. Ali, M. Hamid, S. F. Mahmoud, D. I. Saleh, and H. I. Ahmad, "Classification of Alzheimer Disease Using DenseNet-201 Based on Deep Transfer Learning Technique," PLOS ONE, vol. 19, no. 9, p. e0304995, 2024.

[142] S. E. Sorour, A. A. A. El-Mageed, K. M. Albarrak, A. K. Alnaim, A. A. Wafa, and E. El-Shafeiy, "Classification of Alzheimer's Disease Using MRI Data Based on Deep Learning Techniques," Journal of King Saud University - Computer and Information Sciences, vol. 36, p. 101940, 2024.

[143] S. Praveenkumar, T. Santhoshe, K. B. Jayanthi, and R. Vignesh, "Classification of Alzheimer's Disease in Elderly Indian Population using Artificial Intelligence," in IEEE 9th International Conference for Convergence in Technology (I2CT), 2024.

[144] W.-Y. Yu, T.-H. Sun, K.-C. Hsu, C.-C. Wang, S.-Y. Chien, C.-H. Tsai, and Y.-W. Yang, "Comparative Analysis of Mchine Learning Algorithms for Alzheimer's Disease Classification Using EEG Signals and Genetic Information," Computers in Biology and Medicine, vol. 176, p. 108621, 2024.

[145] S. Parvin, S. F. Nimmy, and M. S. Kama, "Convolutional Neural Network Based Data Interpretable Framework for Alzheimer's Treatment Planning," Visual Computing for Industry, Biomedicine, and Art, vol. 2, p. 00154-x, 2024.

[146] F. Zuo, P. Jing, J. Sun, J. Duan, Y. Ji, and Y. Liu, "Deep Learning-Based Eye-Tracking Analysis for Diagnosis of Alzheimer's Disease Using 3D Comprehensive Visual Stimuli," IEEE Journal of Biomedical and Health Informatics, vol. 28, no. 5, pp. 2781-2793, 2024.

[147] A. Shukla, U. N. Bera, S. Upadhyay, R. V. Kshirsagar, P. R. Bachan, and N. Nathani, "Dynamic Explainability in AI for Neurological Disorders: An Adaptive Model for Transparent Decision-Making in Alzheimer's Disease Diagnosis," in IEEE 13th International Conference on Communication Systems and Network Technologies (CSNT), 2024.

[148] G. Kiss, "Early Detection of Alzheimer's Disease Using Artificial Intelligence," Procedia Computer Science, vol. 237, pp. 485-492, 2024. [Online]. Available: https://doi.org/10.1016/j.procs.2024.05.131

[149] P. C. Wong, S. S. Abdullah, and M. I. Shapiai, "Exceptional performance with minimal data using a generative adversarial network for Alzheimer's disease classification," Scientific Reports, vol. 14, p. 17037, 2024. [Online]. Available: https://doi.org/10.1038/s41598-024-66874-5

[150] B. Song and S. Yoshida, "Explainability of three-dimensional convolutional neural networks for functional magnetic resonance imaging of Alzheimer's disease classification based on gradient-weighted class activation mapping," PLOS ONE, vol. 19, no. 5, p. e0303278, 2024. [Online]. Available: https://doi.org/10.1371/journal.pone.0303278

[151] F. Conti, M. Banchelli, V. Bessi, C. Cecchi, F. Chiti, S. Colantonio, C. D'Andrea, M. de Angelis, D. Moroni, B. Nacmias, M. A. Pascali, S. Sorbi, and P. Matteini, "Harnessing topological machine learning in Raman spectroscopy: Perspectives for Alzheimer's disease detection via cerebrospinal fluid analysis," Journal of the Franklin Institute, vol. 361, p. 107249, 2024. [Online]. Available: https://doi.org/10.1016/j.jfranklin.2024.107249

[152] Z. Yuan, X. Li, Z. Hao, et al., "Intelligent prediction of Alzheimer's disease via improved multifeature squeeze-and-excitation-dilated residual network," Scientific Reports, vol. 14, p. 11994, 2024. [Online]. Available: https://doi.org/10.1038/s41598-024-62712-w

