Review Article

Caspian Journal of Internal Medicine 2026 (Summer); 17(3): 517-533
DOI: 10.22088/cjim.17.3.517

Innovative approaches: Utilizing artificial intelligence for early diagnosis of main neurodegenerative diseases

Hadi Ebrahimi (MD) [1, 2]
Ebrahim Hejazian (MD) [3*]
Zohre Eftekhari (DVSc) [4]

1. Department of Surgery, School of Medicine, Ayatollah Rouhani Hospital, Babol University of Medical Sciences, Babol, Iran
2. Mobility Impairment Research Center, Health Research Institute, Babol University of Medical Sciences, Babol, Iran
3. Department of Neurosurgery, Neuroendovascular Division, Babol University of Medical Sciences, Mazandaran, Iran
4. Biotechnology Department, Biotechnology Research Center, Pasteur Institute of Iran, Tehran, Iran

*** Correspondence:**
Ebrahim Hejazian, Department of Neurosurgery, Babol University of Medical Sciences, Babol, Iran

E-mail: sehbums@yahoo.com

Received: 27 May 2024
Revised: 5 April 2025
Accepted: 5 May 2025
Published: 1 Sep 2026

Abstract

Background: By incorporating advanced signal processing and artificial intelligence (AI)/machine learning techniques (MLT) in an automated manner, this system can be trained using extensive patient data, physiological signals, and images. Using state-of-the-art AI models and high-quality clinical data has shown promise in improving prognostic and diagnostic models for neurological diseases. However, it is essential to recognize that AI, machine, and deep-learning algorithms are not universally applicable solutions for all clinical data and inquiries.

Methods: This paper offers a comprehensive review of cutting-edge research on the automated diagnosis of major neurological disorders, with a primary focus on the application of AI techniques. An extensive search was conducted in the PubMed and Scopus databases from September 2023 to January 2025; 220 articles were retrieved from the initial search. After eliminating duplicate entries, a total of 105 distinct articles remained. Subsequently, in March 2025, 4 more articles directly pertinent to the topic of interest were identified and included.

Results: AI methodologies, particularly Support Vector Machines (SVM) and XGBoost, have demonstrated considerable potential in improving the efficacy of screening tests. AI methods enhance neurological disease diagnosis by integrating advanced diffusion MRI techniques and next-generation PET tracers. Deep learning models, such as convolutional neural networks, improve diagnostic precision and facilitate early detection of neurodegeneration and inflammation in various disorders.

Conclusions: Artificial intelligence in combination with conventional methods serves as a valuable resource for the early, precise, and non-invasive identification of neurodegenerative disorders. Additionally, it aids in evaluating treatment efficacy and forecasting the progression of these diseases.

Keywords: Artificial intelligence, Neurological disorder, Computer-aided diagnosis, Feature selection.

Citation:
Ebrahimi H, Abbaszadeh S, Hejazian E, Eftekhari Z. Innovative approaches: Utilizing artificial intelligence for early diagnosis of main neurodegenerative diseases. Caspian J Intern Med 2026; 17(3): 517-533.

Over the past three decades, hospitals and health systems have amassed much unstructured data, including medical imaging data, genomic information, and free text and data streams from monitoring devices. In particular, the advent of artificial intelligence has sparked a revolution in the field, enabling rapid and non-invasive screening, treatment, management, and disease prediction. In addition, advances in imaging and image processing technologies have led to increasingly cost-effective and low-risk analysis. Techniques such as Computed Tomography (CT), Positron Emission Tomography (PET), and Magnetic Resonance Imaging (MRI) have revolutionized the study of the brain by enabling doctors to perform noninvasive evaluations of brain structure and determine the underlying factors contributing to abnormal brain function associated with various diseases (1). Various technologies have been created to study brain structure without invasive surgery (2, 3).

Publisher: Babol University of Medical Sciences

Computed tomography (CT) and magnetic resonance imaging (MRI) are two major advancements that have improved the diagnosis and treatment of neurological disorders. CT generates cross-sectional images using computer-modified x-ray measurements, while MRI uses magnetic fields and radio waves to produce detailed biological images. Different pulse sequences in MRI control image acquisition and tissue visualization, including T1 and T2-weighted imagery for anatomy and pathology and Fluid Attenuated Inversion Recovery (FLAIR) (2, 3).

The management of patients with neuro-oncologic disease increasingly relies on advanced imaging techniques. Two such techniques, Diffusion Tensor Imaging (DTI) and Functional Magnetic Resonance Imaging (fMRI), have emerged as valuable tools for mapping the brain in a noninvasive manner. DTI enables the visualization of white matter pathways, allowing for the analysis of abnormal changes that may not be visible on traditional MRI scans. This is achieved by creating a map of the brain's axon network by measuring water molecule diffusivity. On the other hand, fMRI identifies vital brain areas by detecting increased oxygen levels in the blood during specific tasks, providing insights into neural functions. Over the past two decades, there has been a significant rise in fMRI studies that map brain functions during rest or task performance. However, Resting-State Functional Magnetic Resonance Imaging (rs-fMRI) data has garnered considerable attention (2, 4). Hyperspectral Imaging (HSI) is an emerging imaging modality for medical applications, particularly in disease diagnosis and image-guided surgery. It provides diagnostic information about tissue physiology, morphology, and composition. HSI acquires a three-dimensional dataset called a hypercube, consisting of two spatial and one spectral dimension (5). Intra-operative Ultrasound (IUS) has gained significant interest for its ability to provide real-time visualizations. This diagnostic imaging tool utilizes high-frequency sound waves to create images of bodily structures. Using an external probe and ultrasound gel applied directly to the skin, ultrasound images are captured in real time (6).

Methods

Literature search and selection: A thorough investigation of the current literature on recent advancements in therapeutic agents for neurological diseases was undertaken. The criteria for inclusion were articles written in English, available in full-text, comprehensive, and directly pertinent to the subject matter under investigation. An extensive search was conducted in the PubMed and Scopus databases from September 2023 to January 2025, utilizing keywords associated with Neurological disorders, Artificial Intelligence (AI), Deep and machine learning algorithms, Machine learning, computer-aided design or CAD, conventional neural networks or CNNs, recurrent neural networks RNN, Computed tomography (CT), Computer-modified x-ray, Magnetic resonance imaging (MRI), intraoperative ultrasound, Alzheimer's disease or AD, Parkinson's disease or PD, Dementia, Stroke, Brain tumors, Epilepsy, and Multiple sclerosis or MS. Based on their titles, abstracts, and publication dates, 220 articles were retrieved from the initial search. After eliminating duplicate entries, a total of 105 distinct articles remained. Subsequently, in March 2025, 4 more articles that were directly pertinent to the topic of interest were identified and included. To enhance the clarity and coherence of our arguments, a total of nine more references were integrated throughout the writing process (figure 1).

Main neurological disorders and diagnostic approaches: Neurological disorders cover a broad spectrum of illnesses affecting both the peripheral and central nervous systems. These disorders present in various ways, including muscle weakness, paralysis, seizures, pain, coordination issues, and loss of consciousness. The nervous system can be impacted by over 600 different diseases, such as brain tumors, Parkinson's disease, Alzheimer's disease, multiple sclerosis, epilepsy, dementia, stroke, and brain injuries (7).

Neurological disorders have a significant global impact, affecting millions of people worldwide. Stroke alone claims the lives of over 6 million individuals annually, mainly in low- and middle-income countries. It is estimated that around 50 million people will have epilepsy, and 47.5 million will experience dementia. Detecting abnormal neurological conditions typically requires a neuropathological examination. However, it is important to recognize that atypical neurological conditions may be present in the general population without necessarily indicating a neurological disorder (figure 2) (8, 9). Diagnosing neurological disorders requires a comprehensive approach encompassing anatomical, etiological, and clinical factors. The subsequent sections delineate the critical elements necessary for effective diagnosis:

Anatomical considerations: Determining the locations of lesions within the central nervous, peripheral, or muscular systems is crucial, as specific regions are associated with particular symptoms. Advanced imaging modalities, including MRI and EEG, are utilized to detect irregularities in brain function, facilitating the diagnosis of disorders such as epilepsy and dementia (10).