[153] M. S. Kamal and S. F. Nimmy, "Interpretable Transformers for Alzheimer Disease Diagnosis on Multi-modal Data," in 2024 International Joint Conference on Neural Networks (IJCNN), 2024. [Online]. Available: https://doi.org/10.1109/IJCNN60899.2024.10651416

[154] M. Hatami, F. Yaghmaee, and R. Ebrahimpour, "Investigating the potential of reinforcement learning and deep learning in improving Alzheimer's disease classification," Neurocomputing, vol. 597, p. 128119, 2024. [Online]. Available: https://doi.org/10.1016/j.neucom.2024.128119

[155] S. Alp, T. Akan, M. S. Bhuiyan, E. A. Disbrow, S. A. Conrad, J. A. Vanchiere, C. G. Kevil, and M. A. N. Bhuiyan, "Joint transformer architecture in brain 3D MRI classification: its application in Alzheimer's disease classification," Scientific Reports, vol. 14, p. 8996, 2024. [Online]. Available: https://doi.org/10.1038/s41598-024-59578-3

[156] A. Fania, A. Monaco, N. Amoroso, L. Bellantuono, R. Cazzolla Gatti, N. Firza, A. Lacalamita, E. Pantaleo, S. Tangaro, A. Velichevskaya, and R. Bellotti, "Machine learning and XAI approaches highlight the strong connection between O3 and NO2 pollutants and Alzheimer's disease," Scientific Reports, vol. 14, p. 5385, 2024. [Online]. Available: https://doi.org/10.1038/s41598-024-55439-1

[157] C. Qian and Y. Wang, "MMANet: A Multi-Task Residual Network for Alzheimer's Disease Classification and Brain Age Prediction," IRBM, vol. 45, p. 100840, 2024. [Online]. Available: https://doi.org/10.1016/j.irbm.2024.100840

[158] N. Yousefzadeh, C. Tran, A. Ramirez-Zamora, J. Chen, R. Fang, and M. T. Thai, "Neuron-level explainable AI for Alzheimer's Disease assessment from fundus images," Scientific Reports, vol. 14, p. 7710, 2024. [Online]. Available: https://doi.org/10.1038/s41598-024-58121-8

[159] S. M. Mahim, M. S. Ali, M. O. Hasan, A. A. N. Nafi, A. Sadat, S. A. Hasan, B. Shareef, M. M. Ahsan, M. K. Islam, M. S. Miah, and M. B. Niu, "Unlocking the Potential of XAI for Improved Alzheimer's Disease Diagnosis," 2024.

[160] P. R. Magesh, R. D. Myloth, and R. J. Tom, "An Explainable Machine Learning Model for Early Detection of Parkinson's Disease using LIME on DaTSCAN Imagery," Computers in Biology and Medicine, vol. 126, p. 104041, 2020. [Online]. Available: https://doi.org/10.1016/j.compbiomed.2020.104041

[161] M. Nilashi, H. Ahmadi, A. Sheikhtaheri, R. Naemi, R. Alotaibi, A. A. Alarood, A. Munshi, T. A. Rashid, and J. Zhao, "Remote tracking of Parkinson's Disease progression using ensembles of Deep Belief Network and Self-Organizing Map," Expert Systems with Applications, vol. 159, p. 113562, 2020. [Online]. Available: https://doi.org/10.1016/j.eswa.2020.113562

[162] P. Mounika and S. G. Rao, "Machine Learning and Deep Learning Models for Diagnosis of Parkinson's Disease: A Performance Analysis," in Proceedings of the Fifth International Conference on I-SMAC (IoT in Social, Mobile, Analytics and Cloud), pp. 381-388, 2021. [Online]. Available: https://doi.org/10.1109/I-SMAC52330.2021.9640632