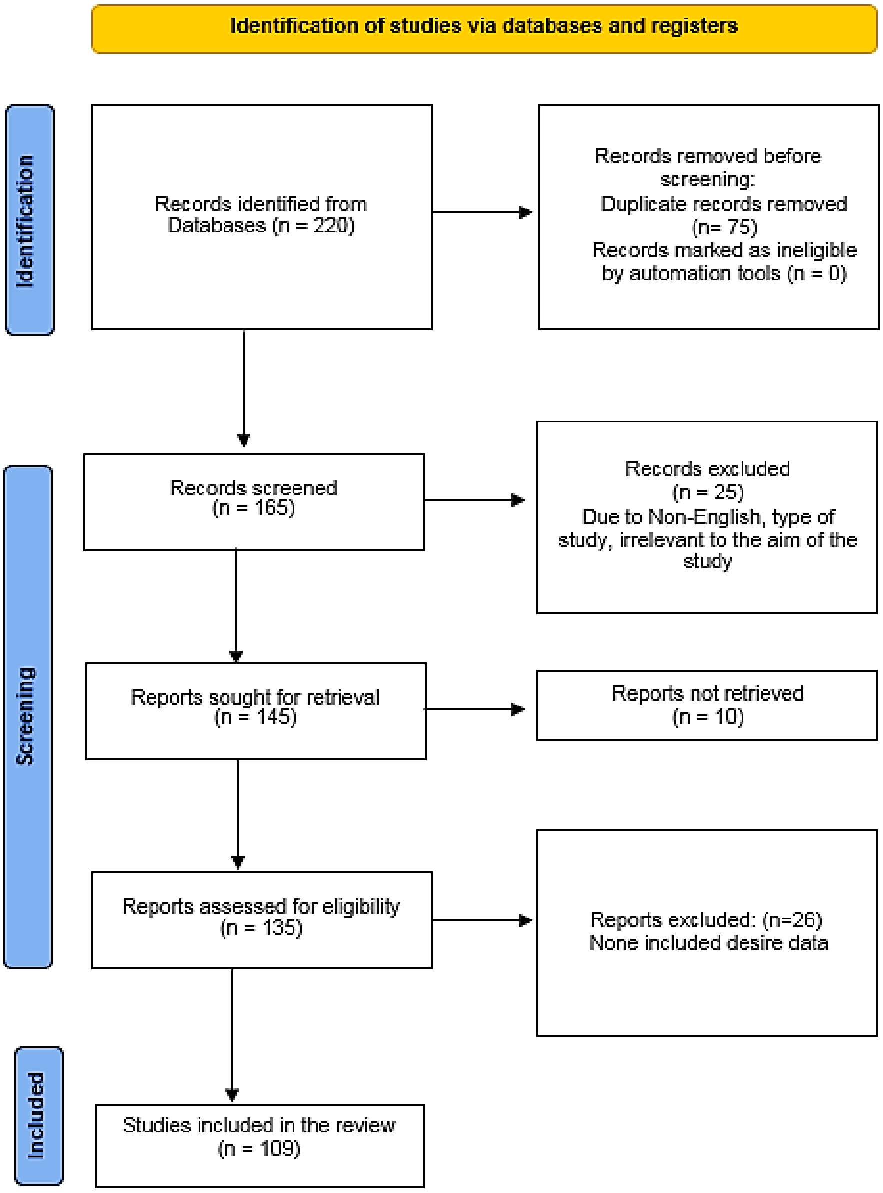

Figure 1. Flow diagram of the steps for including studies in the review study

Clinical assessment: A comprehensive neurological evaluation and detailed patient history are imperative for identifying symptoms that may suggest underlying neurological issues. Additionally, evaluating mental health symptoms is vital, as neurological disorders can present with psychiatric manifestations, thereby requiring collaboration between neurologists and psychiatrists (11).

Technological integration: Applying deep learning and machine learning methodologies enhances diagnostic precision by examining intricate data patterns, thereby facilitating the early identification of conditions such as Alzheimer's and Parkinson's. Furthermore, innovative techniques like discrete wavelet transform have demonstrated potential in classifying neurodegenerative diseases through analyzing gait dynamics and EEG signals (12). Machine learning and neuroimaging are increasingly recognized as essential components in contemporary neurological diagnostics. Artificial intelligence algorithms possess the capability to evaluate a diverse array of data types, which include (13):

- MRI and CT brain scans
- Electroencephalogram (EEG) findings
- Genetic information
- Patient medical histories

The application of AI in data analysis facilitates the identification of subtle alterations in both brain structure and function that may signify the advancement of neurological disorders. Current AI technologies employ advanced algorithms to process and interpret medical data effectively. Among the most promising methodologies are (14):

- Neural networks designed for the analysis of medical imaging
- Systems aimed at predicting disease outcomes
- Platforms dedicated to the analysis of genetic information
- Tools focused on the assessment of cognitive abilities

Genera aspects of artificial intelligence in neurological diagnostics: The inception of AI can be traced back to the 1950s when the perceptron model was introduced. However, it was not until the 1990s that machine-learning techniques became more widely employed (15, 16). Recent technological advancements have bridged the gap between humans and machines, enabling computers to imitate and even surpass natural human intelligence, giving rise to what is known as "artificial intelligence" (AI). AI has the potential to assist surgeons in diagnosing conditions, selecting treatments, and aiding patients in making informed decisions during the pre-operative phase of neurosurgery. In the intra-operative phase, AI can enhance surgeons' performance and reduce errors. In the postoperative care stage, AI can predict prognosis, identify complications, and track data for improved aftercare. By improving predictions in the postoperative phase, pre-operative planning can be optimized to enhance patient care and reduce costs (17, 18).

One instance of machine learning-based computer-aided design (CAD) in neurology involves utilizing deep learning algorithms to analyze MRI or CT scans to detect and categorize brain tumors, aneurysms, and other abnormalities (19). These algorithms can assist neurosurgeons in making more precise and efficient diagnoses, ultimately improving patient treatment outcomes. The advent of machine-learning tools, such as support vector machines and recurrent neural networks, provided scientists with the means to harness the computational power of the era and construct statistical models that were resilient to data variations. These tools also enabled researchers to draw new inferences about real-world problems. Nevertheless, the most significant strides in AI have arguably occurred in the past decade. This can be attributed to the availability of massive-scale data and hardware capable of processing such data, as well as the feasibility of sophisticated deep-learning methods that aim to replicate the data processing capabilities of the human brain (20, 21). Artificial intelligence (AI) can transform the field of neurological diagnostic foresight through the utilization of advanced algorithms and machine learning techniques to examine intricate neurological data. By identifying patterns and anomalies in brain imaging, genetic markers, and patient symptoms, AI can contribute to the early detection and prediction of neurological disorders (20, 22). Moreover, AI can play a crucial role in interpreting medical imaging, such as MRI and CT scans, enabling the identification of abnormalities and potential indicators of neurological conditions. By analyzing extensive patient data, AI can assist in recognizing risk factors and predicting the probability of developing neurological disorders (20, 23, 24).

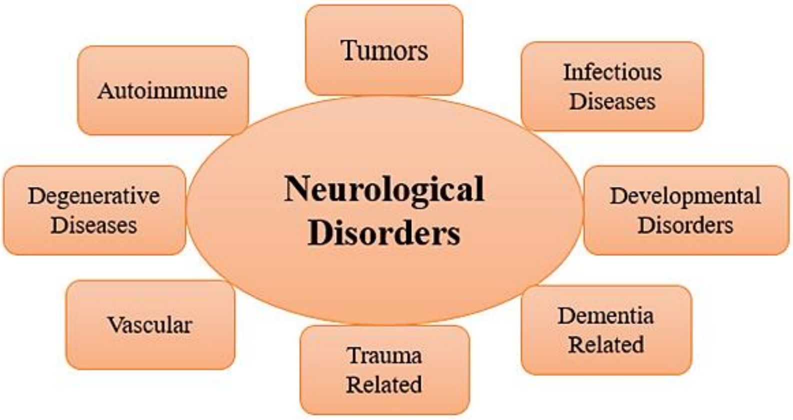

Figure 2. Summary of the most important neurological diseases and disorders

Deep learning is widely acknowledged as the foundation of modern AI. AI has shown significant success in tasks like image classification and prediction in the medical field. For instance, it has been used to detect lung cancer and stroke through computed tomography scans, assess the risk of sudden cardiac death and other heart diseases through electrocardiograms and cardiac MRI, and classify abnormal skin lesions based on dermatological examinations. There have also been early examples of AI proving its worth in neurology, such as identifying structural brain lesions through MRI. A key challenge in clinical AI research is the availability of data with high-quality clinical outcome labels, rather than the lack of robust AI algorithms and computational resources. AI and deep learning offer a framework that can potentially address various disease-related questions by utilizing complex and comprehensive model architectures, provided there is a sufficient quantity and quality of training data (figure 3) (25, 26).

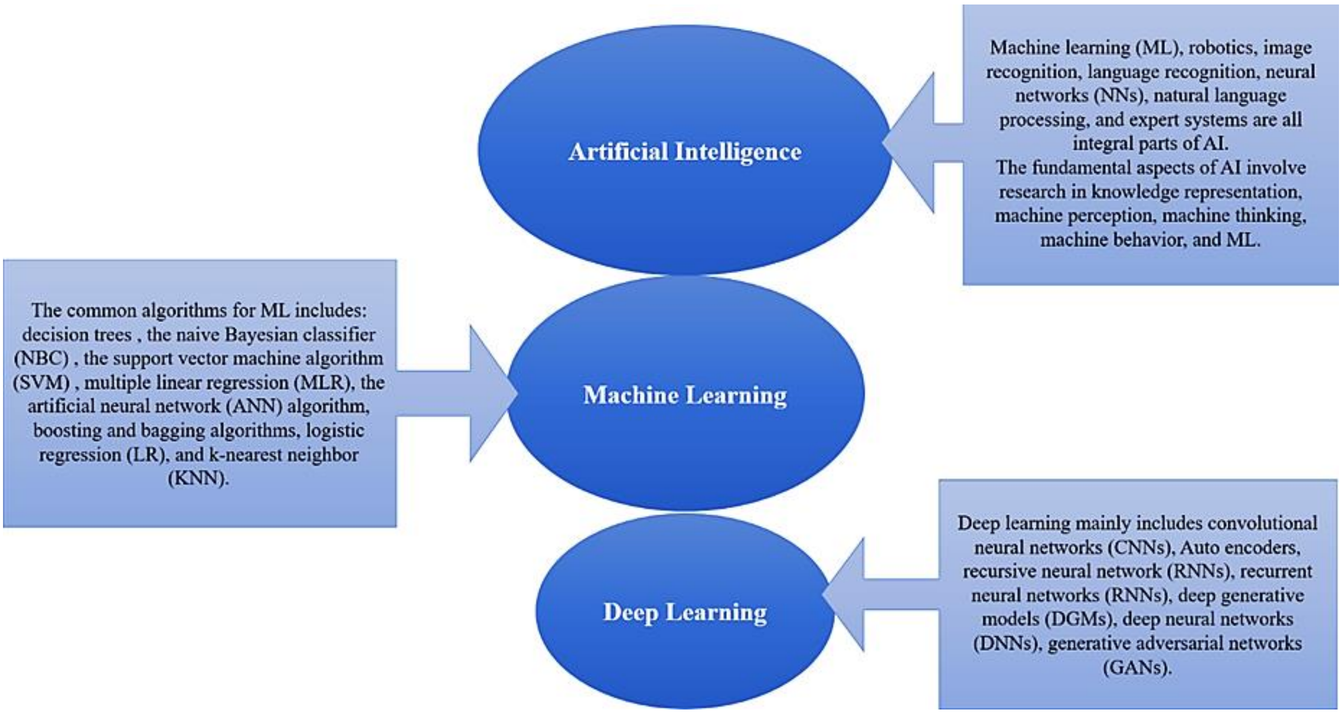

Figure 3. Summary of the field and relationship of AI, ML and DL (20, 21, 109)

The potential impact of AI, machine learning (ML), and deep learning (DL) on the field of neurosurgery cannot be overstated. AI aims to replicate human intelligence in computer systems. At the same time, ML, a subset of AI, combines computer science and statistics to enable computers to learn patterns from data through experience without needing external programming. Just as our brain evolves as we mature, ML also evolves as it learns. Essentially, ML functions like medical students and resident doctors, assimilating rules from data and applying them to diverse patients, albeit on a much larger scale with vast amounts of data. In the realm of medical sciences, ML primarily employs supervised learning through training algorithms such as logistic regression, support vector machines, and random forests (27).

The fusion of high-resolution radiological imaging and electrophysiological data, widely accessible, has become the favored method, granting neurosurgeons unparalleled, non-invasive entry into the intracranial domain. Neurosurgeons typically draw upon clinical expertise and evidence from patient cases to guide their decisions and offer prognoses (28). The implementation of computer-assisted diagnosis (CAD) and AI can serve as a viable solution to certain challenges faced in the field of neurosurgical care. AI and CAD can greatly aid neuroradiologists and neurosurgeons in rendering effective and efficient diagnoses by harnessing a wealth of anatomical, morphological, and connectivity data. Consequently, this technology expedites the triage process, facilitating prompt treatment initiation while minimizing human labor and financial burdens. Numerous research studies have corroborated the pivotal role of door-to-needle times in reducing mortality rates and enhancing prognosis (29). Delays in delivering emergency care for conditions like stroke arise primarily due to the acquisition and interpretation of radiological images, as well as limited access to neurologists. Leveraging AI can expedite the acquisition and interpretation of brain imaging, thereby assisting clinicians in enhancing the precision of their diagnostic capabilities. Moreover, AI can autonomously engage in the automatic classification of epilepsy type, exhibiting an accuracy of 60% as compared to clinician accuracy of 62%. Furthermore, AI demonstrates an accuracy of 86% in predicting tumor type and glioma, 56% in diagnosing acute ischemic events, and over 90% in identifying cerebral aneurysms (30, 31).

AI algorithms have been employed in pre-operative planning to carry out tasks such as automatic tumor segmentation, localization of the epileptogenic zone, identification of suitable candidates for epileptic surgery, prediction of symptomatic cerebral vasospasm after aneurysmal subarachnoid hemorrhage, and anticipation of tissue damage ensuing acute ischemic stroke. One example of the utility of these algorithms lies in the classification of epilepsy and tumors, which can be prone to subjectivity, thereby resulting in divergent decision-making among neurosurgeons. Implementing robust frameworks and outlines through AI algorithms can mitigate the subjective interpretation of data, thus leading to the identification of conditions necessitating neurosurgical interventions (32, 33). ML is crucial in classification tasks, such as categorizing lumbar disk degeneration based on MRI scans and clustering patients with osteoporotic vertebral fractures according to their pain progression. ML has demonstrated 72% accuracy in diagnosing pediatric posterior fossa tumors in classifying them into different types, surpassing neuroradiologists in certain scenarios. Furthermore, ML has proven effective in classifying intra-axial cerebral tumors and sellar-suprasellar masses, improving the diagnostic accuracy of radiologists (34, 35).

AI has already showcased its capabilities in multiple domains of neurosurgery, including surgical preparation, guidance, and image interpretation. The forthcoming years are filled with excitement as AI's role in neuroscience continues to grow, potentially leading to a transformative change in the field. Initially employed as a precise instrument for personalized healthcare, AI has the potential to assist neurosurgeons in developing customized treatment strategies (36). Through meticulous analysis of extensive patient data, medical records, imaging, and genomics, machine learning can identify patterns that predict individual patient treatment responses. Additionally, AI plays a crucial role in surgical planning and navigation by carefully processing patient imaging to offer precise surgical guidance and real-time feedback during procedures, ultimately reducing errors. Moreover, AI enhances the efficiency and accuracy of large-scale data processing, leading to improved diagnoses and the discovery of innovative therapies. Lastly, AI revolutionizes medical education by providing new opportunities for accessing data repositories, such as operative videos, to personalize learning and enhance patient education (37, 38)

Dementia conventional and modern AI detection methods: Dementia is a progressive condition that affects various cognitive functions, including memory, orientation, thinking, calculation, language, comprehension, judgment, and learning capacity (39). Multi-modal approaches incorporating audio data have demonstrated potential in forecasting the onset of dementia. A model based on automatic speech recognition (ASR), utilizing the Whisper framework alongside RoBERTa regression, is capable of deriving Mini-Mental State Examination (MMSE) scores from audio recordings of patients, resulting in a root mean square error (RMSE) that is lower than the established baseline (40, 41).

Integrating audio spectrograms with sophisticated language models, including Whisper and transformer-based feature extraction techniques, has yielded an F1 Score of 86.42%, significantly surpassing the performance of single-modality methods. Furthermore, prosody-driven techniques emphasize anonymizing speaker embeddings while preserving their diagnostic relevance, achieving a commendable F1 Score of 74% in dementia detection (42, 43). The utilization of AI techniques enhances the effectiveness of dementia screening tests. This is primarily because more features can be extracted from a single test, thereby reducing errors caused by subjective judgments. Additionally, AI elevates the level of automation in dementia screening. When compared to traditional cognitive tests, AI-based computerized cognitive tests demonstrate an approximately 4% improvement in discrimination sensitivity and a 3% improvement in specificity. Regarding speech, conversation, and language tests, the combination of acoustic and linguistic features yields the most favorable outcome, with an accuracy of approximately 94%. Furthermore, applying deep learning techniques in brain scan analysis achieves an accuracy of around 92% (44).

Some studies employed conventional neural networks (CNNs), reaching the highest and lowest accuracy, but others used ANN and RNN. Some research compared multiple DL models, with accuracy ranging from 59.8% to 98.86%. A model using SVM and a second using a combination of MobileNet and Block 11 addition and SVM were noted. Previous research revealed a gradient-boosting model (GBM) and a Residual Neural Network (ResNet-50), respectively, with 91.3% and 98.99% accuracy. Additionally, to predict dementia types in advance, ANN, MRI data, and labeling segments have been most frequently used. An SVM model was the most incorporated algorithm in detecting MCI. Advanced ML models such as ANN can have the ability to detect MCI. Most studies utilized AI in conjunction with magnetic resonance imaging (MRI) to diagnose Dementia. Some studies used positron emission tomography (PET) and MRI. The remaining research used EEG and cognitive data to diagnose dementia with AI models. According to a previously published systematic review, support vector machines (SVM) and XGBoost represent prominent methodologies within the domain of early dementia detection, each exhibiting distinct advantages and disadvantages regarding sensitivity and specificity. SVM demonstrates a particular proficiency in handling imbalanced datasets, frequently attaining sensitivity and specificity rates that surpass 90% across various studies, thus aiding in identifying subtle symptoms during the preliminary stages of dementia. However, it encounters challenges related to scalability and necessitates substantial computational resources. In contrast, XGBoost is esteemed for its flexibility and rapid processing abilities, effectively managing various input features, with sensitivity levels generally falling between 80% and 85%. While both models demonstrate efficacy, SVM is recognized for its enhanced specificity, which is essential for ensuring diagnostic accuracy. Conversely, XGBoost offers advantages in sensitivity but necessitates extensive tuning to attain optimal performance (45).