[163] O. Karaman, H. Çakın, A. Alhudhaif, and K. Polat, "Robust automated Parkinson disease detection based on voice signals with transfer learning," Expert Systems with Applications, vol. 178, p. 115013, 2021. [Online]. Available: https://doi.org/10.1016/j.eswa.2021.115013

[164] A. Nogales, Á. J. García-Tejedor, A. M. Maitín, A. Pérez-Morales, M. D. del Castillo, and J. P. Romero, "BERT Learns From Electroencephalograms About Parkinson's Disease: Transformer-Based Models for Aid Diagnosis," IEEE Access, 2022. [Online]. Available: https://doi.org/10.1109/ACCESS.2022.3201843

[165] G. Pahuja and B. Prasad, "Deep learning architectures for Parkinson's disease detection by using multi-modal features," Computers in Biology and Medicine, vol. 146, p. 105610, 2022. [Online]. Available: https://doi.org/10.1016/j.compbiomed.2022.105610

[166] F. Chen, C. Yang, and M. Khishe, "Diagnose Parkinson's disease and cleft lip and palate using deep convolutional neural networks evolved by IP-based chimp optimization algorithm," Biomedical Signal Processing and Control, vol. 77, p. 103688, 2022. [Online]. Available: https://doi.org/10.1016/j.bspc.2022.103688

[167] D. Yao, W. Chi, and M. Khishe, "Parkinson's disease and cleft lip and palate of pathological speech diagnosis using deep convolutional neural networks evolved by IPWOA," Applied Acoustics, vol. 199, p. 109003, 2022. [Online]. Available: https://doi.org/10.1016/j.apacoust.2022.109003

[168] A. Rana, A. Dumka, R. Singh, M. Rashid, N. Ahmad, and M. K. Panda, "An Efficient Machine Learning Approach for Diagnosing Parkinson's Disease by Utilizing Voice Features," Electronics, vol. 11, p. 3782, 2022. [Online]. Available: https://doi.org/10.3390/electronics11223782

[169] S. Sangeetha, P. C. D. Kalaivaani, K. Baskar, and T. Kumaravel, "Deep Learning-based Early Parkinson's Disease Detection from Brain MRI Image," in Proceedings of the 7th International Conference on Intelligent Computing and Control Systems (ICICCS), 2023. [Online]. Available: https://doi.org/10.1109/ICICCS56967.2023.10142754

[170] R. Guatelli, V. Aubin, M. Mora, J. Naranjo-Torres, and A. Mora-Olivari, "Detection of Parkinson's disease based on spectrograms of voice recordings and Extreme Learning Machine random weight neural networks," Engineering Applications of Artificial Intelligence, vol. 125, p. 106700, 2023. [Online]. Available: https://doi.org/10.1016/j.engappai.2023.106700

[171] M. Nilashi, R. A. Abumalloh, S. Y. M. Yusuf, H. H. Thi, M. Alsulami, H. Abosaq, S. Alyami, and A. Alghamdi, "Early diagnosis of Parkinson's disease: A combined method using deep learning and neuro-fuzzy techniques," Computational Biology and Chemistry, vol. 102, p. 107788, 2023. [Online]. Available: https://doi.org/10.1016/j.compbiolchem.2022.107788

[172] M. Camacho, M. Wilms, P. Mouches, H. Almgren, R. Souza, R. Camicioli, Z. Ismail, O. Monchi, and N. D. Forkert, "Explainable classification of Parkinson's disease using deep learning trained on a large multi-center database of T1-weighted MRI datasets," NeuroImage: Clinical, vol. 38, p. 103405, 2023. [Online]. Available: https://doi.org/10.1016/j.nicl.2023.103405

[173] S. W. Akram and A. P. S. Kumar, "In-Depth Analysis of Parkinson's Disease: A Comprehensive Approach," in 2023 International Conference on Artificial Intelligence and Smart Communication (AISC), 2023. [Online]. Available: https://doi.org/10.1109/AISC56616.2023.10085219

[174] N. Bhandari, R. Walambe, K. Kotecha, and M. Kaliya, "Integrative gene expression analysis for the diagnosis of Parkinson's disease using machine learning and explainable AI," Computers in Biology and Medicine, vol. 163, p. 107140, 2023. [Online]. Available: https://doi.org/10.1016/j.compbiomed.2023.107140