Epilepsy incidence and AI detection approaches: Epilepsy, a chronic neurological disorder, is defined as a condition in which the brain has a persistent tendency to generate epileptic seizures. The diagnosis of epilepsy requires the occurrence of at least one epileptic seizure. Epilepsy can affect individuals of all ages and both genders. To diagnose epileptic seizures, it is necessary to differentiate between provoked and chronic seizures. The overall incidence of epilepsy ranges from 23 to 190 per 100,000 of the population. The prevalence of epilepsy is lower at early ages and gradually increases with aging. In the field of epilepsy research, wavelet transform (WT) has been widely used for electroencephalogram (EEG) analysis, seizure detection, and epilepsy diagnosis (46, 47)

Machine learning and artificial intelligence (ML/AI) tools have been developed to assist clinicians in almost all clinical decision-making processes, including predicting future epilepsy in high-risk individuals, detecting and monitoring seizures, differentiating epilepsy from similar conditions, utilizing data to improve neuroanatomical localization and lateralization, as well as monitoring and predicting response to medical and surgical interventions. Additionally, we examine pragmatic, ethical, and fairness considerations in creating and utilizing ML/AI tools, including chatbots founded on Large Language Models (48). Next, deep learning applications in neuroimaging for epilepsy can be utilized for diagnosis, lateralization, automated lesion detection, presurgical evaluation, and predicting postsurgical outcomes. The application of deep learning in neuroimaging research focused on individuals with epilepsy facilitates the detection of irregular patterns within intricate datasets (49, 50). Automatic seizure detection has been explored using EEG data through the application of supervised machine learning techniques, including k-nearest neighbors (k-NN), support vector machines (SVM), and advanced deep learning methods. Both scalp EEG and invasive EEG recordings have been utilized in this context. These approaches aim to analyze the spatio-temporal characteristics of EEG signals to differentiate between ictal and interictal states (51).

Random Forest, a technique within ensemble learning, has been utilized for the detection of seizures. By integrating numerous decision trees, Random Forest is adept at managing intricate and noisy electroencephalogram (EEG) data. Research conducted by Dhondiyal & Dimri, 2024 enhanced the Random Forest algorithm through the application of the Discrete Wavelet Transform (DWT) for feature extraction, resulting in a seizure detection accuracy of 98%. This methodology not only enhanced the performance of classification but also yielded interpretable outcomes, positioning it as a valuable resource for clinical use (52). Extensive research has been undertaken in the field of automated diagnosis of epileptic seizures utilizing machine learning (ML) and deep learning (DL) algorithms; however, there remains a scarcity of functional hardware and software solutions capable of real-time recognition. For instance, a novel approach employing an ensemble of pyramidal one-dimensional convolutional neural networks (P-1D-CNN) for seizure classification achieved an impressive overall accuracy of 99.1% on the Bonn dataset.

Additionally, a recurrent neural network (RNN) was applied to the same dataset, yielding an accuracy of 99% in distinguishing between epileptic and non-epileptic cases (29). Furthermore, the application of long short-term memory (LSTM) networks for seizure detection has been documented using the dataset from the American Epilepsy Society Seizure Prediction Challenge. Notably, a study utilizing a two-dimensional time-frequency representation of EEG signals in conjunction with convolutional neural networks (CNN) has also been reported, focusing on classifying preictal and interictal segments across three publicly accessible datasets (53). Researches proposed a model that leverages convolutional neural networks (CNN), recurrent neural networks (RNN), and deep convolutional autoencoders to extract spatial and temporal features from raw EEG data (54). Therefore, the conventional techniques, including k-nearest neighbors (k-NN), support vector machines (SVM), and random forests (RF), have established a groundwork for the emergence of more sophisticated deep learning strategies, such as convolutional neural networks (CNNs), long short-term memory networks (LSTMs), and autoencoders. The development of hybrid and multimodal models has further improved performance by incorporating diverse data sources. Nevertheless, obstacles such as data variability, computational demands, and the integration into clinical settings persist. Future investigations should prioritize the creation of robust, interpretable, and real-time systems that can be effectively incorporated into clinical workflows, ultimately enhancing the quality of life for individuals affected by epilepsy.

Alzheimer AI methods for detection: Alzheimer's disease (AD) is the most common cause of dementia, accounting for three-quarters of cases, and is characterized by the presence of neurofibrillary tangles and cortical amyloids (55-57). Artificial intelligence models, especially Convolutional Neural Networks (CNNs), are widely employed in the analysis of MRI and PET imaging for the detection of AD. These models effectively identify distinguishing features within the images, enabling the classification of patients into Alzheimer's and non-Alzheimer's categories with considerable precision (58, 59). The integration of transfer learning with machine learning classifiers, including Support Vector Machines (SVM) and XGBoost, has demonstrated encouraging outcomes. These hybrid models leverage DenseNet architectures for feature extraction, resulting in enhanced specificity and accuracy in the identification of AD (60, 61).

Deep learning techniques such as CNN, LSTM, VGG-TSwinformer, and Graph neural networks show promising outcomes in effectively differentiating brain scans that indicate Alzheimer's disease compared to normal aging. These methods also exhibit the potential to differentiate specific types of dementia. Instead of relying solely on clinicians' subjective judgment, deep learning approaches possess substantial potential in offering automated and objective measurements, thereby reducing the variability among subjects (62, 63). Three-dimensional convolutional neural networks (3D CNNs) have demonstrated significant potential in the analysis of MRI data for the diagnosis of Alzheimer's disease. Research utilizing a 3D CNN architecture derived from ResNet3D-18 attained an accuracy rate of 95% in categorizing the stages of AD progression, which is comparable to the diagnostic performance of neurologists (64).

Transfer learning has been employed to enhance model performance by utilizing pre-trained networks on large datasets. For instance, ResNet-50, a pre-trained CNN, was fine-tuned to classify AD stages with an accuracy of 95.63%. Additionally, multimodal fusion of MRI, PET, and clinical data has been explored to improve diagnostic accuracy (65). RNNs have been used to analyze cerebrospinal fluid (CSF) biomarkers such as amyloid-beta (Aβ42), total tau (t-tau), and phosphorylated tau (p-tau181). The AlzNet model, which combines CNNs and RNNs, demonstrated high accuracy (92.5%) in differentiating AD, mild cognitive impairment (MCI), and healthy controls (66). ML, for instance, Boltzmann machine, SVM, logistic regression, decision tree, and ANN, are used for AD diagnosis (67, 68). Furthermore, Ho et al. explored the application of noninvasive near-infrared spectroscopy for diagnosing AD, achieving a peak accuracy of 90.91% with a CNN-LSTM deep learning model. These approaches facilitate the diagnosis of AD in a noninvasive and portable manner, thereby aiding in the formulation of personalized treatment strategies and monitoring disease advancement (69). Artificial intelligence has transformed the diagnosis and monitoring of Alzheimer's disease through the application of deep learning, ensemble techniques, and the integration of multimodal data such as MRI, PET, and clinical data with multi-fusion joint learning. These methodologies have demonstrated significant accuracy and have offered interpretable insights, rendering them essential resources for healthcare professionals.

Parkinson's disease prevalence and AI diagnostic approaches: Parkinson's disease (PD) is a highly prevalent neurodegenerative condition that affects a significant portion of the elderly population aged 60 years and above, with a prevalence rate of 1%. It impacts approximately 1-2 individuals per 1,000. In developed nations, the approximate occurrence of PD is 0.3% within the overall population, 1.0% in individuals aged 60 years and above, and 3.0% in individuals aged 80 years and above. The estimated rate at which PD develops is said to vary between 8 and 18 cases per 100,000 individuals per year. The global incidence of PD has witnessed a substantial increase, more than doubling from 1990 to 2016, reaching 6.1 million individuals and 1.02 million in 2017 (70). This escalation can be attributed to the growing number of elderly individuals and the age-standardized prevalence rate. PD is a gradually progressive neurological disorder that manifests motor and non-motor symptoms, encompassing various facets of movement, including planning, initiation, and execution (70, 71). Previous studies present a proposed methodology that utilizes Convolutional Neural Networks (CNN) to classify Magnetic Resonance Imaging (MRI) and Single-Photon Emission Computed Tomography (SPECT) images obtained from subjects diagnosed with Parkinson's disease (PD), Subjects without Evidence of Dopaminergic Deficit (SWEDD), and control subjects. The objective of this approach is to accurately identify regions of interest that are closely associated with PD (72-74). To improve the imaging diagnosis of PD, a model is proposed for early detection using image processing and artificial neural networks (ANN). The effectiveness of manually crafted machine learning models for PD diagnosis depends on factors like database size, number of classes, measurement uncertainties, and features. The methodology used is also crucial, with simpler binary procedures than multiclass ones. Deep networks can extract multiple levels of features, with higher-level features capturing data semantics and ensuring robustness. Features from initial layers are generalizable and transferable across tasks, enabling networks trained on specific data to be used in different domains (75).

Recently, a variety of machine learning methodologies, including Random Forest, K-Nearest Neighbors, and Naive Bayes, have been utilized to identify PD through MRI data. These algorithms, when coupled with XAI strategies such as LIME, enhance the interpretability and reliability of the predictions, thereby assisting clinicians in comprehending the rationale behind the decision-making processes (76). A comparative evaluation of machine learning techniques, including AdaBoostClassifier and GradientBoostingClassifier, underscores the superiority of the KNeighborClassifier, which achieves an impressive accuracy rate of 95% in diagnosing PD based on biomedical characteristics (77, 78). Explainable AI Techniques Models grounded in explainable AI, such as Gradient Boosting Trees (GBT), are advocated for the analysis of speech data in the context of PD detection. These models possess the capability to archive data within Apache Cassandra databases, facilitating a longitudinal analysis of evolving patterns (79). Deep learning methodologies employing a modified Attention ResNet18 architecture along with Mel-Spectrogram features have exhibited remarkable accuracy (97.8%) in categorizing PD from vocal signals. Approaches such as Grad-CAM and LIME offer justifications for the model's predictions, thereby enhancing the transparency of the model (80). Speech Signal Analysis AI-based systems prioritize the analysis of speech signals as a non-invasive strategy for the early detection of PD. These systems necessitate a minimum sample size to ensure reliable assessment and utilize metrics like weighted precision and recall to mitigate class imbalances commonly found in PD datasets (79).