[175] M. Hireš, P. Drotár, N. D. Pah, Q. C. Ngo, and D. K. Kumar, "On the inter-dataset generalization of machine learning approaches to Parkinson's disease detection from voice," International Journal of Medical Informatics, vol. 179, p. 105237, 2023. [Online]. Available: https://doi.org/10.1016/j.ijmedinf.2023.105237

[176] A. Kumar, V. L. Kouznetsova, S. Kesari, and I. F. Tsigelny, "Parkinson's Disease Diagnosis Using miRNA Biomarkers and Deep Learning," Frontiers in Bioscience (Landmark Edition), vol. 29, no. 1, p. 4, 2024. [Online]. Available: https://doi.org/10.31083/j.fbl2901004

[177] G. S. Krishna, K. Supriya, V. Mishra, and S. Kumar, "Parkinson's Disease Detection from Speech Signals using Explainable Artificial Intelligence," in TENCON 2023 - 2023 IEEE Region 10 Conference, 2023. [Online]. Available: https://doi.org/10.1109/TENCON58879.2023.10322532

[178] B. Majhi, A. Kashyap, S. S. Mohanty, S. Dash, S. Mallik, A. Li, and Z. Zhao, "An improved method for diagnosis of Parkinson's disease using deep learning models enhanced with metaheuristic algorithm," BMC Medical Imaging, 2024. [Online]. Available: https://doi.org/10.1186/s12880-024-01335-z

[179] S. Roy, T. Pal, and S. Debbarma, "A Comparative Analysis of Advanced Machine Learning Algorithms to diagnose Parkinson's Disease," Procedia Computer Science, vol. 235, pp. 122-131, 2024. [Online]. Available: https://doi.org/10.1016/j.procs.2024.04.015

[180] S. Priyadharshini, K. Ramkumar, S. Vairavasundaram, K. Narasimhan, S. Venkatesh, R. Amirtharajan, and K. Kotecha, "A Comprehensive framework for Parkinson's disease diagnosis using explainable artificial intelligence empowered machine learning techniques," Alexandria Engineering Journal, vol. 107, pp. 568-582, 2024. [Online]. Available: https://doi.org/10.1016/j.aej.2024.07.106

[181] M. Yildirim, S. Kiziloluk, S. Aslan, and E. Sert, "A new hybrid approach based on AOA, CNN and feature fusion that can automatically diagnose Parkinson's disease from sound signals: PDD-AOA-CNN," Signal, Image and Video Processing, vol. 18, pp. 1227-1240, 2024. [Online]. Available: https://doi.org/10.1007/s11760-023-02826-2

[182] Z. Habib, M. A. Mughal, M. A. Khan, A. Hamza, N. Alturki, and L. Jamel, "A novel deep dual self-attention and Bi-LSTM fusion framework for Parkinson's disease prediction using freezing of gait biometric application," Multimedia Tools and Applications, 2024. [Online]. Available: https://doi.org/10.1007/s11042-024-18906-5

[183] S. Saleh, A. Ouhmda, B. Cherrad, M. AlSarem, S. Hamda, A. Albl, M. Mahyoob, and O. Bouattane, "A novel hybrid CNN-KNN ensemble voting classifier for Parkinson's disease prediction from hand sketching images," Multimedia Tools and Applications, 2024. [Online]. Available: https://doi.org/10.1007/s11042-024-19314-5

[184] Y. X. Teo, R. E. Lee, S. G. Nurzaman, C. P. Tan, and P. Y. Chan, "Action tremor features discovery for essential tremor and Parkinson's disease with explainable multilayer BiLSTM," Computers in Biology and Medicine, vol. 180, p. 108957, 2024. [Online]. Available: https://doi.org/10.1016/j.compbiomed.2024.108957

[185] N. Islam, M. S. A. Turza, S. I. Fahim, and R. M. Rahman, "Advanced Parkinson's Disease Detection: A comprehensive artificial intelligence approach utilizing clinical assessment and neuroimaging samples," International Journal of Cognitive Computing in Engineering, vol. 5, pp. 199-220, 2024. [Online]. Available: https://doi.org/10.1016/j.ijcce.2024.05.001

[186] I. K. Veetil, D. E. Chowdary, P. N. Chowdary, V. Sowmya, and E. A. Gopalakrishnan, "An analysis of data leakage and generalizability in MRI based classification of Parkinson's Disease using explainable 2D Convolutional Neural Networks," Digital Signal Processing, vol. 147, p. 104407, 2024. [Online]. Available: https://doi.org/10.1016/j.dsp.2024.104407

[187] M. Mahendran and R. Visalakshi, "An ensemble of ResNet model for classification of Parkinson disease," International Journal of Nutrition, Pharmacology, Neurological Diseases, vol. 14, pp. 9-14, 2024. [Online]. Available: https://doi.org/10.4103/ijnpnd.ijnpnd_22_23

[188] A. R. Palakayala and P. Kuppusamy, "AttentionLUNet: A Hybrid Model for Parkinson's Disease Detection Using MRI Brain," IEEE Access, 2024. [Online]. Available: https://doi.org/10.1109/ACCESS.2024.3420125

[189] J. Yang, S. Williams, D. C. Hogg, J. E. Alty, and S. D. Relton, "Deep learning of Parkinson's movement from video, without human-defined measures," Journal of the Neurological Sciences, vol. 463, p. 123089, 2024. [Online]. Available: https://doi.org/10.1016/j.jns.2024.123089

[190] H. Wang et al., "Deep-Learning-Based Cross-Modality Striatum Segmentation for Dopamine Transporter SPECT in Parkinson's Disease," in IEEE Transactions on Radiation and Plasma Medical Sciences, vol. 8, no. 7, pp. 752-761, Sept. 2024, doi: 10.1109/TRPMS.2024.3398360.

[191] A. R. Palakayala and P. Kuppusamy, "Differentiating Parkinson's Disease from other Neuro Diseases and Diagnosis using Deep Learning with Nature Inspired Algorithms and Ensemble Learning," Procedia Computer Science, vol. 235, pp. 588-597, 2024. [Online]. Available: https://doi.org/10.1016/j.procs.2024.04.058

[192] V. Dentamaro, D. Impedovo, L. Musti, G. Pirlo, and P. Taurisano, "Enhancing early Parkinson's disease detection through multimodal deep learning and explainable AI: insights from the PPMI database," Scientific Reports, vol. 14, p. 20941, 2024. [Online]. Available: https://doi.org/10.1038/s41598-024-70165-4

[193] R. M. Al-Tam, F. A. Hashim, S. Maqsood, L. Abualigah, and R. M. Alwhaibi, "Enhancing Parkinson's Disease Diagnosis Through Stacking Ensemble-Based Machine Learning Approach," IEEE Access, vol. 12, pp. 79549-79567, 2024. [Online]. Available: https://doi.org/10.1109/ACCESS.2024.3408680

[194] S. Desai, H. Chhinkaniwala, S. Shah, and P. Gajjar, "Enhancing Parkinson's Disease Diagnosis through Deep Learning-Based Classification of 3D MRI Images," Procedia Computer Science, vol. 235, pp. 201-213, 2024. [Online]. Available: https://doi.org/10.1016/j.procs.2024.04.023

[195] N. S. S. C. Reddy, P. M. D. Venkat, G. Rohith, and S. Murugaveni, "Enhancing Spiral and Wave Drawing Analysis for Disease Diagnosis Using VGG19 with Attention Mechanism," in IEEE RAEEUCCI Conference, 2024. [Online]. Available: https://doi.org/10.1109/RAEEUCCI61380.2024.10547766