The research utilizes an adapted Attention ResNet18 framework integrated with Squeeze-and-Excitation modules, focusing on the analysis of Mel-Spectrogram features derived from auditory signals. The model achieved a remarkable classification accuracy of 97.8%, underscoring its efficacy in the non-invasive detection of PD. Furthermore, methodologies such as Grad-CAM, Integrated Gradients, and LIME were implemented to elucidate the model's predictions, thereby augmenting the interpretability of the artificial intelligence system in the diagnosis of Parkinson's disease (79). While the application of AI in the detection of Parkinson's disease presents promising progressions in early diagnosis, obstacles persist in guaranteeing the generalizability and robustness of the models across varied patient populations. The integration of XAI techniques is vital for alleviating the "black box" characteristics of AI models, thereby promoting higher acceptance and trust within clinical environments. Ongoing research and development in this domain are imperative to refine these technologies and enhance patient outcomes.

Multiple sclerosis prevalence, conventional and novel detection methods: Multiple sclerosis (MS) typically presents in young adults aged 20 to 30, with symptoms such as unilateral optic neuritis, partial myelitis, sensory disturbances, or brainstem syndromes like internuclear ophthalmoplegia. These symptoms develop gradually over several days. The prevalence of MS worldwide ranges from 5 to 300 per 100,000 individuals and tends to be higher in regions located at higher latitudes. Compared to the general population, individuals with MS have a lower overall life expectancy, and the condition affects women more frequently (3:1 ratio) (81, 82).

The diagnosis of MS relies on a combination of clinical signs and symptoms, radiographic findings (such as magnetic resonance imaging), and laboratory results (such as the presence of cerebrospinal fluid-specific oligoclonal bands). Magnetic resonance imaging (MRI) is increasingly used to aid in diagnosing MS and identify any atypical characteristics that may suggest an alternative diagnosis. Both brain and spinal cord MRIs are used to determine the presence of dissemination in space (DIS) and to identify signs of dissemination in time (DIT) in patients with a typical Clinically Isolated Syndrome (CIS) (81). IS can be recognized by the existence of one or more MRI T2-hyperintense lesions that display the characteristic features of MS in two or more of the four regions of the Central Nervous System (CNS): periventricular, cortical or juxtacortical, infratentorial, and the spinal cord. DIT can be evidenced by the simultaneous presence of gadolinium-enhancing and non-enhancing lesions at any given time, the detection of a new T2 lesion, or the occurrence of a gadolinium-enhancing lesion in a follow-up MRI. The examination of cerebrospinal fluid (CSF) remains a valuable diagnostic tool, especially in situations where clinical and MRI evidence is insufficient to confirm the diagnosis of multiple sclerosis (MS) (81). Previously, visually evoked potentials (VEPs) were utilized as part of the diagnostic criteria for multiple sclerosis (MS). An abnormal VEP, characterized by a delayed response but a well-preserved waveform, was considered objective evidence of a second lesion if the clinical presentation did not involve the visual pathway. However, the 2017 criteria now recommend further studies to determine the role of VEPs and optical coherence tomography (OCT) in supporting the diagnosis of MS, resulting in excluding VEPs from the criteria. Nevertheless, in clinical practice, VEPs can still provide valuable insights, especially in cases where a patient presents with progressive spinal cord syndrome and a normal brain MRI (83-85).

Empirical research has indicated that deep learning classifiers, particularly Convolutional Neural Networks (CNNs), attain remarkable accuracy rates, reaching as high as 99.5% in the identification of multiple sclerosis lesions within MRI scans. The advent of the Gelu Error Activation Function (GERF) has resulted in an enhancement of prediction accuracy to 94.46%, thereby underscoring the potential of novel algorithms in augmenting artificial intelligence performance(86,87). The research utilizes an adapted Attention ResNet18 framework integrated with Squeeze-and-Excitation modules, focusing on the analysis of Mel-Spectrogram features derived from auditory signals. The model achieved a remarkable classification accuracy of 97.8%, underscoring its efficacy in the non-invasive detection of PD. Furthermore, methodologies such as Grad-CAM, Integrated Gradients, and LIME were implemented to elucidate the model's predictions, thereby augmenting the interpretability of the artificial intelligence system in the diagnosis of Parkinson's disease (87). An adapted fuzzy inference system that leverages visually evoked potentials (VEP) has accomplished an accuracy of 90% in differentiating multiple sclerosis patients from healthy controls, thereby illustrating the adaptability of artificial intelligence applications across various diagnostic frameworks (88). In the other research, an artificial intelligence-driven model for the detection of Multiple Sclerosis, attaining an accuracy of 97.97% through the k-nearest neighbors' algorithm and 92.94% with the Random Forest method when applied to FLAIR images introduced. This model employs sophisticated techniques for feature extraction and selection from MRI scans, enhancing the precision of the diagnostic process (89).

Studies reported that MRI was utilized in 20 studies, while OCT was used in six studies. Additionally, serum and cerebrospinal fluid markers were examined in six studies, and movement function was assessed in three studies. Furthermore, other modalities, such as breathing and evoked potential, were employed to detect MS through the use of AI. Consequently, the diagnosis of MS based on novel markers and AI has emerged as a burgeoning area of research. MRI images are the primary focus, followed by images obtained from OCT, serum and CSF biomarkers, and markers associated with motor function. These findings demonstrate that AI advancements can significantly transform how we monitor and diagnose our patients with MS (90).

Brain tumors diagnostic methods by utilizing AI and conventional approaches: Brain tumors can have their origin not only in the brain but also in other parts of the body, eventually spreading to the brain. The impact on the nervous system depends on the tumor's growth rate and location. When it comes to treating brain tumors, it is crucial to consider three key factors: the type, size, and location of the tumor. Magnetic resonance imaging (MRI) is vital in diagnosing and segmenting brain tumors, as it offers valuable information about the anatomical structures and any abnormal tissue (33).

This information is highly beneficial for treatment planning and follow-up procedures. Due to the intricate nature of brain tissue, the manual diagnosis of brain and tumor tissues is an extremely time-consuming process that heavily relies on the expertise of the operator. Moreover, the absence of skilled professionals to examine the images hinders the effectiveness of traditional methods in diagnosing this critical condition (91, 92). Hence, using automated methods can greatly assist in meticulously examining tumors. Generally, the analysis of brain tumors is conducted through MRI imaging, which is widely used in imaging clinics due to its ability to provide a diverse range of sequences, including T1, T2, T1C, diffusion-weighted imaging (DWI), and Flair. These sequences have proven effective in detecting various abnormalities in the human brain (93, 94). Convolutional Neural Networks (CNNs) have become fundamental in the detection of brain tumors, primarily due to their capacity to autonomously extract layered features from medical imaging data. Numerous studies have validated the efficacy of CNNs in recognizing brain tumors, with architectures such as ResNet50, DenseNet, and EfficientNet achieving notable accuracy levels (95, 96). DenseNet169 model has demonstrated outstanding performance, with metrics such as accuracy, precision, recall, and F1-score all surpassing 0.9983 when evaluated on the Bangladesh Brain Cancer MRI Dataset (95). EfficientNetB4 model has shown remarkable outcomes, attaining 100% accuracy for cases without tumors, 100% for meningiomas, 99.8% for pituitary tumors, and 98.7% for gliomas (95). Autoencoders and Generative Adversarial Networks (GANs) have been utilized to mitigate data limitations and enhance the generalizability of models. Techniques based on GANs facilitate the generation of synthetic MRI images, thereby increasing dataset diversity and bolstering model resilience. For example, noise-to-image and image-to-image GANs have been employed to augment MRI datasets, leading to improved performance in tumor detection tasks (97). Recently, Vision Transformers have been incorporated into frameworks for brain tumor detection, providing additional features that complement CNNs. Hybrid models combining CNNs and ViTs have achieved impressive metrics, including precision, recall, and overall accuracy of 98% in tasks related to brain tumor detection (98).

The rise of Explainable AI techniques in medical imaging has been significant, as they address the opaque nature of deep learning models. These methodologies offer visual interpretations of model decisions, thereby enhancing trust and practical application in clinical settings. Grad-CAM and Its Variants: Gradient-weighted Class Activation Mapping (Grad-CAM) and its derivatives have gained significant traction in the visualization of model decision-making processes. These methodologies emphasize specific areas of interest within MRI images, thereby assisting clinicians in interpreting model predictions (99). The integration of SHAP (Shapley Additive Explanations) and LIME (Local Interpretable Model-agnostic Explanations) into tailored convolutional neural network (CNN) architectures has been instrumental in enhancing the transparency of tumor detection processes (100). A U-Net framework utilizing ReLU activation has been synergistically combined with Capsule Networks (CapsNets), resulting in an impressive accuracy of 99.2% in brain tumor classification. This methodology capitalizes on the segmentation prowess of U-Net alongside the feature extraction capabilities of CapsNets (101).

A hybrid architecture that merges VGG-16 with ResNet-50 has achieved an average accuracy of 97% across diverse brain tumor datasets, showcasing enhanced generalization and feature learning (102). Techniques such as rotation, flipping, and zooming have been employed to enlarge datasets and mitigate overfitting. These approaches have proven particularly beneficial in improving model efficacy on imbalanced datasets (96). Bayesian Optimization technique has been utilized to fine-tune hyperparameters in deep learning models, leading to improved accuracy and a reduction in the need for manual adjustments (103). AI detection techniques have transformed the identification of brain tumors in medical imaging, providing exceptional accuracy, reliability, and clarity. The incorporation of deep learning algorithms, explainable AI, and hybrid frameworks has established a new standard for diagnostic accuracy. As this domain progresses, forthcoming research will aim to improve the generalizability, interpretability, and practical application of these models in clinical settings.

Stroke prevalence and new AI methods: Stroke is a clinical syndrome characterized by a prolonged cerebral deficit lasting more than 24 hours, with no identifiable cause other than vascular problems. In developed countries, approximately 75-80% of strokes are attributed to brain ischemia, while 10-15% are caused by intracerebral hemorrhage. The diagnosis of stroke primarily depends on the clinical assessment conducted by a specialist. Traumatic brain injury stands as a leading cause of disability and mortality among young adults and children worldwide. In the United States alone, over five million individuals suffer from disabilities associated with traumatic brain injury (104, 105). The application of AI in the realm of stroke detection is a swiftly advancing area, characterized by the development of various AI models and platforms aimed at improving both the accuracy and speed of diagnoses. RapidAI, an AI-driven software platform, is specifically engineered to assist healthcare professionals in identifying large vessel occlusion (LVO) and intracranial hemorrhage (ICH) through the analysis of CT images, thereby enhancing the efficiency of diagnostic processes alongside clinician evaluations (106). Additionally, other AI models, such as Claude 3.5 Sonnet, have demonstrated significant potential in recognizing acute ischemic stroke (AIS) from diffusion-weighted imaging (DWI), exhibiting superior sensitivity and specificity when compared to alternative models like ChatGPT-4o (107, 107).

These developments underscore the promising role of AI in improving stroke detection, although challenges related to accuracy and clinical implementation persist. RapidAI is tailored to support the identification of LVO and ICH, enhancing the interpretation of CT scans by clinicians. It has shown promise in decreasing the turnaround time for radiology reports, achieving a sensitivity of 92% and a specificity of 100% for ICH detection when used in conjunction with clinician assessments. However, the platform's influence on other clinical outcomes, such as mortality rates and quality of life, remains unclear due to insufficient evidence (106). Claude 3.5 Sonnet has surpassed ChatGPT-4o in the detection of AIS from DWI, demonstrating higher specificity (74.5% compared to 3.6%) and a greater level of agreement with radiologists ($\kappa = 0.691$ versus $\kappa = 0.036$). Despite its enhanced performance, Claude 3.5 Sonnet still encounters challenges regarding accuracy, indicating the necessity for further advancements (107). A new approach for assessing stroke detection sensitivity within emergency medical communication centers (EMCC) demonstrated a sensitivity rate of 76.8%, surpassing that of conventional methods. Factors including ischemic strokes and particular symptoms such as aphasia and dysarthria were found to have a positive correlation with the suspicion of stroke, which is crucial for the advancement of future AI decision-support tools. Although AI technologies like RapidAI and Claude 3.5 Sonnet show potential for enhancing stroke detection, their deployment must take into account ethical considerations and issues of equity, including data privacy and fair access (108). Continued research and development are essential to tackle these challenges and improve the clinical utility of AI in stroke diagnosis.

Conclusion

Artificial intelligence (AI) has demonstrated significant potential in neurology for detecting and diagnosing various neurological disorders. AI algorithms facilitate swift and precise analysis of extensive datasets, resulting in more effective diagnostic outcomes. The following are some AI applications in neurology for detection and diagnosis:

Enhanced diagnostic precision: Artificial intelligence has the potential to significantly improve the precision of diagnosing neurodegenerative disorders such as Alzheimer's, Parkinson's, and Stroke by processing intricate data derived from electroencephalography (EEG), neuroimaging, and wearable technology. This advancement may facilitate earlier and more accurate diagnoses, thereby minimizing the duration patients endure while awaiting a conclusive diagnosis.

Non-invasive patient monitoring: The application of AI alongside wearable devices and smartphones enables the continuous, non-invasive observation of patients' health conditions. This approach allows for at-home monitoring, which is more convenient and less anxiety-inducing compared to regular hospital visits.

Economic viability: The adoption of AI technologies for diagnostic and monitoring purposes has the potential to reduce healthcare expenses. By supporting remote patient monitoring and decreasing reliance on extensive hospital facilities, AI can enhance the accessibility and affordability of healthcare services for patients.

Customized treatment strategies: AI can play a crucial role in evaluating treatment efficacy and forecasting disease progression. This functionality empowers healthcare providers to customize treatment strategies for individual patients, thereby enhancing health outcomes and overall quality of life.

Collaborative interdisciplinary efforts: The incorporation of AI into clinical settings requires a collaborative effort between information technology experts and healthcare practitioners. This interdisciplinary strategy ensures that AI tools are developed and implemented effectively, merging technical proficiency with medical insight.

Acknowledgments

I would like to thank Babol University of Medical Sciences for their utmost support.

Ethics approval: Not applicable.

Funding: This research did not receive any external funding or grants.

Conflict of interests: The authors declare that there is no conflict of interest regarding the publication of this paper.

Authors' contribution: Hadi Ebrahimi: Conceptualization, Methodology, Validation, Investigation, Data curation, Writing-original draft, Writing-review & editing. Zohre Eftekhari: Conceptualization, Methodology, Resources, Writing-review & editing, Supervision. Saber Abbaszadeh and Ebrahim Hejazian: Conceptualization, Methodology, Formal analysis, Resources, Data curation, Writing-review & editing, Supervision, Project administration.

References

1. Turner R, Jones T. Techniques for imaging neuroscience. Br Med Bull 2003; 65: 3–20.
2. Hecht MJ, Fellner F, Fellner C, et al. MRI-FLAIR images of the head show corticospinal tract alterations in ALS patients more frequently than T2-, T1-and proton-density-weighted images. J Neurol Sci 2001; 186: 37–44.
3. Ganzetti M, Wenderoth N, Mantini D. Whole brain myelin mapping using T1-and T2-weighted MR imaging data. Front Hum Neurosci 2014; 8: 671.
4. Braus DF, Tost H, Hirsch JG, Gass A. Diffusion tensor imaging (DTI) and functional magnetic resonance imaging (fMRI): additional methods for psychiatric research. Nervenarzt 2001; 72: 384–90.
5. MacCormac O, Noonan P, Elliot M, et al. Lightfield hyperspectral imaging in neuro-oncology surgery: an IDEAL 0 and 1 study. Front Neurosci 2023; 17: 1239764.

6. Soloukey S, Vincent AJPE, Satoer DD, et al. Functional ultrasound (fUS) during awake brain surgery: the clinical potential of intra-operative functional and vascular brain mapping. Front Neurosci 2020; 13: 1384.
7. Dumurgier J, Tzourio C. Epidemiology of neurological diseases in older adults. Rev Neurol (Paris) 2020; 176: 642–8.
8. Villa C, Miquel C, Mosses D, Bernier M, Di Stefano AL. The 2016 World Health Organization classification of tumours of the central nervous system. Presse Med 2018; 47: e187–200.
9. Singh K, Malhotra D. Meta-health: Learning-to-learn (meta-learning) as a next generation of deep learning exploring healthcare challenges and solutions for rare disorders: A systematic analysis. Arch Comput Methods Eng 2023; 30: 4081-112.
10. Ji SY, Jayarathna S, Perrotti AM, Kardiasmenos K, Jeong DH. Identifying patterns for neurological disabilities by integrating discrete wavelet transform and visualization. Appl Sci 2024; 14: 273.
11. Igo’r VD, Romanov DV, Ninoy IV. Features of mental disorders in neurological disease. Russ Med 2019; 25: 335–42.
12. Athisakthi A, Pushpa Rani M. Recognize vital features for classification of neurodegenerative diseases. In: Advances in computational intelligence: Proceedings of second international conference on computational intelligence 2018. Springer 2020; pp: 287–301.
13. Khan P, Kader MF, Islam SR, et al. Machine learning and deep learning approaches for brain disease diagnosis: Principles and recent advances. IEEE Access 2021; 9: 37622–55.
14. Alowais SA, Alghamdi SS, Alsuhebany N, et al. Revolutionizing healthcare: the role of artificial intelligence in clinical practice. BMC Med Educ 2023; 23: 689.
15. Raghavendra U, Acharya UR, Adeli H. Artificial intelligence techniques for automated diagnosis of neurological disorders. Eur Neurol 2020; 82: 41–64.
16. Ienca M, Ignatiadis K. Artificial intelligence in clinical neuroscience: methodological and ethical challenges. AJOB Neurosci 2020; 11: 77–87.
17. Raut R. Neurosurgery across the globe. In: Surviving neurosurgery: Vignettes of resilience. Springer 2022; pp: 189–94.
18. Mofatteh M. Neurosurgery and artificial intelligence. AIMS Neurosci 2021; 8: 477-95.
19. Hardy M, Harvey H. Artificial intelligence in diagnostic imaging: impact on the radiography profession. Br J Radiol 2020; 93: 20190840.
20. Ridler C. Artificial intelligence accelerates detection of neurological illness. Nat Rev Neurol 2018; 14: 572.
21. Soori M, Arezoo B, Dastres R. Artificial intelligence, machine learning and deep learning in advanced robotics, A review. Cogn Robot 2023; 3: 54-70.
22. Kang J, Chowdhry AK, Pugh SL, Park JH. Integrating artificial intelligence and machine learning into Cancer clinical trials. In: Seminars in Radiation Oncology. Elsevier 2023; pp: 386–94.
23. Prabhakar B, Singh RK, Yadav KS. Artificial intelligence (AI) impacting diagnosis of glaucoma and understanding the regulatory aspects of AI-based software as medical device. Comput Med Imaging Graph 2021; 87: 101818.
24. Patel UK, Anwar A, Saleem S, et al. Artificial intelligence as an emerging technology in the current care of neurological disorders. J Neurol 2021; 268: 1623–42.
25. Chan H, Hadjiiski LM, Samala RK. Computer-aided diagnosis in the era of deep learning. Med Phys 2020; 47: e218–27.
26. Krauss JK, Lipsman N, Aziz T, et al. Technology of deep brain stimulation: current status and future directions. Nat Rev Neurol 2021; 17: 75–87.
27. Udousoro IC. Machine learning: A review. Semicond Sci Inf Devices 2020; 2: 5–14.
28. He B, Yang L, Wilke C, Yuan H. Electrophysiological imaging of brain activity and connectivity-challenges and opportunities. IEEE Trans Biomed Eng 2011; 58: 1918–31.
29. Zhao W, Zhao W, Wang W, et al. A novel deep neural network for robust detection of seizures using EEG signals. Comput Math Methods Med 2020; 2020: 9689821.
30. Ahmed H, Dada MO, Samaila B. Current challenges of the state-of-the-art of AI techniques for diagnosing brain tumor. Mater Sci Eng 2023; 7: 196–208.
31. Jian A, Liu S, Di Ieva A. Artificial intelligence for survival prediction in brain tumors on neuroimaging. Neurosurgery 2022; 91: 8–26.
32. Ranjbarzadeh R, Caputo A, Tirkolaee EB, Ghoushchi SJ, Bendechache M. Brain tumor segmentation of MRI images: A comprehensive review on the application of artificial intelligence tools. Comput Biol Med 2023; 152: 106405.
33. Gull S, Akbar S. Artificial intelligence in brain tumor detection through MRI scans: advancements and challenges. 1st ed. Artif Intell Internet Things 2021; pp: 241–76.