[196] M. J. Kmiecik, S. Micheletti, D. Coker, K. Heilbron, J. Shi, K. Stagaman, T. Filshtein Sonmez, P. Fontanillas, S. Shringarpure, M. Wetzel, H. M. Rowbotham, P. Cannon, J. F. Shelton, D. A. Hinds, J. Y. Tung, 23andMe Research Team, M. V. Holmes, S. Aslibekyan, and L. Norcliffe-Kaufmann, "Genetic analysis and natural history of Parkinson's disease due to the LRRK2 G2019S variant," Brain, vol. 147, pp. 1996-2008, 2024. [Online]. Available: https://doi.org/10.1093/brain/awae073

[197] Y. Zhao, Y. Liu, J. Li, X. Wang, R. Yang, C. Lian, P. Shan, Y. Wang, Z. Zhan, and C. Fu, "Global joint information extraction convolution neural network for Parkinson's disease diagnosis," Expert Systems With Applications, vol. p. 122837, 2024. [Online]. Available: https://doi.org/10.1016/j.eswa.2023.122837

[198] D. Deng, J. L. Ostrem, V. Nguyen, D. D. Cummins, J. Sun, A. Pathak, S. Little, and R. Abbasi-Asl, "Interpretable video-based tracking and quantification of parkinsonism clinical motor states," npj Parkinson's Disease, vol. 10, p. 122, 2024. [Online]. Available: https://doi.org/10.1038/s41531-024-00742-x

[199] C. Lv, L. Fan, H. Li, J. Ma, W. Jiang, and X. Ma, "Leveraging multimodal deep learning framework and a comprehensive audio-visual dataset to advance Parkinson's detection," Biomedical Signal Processing and Control, vol. 95, p. 106480, 2024. [Online]. Available: https://doi.org/10.1016/j.bspc.2024.106480

[200] M. G. Di Cesare, D. Perpetuini, D. Cardone, and A. Merla, "Machine Learning-Assisted Speech Analysis for Early Detection of Parkinson's Disease: A Study on Speaker Diarization and Classification Techniques," Sensors, vol.

[201] W. Zhang, H. Dai, D. Xia, Y. Pan, Z. Li, W. Wang, Z. Li, L. Wang, and G. Chen, "mP-Gait: Fine-grained Parkinson's Disease Gait Impairment Assessment with Robust Feature Analysis," Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies, vol. 8, no. 3, p. 142, 2024. [Online]. Available: https://doi.org/10.1145/3678577

[202] J. Huang, L. Lin, F. Yu, X. He, W. Song, J. Lin, Z. Tang, K. Yuan, Y. Li, H. Huang, Z. Pei, W. Xian, and C. Y.-C. Chen, "Parkinson's severity diagnosis explainable model based on 3D multi-head attention residual network," Computers in Biology and Medicine, vol. 170, p. 107959, 2024. [Online]. Available: https://doi.org/10.1016/j.compbiomed.2024.107959

[203] K. Kim, S. Lyu, S. Mantri, and T. W. Dunn, "TULIP: Multi-camera 3D Precision Assessment of Parkinson's Disease," in CVPR, 2024.

[204] H. Ahmadi, L. Huo, G. Arji, A. Sheikhtaheri, and S.-M. Zhou, "Early diagnosis of Parkinson's disease using a hybrid method of least squares support vector regression and fuzzy clustering," Biocybernetics and Biomedical Engineering, vol. 44, pp. 569-585, 2024. [Online]. Available: https://doi.org/10.1016/j.bbe.2024.08.009

[205] K. D. Raj, G. J. Lal, E. A. Gopalakrishnan, V. Sowmya, and J. R. Orozco-Arroyave, "A Visibility Graph Approach for Multi-Stage Classification of Parkinson's Disease Using Multimodal Data," IEEE Access, vol. 12, pp. 87077-87096, 2024. [Online]. Available: https://doi.org/10.1109/ACCESS.2024.3416444

[206] H. T. Reddy, Aryagopal, D. V. S. Jagadeesh, M. Anand, P. B. Pati, and B. K. N. Prakash, "Parkinson's Disease Diagnosis from Patients Speech Analysis," in IEEE 9th International Conference for Convergence in Technology (I2CT), 2024. [Online]. Available: https://doi.org/10.1109/I2CT61223.2024.10543434

[207] Alzheimer's Association, "Alzheimer's & Dementia: The Journal of the Alzheimer's Association," 2023.