34. Madhuri GS, Mahesh TR, Vivek V. A novel approach for automatic brain tumor detection using machine learning algorithms. In: Big data management in Sensing. 1st ed. River Publishers 2022; pp: 87–101.
35. Taha AMH, Ariffin D, Abu-Naser SS. A systematic literature review of deep and machine learning algorithms in brain tumor and meta-analysis. J Theor Appl Inf Technol 2023; 10: 21–36.
36. Tangsrivimol JA, Schonfeld E, Zhang M, et al. Artificial intelligence in neurosurgery: A state-of-the-art review from past to future. Diagnostics (Basel, Switzerland) 2023; 13: 2429.
37. Clusmann J, Kolbinger FR, Muti HS, et al. The future landscape of large language models in medicine. Commun Med 2023; 3: 141.
38. Romano MF, Shih LC, Paschalidis IC, Au R, Kolachalama VB. Large language models in neurology research and future practice. Neurolog. 2023; 101: 1058–67.
39. Emmady PD, Schoo C, Tadi P. Major Neurocognitive Disorder (Dementia). In: StatPearls. Treasure Island (FL): StatPearls Publishing 2025. Available from: https://www.ncbi.nlm.nih.gov/books/NBK557444/. Accessed Nov 19, 2022.
40. Hacking C, Verbeek H, Hamers JPH, Aarts S. The development of an automatic speech recognition model using interview data from long-term care for older adults. J Am Med Inform Assoc 2023; 30: 411–7.
41. Pan Y, Mirheidari B, Harris JM, et al. Using the outputs of different automatic speech recognition paradigms for acoustic-and BERT-based alzheimer's dementia detection through spontaneous speech. In: Interspeech 2021; pp: 3810–4.
42. Yang Z, Yeo YH, Jiang R, et al. Injecting visual features into whisper for parameter-efficient noise-robust audio-visual speech recognition. InICASSP 2025-2025 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP) 2025; pp: 1-5
43. Palliya Guruge C, Oviatt S, Delir Haghighi P, Pritchard E. Advances in multimodal behavioral analytics for early dementia diagnosis: A review. In: Proceedings of the 2021 International Conference on Multimodal Interaction 2021; pp: 328–40.
44. Li R, Wang X, Lawler K, et al. Applications of artificial intelligence to aid early detection of dementia: A scoping review on current capabilities and future directions. J Biomed Inform 2022; 127: 104030.
45. Yousefi M, Akhbari M, Mohamadi Z, et al. Machine learning based algorithms for virtual early detection and screening of neurodegenerative and neurocognitive disorders: a systematic-review. Front Neurol 2024; 15: 1413071.
46. Idris A, Alabdaljabar MS, Almiro A, et al. Prevalence, incidence, and risk factors of epilepsy in arab countries: A systematic review. Seizure 2021; 92: 40–50.
47. Beghi E. The epidemiology of epilepsy. Neuroepidemiology 2020; 54: 185–91.
48. Kerr WT, McFarlane KN. Machine Learning and artificial intelligence applications to epilepsy: A review for the practicing epileptologist. Curr Neurol Neurosci Rep 2023; 23: 869–79.
49. Ito Y, Fukuda M, Matsuzawa H, et al. Deep learning-based diagnosis of temporal lobe epilepsy associated with hippocampal sclerosis: An MRI study. Epilepsy Res 2021; 178: 106815.
50. García-Ramó KB, Sanchez-Catasus CA, Winston GP. Deep learning in neuroimaging of epilepsy. Clin Neurol Neurosurg 2023; 232: 107879.
51. Suresh S, Khetavath S. EEG-based epileptic seizure detection using DconvNET. Fusion Pract Appl 2025; 17: 219–31.
52. Dhondiyal SA, Dimri SC. Detection and treatment of epilepsy disease using EEG signals. International Conference on Cybernation and Computation (CYBERCOM), Dehradun, India, 2024; pp: 251–5.
53. Tsiouris K, Pezoulas V, Zervakis M, et al. A long short-term memory deep learning network for the prediction of epileptic seizures using EEG signals. Comput Biol Med 2018; 99: 24-37.
54. Jeong H, Lee K, Kim S, Kang HC, Yang D. Deep learning-based real-time seizure detection and multi-seizure classification on pediatric EEG. Front Neurol 2026; 17: 1726258.
55. Cao Q, Tan CC, Xu W, et al. The prevalence of dementia: a systematic review and meta-analysis. J Alzheimer's Dis 2020; 73: 1157–66.
56. Livingston G, Huntley J, Sommerlad A, et al. Dementia prevention, intervention, and care: 2020 report of the Lancet Commission. Lancet 2020; 396: 413–46.
57. Moon W, Han JW, Bae JB, et al. Disease burdens of Alzheimer's disease, vascular dementia, and mild cognitive impairment. J Am Med Dir Assoc 2021; 22: 2093–9.
58. El-Assy AM, Amer HM, Ibrahim HM, Mohamed MA. A novel CNN architecture for accurate early detection and classification of Alzheimer's disease using MRI data. Sci Rep 2024; 14: 3463.
59. Mohammed EM, Fakhrudeen AM, Alani OY. Detection of Alzheimer's disease using deep learning