[208] G. J. Hankey, "Stroke," The Lancet, vol. 389, no. 10069, pp. 641-654, 2017.

[209] D. S. Reich, C. F. Lucchinetti, and P. A. Calabresi, "Multiple sclerosis," New England Journal of Medicine, vol. no. 2, pp. 169-180, 2018.

[210] A. Compston and A. Coles, "Multiple sclerosis," Lancet, vol. 372, no. 9648, pp. 1502-1517, 2008.

[211] G. E. Thwaites, et al., "Tuberculous meningitis," New England Journal of Medicine, vol. 368, no. 3, pp. 233-242, 2013.

[212] R. S. Fisher, et al., "Epileptic seizures and epilepsy: Definitions proposed by the International League Against Epilepsy (ILAE) and the International Bureau for Epilepsy (IBE)," Epilepsia, vol. 55, no. 4, pp. 475-482, 2014.

[213] J. L. Cummings and D. F. Benson, Dementia: A Clinical Approach, Butterworth-Heinemann, 1992.

[214] D. N. Louis, et al., "WHO Classification of Tumours of the Central Nervous System," Acta Neuropathologica, vol. 131, no. 6, pp. 803-820, 2016.

[215] S. Nakasu, et al., "Malignant transformation of WHO Grade I meningiomas: A case series and literature review," Journal of Neuro-Oncology, vol. 102, no. 1, pp. 189-197, 2011.

[216] S. Melmed, "Pathogenesis of pituitary tumors," Nature Reviews Endocrinology, vol. 7, no. 5, pp. 257-266, 2011.

[217] T. K. Schiefer and M. J. Link, "Schwannomas of the head and neck," Otolaryngologic Clinics of North America, vol. 45, no. 2, pp. 455-473, 2012.

[218] V. Ramaswamy, et al., "Medulloblastoma subgroup-specific outcomes in children: A multicenter study of 260 patients," Journal of Clinical Oncology, vol. 31, no. 22, pp. 2927-2935, 2013.

[219] P. Wesseling and D. Capper, "WHO 2016 Classification of gliomas," Neuropathology and Applied Neurobiology, vol. 44, no. 2, pp. 139-150, 2018.

[220] C. Reitz and R. Mayeux, "Alzheimer disease: Epidemiology, diagnostic criteria, risk factors, and biomarkers," Biochemical Pharmacology, vol. 88, no. 4, pp. 640-651, 2014.

[221] K. Blennow, M. J. de Leon, and H. Zetterberg, "Alzheimer's disease," The Lancet, vol. 368, no. 9533, pp. 387-403, 2006.

[222] R. A. Sperling, et al., "Toward defining the preclinical stages of Alzheimer’s disease: Recommendations from the National Institute on Aging-Alzheimer’s Association workgroups," Alzheimer’s & Dementia, vol. 7, no. 3, pp. 280-292, 2011.

[223] C. M. Tanner and S. M. Goldman, "Epidemiology of Parkinson’s disease," Neurologic Clinics, vol. 14, no. 2, pp. 317-335, 1996.

[224] J. Jankovic, "Parkinson’s disease: Clinical features and diagnosis," Journal of Neurology, Neurosurgery & Psychiatry, vol. 79, no. 4, pp. 368-376, 2008.

[225] V. Viswan, N. Shaffi, M. Mahmud, et al., "Explainable Artificial Intelligence in Alzheimer’s Disease Classification: A Systematic Review," Cognitive Computation, vol. 16, pp. 1–44, 2024. [Online]. Available: https://doi.org/10.1007/s12559-023-10192-x

[226] MiddleBrain, "Parkinson Disease Dataset," Roboflow Universe, 2024. [Online]. Available: https://universe.roboflow.com/middlebrain/parkinson-desease.