models: A systematic literature review. Informatics Med Unlocked 2024; 50: 101551.
60. Alwakid G, Tahir S, Humayun M, Gouda W. Improving Alzheimer's detection with deep learning and image processing techniques. in IEEE Access 2024; 12: pp: 153445-56.
61. Pichandi S, Balasubramanian G, Chakrapani V. Hybrid deep models for parallel feature extraction and enhanced emotion state classification. Sci Rep 2024; 14: 24957.
62. YİĞİT A, Işik Z. Applying deep learning models to structural MRI for stage prediction of Alzheimer's disease. Turkish J Electr Eng Comput Sci. 2020; 28: 196–210.
63. Iizuka T, Fukasawa M, Kameyama M. Deep-learning-based imaging-classification identified cingulate island sign in dementia with Lewy bodies. Sci Rep 2019; 9: 8944.
64. Wu JC, Chien TC, Chang CC, et al. Learning-based progression detection of Alzheimer's disease using 3D MRI images. Int J Intell Syst 2025; 2025: 3981977.
65. Noviandy TR, Idroes GM, Purnawarman A, et al. Enhancing early detection of Alzheimer's disease through MRI using explainable artificial intelligence. Indones J Case Reports 2024 2: 43–51.
66. Sivasundarapandian S, Ramamurthy CK, Boya TN, Matheswaran S. Decoding Alzheimer's AI-powered biomarker analysis for diagnosis and monitoring. In: Deep generative models for integrative analysis of Alzheimer's biomarkers. IGI Global Scientific Publishing 2025; pp: 27–50.
67. Bratić B, Kurbalija V, Ivanović M, Oder I, Bosnić Z. Machine learning for predicting cognitive diseases: methods, data sources and risk factors. J Med Syst 2018; 42: 1–15.
68. Ghaffar Nia N, Kaplanoglu E, Nasab A. Evaluation of artificial intelligence techniques in disease diagnosis and prediction. Discov Artif Intell 2023; 3: 5.
69. Ho TKK, Kim M, Jeon Y, et al. Deep learning-based multilevel classification of Alzheimer's disease using non-invasive functional near-infrared spectroscopy. Front Aging Neurosci 2022; 14: 810125.
70. Ou Z, Pan J, Tang S, et al. Global trends in the incidence, prevalence, and years lived with disability of Parkinson's disease in 204 countries/territories from 1990 to 2019. Front public Heal 2021; 9: 776847.
71. Balestrino R, Schapira AHV. Parkinson disease. Eur J Neurol 2020; 27: 27–42.
72. Rumman M, Tasneem AN, Farzana S, Pavel MI, Alam MA. Early detection of Parkinson's disease using image processing and artificial neural network. In: 2018 Joint 7th International Conference on Informatics, Electronics & Vision (ICIEV) and 2018 2nd International Conference on Imaging, Vision & Pattern Recognition (icIVPR). IEEE 2018; pp: 256–61.
73. Pereira HR, Ferreira HA. Classification of patients with Parkinson's disease using medical imaging and artificial intelligence algorithms. InMediterranean Conference on Medical and Biological Engineering and Computing 2019 Sep 25. Cham: Springer International Publishing 2020; pp: 2043–56.
74. Xu J, Zhang M. Use of magnetic resonance imaging and artificial intelligence in studies of diagnosis of Parkinson's disease. ACS Chem Neurosci 2019; 10: 2658–67.
75. Khachnaoui H, Mabrouk R, Khlifa N. Machine learning and deep learning for clinical data and PET/SPECT imaging in Parkinson's disease: a review. IET Image Process 2020; 14: 4013–26.
76. Subbulakshmi B, Prasanna S, Rakshana Malya A, Mahesh S, Jeevapriya GM. Parkinson's disease detection via MRI: A machine learning approach with XAI integration. In2024 5th International Conference on Data Intelligence and Cognitive Informatics (ICDICI) 2024 Nov 18. IEEE 2024; pp: 948–56.
77. Akram S, Mothadaka A, Shaik P, Mandala M, Pandi N. Comparative analysis using machine learning algorithms to detect Parkinson's disease using voice dataset. Int J Res Appl Sci Eng Technol 2024; 12: 1933–42.
78. Yadav D, Jain I. Comparative analysis of machine learning algorithms for Parkinson's disease prediction. In2022 6th International Conference on Intelligent Computing and Control Systems (ICICCS) 2022 May 25. IEEE 2022; 1334–9.
79. Zayed N, Tawfik N. A random forest-based methodology for superior performance in voice-assisted early detection and remote monitoring of Parkinson's disease. J Electr Syst Inf Technol. 2026; 13: 41.
80. Mukhtar A, Khalid S, Toor WT, Akhtar MS. Detection of Parkinson's disease from voice signals using explainable artificial intelligence. In2024 3rd International Conference on Emerging Trends in Electrical, Control, and Telecommunication Engineering (ETECTE) 2024; pp: 1–6.
81. McGinley MP, Goldschmidt CH, Rae-Grant AD. Diagnosis and treatment of multiple sclerosis: A review. JAMA 2021; 325: 765-79.

82. Tian DC, Zhang C, Yuan M, et al. Incidence of multiple sclerosis in China: a nationwide hospital-based study. Lancet Reg Heal Pacific 2020; 1: 10010.
83. Vidal-Jordana A, Rovira A, Arrambide G, et al. Optic nerve topography in multiple sclerosis diagnosis: the utility of visual evoked potentials. Neurology 2021; 96: e482–90.
84. Montolío A, Martín-Gallego A, Cegoñino J, et al. Machine learning in diagnosis and disability prediction of multiple sclerosis using optical coherence tomography. Comput Biol Med 2021; 133: 104416.
85. Mirmosayyeb O, Zivadinov R, Weinstock-Guttman B, Benedict RHB, Jakimovski D. Optical coherence tomography (OCT) measurements and cognitive performance in multiple sclerosis: a systematic review and meta-analysis. J Neurol 2023; 270: 1266–85.
86. Siva RV, Zeema Loveline J, Deepa S. Diagnosis of multiple sclerosis lesion using deep learning models. J Electr Syst 2024; 20: 2354–67.
87. Mercioni MA, Holban Ş, Dumache R. Novel activation function Design for Multiple Sclerosis Detection in Medical Imaging. In2024 E-Health and Bioengineering Conference (EHB) 2024 Nov 14. IEEE 2024; pp: 1–4.
88. Mohsenpourian M, Suratgar AA, Talebi HA, et al. Design of a computational intelligence system for detection of multiple sclerosis with visual evoked potentials. Neurosci Informatics 2025; 5: 100177.
89. Khattap MG, Abd Elaziz M, Hassan HGEMA, Elgarayhi A, Sallah M. AI-based model for automatic identification of multiple sclerosis based on enhanced sea-horse optimizer and MRI scans. Sci Rep 2024; 14: 12104.
90. Nabizadeh F, Masrouri S, Ramezannezhad E, et al. Artificial intelligence in the diagnosis of multiple sclerosis: A systematic review. Mult Scler Relat Disord 2022; 59: 103673.
91. Cash RFH, Weigand A, Zalesky A, et al. Using brain imaging to improve spatial targeting of transcranial magnetic stimulation for depression. Biol Psychiatry 2021; 90: 689–700.
92. Chattopadhyay A, Maitra M. MRI-based brain tumour image detection using CNN based deep learning method. Neurosci informatics 2022; 2: 100060.
93. Su C, Chen X, Liu C, et al. T2-FLAIR, DWI and DKI radiomics satisfactorily predicts histological grade and Ki-67 proliferation index in gliomas. Am J Transl Res 2021; 13: 9182-94.
94. Dong J, Li S, Li L, et al. Differentiation of paediatric posterior fossa tumours by the multiregional and multiparametric MRI radiomics approach: A study on the selection of optimal multiple sequences and multiregions. Br J Radiol 2022; 95: 20201302.
95. Chand M, Murmu MK. Enhancing brain tumor identification with efficientNetB4 in MRI imaging. In2024 5th International Conference on Circuits, Control, Communication and Computing (I4C) 2024 Oct 4. IEEE 2024; pp: 531–7.
96. Noori M, Ahmed M, Ibrahim A, et al. Deep learning-based approaches for accurate brain tumor detection in MRI images. In2024 International Conference on Decision Aid Sciences and Applications (DASA) 2024 Dec 11. IEEE 2024; pp: 1–7.
97. Kumpatla G, Veresi H, Abhishek S. Revolutionizing brain tumour prediction: A pioneering gan-based framework for synthetic data generation. In2023 7th International Conference on I-SMAC (IoT in Social, Mobile, Analytics and Cloud)(I-SMAC) 2023 Oct 11. IEEE 2023; pp: 548–53.
98. Jraba S, Elleuch M, Ltifi H, Kherallah M. Enhanced brain tumor detection using integrated CNN-ViT framework: A novel approach for high-precision medical imaging analysis. In2024 10th International Conference on Control, Decision and Information Technologies (CoDIT) 2024 Jul 1. IEEE 2024; pp: 2120–5.
99. Zhang Y, Hong D, McClement D, et al. Grad-CAM helps interpret the deep learning models trained to classify multiple sclerosis types using clinical brain magnetic resonance imaging. J Neurosci Methods 2021; 353: 109098.
100. Nazir MI, Akter A, Hussen Wadud MA, Uddin MA. Utilizing customized CNN for brain tumor prediction with explainable AI. Heliyon 2024; 10: e38997.
101. Stanley BF, Shajeena J, Leena MA, Saumiya S, Ebenezer R. A Multimodal deep learning architecture for accurate brain tumor detection and classification. In2024 International Conference on Power, Energy, Control and Transmission Systems (ICPECTS) 2024 Oct 8. IEEE 2024; pp: 1–5.
102. Ropa YM, Moon KR, Singh T. Deep learning-based hybrid framework utilizing openCV and CNN for automated brain tumor detection and MRI image classification. In2024 4th International Conference on Sustainable Expert Systems (ICSES) 2024 Oct 15. IEEE 2024; pp: 1674–82.
103. Lakshmi K, Amaran S, Subbulakshmi G, et al. Explainable artificial intelligence with UNet based segmentation and Bayesian machine learning for classification of brain tumors using MRI images. Sci Rep 2025; 15: 690.

104. Saini V, Guada L, Yavagal DR. Global epidemiology of stroke and access to acute ischemic stroke interventions. Neurology 2021; 97: S6–16.
105. Krishnamurthi RV, Ikeda T, Feigin VL. Global, Regional and country-specific burden of ischaemic stroke, intracerebral haemorrhage and subarachnoid haemorrhage: A systematic analysis of the global burden of disease study 2017. Neuroepidemiology 2020; 54: 171-9.
106. Canada's Drug Agency (CDA-AMC). RapidAI for stroke detection. Can J Heal Technol 2024; 4. Available from: https://www.cda-amc.ca/rapidai-stroke-detection. Accessed May 21, 2025.
107. Koyun M, Taskent I. Evaluation of advanced artificial intelligence algorithms’ diagnostic efficacy in acute ischemic stroke: A comparative analysis of ChatGPT-4o and Claude 3.5 sonnet models. J Clin Med 2025; 14: 571.
108. Almutairi A, Wirawan F, Lloyd A, Moullaali T, Clegg G. Methods for improving the identification of acute stroke during ambulance calls: A scoping review. PloS One 2025; 13; 20: e0327653.
109. Kunduru AR. Machine learning in drug discovery: A comprehensive analysis of applications, challenges, and future directions. Int J Orange Technol 2023; 5: 29–37.